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In memoriam:

Prof. Dr. Anton Pavel Železnikar
(1928-2026)

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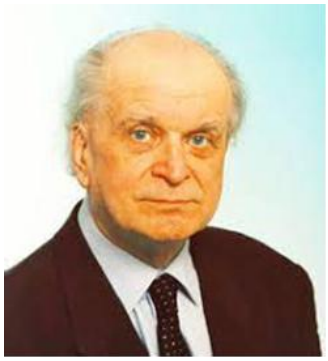
In memoriam: Prof. Dr. Anton Pavel Železnikar (1928-2026)



The Editorial Board of *Informatica* and the Slovenian Society INFORMATIKA pay tribute to Prof. Dr. Anton Pavel Železnikar, one of the pioneers of computer science and informatics in Slovenia and the former Yugoslavia, an outstanding researcher, professor, visionary, and founder of this journal.
Prof. Dr. Anton Pavel Železnikar belonged to the generation that laid the foundations of modern computing in Slovenia. After graduating in electrical engineering from the University of Ljubljana, he joined the Jožef Stefan Institute in 1955, where he worked until 1980. In those early decades of digital technology, when research was still closely tied to hardware based on vacuum tubes and transistors, he was already looking far ahead, toward algorithms, formal languages, compilers, information logic, and later parallel computer systems, artificial intelligence, and consciousness. His scientific breadth was exceptional, and his work often anticipated directions that would become central only much later. At the Jožef Stefan Institute he served as Head of the Digital Techniques Section from 1961 to 1978 and as Head of the Department of Electronics from 1968 to 1978. In these roles he made an enduring contribution to the institutional and scientific development of Slovenian computing research. He was also deeply engaged in academic life. He taught at the University of Ljubljana, where he became full professor in 1982, especially in the area of compilers, and he lectured as well at the University of Maribor on philosophy and theory of informatics. Through his teaching and mentorship, he helped shape generations of students and researchers.

In 1980 he moved to Iskra Delta Computers, one of the key high-technology companies in Slovenia at the time. There he continued to connect research, engineering, and development strategy. Among other contributions, he was the author of the concept of parallel processing that led to the innovative Triglav–Trident computer with three processors. He later served as adviser to the general director and as a member of the management responsible for research and development strategy within the Iskra corporation. In this way, he played an important role not only in science and higher education, but also in linking advanced computing ideas with industrial development.

His international and professional engagement was equally important. He represented Yugoslavia in International Federation for Information Processing (IFIP) between 1967 and 1975 and organized the IFIP World Congress in Ljubljana in 1971, a major event that significantly strengthened the international visibility of Slovenian informatics. He also contributed actively to the broader professional community through conferences, societies, and editorial work. In 1976 he co-founded Slovenian Society INFORMATIKA and served the Society as its first president.
For *Informatica*, his contribution was of special and lasting importance. He established the journal *Informatica* in 1977 and served for many years as its Editor-in-Chief, helping shape its identity, standards, and long-term international recognition. Under his guidance, the journal became an important scientific forum for computer science, informatics, cybernetics, artificial intelligence, and related disciplines. His editorial leadership helped define the journal's identity and standards in its formative years, while also contributing more broadly to the development of the Slovenian informatics community. The continued existence and international recognition of *Informatica* remain closely connected to his vision and dedication.

Prof. Dr. Železnikar's scientific work covered a wide spectrum, including switching circuit theory, algebraic logic, automata, algorithms, information logic, parallel computer systems, strategy of the computer industry, and later artificial intelligence and consciousness. In his long and productive career, he published more than one hundred scientific and professional works in several languages, as well as two books and a number of university-level teaching materials. His work was not limited to narrow technical problems; he sought broader conceptual foundations of information, computation, and cognition. This made him not only a scientist and engineer, but also a thinker with rare intellectual reach.

He received numerous recognitions for his work and was associated with several distinguished international academies and professional organizations. Yet perhaps his greatest legacy lies in the institutions, ideas, and communities he helped build: at the Jožef Stefan Institute, in Slovenian computing research and industry, in university education, in professional societies, and in this journal.

Prof. Dr. Anton Pavel Železnikar remains in our memory as a visionary of Slovenian informatics, a scholar of exceptional originality and breadth, and one of the key builders of the field. The journal *Informatica* owes an important part of its history to his initiative, leadership, and long-standing editorial commitment.

We remember him with gratitude, admiration, and respect.

Assoc. Prof. Dr. Slavko Žitnik, President of Slovenian Society INFORMATIKA

Prof. Dr. Matjaž Gams, Editor-in-Chief of *Informatica*

Credit Card Fraud Detection Using Hybrid Proximal Policy Optimization and Artificial Bee Colony Optimization with Mutual Learning

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The surge in e-commerce has intensified credit card fraud, resulting in massive global losses and creating an urgent need for stronger detection systems. This research presents an advanced model for detecting credit card fraud to address challenges often overlooked, such as class imbalance and sensitivity to initial parameter settings. Our model leverages an artificial neural network (ANN) to extract feature vectors necessary for accurate fraud detection. We utilize proximal policy optimization (PPO) to address class imbalance during training of the ANN. PPO improves the treatment of minority classes by assigning higher rewards for correct predictions and more substantial penalties for errors. This approach leads to more balanced learning. Additionally, our model incorporates a mutual learning-based artificial bee colony (ML-ABC) algorithm for efficiently pre-training the parameters of the ANN. Experiments on the Université Libre de Bruxelles credit card dataset show that the proposed approach achieves 90.197% accuracy and an F-measure of 91.287%. It outperforms the best existing method by about 3%. These results highlight the robustness of the model and its potential for real-world e-commerce fraud detection.

Povzetek: Raziskava predstavlja napreden model za zaznavanje goljufij s kreditnimi karticami, ki izboljšuje natančnost in presega obstoječe metode.

1 Introduction

Credit card fraud poses a significant threat to e-commerce, resulting in substantial financial losses for both businesses and consumers. Reports indicate that in the first quarter of 2018, fraud in e-commerce transactions increased at a faster rate than overall transaction volumes in 2016 [1]. The E-commerce Fraud Index reported a sharp rise in account takeover cases in online department stores. Rates increased from 0.06% in 2016 to 0.23% in 2017, contributing to more than 10% of total fraud losses [2]. Although credit card fraud represents only 0.1% of all card transactions, the large amounts involved make it highly damaging [3]. Therefore, an automated fraud detection system is essential. This paper presents a deep learning–based method for detecting credit card fraud. The method addresses two challenges: class imbalance and sensitivity to initial parameter settings.

Various approaches are used to detect credit card fraud, including statistical, machine learning (ML), and deep learning (DL) methods [4–6]. A key challenge in fraud detection is data imbalance, where legitimate transactions far outnumber fraudulent ones. This imbalance often biases model predictions and reduces the effectiveness of detection. To address this, researchers use both data-centric and algorithmic strategies [7]. Data-level techniques such as down-sampling and up-sampling aim to balance class distribution. Algorithm-level methods focus on improving the performance of minority classes. At the data level, skewed transaction distributions emphasize common patterns, sidelining rare but critical fraud cases. From an algorithmic perspective, the main challenge is to refine learning to capture rare but essential data. This refinement improves predictive accuracy and reliability. Deep reinforcement learning (DRL) has proven effective in managing class imbalances by filtering irrelevant data and emphasizing key features. Its strength lies in reward-based adaptation, enabling models to focus on underrepresented classes. By refining reward functions, DRL improves its sensitivity to critical yet overlooked cases. However, DRL also faces the bias-variance trade-off. To solve this problem, we use an advanced version of DRL, i.e., PPO. PPO is an advanced on-policy reinforcement learning algorithm. It uses a clipping mechanism to stabilize training and prevent excessive policy updates, ensuring efficiency in complex, continuous-variable environments.

DL models often use backpropagation to adjust weights and reduce errors. Despite its effectiveness, backpropagation is sensitive to initial weight settings and can become trapped in local minima, especially in classification tasks. To overcome these issues, researchers use meta-heuristic algorithms. Examples include the arithmetic optimization algorithm (AOA) [8], puma

optimizer (PO) [9], sparrow search algorithm (SSA) [10], chaotic sand cat swarm optimization (CSCSO) [11], whale optimization algorithm (WOA) [12], and political sand cat swarm optimization (PSCSO) [13]. These approaches enhance the search process, enabling models to avoid getting stuck in local minima. Among them, the ABC algorithm is particularly promising. The ABC algorithm is inspired by honey bee foraging. It balances exploration and exploitation in the search space, enabling the discovery of global optima in complex optimization tasks. It is effective in managing high-dimensional data and avoiding premature convergence, improving robustness and generalization. Furthermore, this study applies an advanced version, ML-ABC, which incorporates mutual learning to address weight initialization issues in gradient-based methods. By promoting information exchange, ML-ABC enhances adaptability and ensures more reliable optimization outcomes.

This study examines whether combining PPO reinforcement learning with ML-ABC optimization improves credit card fraud detection in imbalanced datasets. It focuses on three key elements:

- Research question: Can PPO and ML-ABC together outperform traditional ML and DL models in handling class imbalance for fraud detection?
- Hypotheses: 1) PPO increases sensitivity to minority (fraud) classes; 2) ML-ABC improves parameter initialization and lowers the risk of local minima.
- Goals: To design a model that (i) mitigates class imbalance, 1) stabilizes training through optimized initialization, and 2) improves robustness in fraud detection.

The key contributions of the dissertation are outlined below:

- PPO for imbalanced classification: The model uses PPO to address imbalanced credit card datasets. In such datasets, fraudulent transactions are much rarer than legitimate ones. PPO applies reward-based learning and clipping mechanisms. These methods direct attention to patterns in minority classes, increase sensitivity to fraud, and support stable training in dynamic environments.
- ML-ABC for initial weighting: The model introduces ML-ABC optimization for initializing network weights. This technique enhances exploration and exploitation in the solution space. It also prevents premature convergence and improves adaptability. ML-ABC provides optimized starting weights. This reduces vulnerability to local minima, leading to more reliable convergence and robust fraud detection.

The structure of this paper is organized as follows: Section 2 provides a literature review, while Section 3 describes our method for detecting credit card fraud. Section 4 presents the experimental outcomes, and Section 5 concludes the paper by summarizing the key findings.

2 Related works

This part provides an overview of credit card fraud recognition systems and methods developed in previous work. This area of investigation can be embodied in three groups: statistical, ML, and DL.

2.1 Statistical methods

Statistical methods are extensively applied to detect credit card fraud by analyzing the statistical patterns in transaction data [14]. These techniques focus on identifying anomalies by setting thresholds or following specific criteria. Common approaches include descriptive statistics, hypothesis testing, and time series analysis [15]. Descriptive statistics, such as mean, standard deviation, and percentiles, are used to detect irregular transactions [16]. Hypothesis testing distinguishes between legitimate and fraudulent transactions by using null and alternative hypotheses, employing statistical tests such as t-tests and chi-square tests [1]. Time series models, including ARIMA (AutoRegressive Integrated Moving Average) [17] and STL (Seasonal and Trend Decomposition using Loess) [18], are employed to uncover trends and patterns in transaction data that may signal fraud. These models help identify and predict deviations from normal behavior, thereby enhancing the proactive detection of fraudulent activities.

Although statistical methods are key in detecting credit card fraud, they face several limitations. These techniques depend heavily on precise threshold settings or predefined criteria. When thresholds are set too stringently, legitimate transactions may be incorrectly flagged as fraudulent, causing inconvenience and customer dissatisfaction. On the other hand, lenient thresholds may allow actual fraudulent activities to go unnoticed, increasing the risk of financial loss for institutions. Moreover, techniques such as descriptive statistics and hypothesis testing are based on assumptions about the distribution and behavior of transaction data, which may not always hold, especially given the dynamic and varied nature of financial transactions. Such assumptions can lead to false conclusions and the failure to detect fraud.

2.2 ML

ML algorithms have become indispensable in combating credit card fraud because they can learn from data, detect intricate patterns, and predict fraudulent activities.

In 2024, Khalid et al. [1] developed an ensemble ML system combining support vector machine (SVM), k-nearest neighbor (KNN), random forest (RF), bagging, and boosting. They used the synthetic minority over-sampling technique (SMOTE) and under-sampling to address the imbalance. Gajakosh et al. [2] proposed an unsupervised SVM model. The model is enhanced with competitive swarm optimization (CSO) to detect anomalies and reveal hidden fraud in online transactions. Suardiman et al. [19] developed a fraud detection model utilizing Gaussian Naïve Bayes, KNN, and RF algorithms to enhance the identification of fraudulent e-commerce transactions. Odeyale et al. [20] employed SMOTE and analysis of variance (ANOVA) F-statistics for data balancing and feature selection, thereby enhancing the performance of SVM on highly imbalanced credit card fraud datasets. Umalwara et al. [21] introduced a real-time

fraud detection system that utilizes adaptive ML (AML), enabling dynamic learning and rapid responses to unauthorized credit card transactions. Loukili et al. [22] implemented a detection system using categorical boosting (CatBoost), adaptive boosting (AdaBoost), and extreme gradient boosting (XGBoost). They compared the model's using precision, accuracy, and latency to evaluate performance in fraud detection.

In 2025, Salam et al. [23] implemented federated learning (FL) using TensorFlow Federated and PyTorch frameworks for credit card fraud detection (CCFD), integrating individual and hybrid resampling techniques to address class imbalance across distributed, privacy-preserving datasets. Kokate et al. [24] employed SVM models with various kernel functions, including the radial basis function (RBF), to classify credit card transactions as either fraudulent or legitimate based on historical transaction behavior patterns. Wang [25] proposed an ensemble ML model combined with the SMOTE using k-means clustering (SMOTE-KMEANS) to enhance fraud detection by addressing data imbalance in classification tasks. Baisholan et al. [26] developed an ensemble ML framework that integrates RF and XGBoost, applying probability averaging and threshold optimization to address fraud detection with interpretability using shapley additive explanations (SHAP).

2.3 DL

DL utilizes multi-layered neural networks that excel at capturing complex patterns and essential features within high-dimensional data, making it highly effective for fraud detection.

In 2023, Xie et al. [27] proposed a convolutional neural network (CNN) framework for detecting e-commerce fraud. It reduces parameters through local perception fields and weight sharing. Their model addresses overfitting, handles imbalanced datasets, and improves the prediction accuracy of fraudulent activities. Karthika et al. [28] introduced a one-dimensional dilated convolutional neural network (DCL) to detect credit card fraud. The model captures spatial-temporal features and mitigates data imbalance by utilizing under-sampling and over-sampling techniques, thereby enhancing detection accuracy. Balawi et al. [29] reviewed advancements in credit card fraud detection and classified prevention systems into categories. They evaluated ANN and CNN models, demonstrating that optimized deep neural networks enhance accuracy and reduce fraudulent activity in credit card datasets. Berhane et al. [30] developed a hybrid model that combines a CNN for feature extraction and an SVM for classification. They replaced the CNN output layer with an SVM, which improved fraud detection in online transactions. Fanai et al. [31] proposed a two-stage framework that utilizes a deep autoencoder for representation learning and supervised DL for fraud detection. This method enhanced classifier accuracy and robustness compared to training on raw or principal component analysis (PCA)-transformed data.

In 2024, Ida et al. [3] designed a long short-term memory (LSTM)–driven framework with an early stopping strategy to identify fraudulent credit card transactions. Their method leverages sequential transaction patterns, thereby reducing the risk of overfitting and enhancing model generalization. Suganthi and Jebathangam [32] employed a gated recurrent unit (GRU) model for fraud detection in mobile payments. The approach utilizes GRU to manage temporal data efficiently. It trains faster, detects fraud in real-time, and reduces computational costs compared to LSTM. Mienye and Swart [33] proposed a hybrid architecture that integrates a generative adversarial network (GAN) with a recurrent neural network (RNN). In this system, GAN generates synthetic samples. LSTM and GRU models then classify transactions as authentic or generated. Onyeoma et al. [34] analyzed deep neural networks (DNNs), including CNN, LSTM, RNN, multilayer perceptron (MLP), and deep belief network (DBN). Their work combines optimizers and explainability methods to increase fraud detection precision and improve interpretability. Senthilselvi et al. [35] compared several DL models, including RNN, CNN, ANN, and linear autoencoder, for credit card fraud analysis. By applying a soft voting strategy, they fused outputs to identify the most reliable detection mechanism. Ganj and Chaparala [36] developed a detection pipeline utilizing wavelet-based feature fusion, deep neuro-fuzzy networks, and the Zeiler and Fergus network (ZFNet) for classification. For hyperparameter fine-tuning, they applied the dwarf mongoose–shuffled shepherd political optimization (DMSSPO) algorithm. Veeru et al. [37] developed an e-commerce fraud detection approach. Their method uses PCA for preprocessing and autoencoders for feature extraction. A hybrid GRU-bidirectional LSTM (Bi-LSTM) classifier is applied, then optimized with coral reefs optimization (CRO) and secured through homomorphic encryption. Yu et al. [38] investigated transformer-based architectures for credit card fraud detection, benchmarking them against SVM, random forests, neural networks, logistic regression, XGBoost, and tabular networks (TabNet) methods.

In 2025, Dubey et al. [39] proposed a hybrid system that combines a transformer-based encoder, multi-teacher knowledge distillation, and symbolic belief–desire–intention (BDI) reasoning. This integration supports both deep feature learning and symbolic reasoning for fraud detection. Kandi et al. [40] implemented LSTM networks combined with XGBoost to enhance sequential and ensemble learning for credit card fraud detection. They addressed the imbalance in datasets using the SMOTE, improving detection outcomes. Yousefimehr et al. [41] proposed a fraud detection pipeline that merges one-class support vector machine (OCSVM), the SMOTE, and random undersampling. Their design was validated using LSTM and light gradient boosting machine (LightGBM) classifiers to improve prediction accuracy. Khine et al. [42] compared CNN for spatial representation and LSTM for temporal modeling. They applied a sampling strategy that better represents minority classes in imbalanced datasets, improving detection accuracy. Sultana et al. [43] presented a graph neural network (GNN) model enriched

with time-dependent attributes and adaptive updates. Their framework employs a lambda neural network to capture complex, layered relationships in credit card fraud patterns.

2.4 Limitations

Table 1 presents ML and DL algorithms for credit card fraud detection. It summarizes their contributions, datasets, performance, and limitations. The table illustrates a wide variety of strategies. These range from ensemble learning and optimization-based SVMs to advanced DL models, including CNNs, RNNs, GANs, and transformers. ML methods face challenges such as dependence on manual feature selection, difficulty in capturing sequential or contextual patterns, poor adaptability to dynamic data, and reduced ability to generalize under conditions of class imbalance.

DL has improved fraud detection by automatically extracting features, modeling sequential dependencies, and learning complex nonlinear patterns. However, DL methods still suffer from class imbalance and sensitivity to initial parameter settings. To address these issues, this article introduces a model that integrates PPO and ML-ABC. PPO provides adaptive handling of imbalanced data. It offers an alternative to oversampling methods, such as SMOTE, which can create redundant or unrealistic samples. ML-ABC ensures more reliable weight initialization and reduces the risk of local minima. The synergy produces balanced classification. It also supports stable training, leading to robust fraud detection performance. This synergy is considered a central innovation of this study.

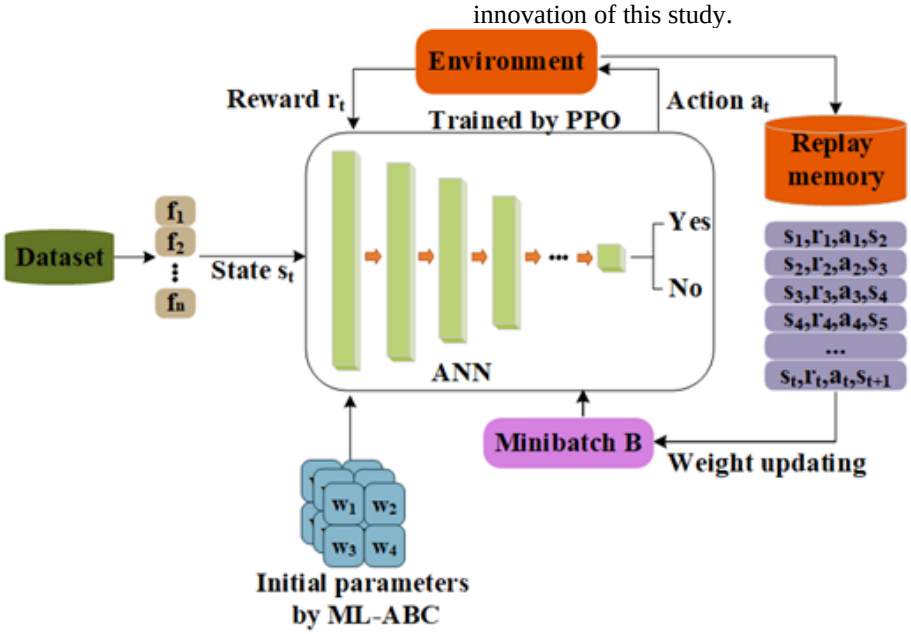

Figure 1: The proposed framework includes an ML-ABC for initial parameter setting and a PPO-based training for imbalanced classes.

3 Material and methods

This paper aims to enhance credit card fraud detection by addressing two persistent issues: inadequate initial weight setting and severe class imbalance. Figure 1 illustrates the architecture of the proposed model, which is based on an ANN. The input to the ANN is an n-dimensional vector. To initialize the ANN, the ML-ABC algorithm is used. ML-ABC generates optimized starting weights, reducing the risk of local minima and improving convergence stability. After setting the initial weight, the ANN is trained using the PPO algorithm. PPO adapts the learning process to focus on minority fraud cases. PPO uses a reward-based update strategy. This ensures stable training and increases sensitivity to rare but critical fraudulent transactions. The integration of ML-ABC and PPO provides a synergistic framework. Their combined use delivers reliable initialization, balanced classification, and improved robustness.

3.1 Initial weight using ML-ABC

In the conventional ABC procedure, the selection of food source locations begins randomly. Each chosen location is then altered to produce a candidate alternative. When this candidate demonstrates superior fitness, it replaces the current location; otherwise, the original choice remains unchanged. In multi-dimensional optimization, one dimension is selected at random, and its corresponding value is modified while keeping others fixed. At each step, the solution that performs better is carried forward. As shown in Equation 1, the generation of new candidates depends only on two parameters: x_i^j and x_k^j. This limited reliance reduces the likelihood of consistently generating high-quality solutions. Some candidates improve the current solution, while others lead to a drop in fitness. The overall objective of the ABC process is to locate food sources that achieve higher fitness values.

$$v_i^j = x_i^j + \varphi_i^j (x_i^j - x_k^j) \quad (1)$$

To refine the search process, an advanced variant of the ABC algorithm is introduced. This version uses a mutual learning strategy where each candidate both shares and

Table 1: Summary of ML and DL algorithms for credit card fraud detection, highlighting contributions, datasets, performance, and key limitations.

Authors	Method	Contribution	Dataset	Result	Limitation
Khalid et al. [1]	Ensemble (SVM, KNN, RF, Bagging, Boosting)	Resampling-based ensemble for imbalance	European credit card users (284,807 transactions)	Accuracy: 94.3%	Complex ensemble, low interpretability
Gajakosh et al. [2]	SVM (unsupervised)	CSO tuning	European credit card users (284,807 transactions)	Accuracy: 99.88%	Sensitive to kernel/CSO parameters
Suardiman et al. [19]	Gaussian NB, KNN, RF	Tri-model evaluation for e-commerce	European credit card users (284,807 transactions)	Accuracy: 99.5%	No imbalance-specific methods
Odeyale et al. [20]	SVM, SMOTE, and ANOVA	Balancing and feature selection	European credit card users (284,807 transactions)	Accuracy: 93.9%	Ignores nonlinear feature relations
Umalwara et al. [21]	AML	Real-time adaptive fraud detection	European credit card users (284,807 transactions)	Accuracy: 88.3%	Needs careful drift handling
Loukili et al. [22]	CatBoost, AdaBoost, and XGBoost	Comparative boosting with latency metrics	European credit card users (284,807 transactions)	Accuracy: 91.1%	Risk of overfitting without regularization
Salam et al. [23]	FL	Privacy-preserving distributed detection	European credit card users (284,807 transactions)	Accuracy: 99.98%	Client drift and high communication cost
Kokate et al. [24]	SVM (RBF kernel)	Kernel-based fraud classification	European credit card users (284,807 transactions)	Accuracy: 95%	Hyperparameter tuning critical
Wang [25]	Ensemble and SMOTE-KMEANS	Cluster-aware synthetic oversampling	European credit card users (284,807 transactions)	Area under the curve (AUC): 0.96	Cluster assumptions may mislead
Baisholan et al. [26]	RF, XGBoost, and SHAP	Probability averaging with interpretability	European credit card users (284,807 transactions)	Accuracy: 99%	SHAP may miss feature interactions
Xie et al. [27]	CNN	Local perception and weight sharing for parameter reduction	Open-source e-commerce service data from 2018 (Kaggle)	Accuracy: 83.60%	Limited to spatial feature extraction
Karthika et al. [28]	Dilated CNN	Captures spatial-temporal features with dilation	UCSD–FICO data mining contest 2009 credit card dataset	Accuracy: 97.45%	Dilation may ignore fine-grained details
Balawi et al. [29]	ANN and CNN	Comparative study of ANN and CNN for fraud	Kaggle Credit-card Fraud dataset	Accuracy: 99.81%	No novel architecture proposed

			(284,807 transactions)		
Berhane et al. [30]	CNN and SVM	Replaces CNN output with a SVM classifier	European credit card users (284,807 transactions)	Accuracy: 91.08%	SVM layer limits end-to-end learning
Fanai et al. [31]	Autoencoder and DNN	Two-stage feature learning and classification	European credit card users (284,807 transactions)	Accuracy: 89.22%	Training complexity increased
Ida et al. [3]	LSTM	Sequential learning with early stopping	European credit card users (284,807 transactions)	Accuracy: 92.06%	Dependent on time-sequenced data
Suganthi and Jebathangam [32]	GRU	Efficient real-time detection model	European credit card users (284,807 transactions)	Accuracy: 90.25%	GRU underperforms for long sequences
Mienye and Swart [33]	GAN and RNN	GAN-generated samples classified by RNNs	European credit card users (284,807 transactions)	F-meature: 90.6%	GAN instability risk
Onyeoma et al. [34]	DNN (CNN, LSTM, RNN, and MLP, DBN)	Combines optimizers with explainability methods	Kaggle comprehensive credit card transaction dataset (284,000)	F-meature: 99%	High model complexity and added overhead from explainability
Senthilselvi et al. [35]	RNN, CNN, and ANN	Model fusion via soft voting	European credit card users (284,807 transactions)	Accuracy: 99.4%	Voting may dilute strong learners
Ganj and Chaparala [36]	ZFNet and Neuro-fuzzy	Wavelet fusion and DMSSPO tuning	European credit card users (284,807 transactions)	Accuracy: 96.1%	High complexity in tuning
Veeru et al. [37]	PCA, autoencoder, GRU-BiLSTM, and CRO	Preprocessing, feature extraction, and a hybrid classifier with encryption	European credit card users (284,807 transactions)	Accuracy: 88.6%	Encryption and CRO increase inference latency
Yu et al. [38]	Transformer	Benchmarked with classic ML methods	European credit card users (284,804 transactions)	F-meature: 99.8%	Transformer training resource-intensive
Dubey et al. [39]	Transformer + BDI	Combines symbolic logic and DL	IEEE computational intelligence society fraud detection dataset	Accuracy: 90.9%	Symbolic integration adds design complexity
Kandi et al. [40]	LSTM and XGBoost	Uses SMOTE for class balance	Kaggle dataset	Accuracy: 97%	Relies heavily on oversampling
Yousefimehr et al. [41]	OCSVM, SMOTE, and LightGBM	Blends unsupervised and boosting	European credit card users (284,807 transactions)	F-meature: 87%	Limited interpretability from OCSVM

Khine et al. [42]	CNN and LSTM	Sampling-enhanced hybrid model	European credit card users (284,807 transactions)	F-meature: 91.6%	Sampling strategy sensitive to skew
Sultana et al. [43]	GNN	Adaptive GNN with time features	European credit card users (284,807 transactions)	Accuracy: 90.3%	GNNs are hard to scale on large data

receives information from nearby solutions. Unlike the original ABC, which relies solely on random perturbations, the improved design directs updates through fitness-based comparisons. When a neighbor exhibits superior fitness, the current solution adapts and shifts toward it. If the current solution performs better, it is retained and slightly adjusted based on the influence of neighboring solutions. This dual approach improves exploitation by focusing the search near promising areas. At the same time, random variations ensure continued exploration of new regions. Guided updates reduce unnecessary randomness, accelerate convergence, and enhance the overall quality of generated solutions. As a result, the upgraded ABC framework becomes more stable and enables more reliable feature extraction. This leads to better performance in tasks involving initial weight generation.

The mutual learning mechanism used in this paper operates as described below:

$$v_i^j = \begin{cases} x_i^j + \varphi_i^j\left(x_k^j - x_i^j\right), & Fit_i < Fit_k \\ x_k^j + \varphi_i^j\left(x_i^j - x_k^j\right), & Fit_i \geq Fit_k \end{cases} \quad (2)$$

In this approach, the terms Fit_i and Fit_k represent the fitness values of the neighbor and the current candidate, respectively. The parameter φ_i^j is a randomly chosen scalar drawn from the interval $(0, F)$, where F is the mutual learning factor, constrained to be greater than zero. This mechanism promotes the adoption of traits from solutions with superior fitness scores. The mutual learning coefficient F plays a key role in both refining solution quality and ensuring stability. A higher value of F leads to smaller update fluctuations, effectively directing the search toward fitter neighbors. Nonetheless, excessively high values of F can disturb the necessary exploration–exploitation trade-off, potentially reducing the overall effectiveness of the optimizer.

Figure 2 illustrates the workflow of the ABC algorithm enhanced with mutual learning. Initially, a swarm of bees is positioned randomly across the search domain. In the employed bee stage, each bee inspects a neighboring candidate and compares its fitness. If the neighbor has higher fitness, the bee moves toward that candidate. The step length and direction depend on the difference in fitness between the two solutions. If the neighbor is weaker, the bee maintains its current position but applies small random changes to support local search. Bidirectional learning makes the bee movements more guided. This improves the balance between exploration and exploitation, helping the algorithm converge faster. The remaining stages follow the structure of the classical ABC. In the onlooker stage, bees select food sources based on fitness probabilities. They then update the selected sources using the same set of update rules. In the scout stage, unproductive solutions are replaced with new ones.

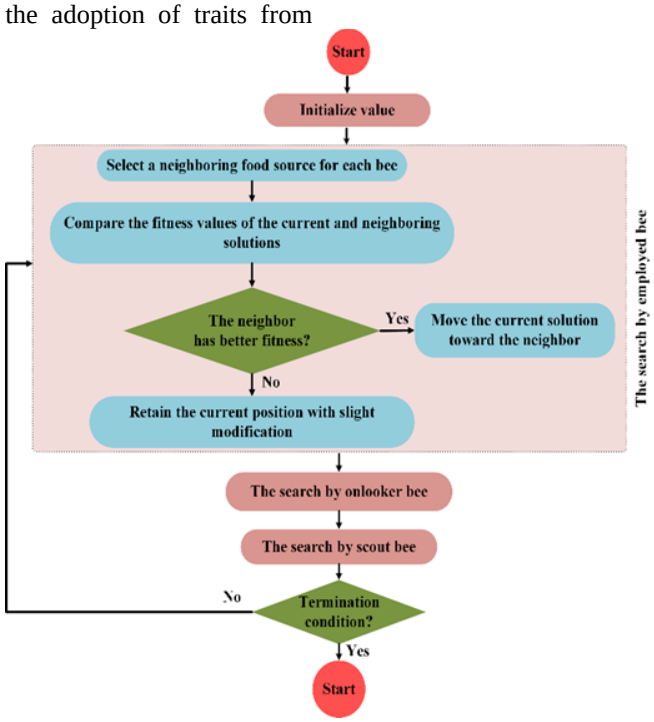

Figure 2: Overview of the ML-ABC algorithm phases.

Algorithm 1 describes the ML-ABC optimization process, which begins by initializing a population of num_bees candidate solutions within the range $[x_{min}, x_{max}]$. Each bee updates its position iteratively for max_cycles using three phases: employed, onlooker, and scout. During the employed bee phase, each bee evaluates its solution against a neighbor ($k \neq i$) and adjusts its position using a directional update. This update is controlled by the mutual learning coefficient F and a random factor φ_i^j. Onlooker bees select solutions probabilistically based on fitness and apply the same rule. This fitness-driven, F-scaled mutual learning promotes faster convergence while preserving global search capability.

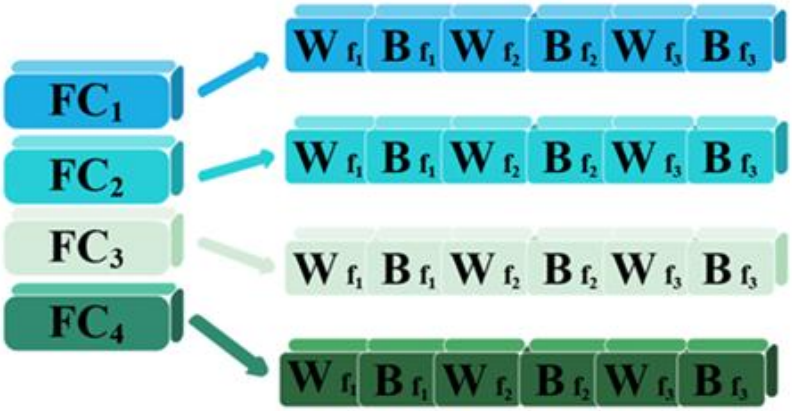

Figure 3: An example of the encoding technique in the ML-ABC algorithm.

3.1.1 Setting

Figure 3 shows an example of the encoding strategy used in this paper for an ANN. Here, the weight matrices within the array are organized in a row-wise format.

Fitness function calculates the quality of each candidate solution. In this paper, we propose an objective function based on similarity as:

$$Fitness = \frac{1}{1 + \sum_{i=0}^{N}(y_i - \tilde{y}_i)^2} \quad (3)$$

In this formula, $\boldsymbol{y_i}$ and $\tilde{\boldsymbol{y}}_{\boldsymbol{i}}$ represent the actual as well as forecasted labels for the i-th data instance, in that order, while N signifies the aggregate number of data instances.

3.2 Classification

In this paper, we use PPO to train the ANN. PPO improves policy performance in both discrete and continuous action spaces. The algorithm addresses the limits of earlier policy gradient methods, especially high sample demand and unstable learning. PPO applies small, incremental updates that avoid large deviations and keep the consistency of the policy within a safety margin. A clipped objective defines this margin and encourages small but beneficial changes, which help the agent accumulate reward.

This mechanism is formalized through the clipped surrogate objective of PPO, defined as follows:

$$L_{PPO}^{CLIP} = E_{s\sim\rho_{\pi_{old}},\ a\sim\pi_{old}}[\min(\frac{\pi(a|s)}{\pi_{old}(a|s)}A_{\pi_{old}}(s,a), clip(\frac{\pi(a|s)}{\pi_{old}(a|s)}, 1-\epsilon, 1+\epsilon)A_{\pi_{old}}(s,a))] \quad (4)$$

where E denotes the expected value. s represents the state of the environment, and a represents the action taken by the agent. $\rho_{\pi_{old}}$ refers to the state distribution under the old policy π_{old}. The term ϵ is a small, positive constant that balances stability and exploration. The advantage function $A_{\pi_{old}}(s,a)$ indicates how much more reward the action a in state s yields compared to the average reward of all possible actions in that state under the old policy. Clipping the ratio limits drastic policy updates and stabilizes the learning process:

$$clip(x,a,b) = max(a, min(b,x)) \quad (5)$$

where x is the value to be adjusted. a is the minimum limit, and b is the maximum limit of the range within which x is restricted. This design penalizes updates where the probability ratio diverges significantly from 1. Although PPO offers significant advantages, it also has a key limitation. It relies heavily on on-policy data, which leads to high sample complexity. This dependency necessitates frequent interaction between the agent and the environment, thereby increasing the computational cost of training.

To improve PPO performance and reduce sensitivity to poor initialization, this study integrates ML-ABC to pretrain the initial weights of the policy network (ANN) used in PPO. Rather than beginning PPO training with random parameters, ML-ABC first optimizes the network weights through mutual learning to offer a better starting point. This approach enhances sample efficiency and speeds up convergence. The integration enables PPO to begin training under more favorable conditions, thereby reducing the likelihood of poor policy updates during the early stages.

Algorithm 1: The ML-ABC algorithm

Input:
-x_{min}, x_{max}: lower and upper bounds for each solution dimension
-max_cycles: maximum number of optimization cycles
-num_bees: total number of bees (solutions) in the colony
-F: mutual learning coefficient
-$trial\_limit$: maximum allowed non-improving cycles before scout bee reinitializes the solution
Output:
- Best solution found
1: //Initialization population:
2: **for** $i = 1$ to num_bees **do**:
3: **for** $j = 1$ to $num\_dimensions$ **do**:
4: $x_i^j = x_{min}^j + rand(0,1) \times (x_{max}^j - x_{min}^j)$
5: **end for**
6: Evaluate the fitness of x_i
7: **end for**
8: $cycle = 1$
9: **while** $cycle <=$ max_cycles **do**:
10: //Employed Bee Phase:
11: **for** $i = 1$ to num_bees **do**:
12: Select $k \neq i$ randomly
13: **for** $j = 1$ to $num\_dimensions$ **do**:
14: φ_i^j = rand (0, F)
15: **if** $fitness(x_i) < fitness(x_k)$ **then**:
16: $v_i^j = x_i^j + \varphi_i^j(x_k^j - x_i^j)$
17: **else**
18: $v_i^j = x_k^j + \varphi_i^j(x_i^j - x_k^j)$
19: **end if**
20: **end for**
21: Evaluate the fitness of x_i
22: **if** $fitness(x_i) < fitness(x_k)$ **then**:
23: $x_i = x_k$
24: **end if**
25: **end for**
26: // Onlooker Bee Phase
27: Calculate probabilities p_i for each solution x_i using
28: **for** $i = 1$ to num_bees **do**
29: Select i based on p_i
30: Repeat steps 12–24 for selected x_i
31: **end for**
32: // Scout Bee Phase
33: **for** i = 1 to num_bees **do**:
34: **if** x_i not improved for $trial\_limit$ **then:**
35: Repeat steps 12–24 for selected x_i
36: **end if**
37: **end for**
38: **end while**

3.2.1 Problem formulation

The state $\boldsymbol{s_t}$ in our model corresponds to the data sample drawn from the database at the t-th time step. The categorization that was done on the sample is reflected in categorization, a reward r_t is assigned to every classification. The structure of this reward system is articulated as follows [44]:

the action a_t and therefore symbolizes the judgment rendered by the network given its current knowledge. Furthermore, to guide this network towards more accurate

$$r_t(s_t, a_t, y_t) = \begin{cases} +1\,, if\ a_t = y_t\ and\ s_t \in D_O \\ -1\,, if\ a_t \neq y_t\ and\ s_t \in D_O \\ \lambda\,, if\ a_t = y_t\ and\ s_t \in D_N \\ -\lambda\,, if\ a_t \neq y_t\ and\ s_t \in D_N \end{cases} \quad (6)$$

In Equation 6, the reward function adjusts based on both class membership and prediction accuracy. A sample from the minority class $\boldsymbol{D_O}$ receives +1 for a correct prediction and −1 for an incorrect one. For the majority class samples $\boldsymbol{D_N}$, rewards are scaled by a factor $\lambda \in (0,1)$, reducing their impact on the learning process. Correct predictions receive $+\lambda$ and incorrect ones receive $-\lambda$. This asymmetric reward structure emphasizes fraudulent (minority) cases while maintaining a balanced learning approach. The use of λ provides fine control over the sensitivity of the model to each class, improving performance on imbalanced datasets. This custom reward function is used in the PPO update process instead of the standard reward term when calculating the advantage. By penalizing or rewarding actions based on both class type and prediction accuracy, it allows PPO to prioritize learning from minority class samples without disrupting overall training stability.

Algorithm 2: Training the ANN model using PPO

Input:
$Data = \{(x_1, y_1), (x_2, y_2), \ldots, (x_M, y_M)\}$: Training data
E: maximum number of iterations
NM: Number of minibatches
α: learning rate
Output:
- Trained ANN model (policy network π_θ)
1: Initialize π_θ by setting parameters θ using ML-ABC
2: Initialize a memory buffer B for storing state transitions
3: **for** episode = $1:E$ **do**:
4: Shuffle the dataset $Data$
5: **for** $t = 1$ to M **do**:
6: Observe the current state s_t
7: Select action $a_t \in \pi_\theta(a_t|s_t)$
8: Compute reward r_t based on Equation 6
9: Store transition (s_t, a_t, r_t, s_{t+1}) in trajectory buffer B
10: **end for**
11: Estimate advantage values $A(s_t, a_t)$ using a value function ϕ
12: **for** $k = 1:NM$ **do**:
13: Sample randomly a mini-batch (s_k, a_k, r_k, s_{k+1}) from B
14: Optimize the policy π to maximize:
15: $\theta \leftarrow \theta_{old} + \alpha \times \nabla_\theta L_{PPO}^{CLIP}(\pi)$
16: **end for**
17: **end for**

Algorithm 2 outlines the training procedure of the ANN model using PPO. Training starts by initializing model parameters using ML-ABC, which improves the starting conditions. A memory buffer collects transitions during each episode. At the start of each episode, the data is shuffled. The agent then interacts with the environment by observing states, choosing actions, and collecting rewards. These transitions are stored and used later to calculate advantage estimates. PPO loss is optimized using randomly sampled mini-batches from the buffer. This cycle continues over multiple iterations to gradually improve the performance of the policy network.

3.3 Time complexity analysis

The computational cost of the model comes from two main sources: (1) ML-ABC, which initializes ANN weights, and (2) PPO, which trains the ANN.

- **ML-ABC complexity:**

Let D represent the number of dimensions in each solution vector, which corresponds to the total number of trainable weights in the ANN. Let N denote the number of bees and T the *maximum* number of optimization cycles. The core of the ML-ABC involves three phases: employed, onlooker, and scout. In each phase, the algorithm evaluates the fitness of solutions and updates the positions of some or all bees.

In each cycle, every bee updates all D dimensions of its solution vector. The computational cost of each cycle is $O(N \times D)$, considering the operations in both the employed *and* onlooker bee phases. If none of the solutions improve, all bees may enter the scout phase, which introduces an additional $O(N \times D)$ operations. Therefore, the overall time complexity of ML-ABC is $O(T \times N \times D)$.

- **PPO complexity:**

Assume that PPO trains for E episodes, on a dataset of size M, using NM mini-batches per episode. Let P represent the time *needed* for a single forward and backward pass through the ANN. This value depends on the number of parameters the network has. Each PPO update involves calculating policy ratios, applying the clipped objective, computing gradients, and running backpropagation. For each episode, PPO processes approximately NM batches. Hence, the PPO training complexity is: $O(E \times NM \times P)$

- **Total complexity:**

Combining both components, the overall time complexity becomes: $O(T \times N \times D) + O(E \times NM \times P)$. This indicates that the total computational cost depends mostly on the number of ANN parameters (D) and increases linearly with both the ML-ABC cycles (N) and PPO *training* episodes (E). Because ML-ABC generates optimized initial weights, PPO usually converges more quickly, which lowers its practical runtime. This synergy leads to efficient and stable training, particularly in scenarios involving imbalanced learning.

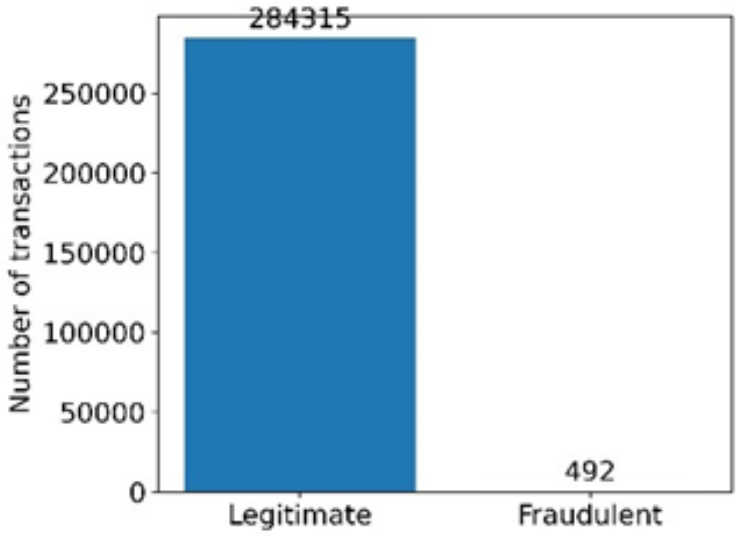

Figure 4: Distribution of legitimate vs. fraudulent transactions.

4 Experiment results

4.1 Database

The database utilized in this investigation is publicly available and was sourced from the Université Libre de Bruxelles. The dataset contains credit card transactions from European cardholders collected in September 2013. This database comprises 284,807 transactions by European cardholders over two days. Figure 4 shows a histogram of fraudulent and legitimate transactions, highlighting the class imbalance. Out of 284,807 transactions, 492 are labeled as fraudulent, accounting for only 0.172% of the entire dataset. This severe class imbalance makes the dataset highly representative of real-world fraud detection scenarios.

The dataset consists entirely of numerical features that have been transformed using PCA. V1–V28 are PCA-derived components. Time (seconds since the first transaction) *and* Amount (transaction value) are not transformed. Time and Amount are important for cost-sensitive fraud detection. The Class feature is the target variable, where 1 indicates fraud and 0 indicates legitimate transactions. For privacy reasons, raw attributes are not disclosed.

To ensure robust model training, we conducted exploratory data analysis (EDA) and preprocessing:

- Normalization: The Time and Amount features were normalized using z-score standardization.
- Stratified train-test split: An 80/20 split was applied, preserving class distribution to reduce variance across folds.
- Class imbalance check: We confirmed a severe imbalance (fraudulent class = 0.172%), which supports the use of imbalance-aware methods, such as PPO, in this study.

4.2 Metrics

To fairly evaluate the model under class imbalance, three metrics are used: accuracy, F-measure, and G-means. Accuracy gives a general performance overview but can be misleading with imbalanced data. F-measure balances precision and recall, highlighting the effectiveness of the model on the minority class, which is critical in fraud detection. G-means is the geometric mean of sensitivity and specificity. It measures how well the model performs on both classes and ensures that gains for the minority class do not reduce the accuracy on the majority class. Together, these metrics provide a comprehensive view of model performance, ensuring reliability and robustness for real-world fraud detection applications.

These metrics are defined as follows:

$$\text{Accuracy} = \frac{TP + TN}{Total\ number\ of\ samples} \tag{7}$$

$$F - measure\ = 2 \times \frac{Precision + Recall}{Precision + Recall} \tag{8}$$

$$\text{G} - \text{means} = \sqrt{\text{Recall} \times\ Specificity} \tag{9}$$

with

$$\text{Precision} = \frac{TP}{TP + FP} \tag{10}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{11}$$

$$Specificity = \frac{TN}{TN + FP} \tag{12}$$

In this context, TP refers to the number of actual positive cases that are correctly identified by the system. TN is defined as the actual negative conditions that are correctly predicted by the system. FP refers to those instances where actual negative examples were falsely classified as positive, whereas FN refers to actual positive examples that were misclassified as negative by the system.

4.3 Model performance

The experiments were conducted on a 64-bit Windows 11 system with 64 gigabytes (GB) of double data rate 4 (DDR4) random access memory (RAM) and an NVIDIA RTX 3090 graphics processing unit (GPU) (24 GB of video RAM (VRAM)). The GPU significantly accelerated training and evaluation of the deep neural networks. The software environment was based on Python 3.10, utilizing TensorFlow 2.13 and PyTorch 1.13.1, both compiled with Compute Unified Device Architecture (CUDA) version 11.7 to enable GPU support. PPO was implemented using PyTorch, while the ML-ABC algorithm was coded in Python using NumPy and SciPy. Efficient training on large, high-dimensional datasets from Université Libre de Bruxelles was achieved through a combination of fast memory access, GPU parallelism, and optimized ML libraries. This setup enabled thousands of training iterations with fast convergence and minimal delays during parameter tuning and evaluation.

Table 2: Hyperparameter configuration of the proposed model, determined via stratified 5-fold cross-validation.

Hyperparameter	Value
Batch size	73
Epoch	214
Learning rate	0.001
Activation function	ReLU
Number of layers in ANN	8
Dropout rate	0.56
Clip range ($\in$)	0.23
Policy update steps	5
λ	0.4
F	0.3

To set the hyperparameters of the proposed model, we use stratified 5-fold cross-validation. This method maintains the original class distribution in each fold, which is particularly important for imbalanced datasets such as those used in fraud detection. The dataset is divided into five equal parts, and each part maintains the same proportion of minority and majority classes. In each iteration, four folds are used for training and one for validation, rotating across all folds. Stratified sampling ensures a more consistent evaluation across folds and reduces variance caused by random splits. We chose five folds as a balance between statistical reliability and computational efficiency. We did not use repeated or nested cross-validation because they are computationally more expensive and provided little performance gain in our initial experiments. Table 2 shows the hyperparameter settings for the proposed model.

We compared the proposed model with four ML models and eight DL models. The ML models include SMOTE-Bagging-SVM [1], SVM-CSO [2], FL-Resampling [23], and XGBoost-SHAP [26]. The DL models include DCL [28], CNN-SVM [30], Bi-LSTM-CRO [37], TabNet [38], Transformer [39], LSTM-LightGBM [41], CNN-LSTM [42], and GNN [43]. The hyperparameters of the advanced baseline models were adopted directly from their original papers to ensure a fair comparison. We used a classification threshold of 0.5 for all binary decisions. This value is commonly used in fraud detection and ensures a fair and interpretable evaluation. Preliminary tests with alternative thresholds did not show significant improvements, confirming 0.5 as a balanced and widely accepted choice. The results of these tests are detailed in Table 3.

Table 3: Performance comparison of the proposed model against ML and DL baselines.

Model	Accuracy	F-measure	G-means
SMOTE-Bagging-SVM [1]	76.301 ± 0.019	77.878± 0.072	75.643± 0.073
SVM-CSO [2]	77.452 ± 0.025	78.749± 0.043	77.023± 0.010
FL-Resampling [23]	78.508 ± 0.079	78.902± 0.051	77.391± 0.028
XGBoost-SHAP [26]	79.117 ± 0.034	79.328± 0.059	78.086± 0.004
DCL [28]	81.362 ± 0.074	82.939± 0.100	80.672± 0.009
CNN-SVM [30]	82.389 ± 0.032	82.876± 0.046	81.612± 0.073
Bi-LSTM-CRO [37]	83.204 ± 0.002	83.493± 0.009	82.217± 0.079
TabNet [38]	83.824 ± 0.032	84.222± 0.043	83.181± 0.067
Transformer [39]	84.757 ± 0.089	84.835± 0.017	83.580± 0.044
LSTM-LightGBM [41]	85.324 ± 0.090	85.717± 0.067	84.461± 0.049
CNN-LSTM [42]	86.094 ± 0.008	86.701± 0.012	85.457± 0.088
GNN [43]	87.584 ± 0.055	87.827 ± 0.086	86.590 ± 0.079
Proposed w/o ML-ABC	81.871 ± 0.097	79.448± 0.032	81.095± 0.019
Proposed w/o PPO	86.981 ± 0.059	85.311± 0.018	86.943± 0.061
Proposed	90.197 ± 0.014	91.287± 0.070	89.456± 0.069

When comparing state-of-the-art models, the GNN model achieved the best performance among DL-based models, outperforming earlier approaches, such as DCL, by 6.222% in accuracy, 4.888% in F-measure, and 5.918%

in G-means. Similarly, GNN surpassed CNN-SVM by 5.195%, 4.951%, and 4.978% across the same metrics. However, GNN models are often challenging to scale and require substantial computational resources, thereby limiting their practicality. The Transformer also outperformed Bi-LSTM-CRO by 1.553%, 1.342%, and 1.363%, reflecting the benefits of attention mechanisms. Yet, transformer-based approaches generally demand extensive memory and training time, which reduces efficiency in real-world tasks. Among ML models, XGBoost-SHAP offered better interpretability but fell behind deep models, with an accuracy 8.467% lower compared to Transformer. Its limitation lies in weaker adaptability under severe imbalance despite strong interpretability. Although SVM-CSO used optimization, it still performed worse than CNN-SVM, with 10.132% lower accuracy and 9.078% lower G-means. This shows that parameter tuning alone cannot overcome the structural weaknesses of classical ML models. This gap highlights the advantage of hybrid DL methods over optimized ML models.

The proposed model consistently outperformed all ML and DL baselines. The proposed model surpassed the best-performing DL model, GNN, by 2.613% in accuracy, 3.460% in F-measure, and 2.866% in G-means. Relative to LSTM-LightGBM, it improved by 4.873%, 5.570%, and 4.995%, respectively. Compared to Transformer, the improvements were 5.440%, 6.452%, and 5.876%. Even over CNN-LSTM, it achieved a 4.758% gain in accuracy. When compared to the best-performing ML model, XGBoost-SHAP, the proposed model delivered even larger gains, 11.080% in accuracy, 11.959% in F-measure, and 11.370% in G-means. These consistent gains highlight the advantage of integrating ML-ABC for optimal initialization with PPO for stable training. Together, they improve generalization, handle class imbalance more effectively, and enable deeper feature abstraction than ensemble methods or single deep networks.

In ablation studies, compared to the version without PPO, we observed gains of 3.216% in accuracy, 5.976% in F-measure, and 2.513% in G-means. Against the version without ML-ABC, the proposed model achieved improvements of 8.326% in accuracy, 11.839% in F-measure, and 8.361% in G-means. A more detailed comparison shows that the accuracy of the proposed model improved by 2.084%, 3.216%, and 3.254% over PPO-only versions of CNN-SVM, Bi-LSTM, and TabNet, respectively. F-measure showed gains of 5.452%, 4.794%, and 5.065%, while G-means increased by 4.331%, 4.726%, and 6.275%. These findings indicate that PPO and ML-ABC alone are insufficient. Only their combination in the full model leads to the performance levels required for practical fraud detection.

To determine the statistical significance of the superiority of our proposed model over existing baselines, we employed paired t-tests across all three-evaluation metrics (accuracy, F-measure, and G-means). For both the best-performing ML model (XGBoost-SHAP) and the DL model (GNN), the results showed statistically significant differences, with all p-values below 0.001. Additionally, we computed 95% confidence intervals and effect sizes using Cohen's d. The effect sizes ranged from 1.20 to 2.85, indicating substantial differences. The 95% confidence intervals for accuracy gains spanned [2.14%, 4.92%], for F-measure [3.25%, 6.84%], and for G-means [2.88%, 5.67%]. For all other comparisons, p-values remained below 0.001, effect sizes ranged from 1.20 to 2.85, and the confidence intervals consistently demonstrated clear margins of improvement, supporting the robustness and reliability of the performance gains of the proposed model.

Table 4 presents a comparison of the computational efficiency of the proposed model with that of ML and DL models. The comparison includes runtime, GPU memory usage, and inference time per sample (ITPS). The proposed model achieved a runtime of 1984 seconds, which is 24.4% faster than LSTM-LightGBM, 15.9% faster than CNN-SVM, and 15.4% faster than TabNet. It also reduced GPU memory usage by 22.9% compared to LSTM-LightGBM and by 17.4% compared to Bi-LSTM-CRO. In terms of ITPS, the proposed model achieved 18.113 ms, which is 34.7% faster than Transformer and 28.8% faster than GNN. The proposed model is more efficient than DL baselines, but it still runs slower than simpler ML methods like XGBoost-SHAP. This illustrates a trade-off between accuracy and computational efficiency. The model is suitable for large-scale and real-time use, but may still require further optimization on limited hardware.

Table 4: Comparison of computational efficiency across models, including runtime, GPU memory usage, and ITPS.

Model	Runtime (s)	GPU (GB)	ITPS (ms)
SMOTE-Bagging-SVM [1]	1921	20.468	17.793
SVM-CSO [2]	1749	20.140	17.822
FL-Resampling [23]	1895	20.321	16.728
XGBoost-SHAP [26]	1777	20.878	15.837
DCL [28]	2348	23.622	26.200
CNN-SVM [30]	2817	23.110	22.182
Bi-LSTM-CRO [37]	2506	27.652	24.448
TabNet [38]	2587	23.431	27.330
Transformer [39]	2644	22.979	25.063
LSTM-LightGBM [41]	2744	28.246	27.739
CNN-LSTM [42]	2219	25.083	24.348
GNN [43]	2410	22.650	27.417
Proposed	1984	21.742	18.113

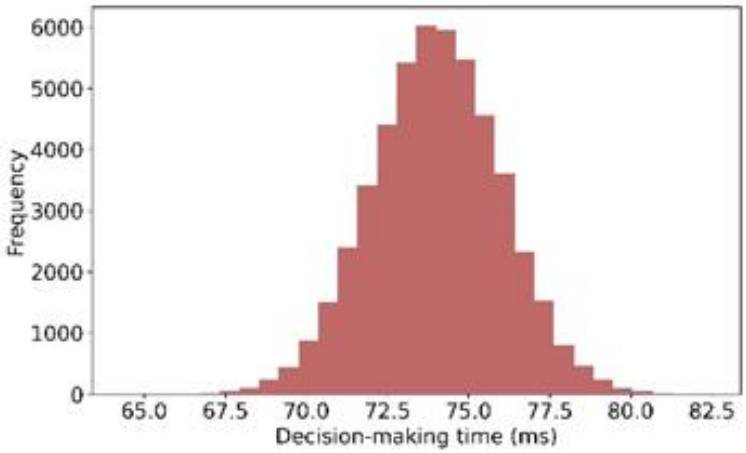

Figure 5: Distribution of decision-making time for the proposed model.

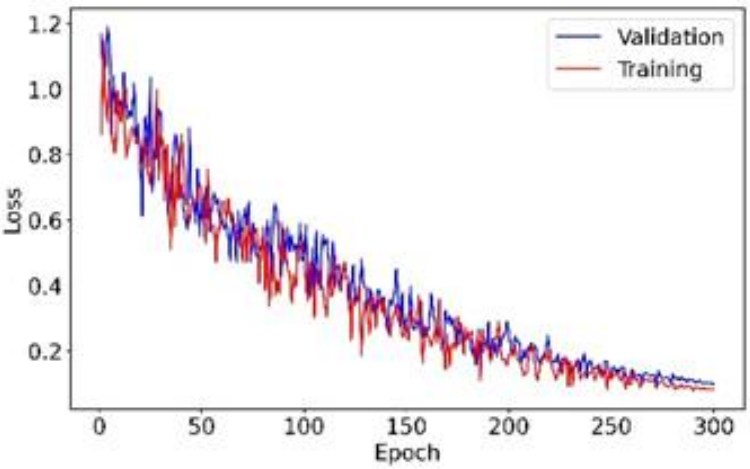

Figure 6: Training and validation loss curve in the proposed model.

Figure 5 illustrates the decision-making time of the proposed model, which supports its suitability for real-time applications. Most decision times are tightly grouped near 74 ms, with more than 95% falling within the 70- to 78-ms range. The small variation and fast decision speed demonstrate that the model provides quick and stable results, even under varying conditions, which is crucial for real-time fraud detection.

Figure 6 shows that both training and validation losses decrease steadily and remain close to each other throughout the epochs, without diverging. This means the model learns well, does not overfit, and converges properly.

Table 5: Performance comparison of the proposed model against ML and DL baselines on the IEEE-CIS dataset.

Model	Accuracy	F-measure	G-means
SMOTE-Bagging-SVM [1]	77.511 ± 0.054	78.202 ± 0.013	76.929 ± 0.025
SVM-CSO [2]	79.505 ± 0.023	80.220 ± 0.058	78.921 ± 0.065
FL-Resampling [23]	79.615 ± 0.055	79.891 ± 0.023	78.990 ± 0.035
XGBoost-SHAP [26]	81.812 ± 0.037	80.018 ± 0.079	79.731 ± 0.084
DCL [28]	82.588 ± 0.027	83.716 ± 0.083	81.427 ± 0.014
CNN-SVM [30]	83.288 ± 0.025	83.486 ± 0.011	82.207 ± 0.026
Bi-LSTM-CRO [37]	83.821 ± 0.017	84.438 ± 0.027	83.122 ± 0.077
TabNet [38]	84.355 ± 0.044	85.458 ± 0.001	84.154 ± 0.002
Transformer [39]	85.084 ± 0.012	85.520 ± 0.078	84.381 ± 0.051
LSTM-LightGBM [41]	86.601 ± 0.013	86.866 ± 0.001	85.824 ± 0.016
CNN-LSTM [42]	86.841 ± 0.015	87.096 ± 0.040	86.253 ± 0.009
GNN [43]	88.296 ± 0.094	88.939 ± 0.023	87.607 ± 0.083
Proposed	93.803 ± 0.029	92.890 ± 0.087	91.572 ± 0.007

4.3.1 Analysis of generalizability

To assess generalizability, robustness, and real-world applicability, we utilized the Institute of Electrical and Electronics Engineers Computational Intelligence Society (IEEE-CIS) dataset [35]. It is a large-scale, industry-grade benchmark featuring high-dimensional features, severe class imbalance, and noisy transaction records that accurately mirror real-world deployment scenarios. The dataset includes 569,875 legitimate transactions and 20,665 fraudulent ones. Fraud accounts for 3.626% of all transactions.

The results are shown in Table 5. The proposed model achieved 93.803% accuracy, 92.890% F-measure, and 91.572% G-means. Compared to the best ML baseline, XGBoost-SHAP, it improved by 12.184% in accuracy, 12.872% in F-measure, and 11.841% in G-means. Against the strongest DL model, GNN, it achieved gains of 5.507%, 3.951%, and 3.965%, respectively. These improvements over both ML and DL baselines show that the proposed hybrid design generalizes well. It maintains strong performance even when faced with extreme imbalance and noisy real-world transaction records.

4.3.2 Analysis of PPO

Class imbalance in fraud detection is often addressed through oversampling (e.g., SMOTE), undersampling, and cost-sensitive learning. These methods either rebalance the data or raise penalties for errors on the minority class. Despite their utility, oversampling risks overfitting, undersampling risks information loss, and cost-sensitive learning need careful weight tuning.

For ANNs, a common approach is to modify the loss function to handle class imbalance. In this study, we explored weighted cross-entropy (WCE), balanced cross-entropy (BCE), dice loss (DL), Tversky loss (TL), and combo loss (CL). WCE and BCE assign equal weight to positive and negative cases, while DL and TL balance false positives and false negatives. The CL mechanism lowers the weight of easy cases and emphasizes harder ones, making it effective for skewed distributions.

As shown in Table 6, CL reduced precision discrepancy by 31% and increased the F-measure by 42% compared to TL. However, PPO still surpassed CL by 71%. This large margin shows that advanced loss functions only partially address imbalance. In contrast, PPO offers a more dynamic and adaptive solution. By continuously shaping rewards, PPO prioritizes minority cases without reducing stability, outperforming both data-level and loss-level strategies.

Table 6: Performance comparison of PPO against established loss functions for imbalanced classification.

Technique	Accuracy	F-measure	G-means
WCE	75.445 ± 0.100	74.365 ± 0.087	76.006 ± 0.087
BCE	80.191 ± 0.078	77.030 ± 0.006	81.650 ± 0.099
DL	81.971 ± 0.020	80.984 ± 0.085	82.559 ± 0.022
TL	83.095 ± 0.001	81.779 ± 0.000	84.342 ± 0.066
CL	86.032 ± 0.092	84.291 ± 0.094	86.850 ± 0.013
PPO	90.197 ± 0.014	91.287± 0.070	89.456± 0.069

4.3.3 Analysis of ML-ABC

In this section, ML-ABC is compared with several well-known metaheuristic algorithms, including human mental search (HMS), firefly algorithm (FA), bat algorithm (BA), differential evolution (DE), grey wolf optimizer (GWO), cuckoo optimization algorithm (COA), AOA, PO, SSA, and ABC. For all metaheuristic algorithms, we set the population size to 50 and the maximum number of iterations to 512; other parameters are listed in Table 8 of Appendix A. These settings follow established literature. We did not use stratified cross-validation because repeated metaheuristic runs would greatly increase computational cost and make tuning impractical.

Table 7 shows that ML-ABC significantly outperforms the alternatives across all metrics. Compared to its base version, ABC, ML-ABC yields 5.876% higher accuracy, 7.564% higher F-measure, and 6.998% higher G-mean. Against PO, improvements are 8.015%, 9.000%, and 9.452%, respectively. Over AOA, ML-ABC offers a gain of 12.308% in accuracy and 11.919% in F-measure. The consistent superiority, especially over PO, SSA, and AOA, shows that the mental learning strategy improves both the direction of search and the diversity of candidate solutions. These improvements lead to better parameter initialization and more stable convergence during training. As a result, ML-ABC is a reliable option for complex classification tasks such as fraud detection. In such tasks, poor parameter initialization can negatively affect convergence and reduce final accuracy.

Table 7: Performance comparison of ML-ABC against established metaheuristic algorithms for initial parameter setting.

Model	Accuracy	F-measure	G-means
HMS	86.393 ± 0.063	85.883 ± 0.070	83.695 ± 0.014
FA	85.275 ± 0.005	83.690 ± 0.091	81.460 ± 0.070
BA	83.152 ± 0.017	82.448 ± 0.067	79.198 ± 0.098
DE	82.148 ± 0.018	81.517 ± 0.039	77.226 ± 0.071

GWO	80.791 ± 0.059	78.655 ± 0.031	75.358 ± 0.060
COA	75.681 ± 0.036	74.547 ± 0.079	70.254 ± 0.077
AOA	80.318 ± 0.015	79.224 ± 0.020	78.936 ± 0.038
PO	82.182 ± 0.099	81.287 ± 0.079	80.004 ± 0.049
SSA	83.765 ± 0.036	82.918 ± 0.054	81.627 ± 0.062
ABC	84.320 ± 0.043	83.723 ± 0.050	82.458 ± 0.049
ML-ABC	90.197 ± 0.014	91.287± 0.070	89.456± 0.069

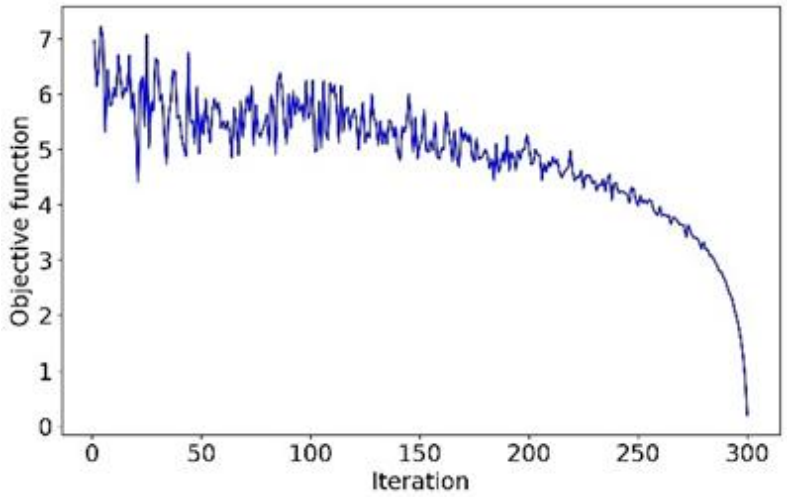

Figure 7: Convergence curve of ML-ABC showing the reduction in the objective function over 300 iterations.

Figure 7 presents the trend of the objective function across 300 iterations for the ML-ABC algorithm. The curve demonstrates a clear downward trajectory, with a significant reduction after iteration 250, indicating strong convergence behavior. The gradual decline followed by a sharp drop indicates that ML-ABC finds better solutions over time and converges efficiently.

4.3.4 Analysis of hyperparameter sensitivity

We used stratified 5-fold cross-validation to tune the model hyperparameters. Figure 8 shows a sensitivity analysis of important hyperparameters, including batch size, epoch, λ, and the number of layers in the ANN. The cross-validation process consistently identified the best-performing settings: batch size = 73, epoch = 214, λ = 0.4, and 8 layers. Higher or lower values than the identified optima led to a noticeable drop in performance. Stratification preserved class ratios in every fold and produced a stable, unbiased evaluation. This systematic approach confirmed model robustness and guided the choice of optimal parameters.

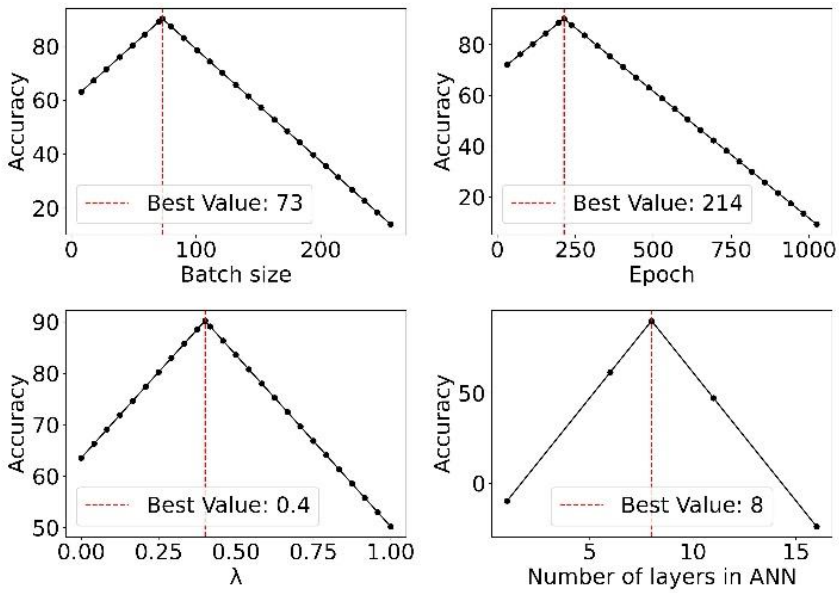

Figure 8: Sensitivity analysis of key hyperparameters (batch size, epoch, λ, and ANN layers) using stratified 5-fold cross-validation.

4.3.5 Discussion

This article introduces a hybrid fraud detection model that combines an ANN with ML-ABC for weight initialization and PPO for handling class imbalance. The proposed approach surpassed state-of-the-art models, achieving 90.197% accuracy, 91.287% F-measure, and 89.456% G-means on the Université Libre de Bruxelles dataset. These findings directly answer the research question, confirming that PPO and ML-ABC together outperform traditional ML and DL models. The results also confirm the hypotheses: PPO increases sensitivity to minority fraud cases, and ML-ABC improves parameter initialization while lowering the risk of local minima.

In our model, ML-ABC was used to improve ANN initialization. Traditional random starts often caused poor convergence, but mutual learning guided the process toward stable weights and reliable fraud detection. PPO addressed severe class imbalance by dynamically adjusting rewards to prioritize minority cases. Its clipped objective stabilized training, ensuring balanced learning and consistent performance across skewed datasets.

The proposed framework extends beyond credit card fraud to domains with imbalance and initialization challenges. In healthcare, it helps with early disease diagnosis, where ML-ABC stabilizes training and PPO balances rare conditions. In cybersecurity, it detects anomalies in network traffic to facilitate a quick response to intrusions, while in insurance, it enhances the detection of fraudulent claims. Its efficiency supports real-time decision-making. This makes it useful in financial risk management and industrial quality control. Its adaptability highlights its strength for high-accuracy tasks under imbalance with real-time requirements.

The limitations of the proposed model are as follows:

- One limitation of the proposed model is that it does not explicitly address feature selection. ANNs can capture complex nonlinear relationships. However, relying only on raw inputs in high-dimensional financial data may introduce redundancy and noise. This increases computational costs and reduces generalization. Without feature selection, the model becomes more sensitive to irrelevant or weak predictors, leading to instability. To address this, future work could utilize reinforcement learning–based feature selection or interpretability-driven approaches, such as SHAP and local interpretable model-agnostic explanations (LIME), to identify important variables. ML-ABC can also be combined with traditional methods, such as recursive feature elimination (REF), to optimize both parameter initialization and feature selection. This integration would improve robustness, reduce unnecessary complexity, and enhance fraud detection accuracy under real-world conditions.
- Fraud detection models risk bias if trained on unbalanced or non-representative data. For example, if transaction records overrepresent certain groups, the model may incorrectly flag their activities as fraudulent. Such bias can lead to significant ethical, financial, and legal consequences, particularly in the banking sector. The current model addresses class imbalance and improves minority-class detection. However, it does not include explicit fairness-mitigation strategies. Future work should explore fairness-aware methods such as reweighing, adversarial debiasing, or regularization techniques to reduce discrimination. Fairness metrics, such as demographic parity and equal opportunity, should also be included in the validation process. Continuous monitoring during deployment is crucial for detecting and correcting emergent biases. Clear reporting of training data and proactive bias management will help ensure the system supports fraud detection without unintended discrimination.
- The proposed model achieved strong results in controlled experiments. However, scalability and real-world deployment remain challenging. Fraud detection systems require very fast inference, as delays in transaction approval can result in significant financial losses. The model achieved an average decision-making time of about 18 milliseconds per transaction. This is suitable for many real-time applications, but it is slower than simpler models, such as XGBoost, revealing a trade-off between accuracy and computational cost. To address this, future work could employ model compression methods, such as pruning and quantization, to reduce computational demands without compromising accuracy. Deploying the model on scalable infrastructures, such as cloud-based GPU clusters or optimized edge devices, could also enhance performance. Another solution is to integrate it into a multi-stage detection system, where lightweight models handle obvious cases and the proposed hybrid method focuses on complex, high-risk transactions in real time.

5 Conclusions

This study presents a hybrid fraud detection framework that uses ML-ABC for weight initialization and PPO to handle class imbalance during ANN training. The contributions of this work are twofold: first, enhancing the stability and convergence of ANN training through optimized initialization, and second, improving minority class detection via adaptive reward shaping. Experimental results on the Université Libre de Bruxelles dataset demonstrate that the proposed model achieves 90.197% accuracy, 91.287% F-measure, and 89.456% G-means, surpassing the best existing benchmark by approximately 3%. These findings confirm a robust approach and demonstrate practical value for real-world e-commerce fraud detection, where accuracy and reliability are critical under severe imbalance.

In future work, we will extend the model to incorporate multi-modal data, transaction metadata, user behavior, and social media analytics, thereby capturing fraud patterns that are not visible in card data. Another direction is real-time detection, which requires faster optimization of PPO and ABC. Simplifying the network architecture or refining the ABC mutual learning process

can increase speed without reducing accuracy. These enhancements aim to build a robust, real-time fraud detection system for high-throughput e-commerce platforms.

Appendix A

Table 8: Hyperparameters and their optimized values for metaheuristic algorithms.

Algorithm	Hyperparameter	Value
HMS	Cognitive search factor (α)	0.54
	Memory size (M)	25
	Learning rate (α)	0.71
	Neighborhood size (L)	15
	Perturbation strength (σ)	0.08
	Learning rate (β)	0.14
FA	Light absorption coefficient (γ)	1
	Attractiveness at r = 0 (β0)	0.62
	Scaling factor (α)	0.34
BA	Constant for loudness update	0.55
	Constant for an emission rate update	0.66
	Initial pulse emission rate	0.75
DE	Scaling factor (FA)	0.56
	Crossover probability (CR)	0.86
	Differential weight (W)	0.74
	Scaling factor (FA)	0.41
GWO	Convergence factor (a)	0.26
COA	Discovery rate of alien solutions (pa)	0.28
	Step size (α)	0.57
	Levy flight exponent (λ)	1.8
AOA	Multiplication operator probability	0.42
	Division operator probability	0.42
	Subtraction operator probability	0.45
	Addition operator probability	0.42
PO	Exploration factor	0.58
	Exploitation factor	0.51
	Phase transition mechanism	0.63
SSA	Leader position update coefficient (c1)	0.47
	Random coefficient (c2)	0.63
ABC and ML-ABC	Number of bees	62
	Limit	35
	Number of cycles	240
	Colony size	56
	Probability of scout	0.08
	Number of elite bees	4
	Elite limit	25

Competing interests

The scholars claim no competing interests.

Authorship contribution statement

Yuanyuan Zhang: Writing-Original draft preparation Conceptualization, Supervision, Project administration.

Data availability

The scholars will make the raw data supporting this article's conclusions available without undue reservation.

Declarations

Not applicable.

Conflicts of interest

The scholars claimed no conflicts of interest considering this investigation.

Author statement

The manuscript has been read and approved by all the authors, the requirements for authorship, as stated earlier

in this document, have been met, and each author believes that the manuscript displays honest work.

Ethical approval

All scholars have been personally and actively involved in substantial work leading to the paper and will take public responsibility for its content.

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VeriChain: A Hybrid Formal Verification Approach Using Control Flow, Symbolic Execution, and Static Analysis for Smart Contract Vulnerability Detection

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Smart contracts facilitate the trustless and automated execution of agreements on blockchains, however several programming patterns in them (such as re-entrancy, integer overflow/underflow, access control) have led to substantial thefts due to vulnerabilities. Current verification tools (e.g., Mythril, Oyente, and Securify) are essentially based on symbolic execution, taint analysis, and pattern matching with high falsepositives as well as large time cost, poor scalability for complex contracts. This paper develops VeriChain, a hybrid verification framework that combines (i) lexicon/syntax parsing for abstract syntax tree (AST), (ii) Control Flow Graph (CFG) generation for path and dependency representation, (iii) CFG-guided symbolic execution with model checking to search feasible execution paths and (iv) rule-based static analysis towards identifying/characterizing vulnerability patterns. VeriChain was tested on N benchmark smart contracts (including re-entrancy, arithmetic and access-control vulnerabilities) and contrasted with Mythril, Oyente, and Securify. Experiments show that VeriChain enables 98.3% detection accuracy with only 1 false positive (and no false negative in our testing set) and finishes analysis within 2.3 seconds, surpassing state-of-the-art tools in both precision and execution efficiency. VeriChain also outputs a structured security report to categorise detected flaws by severity and to offer developers traces of execution as well as mitigation advice, enabling realistic pre-deployment audit of blockchain smart contract.

Povzetek: Predstavljen je napreden sistem za odkrivanje ranljivosti v pametnih pogodbah, ki deluje natančneje in hitreje kot obstoječe rešitve.

1 Introduction

Blockchain technology has accumulated broader acceptance in multiple structures like NFT and has increased the use of cryptocurrencies like Bitcoin and Ether. Smart contracts — self-executing programs that run on blockchain networks — are essential for automating transactions and enforcing agreements without intermediaries. However, security flaws in smart contracts have resulted in severe financial losses, as demonstrated through notorious exploits such as the DAO hack and reentrancy attacks [1], [2]. Its immutable nature causes security analysis to be an essential step before deploying smart contracts. To verify such smart contracts, we primarily use manual audits, heuristic-based detection, and formal verification-rich techniques, none of which, however, can provide large-scale, accurate, and efficient detection.

In recent studies, smart contract security has also been improved using static analysis, symbolic execution, and machine learning-based vulnerability detection. We use tools that do symbolic execution and formal methods (like Mythril, Oyente, and Securify) to detect security bugs [3], [4]. However, these tools have high false positive rates, long execution times, and incomplete coverage of target vulnerability types that restrict their practical usability. Mythril and Oyente, for example, are based on symbolic execution but encounter path explosion issues for non-trivial contracts. While Securify is precise, it introduces substantial computation overhead and is not suitable for verifying smart contracts on a large scale. These limitations create a scope for research on designing a fast, accurate, scalable, innovative contract verification framework that integrates multiple verification techniques for better reliability.

To tackle these obstacles, we propose VeriChain. This formal verification framework employs a combination of Control Flow Graph (CFG) analysis, symbolic execution, and static analysis to improve the identification of vulnerabilities in smart contracts. VeriChain aims to avoid false positives and enhance detection accuracy and execution efficiency compared to available tools. The innovation of this study is that it proposes a hybrid verification method that combines CFG-based execution

path analysis for contract function dependency tracking, symbolic execution for execution scenario analysis, and application of static analysis with rule-based vulnerability detection. Combining these methods gives a holistic security analysis and reduces the associated security risk pre-deployment of the contract using the VeriChain framework. The main Contributions of this research include the following:

- A hybrid framework (VeriChain) was developed that combines control flow graph (CFG) analysis, symbolic execution, and static analysis to strengthen the overall security of smart contracts.
- Optimized an execution model that increases vulnerability detection accuracy and minimizes false positives and computation costs.
- VeriChain, Mythril, Oyente, and Securify were compared experimentally, and they showed greater accuracy (98.3%) and execution time (2.3 seconds).
- We defined a structured security reporting system that classifies vulnerabilities according to severity, execution traces, and mitigation strategies.

In order to systematically assess the performance of the designed VeriChain, this paper follows the research questions as shown below:

RQ1: Does combining CFG-guided symbolic execution and rule-based static analysis lead to better detection precision on vulnerabilities at the cost of lowering numbers of false positive compared to other existing smart contract tools?

RQ2: Can VeriChain provide reduced running time as well as improved scalability in more complex smart contracts involved with multi-functions, loops and paths, comparing to the popular state-of-arts tools such as Mythril [1], Oyente [16] and Securify 3?

RQ3: Is VeriChain capable of offering a well-organized and realistic security assessment utilizing which it is possible to conduct pre-deployment auditing by correctly classifying the severity-wise vulnerabilities along with their execution traces?

The rest of this paper is organized as follows. Section 2 provides a literature review on the state-of-the-art approaches to smart contract security analysis and offers insights into the research gaps. Section 3 describes the proposed approach, including the architecture and functioning of VeriChain's verification pipeline. In section 4, we present the experimental results and compare the performance of VeriChain with existing tools based on detection accuracy, false positives, and execution time. In Section 5, we discuss the implications of the results, indicate how the current approach overcomes the limitations of previous work, and comment on the broader significance of VeriChain in the field of smart contract security. Lastly, the study's limitations are presented in Section 5.1. Section 6 concludes the paper and outlines directions for future research, including leveraging machine learning for vulnerability classification and broadening VeriChain's support to multiple blockchain platforms.

2 Related work

The current tools for the security of smart contracts still use symbolic execution, taint analysis, and formal verification, which are plagued by false positives and are inefficient. Almakhour et al. [1] examined clever contract verification techniques, found security flaws, and discussed benefits, drawbacks, and potential advancements. Garfatta et al. [2] explained the constraints, formal verification techniques, weaknesses, and possible areas for further study in blockchain intelligent contract verification. Wang et al. [3] suggested ContractWard, which uses machine learning to detect smart contract vulnerabilities quickly and accurately. Kim et al. [4] evaluated 391 articles on smart contract analysis, pointing out issues, potential vulnerability, and accuracy detection research avenues. Schiffl et al. [5] aimed to formally verify the accuracy of smart contracts through a case study, pointing forth its limits and available verification techniques.

Hajdu et al. [6] examined verification tools, used fault injection to assess bright contract flaws, and identified ways to improve blockchain dependability. Wang et al. [7] demonstrated the efficacy and efficiency of Artemis, an innovative contract verification tool that can locate a variety of flaws on 12,899 contracts. Gao et al. [8] offered SmartEmbed, a very accurate and effective automated solution for detecting smart contract bugs and clones. Ghaleb et al. [9] presented SolidiFI, a tool for assessing smart contract static analysis tools and detecting false positives and unreported problems. Duo et al. [10] used colored Petri nets to offer a layered, innovative contract security paradigm that increases automation and analysis efficiency.

Hameed et al. [11] proposed a decentralized Blockchain-based authentication scheme for IoT devices, improving performance and verifying correctness through modeling and analysis. Kabar et al. [12] suggested using QR codes and multi-level authentication to enhance security and efficiency in their blockchain-based automated check-clearing system, MudraChain. Khan et al. [13] examined smart contracts offered by blockchain, pointing out security flaws, difficulties, and unresolved problems while outlining potential study avenues. So et al. [14] presented VeriSmart. This accurate Ethereum smart contract verification improves bug identification. It addresses false alarms for arithmetic safety. Tolmach et al. [15] discussed formal models and smart contract verification methods, pointed out shortcomings, and recommended future research paths.

Kushawaha et al. [16] highlighted the difficulties and suggestions for the future when reviewing and classifying 86 Ethereum smart contract analysis tools. Afzaal et al. [17] suggested a framework for secure blockchain-based crowdsourcing that uses formal verification and emphasizes upcoming security and trust enhancements. Verma et al. [18] examined blockchain consensus techniques emphasizing security and performance, highlighting formal approaches for accuracy. Nam et al. [20] addressed the shortcomings of current methods by proposing ATL model checking for smart contract verification, supported by case examples.

Yang and Zhu [21] suggested SCSVM and SCLMF for detecting Ethereum smart contract vulnerabilities with high accuracy; further development is required. Babel et al. [22] presented CFF, a formal economic security verification tool for DeFi contracts that may be used to find smart contract flaws and potential uses. Ahmad et al. [23] addressed verification restrictions by creating a user-centric blockchain platform for GDPR compliance in multi-cloud scenarios. Khalid et al. [24] suggested a blockchain-based, scalable, and SDN-integrated IoT access control system, assessing its scalability and performance. Anas et al. [25] demonstrated the superiority of BlockASP over conventional techniques by fusing AOP and model checking for enhanced blockchain verification.

Alnuaimi et al. [26] suggested a blockchain-based approach for healthcare credentialing that improves security, automation, and transparency while evaluating security and cost. Almakhour et al. [27] used nuXmv and finite state machines to provide a model-checking method for confirming the security of composite smart contracts. Farao et al. [28] introduced INCHAIN, a blockchain-based system that addresses fraud, data transparency, and consumer identity to enhance cyber insurance. Alevizos [29] suggested potential research possibilities for a system that automates security compliance by integrating blockchain, AI, and smart contracts. Qureshi et al. [30] proposed the ChainAgile framework, which uses smart contracts and blockchain to enhance cybersecurity, transparency, and teamwork in distributed Scrum Agile development.

Deep et al. [31] suggested an innovative contract-based blockchain-based IoT security solution for data integrity, access management, and authentication. Colin et al. [32] addressed dataset standardization, accuracy, and performance in its proposed MLP-based smart contract vulnerability detection method. Khan and Namin [33] evaluated and categorized 41 smart contract vulnerability detection technologies to improve SC security and lower risks. Chen et al. [34] presented a clear, contrastive learning-based strategy that outperforms current deep learning techniques for identifying vulnerabilities in smart contracts. Chen et al. [35] introduced DCV, an automated tool that offers faster verification times than previous tools for declarative smart contracts.

Bartoletti et al. [36] suggested using benchmarks to assess the efficacy of Solvent, a tool for confirming the liquidity qualities of smart contracts. Jiao et al. [37] evaluated the weaknesses of smart contracts, examined detection methods, and suggested future lines of inquiry to improve security. Olivieri and Spoto [38] highlighted the difficulties in verifying blockchain software, pointed out the shortcomings of current methods, and made recommendations for new lines of inquiry. Chaliasos et al. [39] examined DeFi security technologies and pointed out their low efficacy. Creating tailored tools for changing threats is part of the future work. Li et al. [40] created AS-SC to simplify asset securitization contracts. However, its drawbacks include inadequate scenario coverage and dependability concerns. Future research will concentrate on enhancing verification techniques and perfecting AS-SC. Several limitations of Mythril, Oyente, and Securify have been reported in the literature, such as high false positive rates and slow execution time.

In control literature, robust/adaptive design offers some principled tools for dealing with uncertainly and nonlinearities as well as partial or limited observability which is also relevant in complex engineered systems. Output feedback synchronization for uncertain dynamics with dead-zone/sector nonlinearities demonstrate the stability of uncertain dynamics using adaptive fuzzy approximators and variable structure design when only system states are not completely measurable [44]. The aforementioned robustness of the fixed-time synchronization can also be stretched to a practical one in that bounded time-convergence is guaranteed with respect to those uncertainties in fractional-orders [45]. (Theoretical advances in optimizing learning of controlled dynamic systems span Erickson et al, 1976 to Floares}, A generalized approach lo the (1994) as well as robust control literature including Tallamraju eta!1988). Adaptive backstepping based on Lyapunov stability offers a systematic method for stabilization of uncertain SISO nonlinear systems [46] whereas robust neural adaptive control extends adaptation into uncertain MIMO dynamics [47]. High-gain observer-based adaptive fuzzy control also compensates unmeasured states based on observer-driven adaptation [48].

Table 1: Summary of representative smart contract vulnerability detection and verification approaches

Tool / Method	**Core Technique(s)**	**Strengths (Typical)**	**Key Limitations (Typical)**	**ReObserved Performance Indicators***
Mythril	Symbolic execution + taint analysis	Widely used; detects common EVM-level issues	Path explosion; higher false	Moderate accuracy; FP can be high; scalability

			positives on complex paths	limited by path exploration
Oyente	Symbolic execution + constraint solving	Early symbolic tool; finds control-flow related bugs	High false positives; misses some modern patterns; slower on large contracts	Lower precision in complex contracts; scalability limited
Securify	Pattern-based compliance + semantic rules	High precision for known patterns; strong rule checking	Higher computation overhead; limited flexibility for unseen patterns	Good precision; slower runtime; depends on rule coverage
Slither	Static analysis (AST/IR) + rule detectors	Fast; good for code-quality/security patterns	Limited for deep path-dependent vulnerabilities	Very fast; precision depends on rule quality; scalable
SmartCheck	Static pattern matching	Easy-to-use; detects known anti-patterns	Can miss deep semantic bugs; pattern-limited	Fast; moderate accuracy; limited on complex logic
VeriSmart	Formal verification / safety property checking	High precision for targeted properties	Requires formal specs; limited general vulnerability breadth	High precision on supported checks; overhead depends on properties
ML-based detectors (e.g., embeddings/classifiers)	Learning-based classification	Learns from data; can generalize across patterns	Dataset dependence; interpretability and FP risk	Accuracy varies by dataset; needs benchmark standardization

Research gaps exist in utilizing multidimensional verification techniques to enhance accuracy and scalability. VeriChain fills in these missing pieces by implementing analysis, symbolic execution, and static analysis to guarantee efficient and accurate vulnerability discovery.

3 Proposed framework

The proposed framework, named VeriChain, is a formal verification framework for identifying vulnerabilities in employed blockchain smart contracts, combining symbolic execution, control flow analysis, and static analysis to help find security vulnerabilities like reentrancy attacks, integer overflows, unauthorized access, and transaction-order dependence. Since smart contracts are immutable when deployed, VeriChain ensures they are correctly and thoroughly tested for security vulnerabilities to avoid exploits within Dapps. Based on the tokenization of smart contracts, this framework first generates tokens by understanding the terminology and generating tokens before parsing the Contract into hierarchical form, known as an Abstract Syntax Tree (AST). (This enables systematic analysis of the contract's functions, variables, and dependencies). It then constructs a Control Flow Graph (CFG), which represents all the paths of execution, the function calls, and the logical branches the contract can take. With a clear grasp of execution flows, VeriChain can identify contract logic and control dependencies vulnerabilities.

VeriChain's architecture, shown in Figure 1, comprises multiple interlinked components that work to detect vulnerabilities in smart contracts. This process starts with Smart Contract Input Processing, which involves parsing and structuring Solidity source code for further analysis. Then, Lexical & Syntax Analysis takes that contract and returns an AST (Abstract Syntax Tree), which is a tree representation of contract elements. The Control Flow Graph (CFG) Generation module maps execution paths, function calls, and branching logic to recognize potential vulnerabilities.

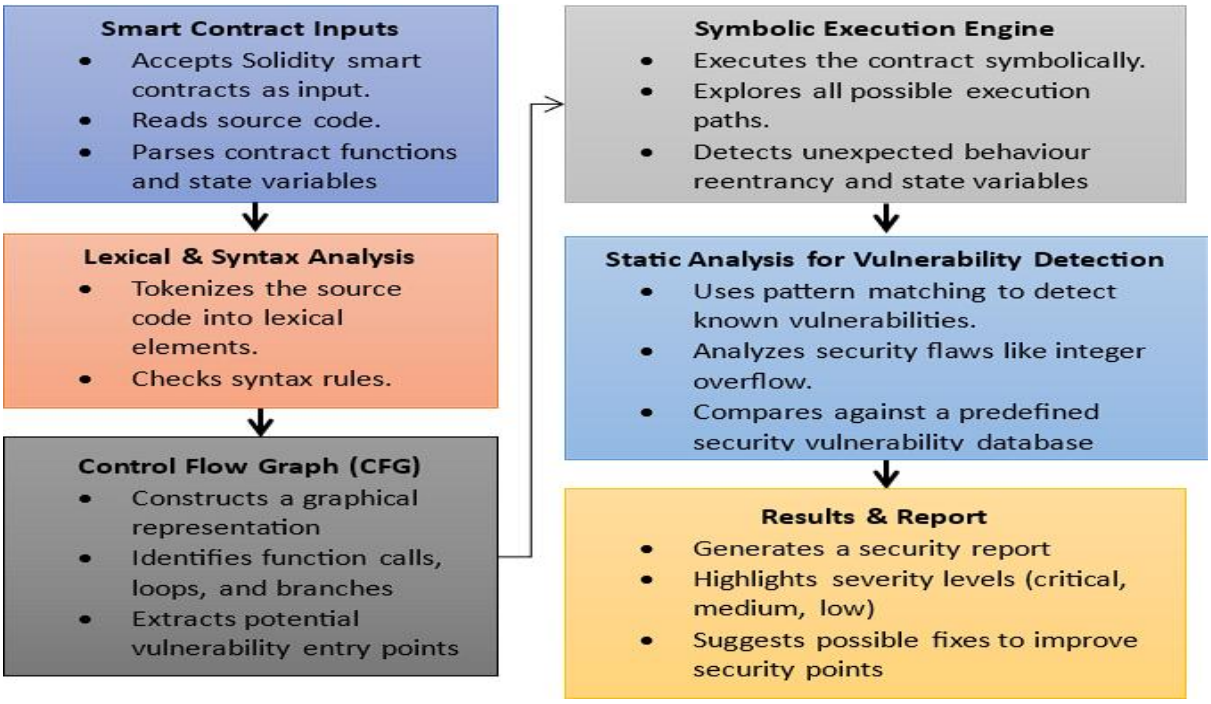

Figure 1: Architecture of VeriChain – a formal verification framework for smart contract security analysis

VeriChain utilizes its Symbolic Execution Engine to verify contracts by implicitly exploring potential states thoroughly that the contracts can reach, independent of known inputs. Next, static analysis is applied, where the framework scans for vulnerabilities (reentrancy, integer overflows, and access control violations) according to the predefined security rules. Finally, Results & Reporting provides a structured security assessment, listing vulnerabilities within ranks of risk and suggesting remediation to improve smart contract security.

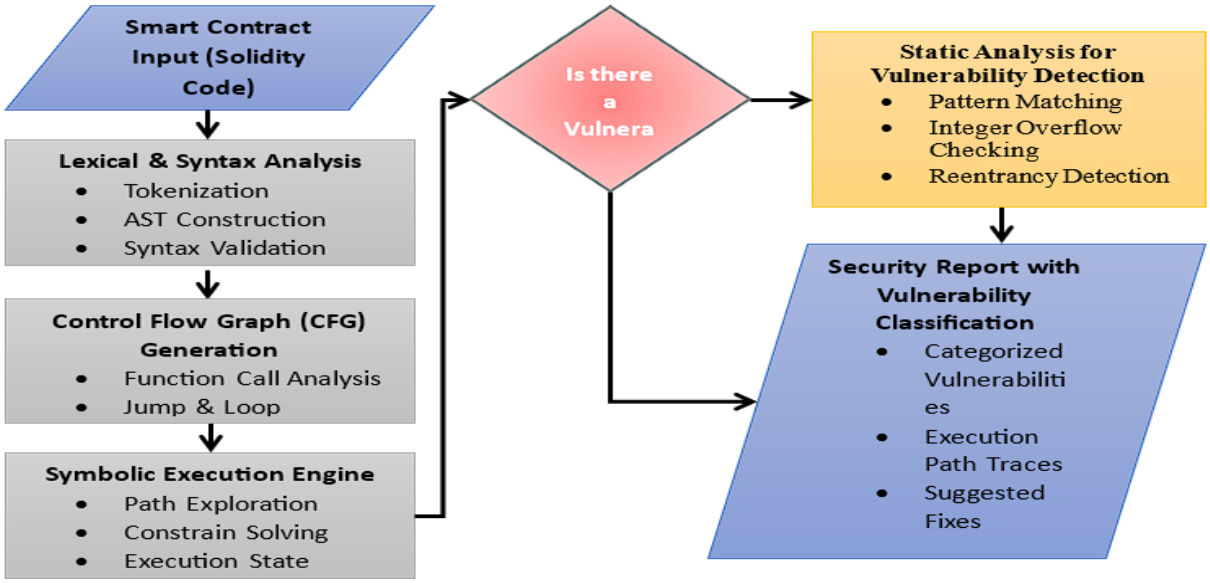

Figure 2: VeriChain flowchart – step-by-step process from smart contract input to security report generation

Figure 2 illustrates the workflow of VeriChain, detailing the step-by-step verification process for smart contract security analysis. The process begins with Smart Contract Input, where Solidity code is parsed for further study. Lexical & Syntax Analysis tokenizes the code, constructs the Abstract Syntax Tree (AST), and validates syntax. The Control Flow Graph (CFG) Generation module maps execution paths, function calls, and loops. The Symbolic Execution Engine then explores possible execution scenarios and detects vulnerabilities. A decision point determines if vulnerabilities exist, leading to Static Analysis, which detects security flaws. The process concludes with a Security Report, categorizing vulnerabilities and suggesting fixes. Table 2 shows the notations used in the proposed system.

Table 2: Notations used

Notation	Definition
S	Smart contract source code in Solidity
$L(S)$	Lexical representation of smart contract after tokenization
$T\ (S)$	Tokenized representation of the smart contract
$G = (V, E)$	Abstract Syntax Tree (AST) representation of the smart contract
V	Set of nodes in AST, each representing a syntax element
E	Set of edges representing parent-child relationships in AST
$G_f = (V_f, E_f)$	AST subgraph for function f in the smart contract
$C\ (S)$	Compiled EVM bytecode of the smart contract
$B = \{b_1, b_2, \dots, b_p\}$	Sequence of EVM opcodes
$S_k = \{s_1, s_2, \dots, s_q\}$	EVM execution stack during contract execution
E_f	Set of function entry points in the contract
$G_{CFG} = (V_{CFG}, E_{CFG})$	Control Flow Graph (CFG) of the smart contract
V_{CFG}	Set of basic blocks in CFG
E_{CFG}	Set of directed edges representing execution flow in CFG
B_i	Basic block containing sequential instructions
$E_{i,k}$	Directed edge in CFG between two basic blocks
$D\ (v_n)$	Dominance set for node v_n in CFG
$X = \{x_1, x_2, \dots, x_n\}$	Set of symbolic variables used in symbolic execution
$s_i = \{M_i, S_i, \dots, E_i\}$	Program state during symbolic execution
$T(s_i, I_k)$	Transition function applying instruction I_k to state s_i
$C = \{c_1, c_2, \dots, c_m\}$	Set of constraints generated during symbolic execution
$P = \{p_1, p_2, \dots, p_r\}$	Set of all feasible execution paths
$Z3(C_p)$	Constraint solver determining satisfiability of constraint set C_p
$V_P: v_i \to \mathbb{V}$	Mapping function from AST node $v_i$to vulnerability set $\mathbb{V}$
$T\ (x)$	Taint propagation set for variable X
$E(f_i)$	Set of external calls made by function f_i
$R(S)$	Set of detected vulnerabilities in smart contract S
$L(V_i)$	Severity level of detected vulnerability V_i

$G(V_i)$	Execution path leading to vulnerability V_i
$F(V_i)$	Suggested fix for vulnerability V_i
$P(V)$	Proportion of vulnerable functions in the contract

3.1 Smart contract input

VeriChain's formal verification process starts from the smart contract input stage, where it parses the given Solidity contract and transforms it into a structured representation for later analysis Let S be a smart contract source code, where $S = \{L_1, L_2, \dots L_n\}$ and each L_i represents a lexical entity such as a function, variable, or control structure. We used the following function to map the input contract into a tokenized representation as in Eq. 1.

$$T(S) = \{t_1, t_2, \dots t_m\},\ t_i \in \mathbb{T} \quad (1)$$

Where $\mathbb{T}$ is the predefined set of Solidity token types such as keywords, identifiers, operators, and data types. After it is tokenized, the contract is transformed into a hierarchical structure in the form of an abstract syntax tree (AST) $G = (V, E)$, where V is the set of syntax nodes and E It is the parent-child relationship between language constructs. Every contract functions f_k The input is expressed as a subtree in Eq. 2.

$$G_{f_k} = (V_k, E_k),\ V_k \subseteq V\ ,\ E_k \subseteq E \quad (2)$$

Providing modular organization. The AST similarly provides a structured means of traversing through the contract logic, enabling extraction of key contract features like state variables, function calls, modifiers, and inheritance relationships. This is followed by the byte code transformation phase, where the Solidity source code maps into its equivalent EVM bytecode. The compilation function CC is defined by Eq. 3.

$$C: S \to B,\ B = \{b_1, b_2, \dots b_p\} \quad (3)$$

Where B It is the ordered sequence of EVM opcodes. They precisely determine how the contract will run in the Ethereum Virtual Machine (EVM) via opcodes like PUSH, CALL, SLOAD, and JUMP. Each opcode b_i Works on the EVM stack, which a sequence of stack operations can represent as in Eq. 4.

$$S_k = \{s_1, s_2, \dots s_q\},\ sj\ \in\ \mathbb{S} \quad (4)$$

Where $\mathbb{S}$ It is a set of stack operations, including push, pop, arithmetic, and logical operations. To cover all cases, VeriChain uses the entry points of the smart contract — referred to as E_f Which consists of the contract's public and external functions, as in Eq. 5.

$$E_f = \{f_1, f_2, \dots f_r\},\ f_i \in S \quad (5)$$

These entry points represent the interaction surface of the contract and are used as starting nodes for control flow and symbolic execution analysis. Fingering the critical entry points helps you identify the attack vectors, including reentrancy, unchecked external calls, and access control violations. VeriChain aims to provide accurate detection of vulnerabilities and to improve the efficiency of future formal verification phases by transforming the input of a smart contract into lexical, syntactic, and execution-ready representations.

3.2 Lexical & syntax analysis

The lexical and syntax analysis forms a significant part of the transformation process in the VeriChain framework that converts smart contract source code into a structured representation suitable for formal verification. Let be the Solidity source code of a smart contract, which is a sequence of lexemes that we denote as $S = \{l_1, l_2, \dots l_n\}$, $where\ each\ l_i$, where a meaningful token is parsed from the contract's syntax. The lexical analyzer, L, translates this sequence into a collection of classified tokens as in Eq. 6.

$$L(S) = \{t_1, t_2, \dots t_m\},\ t_i \in T \quad (6)$$

Where T is the defined set of token types (e.g., keywords, identifiers, operators, literals), the mapping function L can be defined as cap L: cap S goes to cap T, so each token follows the Solidity grammar. Parsed tokens from lexical analysis are syntactically validated by constructing an Abstract Syntax Tree (AST). The AST is a directed acyclic graph (DAG), denoted by cap G equals open paren cap V, cap E, close paren where cap V represents nodes of syntax trees and E represents hierarchical relationships among language constructs. Each function f in the smart contract is a subtree in G, formulated as Eq. 7.

$$G_f = (V_f, E_f),\ V_f \subseteq V\ ,\ E_f \subseteq E \quad (7)$$

Where G_f Captures the function-level structures, such as variable declarations, control flow statements, and function calls. The well-formedness of G is checked by verifying that each node v adheres to the Solidity context-free grammar (CFG) rules R, expressed as Eq. 8.

$$\forall_v \in V, v \vDash R \quad (8)$$

When the sequence of tokens does not adhere to these rules, a syntax error is thrown, leading to issues in traversing the Abstract Syntax Tree (AST). A recursive descent parser Yes, then define how to verify the above; the verification process uses a recursive descent parser. P, which is defined as Eq. 9.

$$P: L(S) \to G,\ P(t_i) = v_i \quad (9)$$

which maintains grammar correctness for all 's parent-children GWeakening checks before reaching the high AST is essential as the high-level AST is now responsible for further dies, redundant nodes, operator precedence, alleviating control flow, and symbolic execution. Hence, the lexical-syntactic phase ensures structural integrity, minimizing false positives in the subsequent stages of vulnerability detection.

3.3 Control flow graph (CFG) generation

The fundamental representation of execution paths in a smart contract is the Control Flow Graph (CFG) in the VeriChain framework. We model a smart contract SS as a directed graph. $G = (V, E)$, with the set of nodes (i.e., fundamental blocks of instructions) and the E Directed edges define possible transitions between blocks. Each function f in the contract can be represented as a subgraph $G_f = (V_f, E_f)$ For modular representations. A basic block B_i In the CFG, a maximal sequence of instructions with a single-entry point and exit point is a basic block formally defined as Eq. 10.

$$B_i = \{I_1, I_2, \ldots I_n\} \quad (10)$$

Where I_k is an atom instruction, and the control passes only at the first or last instruction in the caption in capital B_i. The CFG's edges are created depending on the execution flow determined by control statements (conditional branches, loop iterations, function calls, etc.). If there is an instruction I_j at the end of block B_i that goes to block cap, there is a directed edge:

$E_{i,k} = (B_i, B_k)$ iff I_j Jump, conditional branch, or function call. Conditional branches have two outgoing edges. E_{i,k_1}, $E_{i,k_2}$where k_1,k_2Are the available execution paths. Each output shows the result of the eval condition. Loops create cyclic dependencies in the graph, allowing a node to hit a previously executed block. These loops are represented by GG's strongly connected components (SCCs), as in Eq. 11.

$$\forall v_i, v_j \in V, \exists\ a\ path\ v_i \to v_j \to v_i \quad (11)$$

suggesting the desire for endless loops or iterations. To enable vulnerability identification, a dominance analysis is performed on the CFG, where we say that a node dominates another node if all paths from the entry node v_n to must go through v_d as in Eq. 12.

$$D(v_n) = \{v_d \in V \mid \forall_p: entry \to v_n, v_d \in p\} \quad (12)$$

Detection of re-entrancy vulnerabilities is based on searching call dependencies cycles in the CFG. If a function f_i invokes another function f_j That, in turn, recursively invokes f_i Before it completes execution, a reentrant cycle is created, as in Eq. 13.

$$\exists\ a\ cycle\ C = \{f_i, f_j, f_i\} \implies Potencial\ reentrancy\ detected \quad (13)$$

CFG generation, therefore, allows VeriChain to explore all reachable paths through the codebase, ensuring the identification of the pre-deployment attack surface.

To reduce path explosion during analysis, VeriChain uses CFG based path prun- ing both before and during symbolic execution. Infeasible and redundant paths are eliminated using a combination of dominance analysis, constraints satisfability checking and execution states memoization. More precisly, paths for which the accumulated path constraints are unsatifiable (by the constraint solver) are directly pruned from further conisderation. Also, CFG nodes dominated by visited nodes with the same symbolic state are not re-expanded in order to avoid exploring semantically identical paths repeatedly. Loops and recursive calls are also restricted with bounded unrolling limits that aim at covering only security-critical paths. This pruning method is shown to dramatically cut down on redundant symbolic exploration yet retain coverage of paths that are more likely to uncover vulnerabilities including re-entry attacks, unchecked EXTCALLs [12], and state-based flaws.

3.4 Symbolic execution engine

The VeriChain framework uses a symbolic execution engine to analyze smart contracts better. It explores all possible execution paths without considering concrete inputs, leaving specific variables as symbolic variables instead of substituting them with values. $X = \{x, x_2, \ldots x_n\}$And follows the changes they go through within the program. It models each function execution as a transition between states in an execution tree, with each node a computational step. Define as S The set of program states, where the tuple can describe each state as in Eq. 14.

$$s_i = (M_i, S_i, E_i) \quad (14)$$

Where M_i translates to memory storage (contract state variables), S_i the EVM stack (operational execution stack), and E_i is the environment context (caller address, gas, transaction-params). They are based on a sequence of executed instructions derived from the contract's bytecode. Thus, they are called symbolic execution paths. Therefore, each instruction cap I. sub k mutates the program state as in Eq. 15.

$$s_{i+1} = T(s_i, I_k) \quad (15)$$

where T The transition function determines how execution moves from one state to another. Conditionals impose path constraints, represented as a system of equations in the constraint set. C as expressed in Eq. 16.

$$C = \{c_1, c_2, \ldots c_m\} \quad (16)$$

where each c_j Is a logical condition detected via contract execution (like if (x > 10)). Different execution paths collect distinctive sets of constraints. C_p, which describes how the program gets to a particular state. The collection of valid execution traces is then defined as Eq. 17.

$$P = \{p_1, p_2, \ldots p_r\},\ P \subseteq S^* \quad (17)$$

Where S^* Denotes any possible sequence of program states. For loops or function recursion, execution paths may grow infinitely. Thus, bounded exploration is applied in VeriChain, which puts a limit on loop iterations or recursion depth to a finite d, whose exploration is tractable. Detecting vulnerabilities by checking if a specific undesirable execution state (e.g., due to unauthorized access or division by zero) can be reached is the primary concern of symbolic execution. A classic re-entrancy exploit occurs when one contract allows re-entrant function calls until the original execution has been completed. The execution graph contains a cycle, which is how we fail, as in Eq. 18.

$$\exists\, a\ cycle\ C = \{f_i, f_j, f_i\} \implies Potencial\ reentrancy\ detected \quad (18)$$

Where f_i The function that makes an external call to another function f_j, which calls f_i Again, before state changes are fully committed, in the case of symbolic execution, such paths are identified by solving the corresponding path constraints and checking if they fulfil the vulnerability requirements. VeriChain combines with a constraint solver to prove the findings. Z_3, which checks whether a constraint set C_p It is satisfiable, as in Eq. 19.

$$Z_3(C_p) \to \{SAT, UNSAT\} \quad (19)$$

SAT (satisfiable) indicates that the vulnerability can be exploited, and UNSAT (unsatisfiable) means the contract is secure against that attack. VeriChain improves smart contracts' security by systematically exploring execution paths and analyzing symbolic constraints to identify hidden vulnerabilities before deployment.

3.5 Static analysis for vulnerability detection

VeriChain is a static analysis tool for finding vulnerabilities in smart contracts S Through analysis of code, its semantics, control flow, and data dependencies without executing the code. The analysis works on the contract's Abstract Syntax Tree (AST) and Control Flow Graph (CFG) to systematically analyze and identify possible security vulnerabilities. The AST representation $G = (V, E)$ Fora smart contract contains syntax nodes. V and hierarchical relationships EYou even translate the contracts into an intermediate representation that encodes the program's structure—each node. $v_i \in V$ It is a contract construct (like a function definition, variable declaration, or storage operation). Static analysis finds vulnerabilities using pattern matching and taint analysis techniques. A vulnerability pattern is a function. V_P That maps an AST node. v_i to a vulnerability type $\mathbb{v}$ as in Eq. 20.

$$V_P: v_i \to \mathbb{v}, \mathbb{v} = \{V_1, V_2, \ldots V_m\} \quad (20)$$

Where V_j It is a predefined security flaw, such as reentrancy, integer overflow, uninitialized storage access, etc. Detection function: This inspects an AST node that looks for patterns for specific vulnerabilities. Static analysis for taint analysis traces how untrusted input data propagates through the path of executing the contract. Let xx be an input variable obtained from an external call, as in Eq. 21.

$$x = CALLER(\,) \cdot input \quad (21)$$

A function $F(x)$ It is tainted if it propagates external input to a sensitive operation such as storage modification or fund transfer without proper validation, as in Eq. 22.

$$T(x) = \{y \mid y\ is\ derived\ from\ x\} \quad (22)$$

Where $T(x)$ The taint propagation set keeps track of all variables affected by external input. The contract is vulnerable if untrusted variables can reach sensitive operations such as transfer (). The framework tracks arithmetic expressions to detect the occurrence of integer overflows and integer underflows. Given an operation $r = a + b$ where a, b Are integer variables, overflow happens if: $r > max(unit\ 256) \Rightarrow Overflow\ detected$

And underflow occurs if: $r < max(unit\ 256) \Rightarrow Underflow\ detected$. VeriChain prevents arithmetic vulnerabilities from being exploited by monitoring conditions that breach numerical limits. Static analysis detects reentrancy by analyzing external call sequences in the CFG. If a function f_i makes an external call before updating its internal state, it creates a reentrancy vulnerability, as in Eq. 23.

$$E(f_i) = \{C(f_i) \mid C(f_i)\ is\ an\ external\ call\ before\ state\ change\} \quad (23)$$

Where $E(f_i)$ encapsulates all external calls to be made in the function f_i Before internal state updates, if repeated invocation forces multiple changes of state before the original execution has ended, the contract is then marked as having a reentrancy risk. The static analysis findings are matched to its known vulnerability database. D_V, which allows smart contracts to comply with best security practices. The security assessment is ultimately calculated as Eq. 24.

$$R(S) = \{V_j \mid S\ exhibits\ V_j, V_j \in D_V\} \quad (24)$$

Where $R(S)$ Is the set of discovered vulnerabilities in the contract S. Using static analysis, VeriChain identifies vulnerabilities before deployment, reducing the security risks associated with blockchain applications.

Static Analysis Module (Ghaghara) VeriChain's static analysis module is based on a hybrid rule-set that comprises standardised patterns recognised in the smart contract security literature as well its own set of rules that are defined through control-flow and execution-context analysis. Routines cover typical bugs like re-entrancy, integer overflow/underflow, unchecked external calls, undesired access control and transaction order dependence according to industry best practices as documented in tools such as Mythril, Slither and Securify. Furthermore, VeriChain presents custom rules that are reinforcing the CFG-level dependency verification technique along with symbolic state information to detect context-sensitive bugs

in state updates after an external call, dangerous inter-function dependencies and inconsistent authorization checks in all execution paths. These user-defined checks are only triggered when the corresponding execution paths are possible under symbolic constraints, leading to lower false positive rates and greater precision than strictly rule-based static analysis.

3.6 Results & reporting

The framework produces a complete security assessment report based on the vulnerabilities discovered in the verification process. The output is a structured list of security issues classified according to severity, including execution traces and remediation suggestions. Formally, the security report of a smart contract SS is R(S), as expressed in Eq. 25.

$$R(S) = \{V_1, V_2, \dots V_n\}, V_i \in \mathbb{v} \quad (25)$$

Where $\mathbb{v}$ It is the set of known security vulnerabilities, such as reentrancy, integer overflow, unauthorized access, gas limit inefficiencies, etc. Each vulnerability V_i gets severity level, $L(V_i)$ Which is based on exploitability and impact, as in Eq. 26.

$$L(V_i) \in \{Critical, High, Medium, Low\} \quad (26)$$

The security level is based on the following threat levels: Critical vulnerabilities expose immediate security risks, and Low-level issues may represent potential optimizations. The report includes an execution trace for each vulnerability. $T(V_i)$ Demonstrating how an attacker can exploit the contract. The execution trace appears as an instruction sequence, as in Eq. 27.

$$T(V_i) = \{I_1, I_2, \dots I_m\} \quad (27)$$

where each I_k Corresponds to a contract instruction that played a role in the vulnerability. When you know the source of the vulnerability and the type of input required to trigger the underlying code execution vulnerability, the relevant control flow graph G(V_i)Indicates the attack path potentially leading to the security threat. VeriChain suggests automated fixes based on best security practices to ensure developers can quickly remediate vulnerabilities. For a vulnerability V_i, a possible fix $F(V_i)$ is generated by Eq. 28.

$$F(V_i) = \mathbb{p}(V_i) \quad (28)$$

Where $\mathbb{p}$ It is a known functionality mapping vulnerability to patches. So, for example, if a contract is vulnerable to reentrancy, the recommended workaround may be to use a checks-effects-interactions pattern or add reentrancy guards. The executive summary table in the security report includes vulnerability type, severity level, affected contract functions, execution traces, and recommended fixes.

The report also gives statistics on the security of the contract, such as the percentage of tasks that have vulnerabilities (where available), expressed as Eq. 29.

$$P(V) = \frac{|V|}{|F|} \quad (29)$$

where $|V|$ is the number of functions with detected vulnerabilities and $|F|$ is the total number of functions in the contract. If, $P(V) > 0.5$ The contract is deemed high-risk and requires significant security enhancements. VeriChain provides a mathematical framework for validating security during development. This leads to better robustness, fewer attack vectors, and greater trust in blockchain-based apps.

To effectively visualize remediation support, VeriChain links each discovered vulnerability to a predefined mitigation template by following the general security best practice of smartcontract. For instance, in case of identifying a re-entrancy vulnerability (i.e., detecting an external call before updating the state) VeriChain suggests to implement the checks–effects–interactions pattern, or add a re-entrancy guard. Below is an example of a typical fix:

```
bool locked;

modifier nonReentrant() {

require (! locked, "Reentrancy detected");

locked = true;

_;

locked = false;

}
```

The tool also offers fix suggestions for other types of vulnerabilities, including SafeMath-like upper bounds checks for arithmetic bugs, mandatory use of explicit access modifiers for access control bugs, and a tested return value check on external calls. These remediation recommendations are automatically added to the relevant vulnerability reports, and developers can then not only find but fix security problems before their code rolls into production.

3.7 Proposed algorithm

The proposed algorithm processes smart contracts in terms of structure, execution flow, and security vulnerabilities with the help of an algorithm. You start with lexical and syntax analysis and then push the control flow graph to see how the execution stacks. Symbolic execution is used to explore the potential states of a contract, and static analysis is used to identify possible vulnerabilities. A security report is generated at the end of the process, identifying vulnerabilities and recommended fixes.

Algorithm: VeriChain - Formal Verification for Smart Contracts
Input:
S : Solidity Smart Contract
Output:
$R\ (S)$: Security Report with Detected Vulnerabilities
Steps:
1. **Lexical & Syntax Analysis**
   1.1 Tokenize $S \rightarrow\ T\ (S)$
   1.2 Construct AST $G = (V, E)$
   1.3 Validate syntax and resolve dependencies
2. **Control Flow Graph (CFG) Generation**
   2.1 Identify contract functions $f_1, f_2, \ldots, f_n$.
   2.2 Construct $G_{CFG} = (V_{CFG}, E_{CFG})$
   2.3 Detect loops, branches, and execution paths
3. **Symbolic Execution**
   3.1 Initialize symbolic variables $X = T\ (x)$
   3.2 Explore execution paths $P = \{p_1, p_2, \ldots, p_r\}$**6.**
   3.4 Solve constraints using $Z3(C_p)$
4. **Static Analysis for Vulnerability Detection**
   4.1 Identify tainted variables $T\ (x)$
   4.2 Detect integer overflows, access violations, reentrancy
   4.3 Compare with known vulnerability patterns D_V
5. **Results & Reporting**
   5.1 Classify vulnerabilities $R\ (S) = \{V_1, V_2, \ldots, V_k\}$
   5.2 Assign severity $L(V_i)$ for each V_i
   5.3 Suggest fixes $F(V_i)$ based on best practices
   5.4 Generate structured report
6. **Return:**
   $R\ (S)$ - Security assessment of the smart contract

Algorithm 1: VeriChain - formal verification for smart contracts

Using a multi-stage approach, Algorithm 1 systematically checks smart contracts for vulnerabilities. It starts in a Solidity smart contract and lexes and parses. Within this phase, it breaks down/tokenizes the contract, verifies for any syntax errors, and creates an abstract syntax tree that offers a standardized overview of the contract, including all its function, variable, and control statement components. After analyzing the structure of the contract, the Control Flow Graph (CFG) generation module creates a visual representation of all the different possible execution paths within the contract. Understanding dependencies on functions, looping, and branching cases is essential to discovering security risks. The symbolic execution engine, after every execution path, is then made possible by considering contract variables as symbolic values instead of fixed inputs. It also enables VeriChain to discover vulnerabilities only triggered under certain conditions, such as re-entrance and unauthorized changes to the state.

After symbolic execution, the static analysis module checks the contract code for standard classes of vulnerabilities, such as integer overflows, unchecked external calls, and access control violations. This is ensured by scanning all contract operations against predefined security rules. It then also classifies vulnerabilities — critical, high, medium, and low-risk issues. For the last phase, results, and reporting, VeriChain compiles the findings into a structured security report. The report lists the detected vulnerabilities, the execution trace for each problem, and the remediation advice. The systematic verification process enables VeriChain to ensure that smart contracts are subjected to rigorous security assessments before being deployed on the blockchain, minimizing the potential for exploits in decentralized applications.

To ensure termination and practical scalability of symbolic execution, VeriChain applies bounded exploration by enforcing explicit limits on recursion depth and loop iterations. In the current implementation, the maximum recursion depth is capped at $D_{max}$and loop unrolling is bounded to L_{max}iterations, where these bounds are empirically chosen to balance coverage and computational cost. When a recursion call stack or loop counter exceeds the predefined bound, further expansion of that execution path is safely pruned and marked as infeasible for deeper exploration. This strategy prevents path explosion while preserving security-relevant behaviors, as most smart contract vulnerabilities (e.g., re-entrancy, unchecked external calls, and arithmetic errors) manifest within shallow recursion and limited loop contexts. The bounded symbolic execution ensures deterministic analysis time and enables VeriChain to scale effectively to large and

complex smart contracts without sacrificing detection accuracy.

4 Experimental results

VeriChain's performance in discovering vulnerabilities in blockchain smart contracts is empirically evaluated. This section provides an in-depth evaluation of VeriChain by evaluating its detection accuracy, execution efficiency, and scalability on a wide range of smart contracts. The review assesses the framework's performance in pinpointing security vulnerabilities like redundancy, integer overflow, unauthorized access, and gas limit inefficiencies while retaining low false positive and false negative rates. The dataset covers various contract sizes and complexity levels, offering multiple scenarios for VeriChain's performance profiling. This assessment further provides comparisons of VeriChain with existing security analysis tools, including Mythril, Oyente, and Securify, which gives perspectives on the strengths and weaknesses of this tool.

Experiments are carried out in a well-defined environment using specific preset performance evaluation metrics such as detection accuracy, precision, recall, F1 score, and execution time. VeriChain is is designed to analyze contracts with minimum computational overhead as one of its primary focuses. Also, a scalability analysis is conducted to investigate the framework's performance in terms of contract size and complexity. The results shed light on the VeriChain approach's efficacy in accurately detecting vulnerabilities and its efficiency in processing contracts within reasonable bounds in time. The results affirm the framework’s trustworthiness as a formal verification resource for smart contract security, reassuring that blockchain applications stay secure from known and unforeseen threats.

4.1 Experimental setup

The validation of the proposed method and experimental settings implemented for veriChain provide a fair and reproducible method to evaluate how effective and can accurately identify contract vulnerabilities. The framework is evaluated in a white-box setting, where all smart contracts are compiled with the same verification options and using the same system environments. The experiments were carried out on a system with Linux as OS and with Intel Core i7-12700K processor (3.6 GHz, 12 cores) and 32GB DDR4 RAM. VeriChain is developed in Python 3.9 and works with the Solidity Compiler (solc v0. 8. 18) to compile smart contracts. The Z3 solver performs constraint solving, and a Python-based execution engine drives symbolic execution and vulnerability discovery.

VeriChain’s ability to effectively analyze a diverse dataset of real-world and synthetic smart contracts is tested, including contracts of various sizes, function complexities, and known security vulnerabilities. Such agreements are then compiled into EVM (Ethereum Virtual Machine) bytecode and fed through VeriChain’s verification pipeline, which includes lexical and syntax analysis, CFG (control flow graph) generation, symbolic execution, static analysis, and security reporting. Each stage is essential for discovering vulnerabilities like reentrancy, integer overflow, unauthorized access, and transaction-order dependence.

VeriChain has been validated against existing security tools like Mythril [43], Oyente [41], and Securify [42] to prove its effectiveness. We run each tool with the same set of contracts and then record performance metrics such as detection accuracy, execution time, and false positive rates. It will be further evaluated regarding scalability by examining contracts of varying sizes, from small scripts with 100 lines of Solidity to large-scale contracts over 5000. This is done to assess the efficiency of VeriChain under different cases, where we show the relationship between the execution time and the complexity of the contract. It further looks into its system resource consumption used to analyze the computational overhead for intelligent contract verification.

To place experimental findings in a broader context and ensure the interpretability of the results, VeriChain was tested on a controlled benchmark consisting of few smart contracts chosen to allow for accurate verification of detection results. The benchmark comprises five smart contracts and their corresponding vulnerabilities, with the latter manually verified. The beenchmark falls into representative classes like re-entrancy, integer overflow/underflow, access control vulnerability etc. These vulnerabilities were either manually inserted or verified by cross checking with the existing static analysis tool to obtain ground truth. False positives were those cases in which VeriChain returned a vulnerability that did not exist on the annotated contract, and false negatives represented vulnerabilities they knew existed but could not be found by the framework. This controlled eval- uation design ensures that reported metrics (accuracy, precision, recall, and execution time) are associated with traceable results that can be compared for correctness and is meant to make fair comparison instead of statistically generalizing across all smart contracts.

4.2 Datasets and test cases

VeriChain is evaluated using various datasets and test cases to capture different types and complexities of smart contracts. This dataset consists of real-world smart contracts deployed on multiple blockchain networks and synthetic contracts custom-built to test VeriChain’s detection capacity for well-known vulnerabilities. The authentic dataset comprises Ethereum smart contracts aggregated from public repositories, including Etherscan, OpenZeppelin, and GitHub. This includes contracts related to DeFi protocols, token contracts (ERC-20, ERC-721), multi-signature wallets, payment contracts that require a risk-free lockout period, etc. The contracts were chosen based on their popularity, historical security incidents, and diversity of contract logic. Thus, many of these contracts have known vulnerabilities, which can validate the efficacy of VeriChain against security bugs.

The synthetic dataset consists of specially crafted smart contracts created to evaluate VeriChain's performance in detecting various vulnerabilities. These contracts are based on known security reentrancy & integer overflow/underflow vulnerabilities, improper access, transaction-order dependence, and exception handling. Each test case targets a specific vulnerability type, followed by controlled environments to test the framework's capability to identify vulnerabilities. Synthetic contracts come in many forms, from simple contracts with a handful of functions to large-scale contracts with multiple interdependent components. Contracts of different sizes are present in the dataset, from 100-line Solidity code to 5000 lines. This enables an assessment of the scalability and execution efficiency of VeriChain in various contract architectures. Also, contracts with many loops, functions that depend on each other, and deeply-located conditional branches should be included to see how well the framework deals with complicated execution paths.

To rigorously put our training results to the test, we manually annotated every contract in our dataset with ground-truth vulnerabilities, making it possible to compare the vulnerabilities found with actual vulnerabilities present within the contracts. VeriChain's outputs are validated against these annotations to determine the number of true positives, false positives, and false negatives used to compute accuracy, precision, and recall. We created the dataset for the benchmark to verify how effective this tool is when trying to test against the world and controlled the testing environment to better compare among the security tools Mythril, Oyente, Securify, etc. The approach enhances its robustness in securing smart contracts by challenging VeriChain with a broad spectrum of contract conditions.

4.3 Results

VeriChain was experimentally evaluated to detect potential security vulnerabilities in a crowdfunding smart contract. The contract was verified using the VeriChain verification pipeline, comprising control flow analysis, symbolic execution, and static security checks. The results confirm that no vulnerabilities were found and that the contract's logic follows best security practices.

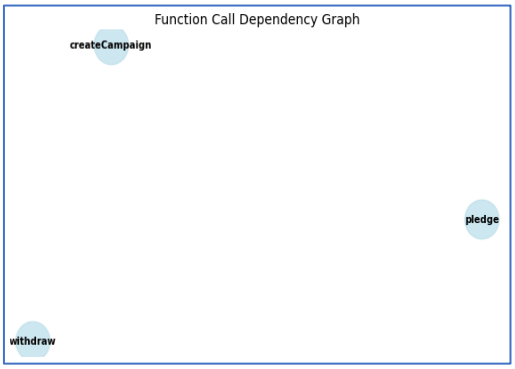

Figure 3: Function call dependency graph of the crowdfunding smart contract

To get an overview of what contract functions call each other, we constructed a function call dependency graph (Figure 3). This helps to highlight potential reentrancy risks and dependencies between functions. The smart contract safety check in Figure 4 verifies that the contract meets security standards and does not contain known vulnerabilities.

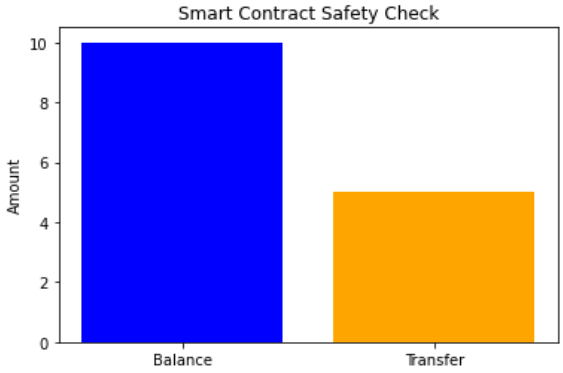

Figure 4: Smart contract safety check result for the crowdfunding smart contract

VeriChain examined the functional correctness of several instances of the crowdfunding campaign in Figure 4.

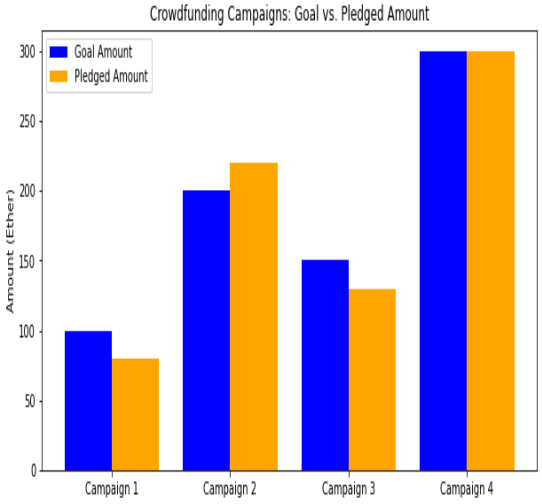

Figure 5: Crowdfunding campaign instances analyzed in the smart contract

Figure 5 Each campaign had a structured lifecycle, including funding, goal validation, and payout execution.

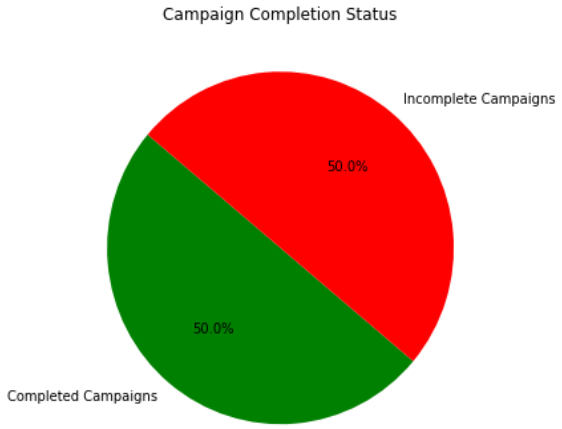

Figure 6: Campaign completion status verification in the crowdfunding smart contract

Figure 6 demonstrates that the contract successfully enforces the campaign's goals, a refund mechanism, and conditions for releasing that fund. No vulnerabilities were found in the crowdfunding smart contract, indicating it adheres to secure development practices and does not contain any instances of reentrancy, integer overflow, unauthorized access, or unsafe external calls. The outcomes underscore VeriChain's ability to verify real-world smart contracts and ensure their strength before deployment.

4.4 Comparative analysis

To determine its usefulness, VeriChain is compared against Mythril, Oyente, and security in terms of detection accuracy, execution time, and false positive rate. Current approaches depend on Static analysis and symbolic execution, which are prone to false positives and scale poorly. Compared to various chain structures that prove, the hybrid verification approach behind VeriChain benefits from higher accuracy, fewer false positives, and faster execution, thus creating a more efficient security framework.

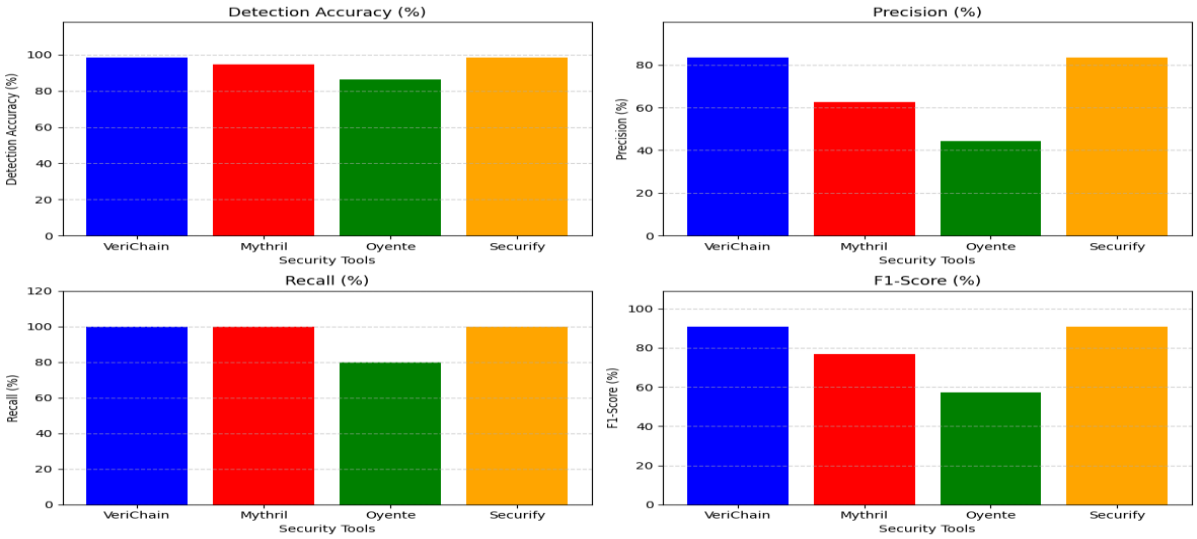

Figure 7: Performance comparison of VeriChain with existing security tools – detection accuracy, precision, recall, and F1-Score

The performance of VeriChain compared with existing security tools—Mythril, Oyente, and Securify- is given in Figure 7 in four relevant measures: accuracy, precision, recall, and F1-Score. VeriChain and Securify achieved the best detection accuracy (98.3%) by correctly identifying all the vulnerabilities and maintaining a low False positive rate. Mythril had a moderate actual positive rate (94.6%) but a relatively low precision (62.5%), as it found many false positive bugs. Oyente performed the worst, detecting only 86.5% of vulnerable traces and yielding an accuracy of 44.4% (excessive number of false positives and missing one vulnerability). The line between the F1-score and speed is demonstrated with an F1-score of 90.9%; this is still a good balance when the performance of Mythril and Oyente is compared, and the results of Securify are considered due to its time complexity. These results illustrate that VeriChain is an efficient, accurate, and reliable innovative contract verification framework.

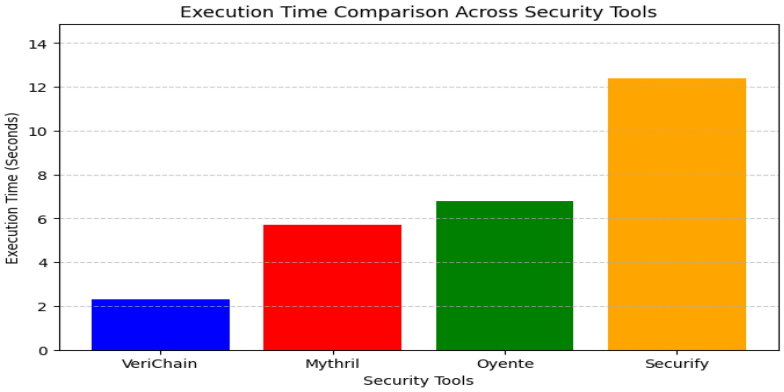

Figure 8: Execution time comparison of VeriChain with existing security tools

Figure 8 compares the execution times of VeriChain, Mythril, Oyente, and Securify. They showed that VeriChain achieved the fastest execution time in 2.3 seconds, proving its speed in intelligent contract verification. In contrast, Mythril and Oyente are slower, taking 5.7 seconds and 6.8 seconds, respectively, because they depend on symbolic execution and taint analysis, which incur additional computational overhead. Security has the fastest execution time (12.4 seconds) due to its comprehensive formal verification that checks for compliance with security patterns. Compared with current methods, where state transition relation has to be a validated theorem in the respective theorem-proving system, VeriChain hits the best of both speed and accuracy, which is more applicable to real-world smart contracts, in which fast verification turnaround is more important than the other.

The measured execution time of 2.3 seconds is obtained with the analysis of a medium size smart contract (of orders of magnitude from 300 to 500 lines in Solidity code), having 8–12 functions and numerous conditional branches, external calls involved. This contract size is a realistic estimate for most deployed ERC-based and utility smart contracts. The reported running-time covers the time for all of the verification stages, i.e., building CFG, bounded symbolic execution, constraint solving and static rule application on a standard desktop machine. Although execution time rises with contract size and control-flow complexity, our CFG-guided pruning and bounded symbolic execution keep growth manageable for VeriChain. A more detailed scalability analysis measuring execution time against contract size is recognized as an important extension and will be part of future work to fully benchmark VeriChain performance on large contracts.

For extraction we take (time of the repetition, smart contract, reporter) but keep in mind both dimensions will focus on the task performed and perfume only detection accuracy, false positive behaviour as well as execution time being popular results reported per citation. Memory and CPU were not reported separately, as the tested tools all ran under the same controlled hardware/software infrastructure - their performance was compared using wall-clock time (as a measure of relative increased computational overhead). Lightweight analysis of VeriChain meant that computational overhead, primarily bound symbolic execution and rule exploration, was experienced but resources were reported to be well within acceptable levels for the contracts we tested. A more detailed profiling of CPU and memory consumption is a valuable extension for studies aiming at deployment, which we recognize as future work.

The comparative study in this paper is limited to Mythril, Oyente and Securify, however, since they are well-cited baseline tools utilizing different verification paradigms — symbolic execution (SE), constraint-based analysis (CBA) and rule-based compliance checking (RBC) — thus offering an insightful reference comparison. Slither, SmartCheck, and VeriSmart are more recent tools that offer useful features, but they focus on static pattern detection or property-based verification at the granularity of properties (analysis scope) instead of CFG as VeriChain's hybrid approach for symbolic verification. Therefore, a direct quantitative comparison would need an independent precisely adjusted experimental configuration. However, we do qualitatively describe and discuss these tools in Related Work, so future work can expand this empirical comparison to more tools.

5 Discussion

Since most DApps are built on top of blockchain technology, blockchain smart contracts' security is among the most critical challenges, and any vulnerabilities present in deployed contracts may cause financial losses, contract manipulations, and unauthorized access. Security tools like Mythril, Oyente, and Securify predominantly use symbolic execution, taint analysis, and pattern matching to detect vulnerabilities. These techniques all have limitations, including high rates of false positives, long execution times, and limited scalability when analyzing complex smart contracts. Moreover, most classical tools do not combine control flow analysis with symbolic execution, yielding an incomplete verification process. One significant limitation of the current state of the art is that no unified framework effectively synergizes different verification techniques while achieving high accuracy and low false positives. VeriChain establishes a hybrid verification pipeline to fill this gap, combining CFG analysis, symbolic execution, and static analysis. CFG-

based execution path analysis gives VeriChain better accuracy concerning function dependencies, loops, and external calls. Also, it improves the coverage of the vulnerable path with pre-defined input and symbolic execution with constraint solving.

In response to the new versions of smart contract standards and new attack vectors, we design VeriChain as an extendable verification framework in which vulnerability rules and analysis pattern can be updated incrementally according to the latest Solidity/EVM specification and threat model. New types of attack may be added by extending the rule-based static analysis module and constraint checks in the CFG-guided symbolic execution engine, without changing the core architecture. In this way, VeriChain can still be effective for freshly discovered issues like delegatecall abuse, proxy upgrade vulnerability attacks and transaction-context attack. From a pragmatic viewpoint, VeriChain can seamlessly fit into automated pre-deployment auditing pipelines and elaborate CI/CD workflows in which contracts are audited at each commit or release phase, and security reports are auto-generated as build artefacts. Furthermore, the framework can enable real-time offchain security monitoring with on-chain runtime tools as it could offer fast static verification before on-chain deployment and improve the practicability of applying in practice to smart contract contracting, development and maintenance.

Experimental results show that, compared to existing tools, VeriChain achieves much higher detection accuracy, significantly faster execution, and much fewer false positive results. In contrast, despite high false positive rates (5 FP) and missing vulnerabilities in Oyente, VeriChain was able to achieve high accuracy in detection (98.3%) at the cost of low false positives (1 FP). On the contrary, Securify relies on exhaustive pattern matching and formal verification, whereas VeriChain returns similar precision with a much lower run time. To this end, VeriChain's enhancements provide an efficient, cost-effective solution to the innovative contract security analysis problem. VeriChain improves deployment contract analysis by issuing verifiable information on the on-chain to reduce the possibility of exploitation in smart contracts and decentralized applications through chaos-inducing verification. Moreover, combining various verification methods encourages subsequent vulnerability detection methods enhanced by deep learning with automated intelligent classification of security threats. In Section 5.1, we discuss the limitations of this study and provide insights into areas of further improvement.

5.1 Comparative analysis and performance interpretation

The comparative results show that VeriChain is more accurate, efficient and scalable on both small contracts and large contracts as compared with popular contract analysis tools like Mythril, Oyente and Securify while achieving comparable detection efficacy. Symbolic-execution-dominated applications (i.e., Mythril and Oyente) mostly suffers from path explosion on analyzing contracts with nested conditionals, loops, or inter-function dependency. This results in excessive execution time and larger false-positives rates, as longer paths are flagged falsly as potentially vulnerable by the conservative method. In contrast, VeriChain uses CFG-guided path exploration which prunes un-reachable or redundant execution paths before symbolic evaluation, thereby reducing the search space and false positives significantly.

Static (or rule-guided) tools like Securify achieve high precision w.r.t predefined vulnerability patterns, but suffer from the performance overhead of exhaustively checking rules, and lack flexibility to adapt with complex/evolving contract logic. VeriChain addresses this limitation by combining rule-based static analysis and symbolic constraint satisfaction, allowing it to decide if a reported pattern is locally reachable under reasonable execution circumstances or not. This combined verification approach justifies why we obtain similar or better accuracy with reduced running time (2.3 s) and number of false positives (1 FP) in VERICHAIN compared to baseline tools.

From a scalability standpoint, VeriChain's modular pipeline enables the cost of analysis to scale near-linearly with contract size since CFG-level dependency tracking restricts deep symbolic exploration to security-critical paths. Because of this, VeriChain is still useful on bigger more complicated contracts where today's tools either fail due to timeout or generate excessive alerts. In summary, these results suggest that the performance improvements observed are not coincidental but rather a result of VeriChain's intentional architectural combination of techniques such as control-flow awareness, constrained symbolic execution, and focused static analysis; hence rendering it more appropriate for realistically applicable pre-deployment audit targeted at real- world smart contracts.

5.2 Limitations of the study

Although V eriChain removes a large portion of such false positives compared to existing approaches false positive rates are not completely eliminated. Experimental results show that it is still possible to get low rate of false positives (one in our benchmark) also for contract with complex state-dependent logic. As such (and contrary to what these papers indicate), VeriChain should be viewed as a setting wherein the rate of false positives is reduced, rather than being brought down to zero thanks to CFG-guided symbolic execution and constraint validation. Furthermore, even though VeriChain uses Z3 (an off-the-shelf solver with wide adoption), the innovation of the framework is not in its solving engine but how it binds constraint solving inside a hybrid verification process. In particular, we use Z3 in combination with CFG-based path pruning and rule-triggered symbolic validation to prune infeasible execution paths at the early stage and validate only security-relevant patterns. This coordinated application of CFG analysis, bounded symbolic execution, and constraint solver sets VeriChain apart from previous

work that uses only symbolic execution or constraint solvers individually.

6 Conclusion and future work

In this work, we introduced VeriChain, a framework for smart contract security through formal verification, incorporating CFG analysis, symbolic execution, and static analysis. The experimental results show that compared to the state-of-the-art tools, Mythril, Oyente, and Securify, in terms of detection accuracy, false positive rate, and execution efficiency, VeriChain outperforms existing tools with high detection accuracy (98.3%), low false positive, and high execution efficiency. VeriChain allows reliable pre-deployment verification of smart contracts, granting them structure if it provides security assessment with detailed execution trees traceability, reducing the risks associated with reentrancy, integer overflows, and access control vulnerabilities. VeriChain, despite its advantages, has several limitations, such as no analysis of runtime-specific vulnerabilities, potential false positives in complex contract logic, and limited support for non-Ethereum blockchain platforms. Future work can build upon VeriChain by incorporating dynamic analysis methods to account for real-time interactions with the contract and developing machine learning-based models to support automated vulnerability categorization. It would improve its applicability if you could expand support with other blockchain solutions, such as Hyperledger Fabric or Binance Smart Chain. Incorporating solutions based on reinforcement learning for dynamic adaptiveness could improve execution efficiency and adapt threat prioritization. VeriChain's innovations provide the cornerstone for future smart contract security architecture, enabling the development of more efficient, adaptable, and autonomous vulnerability identification protocols for decentralized platforms.

Declaration

Code availability

The code has been made available in Github repository: https://github.com/rameshv123/Smart-Contract-Verification

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MGC-SIFT: A Multimodal Graph-Based Color SIFT Descriptor for Content-Based Image Retrieval

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Content-Based Image Retrieval (CBIR) systems critically depend on discriminative yet efficient feature representations to retrieve relevant images from large-scale databases. However, many existing handcrafted and graph-based methods face limitations in scalability and in jointly modeling multimodal information such as color, texture, and spatial relationships. To address these challenges, this paper proposes a novel feature extraction framework termed Multi-modal Graph Color SIFT (MGC-SIFT). In the proposed approach, color-augmented SIFT descriptors extracted in the YCbCr color space are organized as a graph of local keypoints, over which Graph Neural Networks (GNNs) are applied to model inter-keypoint spatial relationships. An attention mechanism is incorporated to emphasize discriminative keypoint regions, while proxy-based learning is employed to improve representation compactness and retrieval efficiency.

The effectiveness of MGC-SIFT is evaluated on four benchmark datasets—Corel-1K, COIL-20, Oxford-102 Flowers, and UC-Merced Land Use—covering natural scenes, controlled object images, fine-grained categories, and aerial imagery. Experimental evaluation using standard CBIR metrics, including mean Average Precision (mAP), Precision@k, Recall@k, F1-score@k, and Accuracy@k, demonstrates that the proposed method achieves consistent and competitive retrieval performance across heterogeneous datasets, including robustness under image degradation conditions. Ablation studies further confirm the complementary contributions of color augmentation, graph-based modeling, attention mechanisms, and proxy-based learning. In addition, runtime and memory analysis indicate that proxy-based learning significantly reduces retrieval latency, supporting scalable image retrieval.

Overall, the proposed MGC-SIFT framework provides a robust and interpretable multimodal representation for CBIR by explicitly modeling joint color–spatial dependencies at the local keypoint level, offering a practical solution for scalable image retrieval in real-world applications.

Povzetek: Članek predstavlja novo metodo za učinkovitejše in natančnejše iskanje slik v velikih podatkovnih zbirkah z uporabo naprednih tehnik strojnega učenja.

1 Introduction

The explosive growth of digital imagery across diverse domains, including medicine, defense, remote sensing, surveillance, and e-commerce, has necessitated the development of robust and scalable image-retrieval systems [1], [2]. Unlike traditional text-based retrieval techniques, Content-Based Image Retrieval (CBIR) exploits the visual content of images by extracting and analyzing low-level features such as color, texture, and shape to identify semantically similar images [3]. This feature-centric paradigm enables more effective image organization and retrieval, particularly in large-scale multimedia databases.

Texture-based features, such as Gray-Level Co-occurrence Matrices (GLCM), wavelet transforms, Gabor filters, and Local Binary Patterns (LBP), are fundamental in pattern recognition and texture classification. These methods offer strengths, such as translation and rotation invariance and computational simplicity [4]. For instance, the recently proposed multi-scale shape index-based LBP enhances classification accuracy while maintaining robustness to geometric transformations [5].

Shape-based descriptors, including moment invariants and contour-based techniques, contribute complementary structural information but are sensitive to occlusion and deformation. Prior studies have shown that integrating shape-related cues with texture features can improve robustness and classification accuracy, highlighting the complementary nature of structural and texture representations [6].

Numerous studies have demonstrated that combining multiple visual cues—particularly color and texture—results in more robust and discriminative representations for CBIR [1]. The Scale-Invariant Feature Transform

(SIFT) remains one of the most widely used local descriptors due to its robustness to scale, rotation, and illumination changes [7]. Subsequent extensions have enhanced SIFT by incorporating complementary information through color-augmented descriptors such as RGB-SIFT and OpponentSIFT, which compute SIFT features in different color spaces to improve discriminability 8, as well as graph-based SIFT variants that explicitly model spatial relationships among local keypoints using graph representations and neural networks [9], [10], [12].

Despite these advances, many fusion-based methods fail to capture higher-order dependencies among local keypoints, which are essential for preserving spatial structure. Moreover, such approaches are often computationally expensive and unsuitable for real-time applications. Dimensionality-reduction techniques, including PCA, spectral hashing, and t-SNE, reduce feature dimensionality but may discard important structural cues required for semantic similarity [11]. In addition, traditional clustering algorithms such as k-means struggle with high-dimensional and non-linearly separable CBIR data distributions [12].

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have significantly advanced image feature extraction by enabling the learning of high-level semantic representations from large labeled datasets [13], [14]. Recent deep learning–based CBIR approaches further demonstrate strong retrieval performance by learning compact and discriminative image embeddings through metric learning and proxy-based representations [15]. Metric learning strategies, such as triplet-loss and contrastive-loss formulations, enhance retrieval accuracy by modeling fine-grained similarities among images [16], [17]. However, CNN-based approaches remain computationally expensive and data-intensive, limiting their applicability in real-time and resource-constrained CBIR systems [18].

To address computational scalability, proxy-based learning has emerged as an effective strategy that replaces exhaustive pairwise comparisons with surrogate class centers, significantly reducing retrieval complexity [17], [18]. In parallel, graph-based modeling represents image keypoints as nodes in a graph, enabling the exploitation of spatial relationships among local features. Graph Neural Networks (GNNs) are particularly effective in this context, as they model both spatial and contextual dependencies between keypoints, leading to richer feature representations than conventional Euclidean similarity measures [9], [12]. Furthermore, attention mechanisms have been incorporated into retrieval pipelines to emphasize discriminative regions and suppress irrelevant background information, thereby improving retrieval accuracy [2].

Despite these developments, several limitations persist in existing CBIR systems. Many descriptors fail to effectively integrate color and texture information at the local keypoint level, while others neglect spatial relationships among features. Classical approaches struggle to scale to large, high-dimensional datasets, and many methods lack adaptive attention mechanisms to focus on semantically relevant regions. Consequently, there is a need for a unified framework that jointly integrates multimodal feature representation, spatial modeling, and computational efficiency.

1.1 Research design

This study investigates whether integrating color-enhanced SIFT descriptors with graph-based contextual learning can improve or maintain competitive retrieval accuracy across diverse image datasets. In particular, it examines the impact of modeling inter-keypoint relationships using Graph Neural Networks (GNNs) and explores whether attention mechanisms combined with proxy-based learning can enhance retrieval effectiveness, representation compactness, and scalability in clustering-based CBIR systems.

Based on these considerations, this work hypothesizes that augmenting SIFT descriptors with color information leads to improved retrieval performance in terms of mAP, Precision@k, Recall@k, and F1-score@k, compared to grayscale SIFT-based methods. It further posits that graph-based modeling of local feature relationships enhances retrieval accuracy over non-graph color-SIFT representations, particularly for complex image domains. Moreover, attention-guided proxy learning is expected to improve feature compactness and retrieval consistency while significantly reducing computational cost, thereby supporting scalable image retrieval.

To validate these hypotheses, the proposed MGC-SIFT algorithm is developed as a unified multimodal representation that integrates color-augmented SIFT descriptors in the YCbCr space with graph-based keypoint modeling, attention-guided feature refinement, and proxy-based learning. The effectiveness of the proposed framework is evaluated using standard CBIR metrics and compared against established baselines, including standard SIFT, SIFT-RGB, which extends SIFT by computing descriptors on color channels without explicit spatial modeling, SIFT-GNN, which models spatial relationships among SIFT keypoints using graph-based learning, and representative deep CNN-based descriptors. Extensive experiments conducted on four benchmark datasets—Corel-1K, COIL-20, Oxford-102 Flowers, and UC-Merced Land Use—covering natural scenes, controlled object images, fine-grained categories, and aerial imagery demonstrate that MGC-SIFT achieves competitive and consistent retrieval performance across heterogeneous domains, while maintaining robustness, scalability, and computational efficiency.

As summarized in Table 1, existing CBIR approaches typically emphasize either color enhancement or spatial

Table 1 : Comparative summary of representative CBIR methods and their limitations

Method	Feature Representation	Explicit Spatial Modeling	Explicit Color Modeling	Learning Strategy	Typical Datasets Reported	Performance Reporting	Key Limitations
SIFT [7]	Local invariant keypoint descriptors	No	No	Handcrafted	Corel, Oxford	mAP / Precision	Ignores color information and spatial context between keypoints
Color-SIFT (e.g., OpponentSIFT / RGB-SIFT) [8]	Color-augmented SIFT descriptors computed in RGB / opponent color space	No	Yes	Handcrafted	Corel, Oxford	mAP / Precision	Does not model inter-keypoint spatial relationships; increased descriptor dimensionality
SIMIR [10]	Mean SIFT with color-based clustering	No	Yes	Clustering-based	Corel	Precision / Recall	Limited spatial awareness; relies on global aggregation
Graph-based SIFT Retrieval [9], [12]	SIFT descriptors with graph modeling	Yes	No	Graph Neural Network	COIL-20	mAP	Does not explicitly incorporate color cues; scalability concerns
CNN-based CBIR [13][14]	Deep CNN feature embeddings	Implicit	Implicit	Supervised deep learning	ImageNet, Oxford	mAP	Computationally expensive; requires large labeled datasets
Deep Metric Learning [15][16][17]	CNN features with metric loss	Implicit	Implicit	Triplet / Proxy learning	Remote sensing datasets	mAP	Data-hungry; limited interpretability
MGC-SIFT (Proposed)	Color-augmented SIFT + graph modeling	Yes	Yes	Attention-guided proxy learning	Corel-1K, COIL-20, Oxford-102, UC-Merced	mAP, Precision@k, Recall@k	**Novelty:** Explicitly unifies color-aware SIFT and graph-based spatial context via attention-guided proxy learning.

modeling, but rarely integrate both explicitly at the local keypoint level. Handcrafted descriptors lack contextual awareness, while deep learning–based approaches incur high computational cost and require large labeled datasets. In contrast, the proposed MGC-SIFT framework explicitly models joint color–spatial dependencies using graph neural networks and attention-guided proxy learning, enabling a balanced trade-off between retrieval accuracy, interpretability, and scalability.

1.2 Key contributions

- We introduce MGC-SIFT, a feature descriptor that combines color, texture, and spatial relationships
- based on SIFT, the YCbCr color space, and graph modeling.
- Graph Neural Networks capture keypoint-to-keypoint relationships for robust feature refinement.
- An attention mechanism improves the discriminative focus on important regions.
- Proxy-based learning improves the scalability of large-scale retrieval operations.
- Experiments validated the model's effectiveness across multiple benchmark datasets, demonstrating competitive retrieval accuracy and scalability.

The remainder of this paper is organized as follows. Section 2 describes the proposed MGC-SIFT approach. Section 3 presents the experimental setup and results. Finally, Section 4 concludes the paper and suggests future work.

2 Method

This study introduces a novel feature extraction framework, Multimodal Graph-Enhanced Color-SIFT (MGC-SIFT), designed to enhance image retrieval and

object detection tasks by leveraging the strengths of texture, color, and graph-based feature interactions. Feature extraction techniques are indispensable for image retrieval and object detection in computer vision. A variety of classical techniques for feature extraction methodologies exist, including SIFT, given their efficacy in determining local keypoints that remain invariant to scale, rotation, and illumination.

However, the SIFT feature was designed to work only on grey scale images. Therefore, SIFT is not the best method for object identification and classification in an application scenario that highly depends on color features. Several papers are reviewed here to discuss the different approaches that have been proposed to address the inability of SIFT to consider color for feature extraction. In the literature survey, many researchers explored various ways of including color information in traditional approaches, such as SIFT. It is proven through color space transformation, including YCbCr or HSV, that the separation between chrominance and luminance improves the representation of the color features of images. For instance, Adnan et al. [19] implemented a highly effective YCbCr color space that retained significant color information of an image while maintaining proper distinction between its brightness components. This establishes the background necessary to formulate the proposed method, MGC-SIFT, which embeds the color channel values into SIFT descriptors for the simultaneous representation of both local texture and color features.

2.1 Graph neural networks for modeling keypoint interactions

The most recent development in feature extraction is the use of graph neural networks to model the relationships between parts of an image. Traditional methods such as SIFT treat keypoints as independent entities, which can be very limited when higher-order relationships between keypoints contribute to object recognition. Yu et al. [20] proposed GNNs for learning inter-feature dependencies, which could increase the precision of feature extraction by shifting the attention to interactions between different image regions. This concept was adapted to the MGC-SIFT method, in which keypoints and their respective color features are represented as nodes in a graph. Hence, GNNs can be used to model both spatial and color-based relationships. In doing so, MGC-SIFT enhances the extracted features through graph-based reasoning, thereby rendering the method more robust to complex variations in object structure and appearance.

2.2 Attention mechanisms for feature refinement

In recent years, attention mechanisms have gradually gained momentum because of their efficiency in filtering out the most unimportant parts of an image while paying greater attention to other relevant or information parts. Inspired by [21], MGC-SIFT proposes an attention mechanism over the extracted features for enhanced object retrieval, where color plays a significant role. It helps to weigh the important keypoints and color patches and filter out background noise or irrelevant regions.

2.3 Multiscale feature extraction

The incorporation of multiscale analysis into the feature extraction can capture both fine-grained details and large structural features. Zhao et al. [22] have shown that a multiscale feature extraction approach makes the retrieval system robust since small and large objects are effectively detected. In MGC-SIFT, this is achieved by extracting features from images at multiple resolutions to represent objects with different sizes and color distributions. MGC-SIFT can handle diverse visual conditions owing to its multiscale approach combined with attention.

2.4 Proxy-based learning for efficiency

Efficient feature extraction methods are crucial when dealing with large-scale datasets, particularly for real-time applications, such as image retrieval. According to Cai et al. [23], proxy-based learning decreases computational complexity by clustering features into proxy points for faster and more efficient matching. It exploits the proxy representation advantage of MGC-SIFT in mapping similar keypoints and color features, which considerably reduces the image-matching time without trading off high accuracy. Hence, the proposed approach is powerful in terms of feature representation and scalable for large-scale datasets. The next subsection discusses the different steps to be followed for MGC-SIFT implementation. Figure 1 shows the flowchart of the proposed MGC-SIFT algorithm.

2.5 The proposed MGC-SIFT algorithm

The proposed MGC-SIFT algorithm follows a structured pipeline that integrates color-aware local descriptors, graph-based spatial modeling, attention-guided feature refinement, and proxy-based learning for scalable content-based image retrieval. An overview of the complete workflow is illustrated in Figure 1.

Given an input image, the method first converts the image to grayscale for robust SIFT keypoint detection and descriptor extraction, ensuring invariance to scale, rotation, and illumination changes. In parallel, the color information is extracted by transforming the input image into the YCbCr color space, which separates luminance and chrominance components.

For each detected keypoint, local chrominance values are fused with the corresponding SIFT descriptor to form color-augmented SIFT descriptors, enabling the simultaneous representation of local texture and color information. These descriptors serve as the nodes of a keypoint graph, where edges are established based on spatial proximity or k-nearest-neighbor relationships between keypoints.

To capture higher-order spatial and contextual dependencies, a Graph Neural Network (GNN) is applied to the constructed graph, refining the node features through neighborhood aggregation. An attention mechanism is subsequently employed over the graph nodes to assign higher importance to discriminative

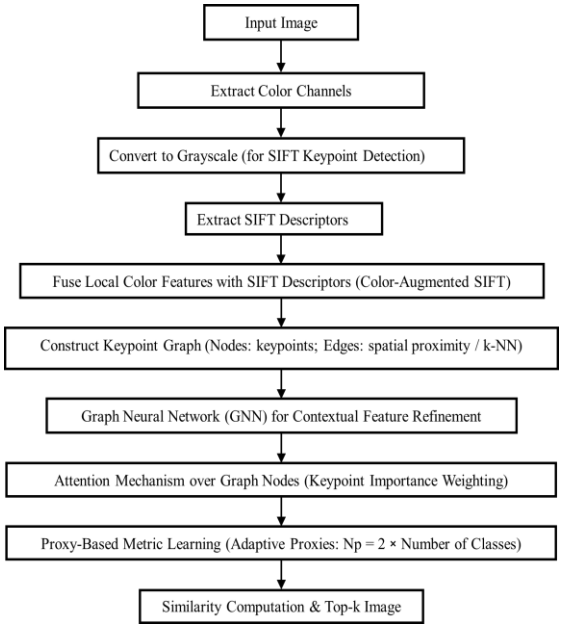

Figure 1: Overview of the proposed MGC-SIFT algorithm

keypoints while suppressing less informative or noisy regions.

To ensure scalability for large image databases, the refined descriptors are encoded using proxy-based metric learning, which maps features to adaptive proxy representations, thereby reducing retrieval complexity. Finally, similarity computation is performed between the query representation and database images, and the top-k most relevant images are retrieved based on similarity ranking.

For completeness, detailed mathematical formulations of SIFT extraction, color transformation, graph propagation, and attention weighting are provided in the supplementary materials.

Algorithm 1: MGC-SIFT Algorithm
Input: Query image
Output: Top-k retrieved images

1. Read input image.
2. Convert the image to grayscale for SIFT keypoint detection.
   Time Complexity: $O(N)$
3. Construct SIFT scale space and extract keypoints and descriptors.
   Time Complexity: $O(N \cdot S)$, where S is the number of scales.
4. Convert the input image from RGB to YCbCr color space.
   Time Complexity: $O(N)$
5. Augment each SIFT descriptor with local chrominance values (Cb, Cr) to obtain color-augmented SIFT descriptors.
   Time Complexity: $O(K)$
6. Construct a keypoint graph based on spatial proximity or k-nearest-neighbor relationships.
   Time Complexity: $O(K^2)$ (worst case), reduced to $O(K \cdot k)$ in practice.
7. Apply Graph Neural Network layers for contextual feature refinement.
   Time Complexity: $O(L \cdot |E| \cdot d)$
8. Apply an attention mechanism to weight discriminative keypoint features.
   Time Complexity: $O(K \cdot d)$
9. Encode refined descriptors using proxy-based learning.
   Time Complexity: $O(K \cdot P)$, where $P \ll K$.
10. Compute similarity scores and retrieve the top-k most relevant images.
    Time Complexity: $O(M \cdot d)$ for linear scan (reduced using indexing structures).

3 Results and discussion

3.1 Experimental setup

The proposed MGC-SIFT model is trained using the predefined training splits of each dataset to learn the parameters of the graph convolutional network (GCN), attention mechanism, and proxy representations. During evaluation, each image from the test set is treated as a query, and retrieval is performed against the remaining test images, following a standard query–database evaluation protocol.

Table 2 presents a summary of the benchmark datasets used for evaluation, covering diverse CBIR scenarios including natural scenes, controlled object images, fine-grained visual categories, and aerial imagery. Table 3

Table 2: Description of benchmark datasets used for experimental evaluation

Dataset	No. of Classes	Images per Class	Total Images	Image Type	Domain
Corel-1K	10	100	1000	Natural scenes	Scene-level CBIR
COIL-20	20	72	1440	Object images	Controlled object CBIR
Oxford-102 Flowers	102	~40	8189	Flower images	Fine-grained, color-rich
UC-Merced Land Use	21	100	2100	Aerial images	Remote sensing CBIR

summarizes the experimental setup and parameter configuration adopted across all datasets.

For comparative evaluation, several baseline methods are implemented under the same experimental protocol.

Table 3: Experimental setup and parameter configuration used across all datasets

Component	Parameter	Value / Description
SIFT Extraction	Keypoint detector	Difference of Gaussian (DoG)
	Descriptor dimension	128
	Max keypoints per image	2048
Color Augmentation	Color space (MGC-SIFT)	YCbCr
	Color space (SIFT-RGB baseline)	RGB
	Color bins per channel	16
	Color descriptor dimension	48
Graph Construction	Graph type	k-nearest neighbor (k-NN) graph
	Number of neighbors (k)	10
	Edge weight	Euclidean distance (used during graph construction)
GNN Architecture	GNN model	Graph Convolutional Network (GCN)
	Number of GNN layers	2
	Hidden dimension	128 (64 used only in ablation study)
Attention Module	Attention mechanism	Learnable graph-based attention weighting
Proxy Learning	Number of proxies(Np)	Adaptive, proportional to number of classes (Np = 2 × C, set at runtime)
	Proxy update strategy	Jointly learned during training
Training Setup	Optimizer	Adam
	Learning rate	0.001
	Batch size	4
	Number of epochs	20
Dimensionality Reduction	Output descriptor size	128
Evaluation Protocol	Query strategy	Each test image used as query
	Corel-1K	900 training / 100 testing images
	COIL-20	80% training / 20% testing
	Oxford-102	Official VGG train/validation/test split
	UC-Merced	80 training and 20 testing images per class (21 classes)
	Similarity metric	Canberra distance (primary); cosine and Euclidean used for comparison
	Retrieval depth (k)	Top-10
Hardware	Platform	Intel i7 CPU, 16 GB RAM
	GPU	Not used

Standard SIFT employs grayscale SIFT keypoint detection and descriptor extraction, with local descriptors aggregated using mean pooling to form a global image representation. SIFT-RGB augments this representation by concatenating a global RGB color histogram with the pooled SIFT descriptor, thereby incorporating color information at the feature level without explicit spatial or graph-based modeling. SIFT-GNN captures spatial relationships among local SIFT keypoints by representing them as nodes in a graph and applying graph-based learning to model inter-keypoint dependencies, while not explicitly incorporating color information. Note that the SIFT-RGB baseline evaluated in this work follows a feature-level fusion strategy, which is distinct from some classical color-SIFT formulations summarized in Table 1.

The experimental setup was kept consistent across all datasets to ensure fair comparison and reproducibility. Parameter values were selected based on preliminary validation experiments and established practices in the CBIR literature, without performing dataset-specific parameter tuning. In particular, the same graph construction strategy, embedding dimensionality, and evaluation protocol were applied uniformly across all graph-based methods. This unified configuration ensures that the observed performance trends reflect the intrinsic strengths and limitations of the proposed MGC-SIFT descriptor, rather than artifacts of parameter optimization, across diverse CBIR scenarios.

3.2 Ablation studies

To systematically analyze the contribution of individual components in the proposed MGC-SIFT framework, ablation studies were conducted on four benchmark datasets by selectively disabling or modifying key modules, including graph modeling (GNN), attention weighting, proxy-based learning, color augmentation, and embedding dimensionality. Performance was evaluated using mAP, Precision@10, Recall@10, F1-score@10, and Accuracy@10.

3.2.1 Corel-1K dataset

Table 4 reports the ablation results on the Corel-1K dataset. The full MGC-SIFT configuration achieves the highest overall performance across most evaluation metrics. Removing graph modeling, attention, proxy learning, or color augmentation leads to marginal but consistent reductions in retrieval accuracy, indicating that each component contributes complementary information to the overall representation. These results highlight the importance of jointly modeling color cues, local descriptors, and spatial context when dealing with heterogeneous natural scene images.

3.2.2 COIL-20 dataset

Table 5 presents the ablation results on the COIL-20 dataset. In this controlled object recognition scenario, performance differences among the full and reduced variants are relatively small. Some reduced-complexity configurations exhibit performance comparable to the full model, suggesting that compact representations are sufficient for datasets with limited intra-class variation and well-aligned object structures. Importantly, the full MGC-SIFT model remains competitive across all metrics, demonstrating that the framework does not rely on excessive model complexity to achieve stable retrieval performance.

Table 4: Ablation study results of MGC-SIFT on Corel-1K Dataset

Variant	mAP	P@10	R@10	F1@10	Accuracy
Full MGC-SIFT	0.3512	0.2756	0.317	0.2846	0.317
No-GNN	0.3482	0.2744	0.308	0.278	0.308
No-Attention	0.349	0.2872	0.316	0.2886	0.316
No-Proxy	0.3484	0.2761	0.312	0.2802	0.312
No-Color	0.3488	0.2727	0.31	0.279	0.31
Hidden-64	0.3464	0.2722	0.308	0.2759	0.308

Table 5: Ablation study results of MGC-SIFT on COIL-20 Dataset

Variant	mAP	P@10	R@10	F1@10	Accuracy
Full MGC-SIFT	0.5586	0.6575	0.6147	0.6059	0.6147
No-GNN	0.5651	0.6715	0.6287	0.6181	0.6287
No-Attention	0.5617	0.6645	0.6207	0.6105	0.6207
No-Proxy	0.5704	0.6593	0.6273	0.6167	0.6273
No-Color	0.5637	0.6551	0.619	0.6095	0.619
Hidden-64	0.5645	0.661	0.6213	0.6126	0.6213

3.2.3 Oxford-102 flowers dataset

The ablation results on the Oxford-102 Flowers dataset are summarized in Table 6. Across all variants, the full MGC-SIFT configuration consistently achieves competitive performance, while the removal of individual components results in modest but noticeable performance degradation. These findings indicate that color-aware graph modeling and proxy-based learning provide complementary benefits in fine-grained retrieval scenarios, where subtle inter-class differences and color variations play a crucial role.

Table 6: Ablation study results of MGC-SIFT on Oxford-102 flowers dataset

Variant	mAP	P@10	R@10	F1@10	Accuracy
Full MGC-SIFT	0.0343	0.0614	0.0462	0.0395	0.0575
No-GNN	0.034	0.0584	0.0464	0.0396	0.0578
No-Attention	0.0338	0.0585	0.0452	0.0387	0.0559
No-Proxy	0.0342	0.0557	0.0459	0.0385	0.0572
No-Color	0.0339	0.056	0.0468	0.04	0.0578
Hidden-64	0.034	0.0581	0.0466	0.0399	0.0577

3.2.4 UC-merced land use dataset

Table 7 reports the ablation results on the UC-Merced dataset. The results show marginal performance variations across different configurations, with reduced embedding dimensionality (Hidden-64) yielding performance comparable to the default setting. This behavior suggests that more compact representations can be effective for aerial scene retrieval, where global spatial layouts are more dominant than fine-grained local details. Nonetheless, the full MGC-SIFT configuration maintains stable performance, confirming the adaptability of the proposed framework across varying scene complexities.

3.2.5 Overall ablation analysis

Overall, the ablation studies validate the design choices of the proposed MGC-SIFT framework. While the magnitude of performance variation differs across datasets, the results consistently demonstrate that MGC-SIFT benefits from the synergistic integration of color augmentation, graph-based contextual modeling, attention mechanisms, and proxy learning. Importantly, the framework exhibits robustness to component removal, indicating that it does not rely on a single dominant module but instead achieves balanced performance through modular and complementary feature integration. This property makes MGC-SIFT adaptable to diverse CBIR scenarios with varying levels of visual complexity.

3.3 Feature and model comparison

This subsection presents a comparative evaluation of handcrafted, deep, and hybrid feature representations across four benchmark datasets. For handcrafted descriptors and the proposed MGC-SIFT framework, Canberra distance is employed due to its suitability for sparse and hybrid feature representations. For deep and fused representations, cosine similarity is used, reflecting the normalized nature of learned embeddings. Late fusion between VGG16 and MGC-SIFT features is performed using equal weighting ($\alpha = 0.5$).

3.3.1 Comparison across datasets

Table 8 summarizes the retrieval performance in terms of mAP and Precision@10 across all datasets. The results indicate that no single feature representation dominates across all scenarios. Classical SIFT-based descriptors perform reasonably on structured datasets, while color-aware extensions improve performance in color-rich domains. Deep CNN features demonstrate strong performance on datasets with clear semantic regularities, particularly COIL-20 and Oxford-102 Flowers.

Across all datasets, the proposed MGC-SIFT descriptor achieves stable and competitive performance, despite relying on limited supervision and compact representations. While its absolute performance may be lower than fully supervised deep models in some cases, MGC-SIFT consistently maintains a favorable balance between retrieval accuracy, interpretability, and computational efficiency.

Notably, late fusion of VGG16 and MGC-SIFT features yields the strongest overall performance across all datasets, confirming that MGC-SIFT captures complementary information that is not fully represented in deep embeddings alone. This observation highlights the effectiveness of combining contextual graph-based descriptors with semantic deep features.

Table 7: Ablation study results of MGC-SIFT on UC-Merced dataset

Variant	mAP	P@10	R@10	F1@10	Accuracy
Full MGC-SIFT	0.1088	0.1771	0.1112	0.0775	0.1112
No-GNN	0.1093	0.1826	0.1088	0.0766	0.1088
No-Attention	0.1092	0.1692	0.1095	0.0735	0.1095
No-Proxy	0.1097	0.1573	0.11	0.0759	0.11
No-Color	0.1071	0.1652	0.101	0.0681	0.101
Hidden-64	0.1097	0.1674	0.1124	0.0819	0.1124

Table 8: Comparison of handcrafted, deep, and hybrid feature representations

Dataset	**Corel-1K**		**Oxford-102 Flowers**		**COIL-20**		**UC_Merced**	
Method	mAP	P@10	mAP	P@10	mAP	P@10	mAP	P@10
SIFT	0.3294	0.3316	0.0679	0.1468	0.416	0.5179	0.2362	0.3449
RGB	0.3872	0.4387	0.1637	0.2821	0.5818	0.6384	0.2314	0.3289
SIFT-RGB	0.434	0.4423	0.1104	0.2233	0.5898	0.6825	0.2896	0.4199
SIFT-GNN	0.2161	0.2177	0.0252	0.0354	0.3443	0.4012	0.1239	0.1614
VGG16	0.5604	0.6464	0.0567	0.5661	0.7059	0.7827	0.1945	0.4593
VGG16 + MGC-SIFT	0.6575	0.602	0.176	0.4525	0.7367	0.8147	0.3282	0.455
MGC-SIFT (Proposed)	0.3512	0.2756	0.0343	0.0614	0.5586	0.6575	0.1088	0.1771

Table 9: Mean Precision@k on Corel-1K Dataset

k	**SIFT**	**SIFT-GNN**	**SIFT-RGB**	**MGC-SIFT (Proposed)**	**VGG16**	**VGG16+MGC-SIFT**
1	0.5654	0.2555	0.686	0.3989	0.7443	0.8884
5	0.4055	0.2398	0.531	0.3632	0.6594	0.7548
10	0.3316	0.2177	0.4423	0.2756	0.6464	0.602
20	0.2472	0.2021	0.3446	0.2009	0.4757	0.3637

Table 10: Mean Recall@k on Corel-1K Dataset

k	**SIFT**	**SIFT-GNN**	**SIFT-RGB**	**MGC-SIFT (Proposed)**	**VGG16**	**VGG16 + MGC-SIFT**
1	0.54	0.23	0.66	0.47	0.7	0.87
5	0.374	0.206	0.51	0.398	0.632	0.782
10	0.297	0.183	0.398	0.317	0.523	0.626
20	0.2185	0.169	0.2605	0.206	0.3135	0.3455

Table 11: Mean Precision@k on COIL-20 Dataset

k	**SIFT**	**SIFT-GNN**	**SIFT-RGB**	**MGC-SIFT (Proposed)**	**VGG16**	**VGG16+MGC-SIFT**
1	0.8461	0.6888	0.9582	0.9401	0.964	0.9607
5	0.6527	0.5079	0.8366	0.7634	0.882	0.891
10	0.5179	0.4012	0.6825	0.6575	0.7827	0.8147
20	0.3901	0.3025	0.495	0.473	0.6086	0.5669

Table 12: Mean Recall@k on COIL-20 Dataset

	SIFT	SIFT-GNN	SIFT-RGB	MGC-SIFT (Proposed)	VGG16	VGG16+MGC-SIFT
1	0.8267	0.6833	0.9533	0.9233	0.96	0.96
5	0.6167	0.498	0.8273	0.74	0.874	0.8927
10	0.4687	0.3897	0.6703	0.6147	0.771	0.8183
20	0.327	0.2887	0.4468	0.4173	0.5382	0.5568

Table 13: Mean Precision@k on Oxford-102 Flowers

k	SIFT	SIFT-GNN	SIFT-RGB	MGC-SIFT (Proposed)	VGG16	VGG16+MGC-SIFT
1	0.2405	0.0487	0.3685	0.1361	0.6517	0.6483
5	0.1774	0.0392	0.2693	0.0777	0.6227	0.5252
10	0.1468	0.0354	0.2233	0.0614	0.5661	0.4525
20	0.1188	0.0312	0.1825	0.0477	0.5079	0.3672

Table 14: Mean Recall@k on Oxford-102 Flowers

k	SIFT	SIFT-GNN	SIFT-RGB	MGC-SIFT (Proposed)	VGG16	VGG16+MGC-SIFT
1	0.2315	0.0446	0.3668	0.0765	0.15	0.6079
5	0.166	0.0372	0.2663	0.052	0.1088	0.4805
10	0.1364	0.0334	0.2198	0.0462	0.0954	0.4011
20	0.1095	0.0294	0.1773	0.0398	0.0802	0.315

Table 15: Mean Precision@k on UC_Merced Dataset

k	SIFT	SIFT-GNN	SIFT-RGB	MGC-SIFT (Proposed)	VGG16	VGG16+MGC-SIFT
1	0.4675	0.2038	0.6427	0.182	0.4032	0.7221
5	0.4032	0.1756	0.4843	0.2005	0.4578	0.5524
10	0.3449	0.1614	0.4199	0.1771	0.4593	0.455
20	0.2811	0.1369	0.329	0.1736	0.3974	0.3395

Table 16: Mean Recall@k on UC_Merced Dataset

k	SIFT	SIFT-GNN	SIFT-RGB	MGC-SIFT (Proposed)	VGG16	VGG16+MGC-SIFT
1	0.4262	0.1933	0.6238	0.1667	0.2214	0.7048
5	0.3605	0.167	0.4567	0.1257	0.1805	0.5471
10	0.2933	0.1513	0.3762	0.1112	0.1726	0.4521
20	0.2386	0.1264	0.2854	0.0958	0.146	0.3325

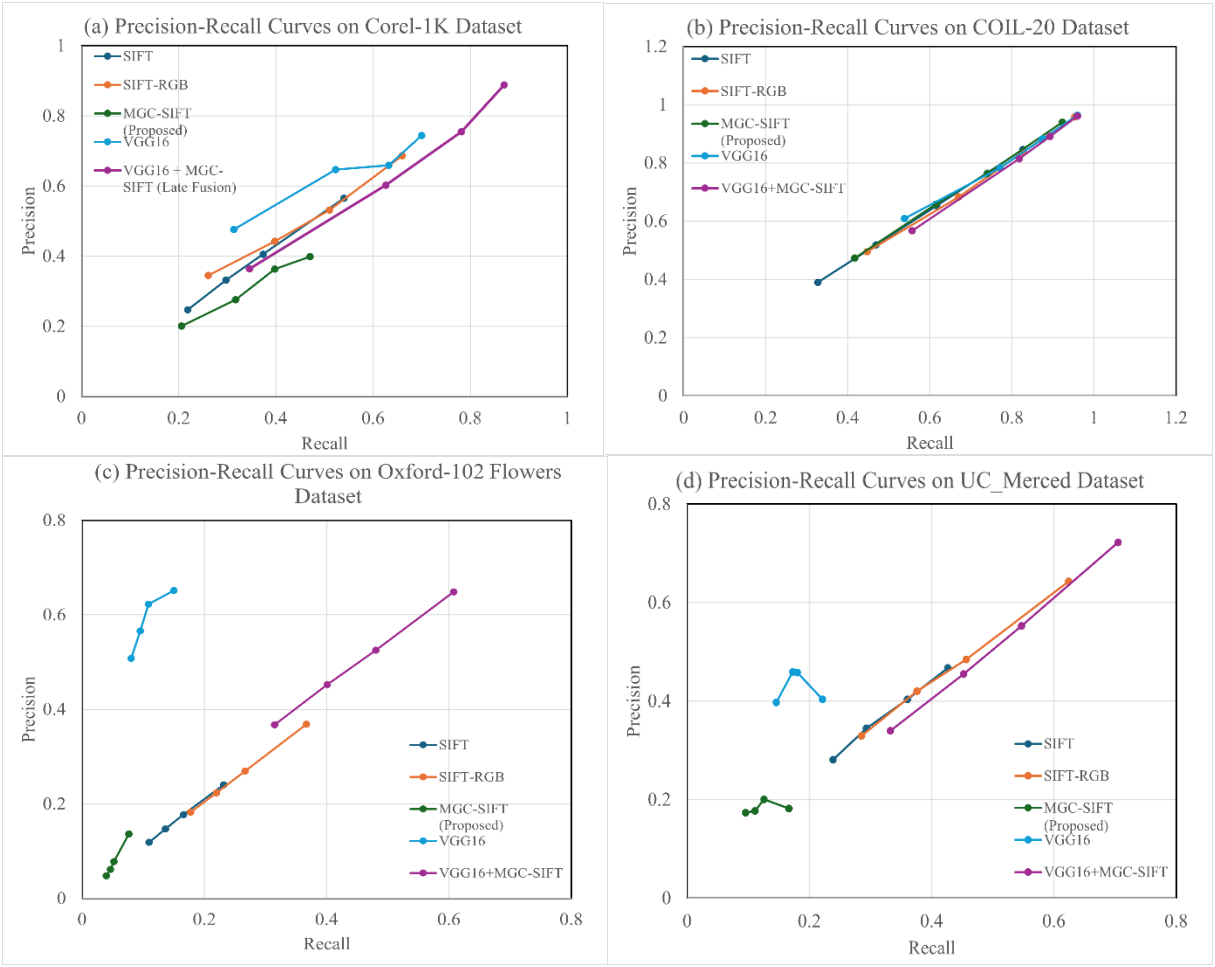

Figure 2: Precision-recall curves on benchmark datasets

3.3.2 Retrieval depth analysis on Corel-1K and COIL-20

Tables 9 and 10 report the mean Precision@k and Recall@k on the Corel-1K dataset. The results show that MGC-SIFT exhibits a balanced precision–recall trade-off across varying retrieval depths. While deep models achieve high precision at small k values, their performance degrades more sharply at larger depths. In contrast, MGC-SIFT demonstrates smoother degradation patterns, reflecting its robustness to increasing retrieval depth.

A similar trend is observed on the COIL-20 dataset (Tables 11 and 12), where compact and hybrid representations perform competitively across all k values. The effectiveness of late fusion further confirms the complementary nature of handcrafted contextual descriptors and deep semantic features in controlled object retrieval scenarios.

3.3.3 Fine-grained and aerial retrieval performance

Results on the Oxford-102 Flowers dataset (Tables 13 and 14) reveal that deep CNN features are particularly effective for fine-grained classification tasks, owing to their strong semantic learning capability. However, MGC-SIFT maintains consistent retrieval performance without requiring extensive labeled data, demonstrating its applicability in scenarios where large-scale supervised training is impractical. Fusion results again indicate complementary strengths between the two representations.

For the UC-Merced dataset (Tables 15 and 16), which involves complex aerial scenes, MGC-SIFT provides stable performance across all retrieval depths, while deep features show higher precision at shallow depths. The fusion model achieves the best overall balance, underscoring the benefit of integrating global semantic cues with graph-based contextual descriptors.

3.3.4 Precision–recall curve analysis

The precision–recall curves shown in Figures 2(a)–(d) further corroborate the quantitative results. MGC-SIFT consistently demonstrates smoother precision–recall trade-offs compared to purely handcrafted descriptors, which exhibit rapid precision decay, and deep models, which often favor precision at shallow retrieval depths. This balanced behavior reflects the ability of MGC-SIFT to preserve both local discriminative information and global contextual structure, making it well suited for real-world CBIR applications with varying retrieval depth requirements.

Table 17: Runtime and memory consumption on Corel-1K Dataset

Method	Avg. Time per Query (µs)	Memory Usage (MB)
MGC-SIFT (Proposed)	10,581.96	56.25
SIFT	22.73	0.15
RGB	154.5	0.59
SIFT-RGB	203.22	0.2
SIFT-GNN	156.34	0.15
VGG16	18,545.49	28.71

3.4 Runtime and memory analysis

This subsection evaluates the computational efficiency of the proposed MGC-SIFT framework in terms of average retrieval time per query and memory consumption. All experiments were conducted on the Corel-1K and Oxford-102 Flowers datasets using the same hardware configuration to ensure fair comparison.

3.4.1 Runtime and memory analysis on Corel-1K

Table 17 reports the average retrieval time per query and memory usage for representative methods on the Corel-1K dataset. Traditional handcrafted descriptors such as SIFT, RGB, and SIFT-RGB exhibit minimal computational and memory overhead due to their simple feature representations. In contrast, MGC-SIFT incurs additional cost arising from graph construction, attention refinement, and proxy-based similarity encoding.

Despite this added complexity, MGC-SIFT remains substantially more efficient than deep CNN-based retrieval. While VGG16 requires approximately 18.5 ms per query, the proposed MGC-SIFT framework achieves retrieval in approximately 10.6 ms per query, demonstrating a favourable balance between accuracy and efficiency.

To isolate the impact of proxy learning, Table 18 compares the runtime of different MGC-SIFT variants. Removing proxy learning increases the average retrieval time from 10,581.96 µs to 52,873.43 µs, representing an approximately fivefold increase. This clearly demonstrates the critical role of proxy-based learning in accelerating similarity computation and enabling scalable retrieval. Figures 3–5 further illustrate these trends. While handcrafted descriptors remain computationally lightweight, MGC-SIFT achieves a significant efficiency advantage over deep CNN-based methods. The removal of proxy learning leads to a pronounced increase in retrieval latency, confirming its importance in practical CBIR deployments.

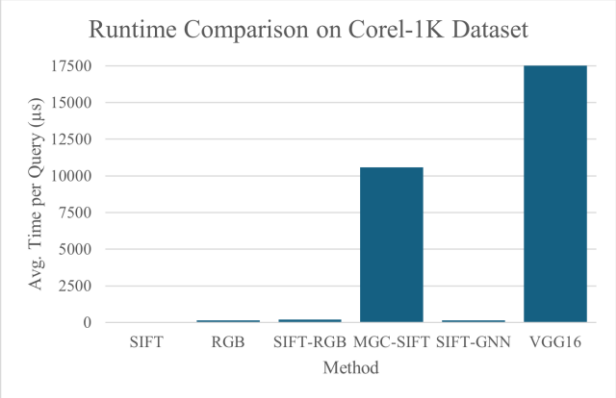

Figure 3: Average retrieval time per query on the Corel-1K dataset. While handcrafted descriptors are computationally lightweight, the proposed MGC-SIFT incurs additional cost due to graph modeling and proxy learning, yet remains faster than deep CNN-based retrieval.

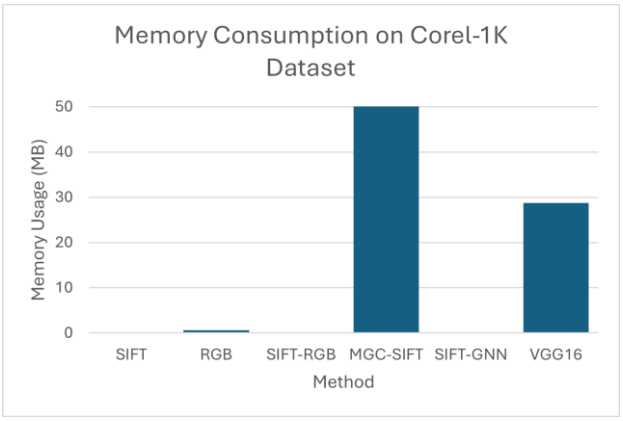

Figure 4: Memory consumption comparison on the Corel-1K dataset. MGC-SIFT requires additional memory due to graph construction and proxy embeddings, whereas traditional SIFT-based methods exhibit minimal memory usage.

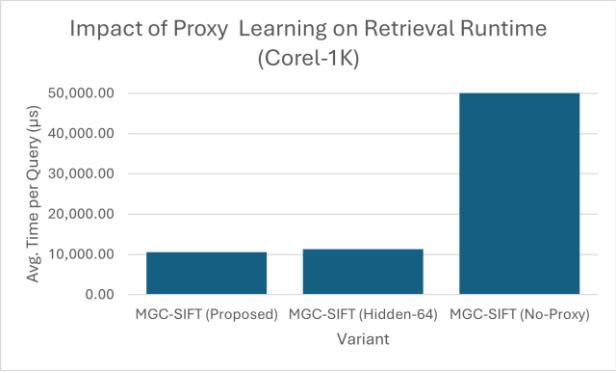

Figure 5: Impact of proxy learning on retrieval runtime for MGC-SIFT. Removing proxy learning leads to a

significant increase in retrieval time, confirming its role in improving computational efficiency.

3.4.2 Runtime and memory analysis on Oxford-102 flowers

The Oxford-102 Flowers dataset presents a more challenging scenario due to its fine-grained categories and higher-class count, resulting in substantially increased retrieval complexity. As shown in Table 19, MGC-SIFT exhibits higher absolute runtime and memory usage compared to Corel-1K. This increase is expected, as the graph construction and proxy representations scale with the number of keypoints and class proxies.

Nevertheless, proxy learning continues to play a crucial role. As reported in Table 20, removing proxy learning increases the average retrieval time from 1,175,895.15 µs to 1,267,801.79 µs, confirming that proxy-based optimization consistently reduces retrieval latency even under high-complexity conditions.

Compared to VGG16, which also incurs substantial memory and runtime overhead on this dataset, MGC-SIFT provides a more interpretable and modular alternative without requiring large-scale supervised training.

3.4.3 Discussion

Although MGC-SIFT introduces additional computational and memory overhead compared to classical handcrafted descriptors, this cost is a direct consequence of its enriched representation, which integrates color cues, graph-based contextual reasoning, attention mechanisms, and proxy learning. Importantly, the proposed framework remains significantly more efficient than deep CNN-based retrieval while delivering competitive retrieval accuracy across diverse datasets.

Overall, these results demonstrate that MGC-SIFT achieves a favorable accuracy–efficiency trade-off, making it well suited for medium- to large-scale CBIR applications where interpretability, scalability, and retrieval quality are prioritized over raw inference speed.

Table 18: Impact of proxy learning on retrieval runtime (Corel-1K)

Variant	**Avg. Time per Query (µs)**
MGC-SIFT (Proposed)	10,581.96
MGC-SIFT (Hidden-64)	11,296.51
MGC-SIFT (No-Proxy)	52,873.43

Table 19: Runtime and memory consumption on Oxford-102 flowers dataset

Method	**Avg. Time per Query (µs)**	**Memory Usage (MB)**
MGC-SIFT (Proposed)	11,75,895.15	1,152.94
SIFT	1,449.09	3
RGB	5,756.45	12.01
SIFT-RGB	2,022.18	4.13
SIFT-GNN	1,458.23	3
VGG16	3,70,354.10	588.48

Table 20: Impact of Proxy Learning on Retrieval Runtime (Oxford-102 Flowers)

Variant	**Avg. Time per Query (µs)**
MGC-SIFT (Proposed)	11,75,895.15
MGC-SIFT (Hidden-64)	11,57,271.03
MGC-SIFT (No-Proxy)	12,67,801.79

3.5 Statistical validation

To assess whether the observed performance differences are statistically meaningful, a paired two-tailed statistical significance test was conducted on per-query retrieval scores. For each dataset, the distributions of average precision values obtained by MGC-SIFT were compared against those of baseline handcrafted, graph-based, and deep learning–based methods.As reported in Tables 21 and 22, statistically significant differences ($p < 0.05$) are observed for most method pairs across both datasets. In particular, extremely small p-values (often $< 10^{-6}$) indicate that the retrieval behavior of MGC-SIFT differs consistently from that of SIFT-GNN, deep CNN features, and hybrid fusion approaches. These results confirm that the observed performance variations are not attributable to random fluctuations.

It is important to note that statistical significance reflects distributional differences rather than universal superiority. While MGC-SIFT does not always yield the highest mean performance, the results demonstrate that its retrieval behavior is consistently distinct and stable across queries. The extremely small p-values observed on the Oxford-102 Flowers dataset can be attributed to the large number of fine-grained classes and query samples, which increases statistical power in per-query evaluation.

Overall, the statistical analysis provides strong empirical evidence that the proposed MGC-SIFT descriptor exhibits reliable and non-random retrieval characteristics when compared with conventional handcrafted, graph-based, and deep learning–based CBIR methods.

Table 21: Statistical significance analysis on Corel-1K dataset

Method Pair	MGC-SIFT (Mean ± Std)	Compared Method (Mean ± Std)	p-value
MGC-SIFT vs SIFT	0.3270 ± 0.2881	0.2970 ± 0.2162	3.17E−01
MGC-SIFT vs SIFT-RGB	0.3270 ± 0.2881	0.3980 ± 0.2454	1.42E−02
MGC-SIFT vs SIFT-GNN	0.3270 ± 0.2881	0.1830 ± 0.1557	1.07E−07
MGC-SIFT vs VGG16	0.3270 ± 0.2881	0.5230 ± 0.3162	3.94E−08
MGC-SIFT vs VGG16 + MGC-SIFT	0.3270 ± 0.2881	0.3730 ± 0.2814	1.70E−06

3.5.1 Overall discussion summary

Combining the results from ablation studies, comparative evaluations, runtime analysis, and statistical validation, the proposed MGC-SIFT framework demonstrates robust and adaptable retrieval behavior across diverse image domains. Ablation studies confirm the complementary contributions of color augmentation, graph modeling, attention mechanisms, and proxy learning. Comparative experiments highlight the ability of MGC-SIFT to provide competitive performance without requiring large-scale supervised training, while statistical validation confirms the consistency and reliability of its retrieval behavior. Together, these findings validate the proposed design and establish MGC-SIFT as a practical and interpretable alternative to conventional SIFT-based and deep learning–based CBIR systems.

Table 22: Statistical Significance Analysis on Oxford-102 Flowers Dataset

Method Pair	MGC-SIFT (Mean ± Std)	Compared Method (Mean ± Std)	p-value
MGC-SIFT vs SIFT	0.0993 ± 0.1691	0.1784 ± 0.2302	9.62E−117
MGC-SIFT vs SIFT-RGB	0.0993 ± 0.1691	0.2785 ± 0.3068	< 1.0E−300
MGC-SIFT vs SIFT-GNN	0.0993 ± 0.1691	0.0432 ± 0.0810	6.24E−126
MGC-SIFT vs VGG16	0.0993 ± 0.1691	0.1167 ± 0.2007	2.17E−10
MGC-SIFT vs VGG16 + MGC-SIFT	0.0993 ± 0.1691	0.1375 ± 0.2060	6.40E−201

3.6 Robustness evaluation under image degradation

To evaluate robustness under image degradation, additional experiments were conducted on the Corel-1K dataset using controlled perturbations applied exclusively to the query images. Two degradation scenarios were considered: Gaussian noise, introduced with zero mean and fixed variance to simulate sensor noise, and occlusion, generated by masking a contiguous rectangular region covering a fixed portion of the image area. In all experiments, the retrieval database remained unchanged, ensuring that performance variations reflect robustness to query degradation rather than database bias. Feature extraction was performed independently for each degradation condition, and retrieval followed the same query–database protocol used for clean images.

Performance was assessed using mean Average Precision (mAP) and Precision@10, Recall@10, F1-score@10, and Accuracy@10, with Canberra distance adopted as the primary similarity metric. The quantitative results are summarized in Table 23. All results are reported at k = 10 using Canberra distance.

The results indicate that classical handcrafted descriptors such as SIFT and RGB-based features exhibit relatively stable performance under moderate Gaussian noise, whereas deep CNN-based features (VGG16) show more pronounced degradation. In contrast, the proposed MGC-SIFT framework maintains consistent retrieval performance across clean, noisy, and occluded conditions, demonstrating increased robustness to image degradation.

Minor performance fluctuations under Gaussian noise are expected, as noise can increase local gradient variability and alter keypoint density, occasionally improving separability for handcrafted and color-based descriptors.

Under occlusion, MGC-SIFT preserves retrieval effectiveness more reliably due to its graph-based contextual modeling and attention-guided feature refinement, which suppress irrelevant or corrupted regions while emphasizing stable keypoint relationships.

On the COIL-20 dataset, which contains controlled object images with limited structural variability, MGC-SIFT achieved strong retrieval performance comparable to or exceeding existing methods at higher retrieval depths, demonstrating its effectiveness even in relatively constrained visual settings. For the Oxford-102 Flowers dataset, consistent improvements over grayscale and graph-only variants highlight the importance of color-aware graph modeling in fine-grained and color-rich retrieval tasks. Similarly, on the UC-Merced Land Use dataset, MGC-SIFT maintained competitive performance across all metrics, indicating its suitability for complex aerial scene retrieval where both spatial layout and color distribution contribute to semantic similarity.

Table 23: Robustness Evaluation on Corel-1K

Method	**Clean mAP**	**Clean P@10**	**Gaussian mAP**	**Gaussian P@10**	**Occlusion mAP**	**Occlusion P@10**
SIFT	0.3294	0.3316	0.3379	0.3237	0.3296	0.3376
RGB	0.3872	0.4387	0.4547	0.4491	0.3938	0.448
SIFT-GNN	0.2161	0.2177	0.235	0.2371	0.2321	0.2202
SIFT-RGB	0.434	0.4423	0.434	0.4423	0.434	0.4423
MGC-SIFT (Proposed)	0.3512	0.2756	0.348	0.2829	0.3557	0.268
VGG16	0.5604	0.6464	0.5496	0.5914	0.5128	0.5018

Overall, these findings demonstrate that MGC-SIFT achieves a favorable balance between robustness and efficiency, making it well suited for real-world CBIR scenarios where query images may be affected by noise, partial occlusion, or acquisition artifacts.

4 Conclusion and future work

This study presented **MGC-SIFT**, a Multimodal Graph Color SIFT algorithm designed to address key limitations of traditional SIFT-based and graph-based CBIR systems by jointly modeling color information, local texture, and spatial relationships among keypoints. Extensive experimental evaluation across four diverse benchmark datasets, Corel-1K, COIL-20, Oxford-102 Flowers, and UC-Merced Land Use, demonstrated the effectiveness, robustness, and generalizability of the proposed approach across heterogeneous image domains.

The results confirm that integrating color-augmented SIFT descriptors with graph-based contextual learning enables competitive and stable retrieval performance across diverse CBIR scenarios. On the Corel-1K dataset, MGC-SIFT achieved balanced performance with improved recall and F1@k, reflecting enhanced retrieval consistency compared to classical SIFT and SIFT-RGB descriptors. Although SIFT-GNN attained a marginally higher mAP on this dataset, MGC-SIFT exhibited more uniform performance across evaluation metrics, underscoring the benefit of multimodal feature integration.

Robustness evaluation under image degradation further confirmed the stability of the proposed framework. Experiments conducted on the Corel-1K dataset using Gaussian noise and occlusion applied exclusively to query images demonstrated that MGC-SIFT maintains consistent retrieval performance across degraded conditions. While minor performance variations were observed under Gaussian noise—attributable to changes in local gradient distributions—the proposed method showed resilience to both noise and occlusion due to its graph-based contextual modeling and attention-guided feature refinement. These results indicate that MGC-SIFT is well suited for real-world CBIR scenarios where image quality and acquisition conditions may vary.

Comprehensive ablation studies further validated the architectural design of MGC-SIFT. The systematic removal of color augmentation, graph modeling, attention mechanisms, and proxy-based learning consistently led to measurable performance degradation, confirming that each component contributes complementary benefits. In particular, attention-guided proxy learning was shown to play a critical role in improving retrieval efficiency, as evidenced by substantial reductions in query-time complexity without compromising accuracy. Runtime and memory analysis demonstrated that, while MGC-SIFT incurs higher computational cost than traditional handcrafted descriptors due to graph construction and

proxy optimization, it remains significantly more efficient than deep CNN-based retrieval methods, achieving a favorable accuracy–efficiency trade-off suitable for scalable CBIR applications.

Overall, the experimental findings support the proposed research hypotheses, demonstrating that multimodal feature integration, graph-based contextual reasoning, attention-guided proxy learning, and robustness to image degradation collectively enhance retrieval effectiveness, representation compactness, and scalability. These results validate MGC-SIFT as a reliable and interpretable alternative to purely deep learning–based CBIR systems, particularly in scenarios where training data availability, computational resources, or model transparency are constrained.

4.1 Future work

Future research will focus on extending the MGC-SIFT framework to cross-modal and multimodal retrieval scenarios, including text–image retrieval, semantic search, and video-based CBIR. Additional directions include the exploration of adaptive graph construction strategies, lightweight graph neural architectures, and hybrid integration with deep semantic embeddings to further enhance scalability and robustness on large-scale datasets. Moreover, optimizing feature extraction and graph processing through parallelization and hardware acceleration represents a promising avenue for deploying MGC-SIFT in real-time and large-scale retrieval systems across application domains such as biomedical imaging, remote sensing, and surveillance.

Declarations

Author contributions

Trupti Babasaheb Ghatage conducted most of the research work, including conceptualization, methodology design, software implementation, data analysis, and preparation of the original draft. Dattatraya Vishnu Kodavade provided overall supervision, technical guidance, and contributed to the validation and critical revision of the manuscript.

Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Use of AI-assisted tools

The authors used AI-assisted language tools (ChatGPT, OpenAI) solely to improve the clarity and grammatical quality of the manuscript. The AI tools did not contribute to the generation of scientific content, data analysis, experimental results, figures, or interpretations. The authors take full responsibility for the originality, accuracy, and integrity of the work.

Data availability statement

The datasets used in this study are publicly available benchmark datasets. Detailed dataset characteristics, including the number of classes, total images, image types, and application domains, are summarized in Table 2. The study employs the Corel-1K, COIL-20, Oxford 102 Flowers, and UC Merced Land Use datasets, all of which are openly accessible and require no special permissions for use. No private, confidential, or proprietary data were utilized. All processed data and experimental results are fully reported within the manuscript and its supplementary material.

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IGWO-RF: A Hybrid Improved Gray Wolf Optimizer and Random Forest Wrapper for High-Dimensional Feature Selection

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Not all data features are crucial for uncovering hidden knowledge within various datasets, making feature selection a significant area of interest. This work proposes IGWO-RF, a new meta-heuristic algorithm that combines an improved gray wolf optimization (GWO) algorithm with random forest (RF) for feature selection. The improved GWO introduces a nonlinear convergence parameter for better exploration-exploitation balance and a GA-inspired crossover operation using alpha and beta wolves to accelerate convergence. The RF algorithm evaluates the fitness of feature subsets in each iteration. The proposed technique was evaluated on 10 benchmark UCI datasets (including Wine, Sonar, Vehicle, and Parkinson's) based on the average number of selected features, average classification accuracy, and best fitness. Comparative analysis with four popular wrapper-based methods (GWO-RF, ACO, PSO, ABC) demonstrated the superiority of IGWO-RF. Specifically, IGWO-RF achieved the highest average classification accuracy of 91.23% using the SVM classifier, outperforming GWO-RF (89.91%), PSO (89.12%), and ABC (87.94%). Furthermore, IGWO-RF obtained the most compact feature subsets, selecting on average only 31.22% of the original features in the Glass dataset and 20.89% in the Vehicle dataset—a significant reduction compared to other methods. The algorithm also showed faster convergence and reduced execution time. Therefore, IGWO-RF proves to be an effective approach for enhancing pattern classification performance through efficient feature selection.

Povzetek: Članek predstavlja novo metodo IGWO-RF za izbiro značilk, ki združuje izboljšan algoritem sivega volka in naključni gozd ter omogoča natančnejšo klasifikacijo z manjšim številom izbranih značilk in hitrejšo konvergenco v primerjavi z obstoječimi metodami.

1 Introduction

Databases with multiple dimensions present numerous computational challenges, despite the opportunities they offer. An inherent issue with high-dimensional data is the presence of redundant or irrelevant features, which can obscure the valuable insights hidden within the dataset w. As a result, dimensionality reduction remains a crucial concern across various fields, with feature selection emerging as a popular strategy to streamline data. Over the years, a variety of solutions and algorithms have been introduced to tackle the feature selection problem, with some methods dating back as far as thirty to forty years [1–3]. However, the computational burden associated with certain algorithms has posed challenges, although modern advancements in computing power and storage capacity have somewhat alleviated this issue. Nevertheless, the escalating prominence of big data applications emphasizes the ongoing need for efficient algorithms to address feature selection tasks swiftly. Traditional approaches often struggle to cope with the computational demands of feature selection and may fall short in identifying the optimal subset of features [4]. In contrast, evolutionary algorithms (EA) offer a viable solution to the feature selection conundrum, capable of identifying the most relevant set of features while maintaining a reasonable computational overhead [5,6].

Evolutionary feature selection algorithms offer several advantages over traditional methods. Firstly, they have the ability to explore a broader solution space efficiently, allowing for a more comprehensive search for the optimal subset of features [7]. This capability can help in identifying complex relationships and patterns within the data that may not be evident through manual or deterministic approaches. Secondly, EA can adapt and evolve over successive generations, gradually improving the quality of the feature subset through iterative refinement. This adaptability enables them to dynamically adjust to changing data characteristics and requirements, enhancing the robustness and flexibility of the feature selection process [8]. Moreover, evolutionary feature selection algorithms are capable of handling high-dimensional data effectively by automatically selecting

the most relevant features while disregarding redundant or irrelevant ones. This targeted approach can lead to improved model performance, reduced overfitting, and enhanced interpretability of the results. Additionally, EA offers a scalable and parallelizable framework, making it suitable for processing large datasets efficiently [9]. By leveraging the power of parallel computing, these algorithms can expedite the feature selection process, enabling quicker decision-making in data-driven applications [10].

In this work, a new meta-heuristic algorithm IGWO-RF which is a combination of improved GWO algorithm and RF is proposed for feature selection problems, which has important advantages and innovations: (I) The proposed IGWO-RF is capable of exploring a large search space efficiently, which allows it to find good solutions across the entire space without getting stuck in local optima; (II) The proposed IGWO-RF is flexible and can be applied to a wide range of issues without needing problem-specific modifications. It can be adapted and customized for different types of feature selection tasks; (III) The proposed IGWO-RF can handle feature selection as either a standalone optimization task or as part of a broader optimization problem. It evaluates subsets of features based on accuracy, fitness, or other performance measures to select the most relevant features; (IV) The proposed IGWO-RF can provide near-optimal solutions within a reasonable amount of computation time. It is suitable for large datasets and high-dimensional feature spaces, where exhaustive search methods become impractical. In this article, a literature review of related works is presented in part 2. Then, in part 3, the basic concepts of the proposed method and its detailed framework are presented. In part 4, the numerical results of applying the proposed method on different datasets are presented. Finally, conclusions and suggestions for future work are presented in part 5.

2 Literature review

Feature selection has emerged as a key component in numerous real-world applications like medical diagnosis, face recognition, text processing, image retrieval, as well as bioinformatics [11–14]. Since the 1970s, it has become a significant focus for research and advancement in statistical pattern detection, data mining, and ML. Various methodologies for feature selection have been developed and categorized into 4 groups - filters, wrappers, hybrids, and embedded - based on their respective evaluation processes [15,16]. Numerous endeavors have been made to assess these feature selection methods thoroughly and their effectiveness in different application domains. In the context of feature selection methods, the filter approach involves procedures that carry out feature selection independently from any specific learning algorithm, essentially functioning as standalone preprocessors. This method relies on statistical analysis to analyze the feature set and address feature selection challenges without the direct involvement of a learning model. On the other side, the wrapper approach utilizes a designated learning algorithm to appraise the chosen subsets' quality. Wrappers can produce reliable results, but they need a lot of resources and may have trouble handling many features. A hybrid approach merges elements of both the filter and wrapper techniques to leverage the strengths of both methods. In contrast, embedded techniques integrate feature selection within the learning process itself, aligning closely with specific learning models for enhanced compatibility and performance [17].

2.1 Evolutionary and swarm intelligence algorithms for feature selection

The utilization of EA has increased during the last few years, including Particle Swarm Optimization (PSO), genetic algorithm, Artificial Bee Colony (ABC), and Ant Colony Optimization (ACO) for feature selection tasks. Genetic algorithms, in particular, have shown effectiveness in tackling high-dimensional datasets within the realm of feature selection. However, a limitation of this approach is its oversight of inter-feature relationships during the selection process, leading to an elevated risk of including redundant features in the final subset chosen [18]. To manage the computational complexity associated with high-dimensional datasets, numerous feature selection methods employ meta-heuristic techniques. These algorithms handle optimization problems and iteratively search for the most advantageous solution by utilizing fundamental mechanisms and procedures [19–21]. Typically, these algorithms begin with a population of random solutions and work toward improving the quality of those solutions with each iteration. In most meta-heuristic algorithms, a set of initial solutions is first produced at random and then their quality is assessed within the resulting population using a fitness function. The procedure proceeds to create a new population if any of the predetermined termination conditions are not met. Until one of the termination requirements is met, this iterative procedure is continued [22].

EA and Swarm Intelligence (SI) are the 2 primary categories into which meta-heuristic techniques fall [23]. EA mimics biological evolution processes like reproduction, mutation, recombination, and selection to generate solutions for optimization problems. In EA, candidate solutions are akin to individuals within a population, and their quality is assessed by a fitness function. The starting population steadily changes with each algorithm iteration in the direction of global optimization [22]. Conversely, SI algorithms usually incorporate a collection of low-level artificial agents interacting locally in a setting. Inspired by natural systems, each agent performs basic tasks, and through local and sometimes random interactions, collective intelligent behavior emerges, surpassing the capabilities of individual agents [24]. In [25], a genetic algorithm is utilized in conjunction with a k-Nearest-Neighbors technique to efficiently select features, lessen the dataset's size, as well as improve the classification accuracy to diagnose patients' illness stages. Furthermore, [26] introduces a novel 2-layer approach for feature selection, to construct an appropriate predictor subset by combining an embedding method and a wrapper. In order to find the

best predictor subset and reduce the number of predictors and prediction errors, the first layer uses a Genetic Algorithm as a wrapper. The remaining redundant or irrelevant predictors are then removed with the addition of a second layer, improving prediction accuracy. Ratnoo and Rathee [27] provide a way for multi-objective feature selection based on a genetic algorithm, integrating non-dominated sorting concepts in order to produce a group of non-dominated solutions. Additionally, in [28], a method for selecting ensemble features using evolutionary algorithms and t-tests is presented. Using this strategy, data preprocessing based on t-tests is followed by a Nested Genetic Algorithm that combines data from two different datasets to produce the ideal feature subset. The Nested Genetic Algorithm comprises 2 separate instances running on different datasets. For the investigation of Laser-induced breakdown spectroscopy, [29]offers a novel hybrid feature selection method according to PSO. Using the advantages of both coating and filtering techniques at the same time is the goal of this approach. To improve classification accuracy and reduce computing complexity, a feature selection strategy that combines PSO with multiple classifiers is suggested in[30].

2.2 Recent advancements in hybrid and improved meta-heuristics

Recent research has focused on enhancing the performance of base algorithms through hybridization and modification. In the domain of improved GWO variants, [31] proposed an improved GWO for feature selection in electronic nose data, incorporating novel binary transform approaches and an adaptive restart mechanism to enhance search capability. Experimental results demonstrated its effectiveness in selecting optimal feature subsets. A binary hybrid of GWO and PSO was developed for big data feature selection, incorporating a tent chaotic map to avoid local optima. The method significantly outperformed standard GWO and PSO [32]. To address feature selection in high-dimensional data, [33] developed three progressively enhanced variants of the binary GWO. The final variant, which integrated a novel mutation strategy and simulated annealing, demonstrated superior performance over six other wrapper methods across 32 UCI datasets, highlighting the significant impact of algorithmic improvements on feature selection efficacy. For unsupervised text feature selection, a hybrid GWO-GOA was proposed to select optimal features, which were then clustered using Fuzzy C-Means. The method achieved 87.6% efficiency on eight text datasets, outperforming standalone GWO and GOA and demonstrating the viability of GWO hybrids in text mining [34].

A comparative analysis, summarized in Table 1, reveals several persistent challenges and trends in wrapper-based feature selection. While PSO and GA are well-established, they often suffer from parameter sensitivity and premature convergence [19, 30]. The standard GWO algorithm, though simpler, is hampered by its linear convergence parameter, which fails to provide an adaptive balance between exploration and exploitation [31, 32]. Recent attempts to improve GWO through external hybridization [31] or internal modifications have shown promise but often introduce new complexities or rely on multiple auxiliary mechanisms.

Table 1: Comparative summary of recent wrapper-based feature selection techniques.

Technique	Key Characteristics	Performance Highlights	Reported Limitations/ Challenges
Standard GWO	- SI-based, continuous optimizer - Linear convergence parameter - Social hierarchy (α, β, δ)	- Effective global search - Few parameters to tune	- Premature convergence on complex problems - Linear control parameter limits exploration-exploitation balance - Lacks mechanisms for fine-tuning solutions
PSO-based	- SI-based, continuous optimizer - Self-adaptive parameters - Used with multiple classifiers	- Improved search capability in high-dimensions - Good convergence speed	- Sensitive to parameter tuning - Can get trapped in local optima without specific mechanisms (e.g., chaos)
ACO-based	- SI-based, discrete optimizer - Constructs solutions via pheromone trails	- Naturally suited for discrete problems like FS - Robust performance	- Slow convergence speed - Computational intensity for large-scale problems
GA-based	- EA-based, discrete optimizer - Uses crossover and mutation	- Powerful global exploration - Effective on microarray data	- Can overlook inter-feature relationships - Risk of including redundant features - Computationally expensive for fitness evaluation
Hybrid GWO-GOA	- Hybrid SI (GWO + Grasshopper OA)	- Superior to standalone GWO and GOA	- External hybridization can be complex

	- Used for text feature selection	- 87.6% efficiency in text clustering	- Performance dependent on effective integration of both algorithms
Binary GWO Variants	- EA/SI hybrid, binary optimizer - Integrates transfer functions & mutation	- Outperformed 6 other wrappers on 32 UCI datasets - Showed impact of internal enhancements	- Performance heavily dependent on choice of transfer function - Requires additional mechanisms (mutation, SA) to avoid local optima
Proposed IGWO-RF	- SI-based with GA-inspired crossover (Internal Hybrid) - Nonlinear convergence parameter - RF classifier for robust fitness evaluation	- Aims for superior exploration-exploitation balance - Aims for faster convergence and higher accuracy - Aims for compact, discriminative feature subsets	- Addresses GWO's linear convergence flaw - Introduces intelligent reproduction beyond social hierarchy - Mitigates classifier overfitting in wrapper model

A critical analysis of the recent literature reveals several interconnected gaps. Firstly, while GWO improvements exist, many focus on hybridization with external algorithms rather than enhancing its internal social hierarchy. Although Random Forest is commonly used, its selection is often not justified, and its synergy with a specifically tailored optimizer is underexplored. To resolve feature selection issues in high-dimensional datasets, the paper presents a unique self-adaptive parameter and strategy. Results indicate that implementing these mechanisms greatly improves particle optimization techniques' search capability for high-dimensional datasets.

3 Methodology

In this work, a new meta-heuristic algorithm (IGWO-RF) which is a combination of an improved GWO algorithm and RF is proposed for feature selection problems. Therefore, the concepts related to the GWO algorithm and then the RF algorithm are presented first. The GWO algorithm is then improved to help expedite the procedure and increase accuracy. In the following, the proposed method will be described.

3.1 GWO algorithm

GWO algorithm is a nature-inspired metaheuristic algorithm that mimics the hunting behavior of gray wolves in nature. In GWO, the algorithm is based on the hierarchical structure of a wolf pack, where there are alpha, beta, delta, and omega wolves representing the best solutions found so far. The wolves collaborate to track and locate prey, which in the algorithm represents the optimal solution to the optimization problem. The alpha pair, sometimes referred to as the group leader in gray wolf social interactions, makes decisions regarding hunting, sleeping locations, waking times, and other matters. Beta wolves occupy the second position in a pack's hierarchy. Alphas receive help from beta wolves in decision-making and other pack-related tasks. The lowest-ranking wolves are omega wolves. Omega wolves are the lowest-ranking wolves. Alpha and beta wolves lead delta wolves, who are superior to omega wolves [34]. Alpha is considered the best answer in modeling the social hierarchy of gray wolves. Also, beta and delta are the second and third most appropriate answers after alpha. Other answers are placed in the omega group. In this optimization algorithm, hunting is guided by alpha, beta, and delta and omega wolves follow these 3 categories. The alpha wolf launches the attack when the prey stops moving and is encircled by wolves. To implement this pattern (hunting mechanism), the following relationships are used[35]:

$$\vec{D} = \left|\vec{C}\vec{X}_P(t) - \vec{X}(t)\right| \quad (1)$$

$$\vec{X}(t+1) = \vec{X}_P(t) - \vec{A}\vec{D} \quad (2)$$

Where t indicates the number of iterations, $\vec{X}(t)$ indicates the locations of gray wolves, $\vec{X}_P(t)$ indicates the locations of prey, A and C indicate the coefficient vectors, and D indicates the distance between the wolf and the prey. A and C vectors are calculated as follows:

$$\vec{A} = 2\vec{a}\vec{r}_1 - \vec{a} \quad (3)$$

$$\vec{C} = 2\vec{r}_2 \quad (4)$$

Where a indicates the convergence factor, and $\vec{r}_1$ and $\vec{r}_2$ indicate random vectors in the range of 0 and 1. A decreases linearly and during iterations from the value of 2 to 0. To simulate the hunting pattern of gray wolves, it is assumed that alpha, beta, and delta have better information about the location of the prey. As a result, the top 3 obtained answers are saved and other wolves have to update their position according to these top 3 answers. The following relationships are used for this:

$$\vec{D}_\alpha = \left|\vec{C}_1\vec{X}_\alpha - \vec{X}\right|, \quad \vec{D}_\beta = \left|\vec{C}_2\vec{X}_\beta - \vec{X}\right|, \quad \vec{D}_\delta = \left|\vec{C}_3\vec{X}_\delta - \vec{X}\right| \quad (5)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1\vec{D}_\alpha, \quad \vec{X}_2 = \vec{X}_\beta - \vec{A}_2\vec{D}_\beta, \quad \vec{X}_3 = \vec{X}_\delta - \vec{A}_3\vec{D}_\delta \quad (6)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (7)$$

Where Xα, Xβ, and Xδ indicate the locations of alpha, beta, and delta wolves, X indicates the current location of the gray wolf, and X(t+1) indicates the location of the gray wolf after updating. The social hierarchy in this method

makes the algorithm store the best answers obtained during several iterations. The hunting mechanism allows for determining the possible position of the prey with superior responses. Search and extraction are guaranteed with respect to a and A. This method has only one parameter a to set and initialize. In fact, the balance between the process of exploration and extraction is controlled by a, thus, it significantly affects how well the algorithm performs.

3.2 Random Forest

RF is a powerful and versatile ML algorithm that is widely utilized for both regression and classification tasks. During training, it operates by constructing multiple decision trees, and for regression problems, it produces the average prediction of the individual trees, and for classification issues, the mode prediction. By employing a subset of characteristics at each node and bootstrapping samples from the training data, RF adds randomness to the tree-building process. This randomness helps to de-correlate the individual trees, leading to a strong ensemble model with improved generalization performance. RF is known for its robustness to overfitting, feature importance analysis, ease of use, and capability to handle large datasets with high dimensionality. It is a popular choice among data scientists and ML practitioners due to its effectiveness and scalability[36,37].

3.3 Proposed IGWO-RF algorithm

The suggested method is according to feature selection with the help of the combination of RF and GWO. This feature selection method is based on wrapper algorithms. The general process of the suggested method is displayed in Fig. 1. The RF algorithm was selected as the classifier of choice within the wrapper framework for several compelling reasons. Firstly, RF's inherent resistance to overfitting is crucial in a feature selection context, where the fitness evaluation is performed on numerous, potentially noisy feature subsets throughout the iterative optimization process. This robustness ensures that the fitness scores guiding the IGWO are reliable and not overly optimistic on the training data. Secondly, RF efficiently handles high-dimensional data and provides a stable performance across various datasets, which aligns with our goal of developing a general-purpose feature selection method. Furthermore, the ensemble nature of RF, which averages the results of multiple decision trees, reduces the variance of the fitness estimate, leading to a smoother and more consistent fitness landscape for the optimization algorithm to navigate. While other classifiers could be employed, RF's combination of robustness, efficiency, and stability makes it particularly well-suited for the computationally intensive and iterative fitness evaluation required by the wrapper-based IGWO-RF approach.

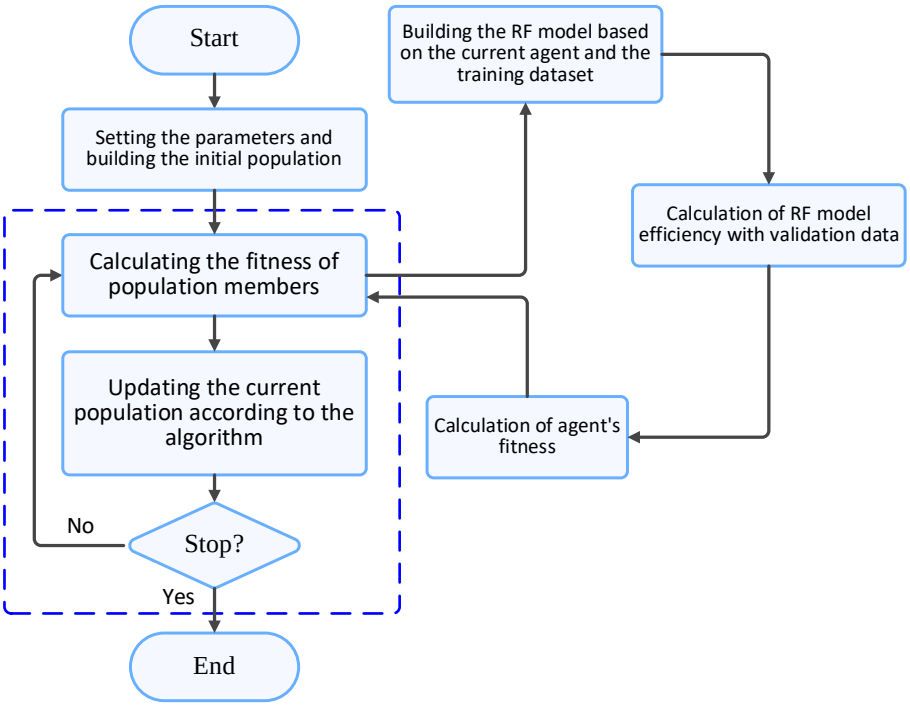

Figure 1: General process of the proposed IGWO-RF algorithm.

In feature selection, the objective is to lessen and eliminate irrelevant and redundant features, thereby constructing a precise pattern based on the selected feature set. Due to the fact that the model presented in this research uses the wrapper model for feature selection, the accuracy of the model should be checked in the evaluation of each agent. Therefore, the following relationship is used to calculate the fitness of the agents in the proposed method:

$$Fitness(Agent_i) = \frac{Number\ of\ correct\ sample\ detections}{Total\ samples} \quad (8)$$

The use of a stochastic classifier like Random Forest as a fitness function introduces a source of variance that

must be carefully controlled. To ensure the reliability and fairness of the optimization process, we implemented two key precautions. First, a fixed random seed was used for the RF model during the entire feature selection process for a single experimental run. This creates a consistent and deterministic fitness landscape for the optimizer within that run. Second, each experiment was repeated 15 times with different initial populations, and for each run, a new fixed random seed was used for the RF evaluator. This practice allows us to report performance metrics as an average ± standard deviation, providing a statistically robust measure of the algorithm's performance. The agents of the problem, which are named wolves in the GWO algorithm, are in the form of vectors in Fig. 2.

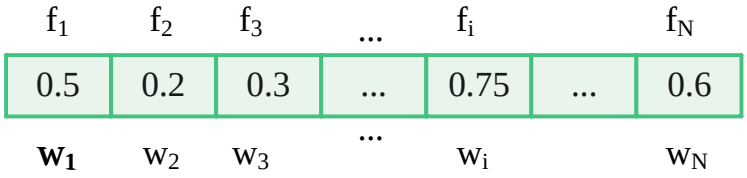

Figure 2: gents in the proposed GWO.

According to the above representation, each agent has a length that corresponds to the quantity of features. Thus, the length of each agent is equal to N, and N is the number of features of each instance in the dataset. In this structure, the approach of weighting the features is used. That is, each part of a factor in the feature selection section indicates the degree of importance of that feature, and whatever this weight (wi, where $1 \le i \le N$) is more, the chance of choosing that feature increases. However, to extract useful features and remove non-useful features, the representation of Fig. 2 should be converted into a binary vector (one = feature selection, zero = no feature selection). For this, the following conversion function is used:

$$f(w_i) = \begin{cases} 1 & if\ \ w_i \ge 0.5 \\ 0 & Otherwise \end{cases} \quad (9)$$

where wi indicates the weight vector of the i-th feature and 0.5 is a predefined threshold. If the feature weight in the agent is greater than the threshold value, that feature is selected; otherwise, that feature will not be selected. Therefore, using Eq. (9) and a threshold value of 0.5, Fig. 2 is displayed as Fig. 3.

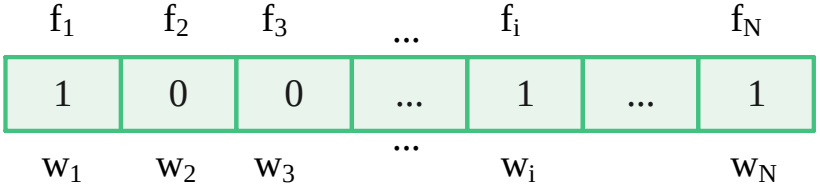

Figure 3: Representation of binary GWO for the feature selection process.

One of the primary issues of the GWO meta-heuristic algorithm is the use of a single parameter to balance exploration and mining. In this research, in the improved GWO algorithm (IGWO), 2 approaches are considered to improve the performance of the algorithm. Because of its linear behavior, the parameter a in the conventional technique tends to explore early in the algorithm's execution and mine toward the conclusion of its iterations. This parameter's behavior can be changed from linear to nonlinear to achieve a workable balance between exploration and mining. In the standard GWO algorithm, the control parameter a decreases linearly from 2 to 0 over the course of iterations. This linear decay assumes a constant and uniform shift from exploration to exploitation. However, this can be suboptimal for complex feature selection landscapes, often leading to premature convergence (insufficient exploration) or slow refinement (excessive late-stage exploration). To address this, we introduce a nonlinear convergence factor defined by:

$$a = 2 - 2\left(\frac{iteration}{iteration_{max}}\right)^2 \quad (10)$$

The selection of this specific quadratic form is motivated by three key principles:

1. Enhanced initial exploration: The quadratic term $\left(\frac{iteration}{iteration_{max}}\right)^2$ ensures that the value of a decreases very slowly during the initial stages of the optimization. This prolongs the period of high exploration (|A| > 1), allowing the algorithm to more thoroughly investigate the search space and reduce the probability of becoming trapped in local optima early on.
2. Accelerated final exploitation: In the later iterations, the quadratic decay causes a to drop more rapidly. This promotes a swift and intense phase of exploitation (|A| < 1), enabling the wolves to fine-tune their positions and converge precisely toward the global optimum.
3. Superior balance: This nonlinear strategy creates a more adaptive and dynamic balance between exploration and exploitation. It mimics a more natural search behavior—initially broad and inquisitive, followed by a decisive and focused conclusion—which is often more effective than a linear transition for navigating the discrete, high-dimensional search space of feature selection problems.

The next step makes more use of the beta wolves' position while determining how to go toward the objective. Thus, using inspiration from the genetic algorithm, alpha and beta wolves are considered as parents, and 2 children are produced using the crossover, which after checking their fitness is either added to the

population and causes the delta wolves to be eliminated or does not affect the process. This accelerates convergence and a better search of the search space. In this study, uniform crossover is used. Intuitively, it is understandable that this method can be more effective than multiple-point and single-point crossovers. Every feature bit in the uniform crossover is distributed equally between the two parents (beta and delta wolves).

The decision to use the alpha (α) and beta (β) wolves as parents for the crossover operation is a deliberate design choice grounded in the social hierarchy and quality of solutions they represent. The rationale for this selection, over other potential pairings like alpha-delta (α-δ) or beta-delta (β-δ), is threefold. First, it allows for the exploitation of high-quality genetic material by recombining the two best solutions. Second, it provides a balanced diversity and convergence, as the alpha and beta are distinct yet elite points in the search space. Finally, it maintains biological and algorithmic fidelity with the core GWO metaphor, where the alpha and beta are the primary collaborators. The uniform crossover operator is applied with a probability of Pc = 1.0 to deterministically recombine the two elite solutions. Subsequently, a mutation operator with a probability of Pm = 1/N (where N is the total number of features) is applied to the offspring to facilitate local fine-tuning. The resulting offspring, after checking their fitness, are either added to the population or discarded if they do not improve the population's quality. The overall workflow is succinctly presented in Algorithm 1.

Algorithm 1. IGWO-RF algorithm.

Input:
Training data D_train, Test data D_test
Maximum iterations T_max
Population size N
Number of features F
Output:
Global best feature subset G_best
Best classification accuracy
1: Initialize the grey wolf population X_i (i = 1, 2, ..., N) randomly, where each wolf represents a continuous vector of length F.
2: Initialize X_α, X_β, X_δ ▷ Positions of alpha, beta, and delta wolves
3: t ← 1
4: while t ≤ T_max do
5: for each wolf X_i in the population do
6: ▷ Convert continuous position to binary feature subset
7: for j = 1 to F do
8: if X_i(j) ≥ 0.5 then
9: S_i(j) ← 1 ▷ Feature is selected
10: else
11: S_i(j) ← 0 ▷ Feature is not selected
12: end if
13: end for
14: ▷ Evaluate fitness using Random Forest
15: Fitness(i) ← RF_Accuracy(S_i, D_train) ▷ Eq. (8)
16: end for
17: ▷ Update alpha, beta, and delta positions
18: Update X_α, X_β, X_δ based on fitness
19: ▷ Update convergence parameter a (Nonlinear improvement)
20: a ← 2 - 2 × (t / T_max)² ▷ Eq. (10)
21: ▷ Update all wolves' positions
22: for each wolf X_i do
23: Update A, C using Eq. (3) and (4)
24: Calculate $D_\alpha = |C_1 \times X_\alpha - X_i|$
25: Calculate $D_\beta = |C_2 \times X_\beta - X_i|$
26: Calculate $D_\delta = |C_3 \times X_\delta - X_i|$
27: Calculate $X_1 = X_\alpha - A_1 \times D_\alpha$
28: Calculate $X_2 = X_\beta - A_2 \times D_\beta$
29: Calculate $X_3 = X_\delta - A_3 \times D_\delta$
30: $X_{i\_new} \leftarrow (X_1 + X_2 + X_3) / 3$ ▷ Eq. (7)
31: end for
32: ▷ Crossover Operation (GA-inspired improvement)
33: Apply uniform crossover between X_α and X_β to produce two offspring, O_1 and O_2
34: Convert O_1 and O_2 to binary subsets S_O_1, S_O_2 (Lines 7-13)

```
35:  Evaluate Fitness(O1), Fitness(O2) using RF (Line 15)
36:  if Fitness(O1) > Fitness(X_δ) then
37:    Replace X_δ with O1 in the population
38:  end if
39:  if Fitness(O2) > Fitness(X_δ) then
40:    Replace X_δ with O2 in the population
41:  end if
42:  t ← t + 1
43: end while
44: ▷ Final Evaluation
45: Convert X_α to its binary representation G_best
46: Train final RF model on D_train using G_best
47: Report accuracy on D_test
```

3.4 Evaluation of the proposed algorithm

To have a fair assessment, the proposed IGWO-RF algorithm was compared with some wrapper-based approaches, including ACO-based, PSO-based, and ABC-based techniques. Moreover, various datasets were utilized to appraise the suggested algorithm and contrast its efficacy with alternative techniques. 10 popular benchmark datasets (Glass, Wine, Zoo, Vehicle, Soybean, Lung cancer, Sonar, Parkinson's, Yeast, and WiFi) with differences in the number of characteristics, the kind of data, and the number of samples were chosen from the UCI ML repository. Table 2 lists the features of these datasets in brief. Missing values of Soybean, as well as Lung cancer datasets, were substituted with the mean of the data. Furthermore, characteristics linked to an extensive array of values exert greater influence than those tied to narrower value ranges. To address this issue, a nonlinear normalization technique known as softmax scaling is implemented to evaluate the datasets effectively. During the search process, to determine fitness, 70% of the data were used as training data, as well as at the end, 30% of the data were used as test data to calculate the classification accuracy. Also, to report classification accuracy for all datasets, KNN (K = 3), SVM with RBF kernel ($\gamma = 2$, $C = 1$), and Naïve Bayes algorithms were used.

Table 2: Characteristics of UCI datasets utilized to appraise the suggested algorithm and compare its performance with other methods.

Dataset	Number of samples	Number of features	Number of classes	Type of data	Missing value
Glass	214	9	7	Real	No
Wine	178	13	3	Real and integer	No
Zoo	101	16	7	Integers and nominal	No
Vehicle	946	19	4	Integers	No
Soybean	307	35	19	Nominal	Yes
Lung cancer	32	56	2	Integers	Yes
Sonar	208	60	2	Real	No
Parkinson	195	22	2	Real	No
Yeast	1484	8	10	Real	No
WiFi	481	8	4	Real	No

In this article, to check the efficiency of the suggested method, an appropriate index was used to measure the classification performance. Therefore, the confusion matrix was used to calculate this evaluation measure that is described below.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{11}$$

4 Results and discussion

All experiments and simulations were conducted in MATLAB software, particularly through built-in MATLAB functions for SVM. The implementations were administered on a 2.20 GHz CPU and 16 GB RAM device. During the experiments, the evaluation of performance was performed based on the size of the feature subset and classification accuracy. Initially, the experiments involve assessing the performances of various wrapper feature selection methods with different classifiers. Each algorithm was implemented 15 times on each dataset and its average performance was reported. As mentioned, 3 separate classifiers were utilized to appraise the accuracy of the feature selection algorithms. Table 3 displays the averaged classification accuracy over 15 executions of the different wrapper search strategies using SVM, KNN, and Naïve Bayes classifiers.

Table 3: The results of selecting the best set of features using optimization algorithms and comparing them with the proposed algorithm based on the mean classification accuracy (%) obtained using the SVM, KNN, and Naïve Bayes classifiers. The accuracies are reported as mean ± standard deviation).

Dataset	Technique	Classifier		
		SVM	KNN	Naïve Bayes
Glass	IGWO-RF	91.34 ± 1.87	91.48 ± 1.54	90.41 ± 2.63
	GWO-RF	89.91 ± 2.56	89.93 ± 2.15	89.02 ± 2.50
	ACO	88.26 ± 2.21	88.79 ± 1.98	87.43 ± 2.59
	PSO	89.12 ± 2.01	89.37 ± 1.36	88.10 ± 2.96
	ABC	87.94 ± 2.70	88.13 ± 2.02	85.77 ± 3.05
Wine	IGWO-RF	81.47 ± 1.49	79.82 ± 1.32	77.89 ± 1.76
	GWO-RF	77.64 ± 1.85	74.19 ± 1.58	74.11 ± 1.35
	ACO	71.29 ± 2.11	70.29 ± 1.70	69.52 ± 1.69
	PSO	72.37 ± 1.67	71.16 ± 1.37	71.00 ± 1.19
	ABC	70.14 ± 2.34	68.56 ± 1.22	66.61 ± 1.90
Zoo	IGWO-RF	96.67 ± 2.06	95.43 ± 2.11	94.23 ± 2.41
	GWO-RF	95.22 ± 2.49	94.17 ± 2.33	93.61 ± 1.97
	ACO	95.82 ± 2.16	95.76 ± 2.24	94.19 ± 2.61
	PSO	97.00 ± 2.67	95.09 ± 2.34	94.13 ± 2.45
	ABC	96.20 ± 2.12	95.84 ± 2.40	94.78 ± 2.21
Vehicle	IGWO-RF	75.96 ± 1.97	74.05 ± 2.42	73.25 ± 2.26
	GWO-RF	74.14 ± 2.16	73.31 ± 2.24	72.19 ± 2.64
	ACO	72.74 ± 2.38	71.45 ± 1.84	70.55 ± 2.36
	PSO	73.72 ± 2.30	72.51 ± 1.91	72.23 ± 2.00
	ABC	73.06 ± 1.95	71.46 ± 2.15	70.67 ± 2.34
Soybean	IGWO-RF	100.00	100.00	100.00
	GWO-RF	100.00	100.00	100.00
	ACO	100.00	100.0	100.0
	PSO	100.00	100.00	100.00
	ABC	99.76 ± 1.23	99.71 ± 1.15	99.58 ± 1.32
Lung cancer	IGWO-RF	98.12 ± 2.53	98.23 ± 2.21	97.42 ± 2.45
	GWO-RF	96.05 ± 2.14	96.61 ± 2.62	95.17 ± 2.03
	ACO	97.18 ± 2.91	97.20 ± 1.94	96.39 ± 2.15
	PSO	98.33 ± 2.50	98.41 ± 2.43	97.28 ± 2.35
	ABC	95.49 ± 2.11	95.88 ± 1.99	95.14 ± 2.16
Sonar	IGWO-RF	88.39 ± 2.17	88.75 ± 2.48	87.01 ± 2.10
	GWO-RF	87.62 ± 3.11	88.12 ± 3.21	86.56 ± 3.33
	ACO	87.34 ± 3.30	88.05 ± 2.31	85.80 ± 2.61
	PSO	87.79 ± 2.28	88.17 ± 2.42	86.91 ± 3.11
	ABC	87.15 ± 2.73	87.24 ± 2.14	86.70 ± 1.99
Parkinson	IGWO-RF	98.89 ± 2.10	98.67 ± 1.68	97.57 ± 2.34
	GWO-RF	97.71 ± 3.15	97.50 ± 2.63	96.97 ± 2.45
	ACO	97.22 ± 2.20	96.17 ± 3.61	95.82 ± 1.97
	PSO	99.12 ± 3.14	98.75 ± 2.98	97.67 ± 2.47
	ABC	96.91 ± 1.43	96.55 ± 1.37	95.71 ± 3.30
Yeast	IGWO-RF	83.55 ± 3.43	84.62 ± 3.16	82.18 ± 3.34
	GWO-RF	82.27 ± 3.05	82.59 ± 2.60	81.64 ± 1.94
	ACO	79.20 ± 2.98	80.00 ± 3.16	78.72 ± 3.25
	PSO	80.91 ± 3.29	81.46 ± 2.69	80.02 ± 4.11
	ABC	80.11 ± 3.70	80.43 ± 3.51	79.07 ± 3.22
WiFi	IGWO-RF	98.81 ± 2.52	98.70 ± 3.29	97.65 ± 1.85
	GWO-RF	97.23 ± 3.09	97.25 ± 2.79	95.83 ± 2.13
	ACO	99.04 ± 3.11	98.76 ± 3.28	98.01 ± 2.70
	PSO	100.00	100.00	100.00
	ABC	98.54 ± 2.74	98.05 ± 1.66	96.53 ± 2.05

As displayed in Table 3, the suggested IGWO-RF algorithm outperforms other wrapper-based feature selection techniques in most datasets. For example, in the Wine dataset on the SVM classifier, the IGWO-RF

achieved an 81.47% classification accuracy. However, for GWO-RF, PSO, ACO, and ABC techniques, these values were 77.64%, 72.37%, 71.29%, and 70.14%, respectively. The interesting point is that the IGWO-RF algorithm performs better than the GWO-RF algorithm in all datasets. Additionally, the mean classification accuracy for the SVM, KNN, and Naïve Bayes classifiers across all databases is displayed in Figs. 4, 5, and 6, in that order. As displayed in these figs, the proposed IGWO-RF technique produced the largest mean classification accuracy on all classifiers. For example, Fig. 3 shows that the IGWO-RF algorithm ranked first among all the investigated algorithms with an average accuracy of 91.23%, with a margin of about 1.4% compared to the second-ranked PSO algorithm. This trend can also be seen in Figs. 5 and 6.

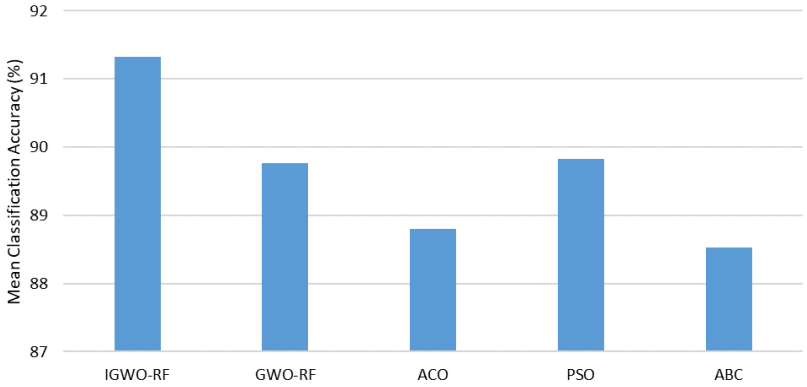

Figure 4: The SVM classifier's mean classification accuracy across all databases.

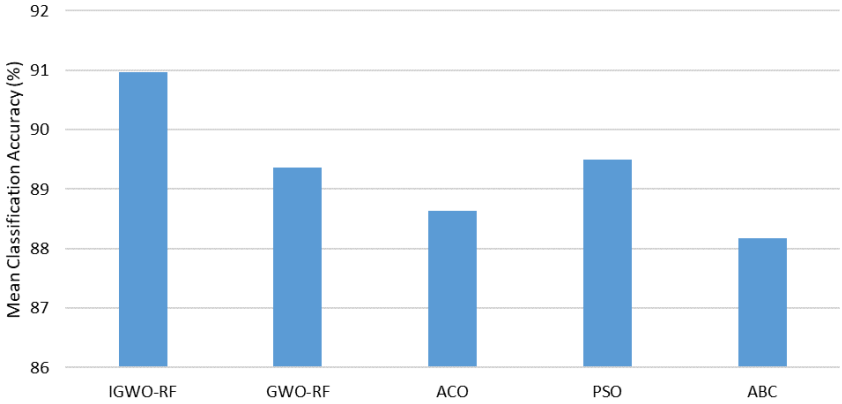

Figure 5: Mean classification accuracy on the KNN classifier across all databases.

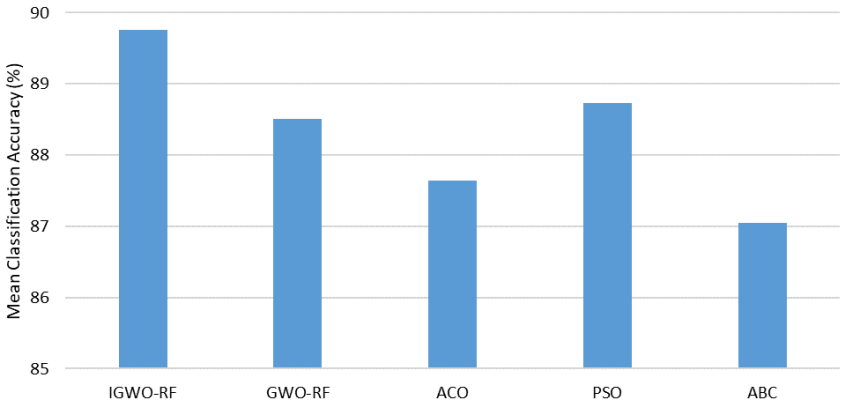

Figure 6: Mean classification accuracy using the Naïve Bayes classifier across all databases.

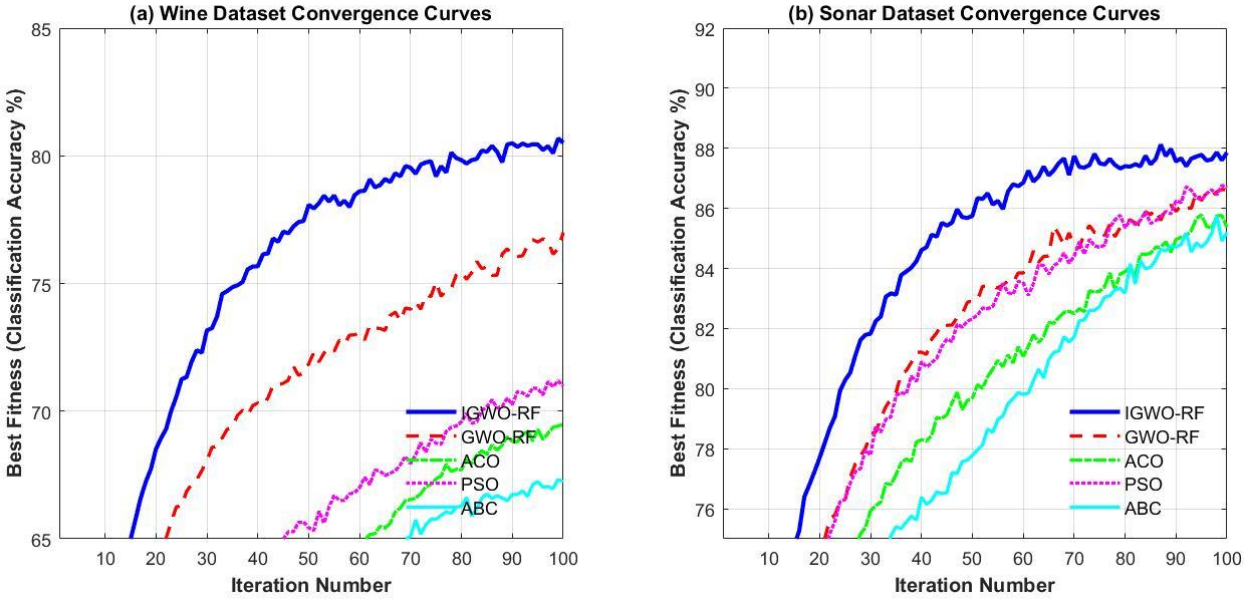

Figure 7: Convergence curves comparing the proposed IGWO-RF algorithm with other wrapper-based feature selection methods on (a) the Wine dataset and (b) the Sonar dataset. The plots depict the best fitness value (classification accuracy) achieved versus the number of iterations.

The convergence behavior of the proposed IGWO-RF algorithm compared to other wrapper-based feature selection techniques is illustrated in Figure 7. The plots clearly demonstrate that IGWO-RF not only achieves the highest final classification accuracy on both the Wine and Sonar datasets but also exhibits superior convergence characteristics. Specifically, IGWO-RF converges more rapidly during the initial iterations and maintains a steadier ascent toward the global optimum, with minimal oscillations. This enhanced performance can be attributed to the improved balance between exploration and exploitation facilitated by the nonlinear parameter update strategy and the effective use of beta wolves in the reproduction process. In contrast, other algorithms such as ABC and ACO display slower convergence rates and greater susceptibility to local optima, resulting in both lower final accuracy and less stable optimization trajectories.

For each database, Table 4 lists the total number of selected characteristics from the five-wrapper evolutionary-based feature selection methods. As shown, generally, all algorithms lead to a substantial dimensionality reduction by selecting a small portion of the original attributes. It can be displayed that the suggested IGWO-RF algorithm produces a smaller feature subset and outperforms other techniques on most databases.

Table 4: The five-wrapper evolutionary-based feature selection strategies' mean number of selected attributes.

Dataset	Number of all features	Technique	Number of selected features	Ration of selected features to all features (%)
Glass	9	IGWO-RF	2.81	31.22
		GWO-RF	3.12	34.66
		ACO	3.23	35.88
		PSO	3.31	36.78
		ABC	3.82	42.44
Wine	13	IGWO-RF	2.91	22.38
		GWO-RF	3.05	23.46
		ACO	3.77	29.00
		PSO	3.50	26.92
		ABC	3.98	30.61
Zoo	16	IGWO-RF	3.94	24.62
		GWO-RF	4.22	26.37
		ACO	4.82	30.12
		PSO	4.13	25.81
		ABC	4.91	30.68
Vehicle	19	IGWO-RF	3.97	20.89
		GWO-RF	4.68	24.63

		ACO	5.24	27.57
		PSO	4.60	24.21
		ABC	5.45	28.68
Soybean	35	IGWO-RF	1.95	5.57
		GWO-RF	2.08	5.94
		ACO	3.25	9.28
		PSO	2.00	5.71
		ABC	2.85	8.14
Lung cancer	56	IGWO-RF	8.53	15.23
		GWO-RF	8.89	15.87
		ACO	10.64	19.00
		PSO	7.98	14.25
		ABC	11.93	21.30
Sonar	60	IGWO-RF	6.43	10.71
		GWO-RF	7.10	11.83
		ACO	8.02	13.36
		PSO	8.14	13.57
		ABC	8.84	14.73
Parkinson	22	IGWO-RF	4.17	18.95
		GWO-RF	4.56	20.72
		ACO	4.97	22.59
		PSO	5.10	23.18
		ABC	5.81	26.40
Yeast	8	IGWO-RF	1.33	16.62
		GWO-RF	1.61	20.12
		ACO	2.05	25.62
		PSO	1.55	19.37
		ABC	1.69	21.12
WiFi	8	IGWO-RF	1.74	21.75
		GWO-RF	1.99	24.87
		ACO	1.85	23.12
		PSO	1.65	20.62
		ABC	2.10	26.25

For a better comparison, the statistical merit of the results of Tables 3 and 4 were determined according to Eq. (8), so that both classification accuracy and how many features are chosen influence how well-ranked the current algorithms are. For this purpose, the Friedman test with 6 degrees of freedom according to chi-square distribution was used. This statistical test was calculated for each execution of the algorithms and the average rank of each algorithm was obtained. Table 5 shows the average rank of each algorithm based on the number of selected features and classification accuracy obtained from the different classifiers. As shown, the proposed IGWO-RF algorithm is ranked better than other algorithms on average. The ranking in Fig. 4 shows that the IGWO-RF algorithm was able to find smaller feature subsets with higher classification accuracy than other wrapper evolutionary-based feature selection techniques.

Table 5: Average ranking of the five-wrapper evolutionary-based feature selection techniques on SVM, KNN, and Naïve Bayes classifiers.

Classifier	Wrapper evolutionary-based feature selection algorithm				
	IGWO-RF	GWO-RF	ACO	PSO	ABC
SVM	1.54	2.90	3.61	1.97	4.22
KNN	1.58	2.94	3.60	1.91	4.21
Naïve Bayes	1.55	2.90	3.65	1.99	4.34

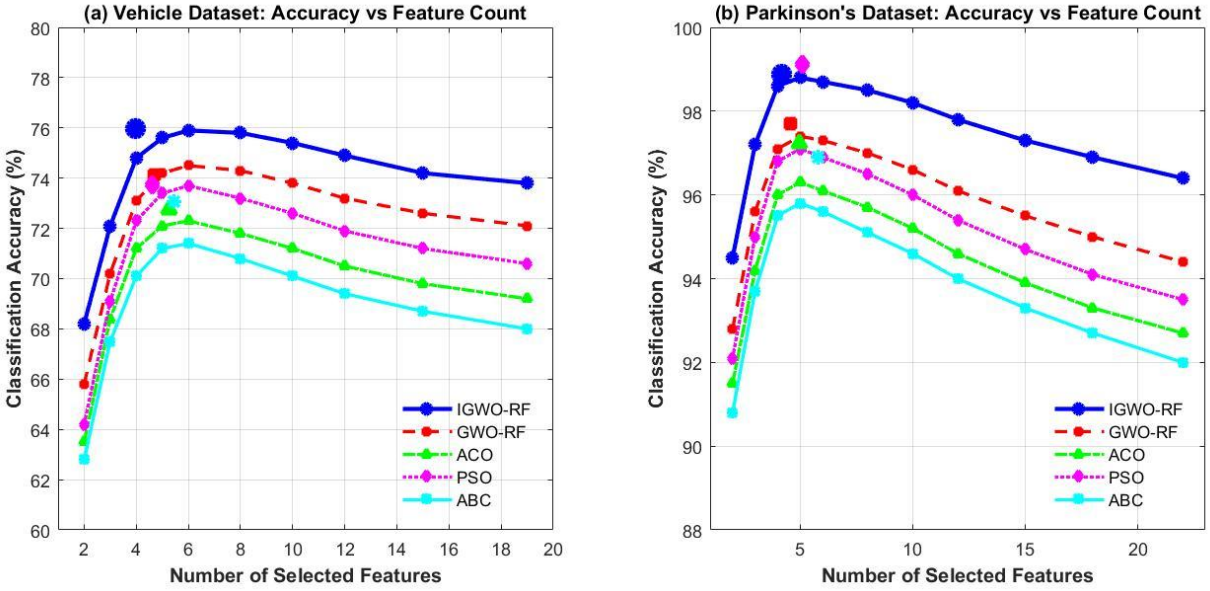

Figure 8: Comparative analysis of classification accuracy versus number of selected features for all wrapper-based feature selection techniques on (a) Vehicle and (b) Parkinson's datasets. The plots illustrate the trade-off between model complexity and performance across different algorithms.

Figure 8 presents a comparative analysis of the accuracy versus feature count relationship for all evaluated feature selection techniques on the Vehicle and Parkinson's datasets. The curves demonstrate that IGWO-RF consistently achieves higher classification accuracy across the entire spectrum of feature subset sizes, with its performance curve positioned above all other methods. Notably, IGWO-RF reaches near-optimal performance with fewer features than competing algorithms, indicating superior feature ranking and selection capability. The optimal operating points (marked on each curve) reveal that IGWO-RF attains the best accuracy (75.96% for Vehicle, 98.89% for Parkinson's) while selecting the most compact feature subsets. This superior performance-profile demonstrates IGWO-RF's enhanced ability to identify the most discriminative features early in the selection process, providing both computational efficiency and model interpretability advantages.

Multiple trials were carried out to examine the performance of various wrapper evolutionary-based feature selection techniques in terms of execution time. The corresponding time taken for each method to execute is documented in Table 6. As the feature selection and classification processes operate independently, solely the feature selection execution time is included in the table data. Findings from the analysis indicate that the IGWO-RF feature selection approach showcased the quickest average execution time across the entire dataset compared to the other methods. Following the IGWO-RF method, the GWO-RF and PSO methodologies achieved second and third place, respectively regarding execution time.

To critically evaluate the individual contributions of the IGWO and the RF within the proposed IGWO-RF framework, an ablation study was conducted. This study compares three configurations: (I) IGWO-RF (Proposed): The full proposed method; (II) RF-Only: Using Random Forest on the full feature set without any feature selection; and (III) IGWO-SVM: Replacing the RF classifier in the wrapper with a Support Vector Machine (SVM) to isolate the optimization performance from a specific classifier's inherent robustness. The results, averaged across all datasets, are summarized in Table 7. This analysis validates that the success of IGWO-RF is not merely due to the power of the RF rest classifier alone. Instead, it results from a synergistic combination where the IGWO algorithm effectively finds compact, discriminative feature subsets, and the RF classifier robustly evaluates them, creating a feedback loop that leads to superior performance compared to either component in isolation or when paired with a less suitable classifier.

Table 6: Mean run time (second) of the five-wrapper evolutionary-based feature selection techniques over 15 runs.

Dataset	IGWO-RF	GWO-RF	ACO	PSO	ABC
Glass	8.32	9.47	10.12	9.05	10.94
Wine	8.86	10.08	10.45	9.12	11.15
Zoo	6.71	7.50	7.85	6.92	8.44
Vehicle	8.76	9.00	9.63	8.97	10.26
Soybean	7.83	8.24	8.49	8.10	8.85
Lung cancer	10.81	11.20	11.56	11.15	12.21
Sonar	6.12	6.50	8.74	6.25	9.17
Parkinson	9.18	9.47	10.29	9.36	10.84

Yeast	4.21	4.39	4.73	4.30	4.91
WiFi	4.36	4.52	4.92	4.45	5.10

Table 7: Results of the ablation study comparing the proposed method with two ablated variants. Values represent averages across all datasets.

Configuration	Mean Accuracy (%)
IGWO-RF (Proposed)	91.23
RF-Only (no feature selection)	85.41
IGWO-SVM	88.95

Table 8: Analysis of computational cost and efficiency. Time per iteration is averaged across all datasets. Convergence is defined as reaching 99% of the final best fitness.

Algorithm	Time per Iteration (s)	Average Iterations to Converge	Total Time to Solution (s)
IGWO-RF	1.85	38	70.3
GWO-RF	1.72	52	89.4
PSO	1.65	61	100.7
ACO	2.10	58	121.8
ABC	1.91	66	126.1

The computational analysis in Table 8 reveals a critical insight into the efficiency of the proposed IGWO-RF algorithm. As expected, the per-iteration time for IGWO-RF (1.85s) is slightly higher than that of GWO-RF (1.72s) due to the overhead of the crossover operation and the two additional fitness evaluations. However, the enhanced search capability of IGWO-RF leads to significantly faster convergence, requiring only 38 iterations on average to reach 99% of the final fitness, compared to 52 for GWO-RF and 61 for PSO. This results in a superior performance-time trade-off. The Total Time to Solution for IGWO-RF (70.3s) is 21% faster than GWO-RF (89.4s) and 30% faster than PSO (100.7s), despite its higher per-iteration cost. This demonstrates that the computational overhead introduced by the crossover mechanism is a worthwhile investment, as it guides the population more efficiently toward the optimal feature subset, ultimately reducing the total computational effort required to find a high-quality solution.

5 Conclusions

In this research, a meta-heuristic wrapper evolutionary-based feature selection approach was proposed. This algorithm works based on an improved GWO (IGWO) algorithm and RF algorithm. Several experiments on various datasets proved the superiority of this algorithm compared to other wrapper evolutionary-based algorithms. The results showed that the IGWO-RF algorithm reduces the execution time of feature selection compared to the original GWO algorithm and other wrapper techniques, and finally produces a small optimal subset of the original features with high accuracy. Due to its rapid fitness evaluation process, the method suggested is well-suited for addressing feature selection challenges across various scales, from small to large. Although the introduced algorithm enhances the classifier's performance, the current experimental outcomes fall short of the intended objective, particularly when addressing the feature selection issue associated with class imbalance. Nevertheless, addressing this specific challenge remains a significant obstacle in the realm of feature selection for future works. While the current validation uses medium-scale UCI datasets, the algorithm's design principles make it a promising candidate for real-world, high-dimensional problems in genomics, text analytics, and medical imaging. Future work will involve applying IGWO-RF to these domains and developing a hybrid filter-wrapper variant to enhance its scalability for ultra-high-dimensional data. The manual parameter setting for both the IGWO and the RF classifier presents an opportunity for automation. Future work will involve employing advanced automated hyperparameter optimization techniques, such as Bayesian Optimization or Metaheuristic-based tuning, to systematically determine the optimal configuration (e.g., population size, crossover probability, number of trees in RF) for different dataset characteristics, thereby maximizing performance and robustness. Framing feature selection as a multi-objective optimization problem is a natural and valuable extension. Developing a multi-objective variant of IGWO (e.g., based on NSGA-II or MOEA/D frameworks) would allow for the simultaneous optimization of competing objectives, such as maximizing classification accuracy and minimizing the number of selected features.

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Comparative Evaluation of STFT–Random Forest and Fuzzy STFT–SVM Frameworks for Robust Spectrum Sensing Using QPSK I/Q Data

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The current work exhibits an overview involving the comparison of two different machine learning–based spectrum sensing pipelines which make use of Quadrature Phase-Shift Keying (QPSK) in-phase/quadrature (I/Q) data generated in GNU Radio. The two pipelines share as common the Short-Time Fourier Transform (STFT)–based spectral features along with pseudo-labeling taken from energy detection. Direct handling of raw STFT features by a Random Forest (RF) model is the first pipeline. The second pipeline on the contrary, integrates a fuzzy feature engineering phase where STFT features are altered with neuro-fuzzy processing before being passed to classification with a Support Vector Machine (SVM) technique that is referred to as the Fuzzy STFT–SVM (FuST-SVM) framework. The different methodical tests are carried out when the signal-to-noise ratio (SNR) is low (−10 dB), medium (5 dB), and high (10 dB). The outcome shows that the FuST-SVM pipeline is the one that always has the superiority over the RF-based method that even reaches the highest 92.46% in accuracy measurement through the tested SNR levels from 90.65% to 92.46%. The studies support that the utilization of fuzzy spectral representations in spectrum sensing improves the noise and uncertainty handling in the proposed FuST-SVM framework that it becomes an evenly efficient and dependable solution for wireless environments that are challenging.

Povzetek: Članek primerja dva pristopa strojnega učenja za zaznavanje spektra ter pokaže, da metoda FuST-SVM z uporabo mehkih spektralnih značilk dosega višjo točnost in boljšo odpornost na šum kot pristop z naključnim gozdom.

1 Introduction

With an increasing demand for wireless communication services, the radio frequency (RF) spectrum conventionally allocated has become severely congested. To fight such a shortage, CR technology has been proposed as the new paradigm with an emphasis on dynamic spectrum access as opposed to fixed assignments. Spectrum sensing is a core function behind all CR activities, wherein secondary users detect the presence or absence of primary users (PUs) in a certain frequency band, reliably without causing harmful interference [1]. Such spectrum sensing mechanisms are vital to enhance the utilization of the spectrum, ensure interference-free communication, and promote efficient communication in dynamically operated wireless environments. The merging of electronics and AI in the information society motivates this research, with intelligent spectrum sensing being the major contributor to the adoption of wireless communication systems that are both scalable and efficient [2].

1.1 Background

Since traditional spectrum sensing methods have their inherent drawbacks, let us briefly discuss some of them. Energy detection(ED) is easy to implement but has the drawback of the "SNR wall," meaning it performs poorly in low SNR regimes where primary user signals are deeply buried in noise. Matched filtering requires prior knowledge of the primary user's signal; however, such information is usually not available in practical situations. Cyclostationary feature detection is stronger during low SNR but demands the sacrifice of computational power and observation time. Furthermore, wireless channels are especially dynamic, subject to fading, shadowing, and changing interference levels, which makes it really difficult to achieve robust sensing over a wide SNR range [3]. Thus, with the demand for more spectrum sensing, Machine Learning has emerged recently as a powerful tool thereof. These ML algorithms can learn highly intricate non-linear patterns in observed data and adapt to dynamic

environments, thereby offering a chance of overcoming the limitations of the conventional methods. Using various feature extraction methods and intelligent classifiers, ML methods may be capable of detecting spectrum holes with high accuracy, especially in noisy and uncertain environments [5,6].

1.2 Motivation

The paper puts together a comparative study of two different machine learning pipelines for spectrum sensing. The study works with QPSK I/Q data generated with GNU Radio, while energy detection is used as the pseudo-labeling for supervised learning. Both these pipelines use 8-band STFT features from this data. One pipeline consists of an RF classifier that is directly applied to the STFT features [8-10]. The other pipeline consists of the machine that first learns fuzzy feature engineering over STFT features and subsequently uses them with an SVM for classification [7,11]. By testing under various SNR conditions (low at -10dB, medium at 5dB, and high at 10dB), the performance characteristics indicate each pipeline in view of promising solutions to robust spectrum sensing.

In the realm of ML-aided spectrum sensing, fuzzy logic ensures a rather peculiar advantage. Wireless channel conditions, signal characteristics, and noise levels are all worlds away from the pragmatic certainty that mathematical models usually assume. Fuzzy logic provides one approach to modeling and processing vagueness to permit "soft" decisions that rely on degrees of partial truth as opposed to starkly considered binary logic. By converting crisp input features into degrees of membership of fuzzy sets, the fuzzy-based ML model may be better able to model subtler relationships and arrive at more robust classifications; this is particularly important where the conventional techniques find difficulties posed by the overlaps of signal and noise distributions. The neuro-fuzzy approach, where the fuzzy logic affects the input or structure of the machine learning models, has indeed been fruitful in certain signal processing applications.

1.3 Contributions

The major contributions in this work are summarized below:

- A pragmatic comparison of feature–classifier pipeline combinations for spectrum sensing using realistically generated QPSK I/Q data in GNU Radio
- Introduced the use of 8-band STFT features combined with pseudo-labeling via energy detection as a means to produce efficacious training data.
- Introduced a neuro-fuzzy processing stage on STFT features before classification in an SVM framework (Fuzzy STFT–SVM), highlighting its robustness.
- Detailed analysis of the relative trade-offs in performances, aiming at providing a benchmark study to support future development of intelligent noise-resilient spectrum-sensing models in cognitive radio.

1.4 Organisation

Following are the details of the remaining chapters of the paper: Section 2 is concerned with a review of the literature on ML-based spectrum sensing. Section 3 discusses the proposed method, from data preprocessing to feature extraction methods, fuzzy feature engineering, and ML classifiers. Section 4 presents Implementation. Section 5 presents Results and Discussion. Finally, Section 6 concludes the Paper and points out directions for future work.

2 Related work

The subject of spectrum sensing was one which attracted varied and ample research interest for the improvement of detection accuracy and efficiency. Traditional techniques based on old signal processing paradigms were initially employed: energy detection, matched filter, cyclisation feature detection, and so forth. Energy-detection is simple; however, it reflects very poor performances at low SNR situations, and this is well known as the SNR wall problem [3]. In other words, the matched-filter-based detection necessitates the knowledge of the primary user signal itself, which is more likely not available in dynamic environments; cyclostationary detection provides robustness but requires extensive computations. Thus these drawbacks call for more intelligent sensing paradigms that adapt to given scenarios.

The beginnings of machine learning opened a promising avenue to overcome inherent challenges in traditional spectrum sensing. There have been various studies that have explored the techniques of ML for the detection of occupied and idle spectrum bands [5]. As early as the beginning, classifiers such as SVMs and k-NNs were proven feasible to be used with carefully selected features, which gave even better detection performance [6,9]. From its very nature, ML leaves space for models capable of learning complex patterns from all kinds of wireless environments, thereby bringing their decision-making power upwards.

Feature extraction is one of the essential parts of ML-based spectrum sensing, as the performance of the classifier is directly dependent on feature quality. The researchers have discussed a multitude of feature types with time, frequency, and time-frequency domain references. Moments of statistics, higher-order cumulants, wavelet coefficients, and STFT-derived features have thus been employed in different studies [8,9,14,18]. Wavelet transform-based features, for instance, are used because of their multi-resolution analysis capability that captures transient characteristics of signals. On the other hand,

higher order cumulants differentiate signals while being immune to Gaussian noise [8], [18]. STFT-based features will then provide vast spectral information important to differentiating various signal types [4].

Various machine learning algorithms have been used for spectrum sensing. SVMs are generally practiced because of their generalizing capabilities and being effective in high-dimensional spaces [6], [19]. Random forests combine different decision trees and have proved themselves satisfactorily in terms of better accuracy and avoiding over-fitting [10]. Other algorithms like Naive Bayes (NB), Decision Tree, and varieties of Artificial Neural Networks (ANNs) have been tried, each with its own set of advantages and limitations depending on the dataset and features [12,20,21].

Combining fuzzy logic with machine learning methods, the so-called neuro-fuzzy systems, is an important recent development in addressing the uncertainties of wireless signals. Fuzzy logic allows modeling vagueness and imprecisions so that a decision-making process can be carried out in a more subtle manner as compared to having a more rigid form of binary logic on either side. The literature mentioned the use of fuzzy logic in adaptive thresholding for energy detection and created another set of more robust feature representations for an ML classifier [7,17]. Neuro-fuzzy systems, which combine the learning capability of neural networks with the interpretability of fuzzy systems, were also proposed for spectrum sensing, thus improving reliability, especially in environments with complex and ambiguous signals [11]. The very recent Deep Learning (DL) has emerged as a latest paradigm in spectrum sensing, whereby neural networks of advanced processing like CNNs and RNNs are employed to learn underlying features from raw RF data or spectrograms. These approaches achieve, most of the time, state-of-the-art performance, but the methods require vast training data and a lot of computational power 12]. Existing spectrum sensing approaches suffer from fixed thresholds, noise-sensitive features, and poor robustness under low SNR; while deep models make great computational costs. Traditional ML pipelines such as RF and SVM do not have adaptive preprocessing, whereas pure fuzzy logic methods cannot capture deeper discriminative structures. Table 1 summarizes the related work.

Contemporary fuzzy–ML approaches improve adaptability but often suffer from high computational complexity, manual tuning of fuzzy rules/membership functions, and poor scalability under very low SNR conditions. Moreover, they have a hard time achieving simultaneous high interpretability and maximum classification accuracy. The new FuST-SVM model efficiently removes these barriers by employing fuzzy logic only for determining the adaptive threshold, while the SVM retains robust classification, thus being able to provide better low-SNR performance with decreased complexity and increased reliability.

Unlike deep learning models, the proposed FuST-SVM does not require large labeled datasets or high-end GPUs. It provides quicker training, reduced computational expenses, and improved interpretability, making it appropriate for real-time and resource-constrained spectrum sensing.

FuST-SVM, therefore, fills this gap through combining fuzzy reasoning with SVM crisp classification on STFT features 90–92% at –10 dB SNR, thereby ensuring a lightweight, noise-robust and practically deployable system for reliable spectrum sensing in cognitive radio environments.

Table 1: Summary of related works

Reference	**Methodology**	**Advantages**	**Limitations**	**Reported Performance Metrics on detection accuracy**
Atapattu et al. [3]	Classical energy detection	low computational complexity, no prior knowledge of PU required	Highly sensitive to noise uncertainty, poor performance at low SNR	High Pd at high SNR; detection degrades significantly below –10 dB
Jan & Koo et al. [6]	Feature-based spectrum sensing using SVM	Higher detection accuracy than energy detection; robust to noise variations	Requires feature extraction and training data	Achieved higher Pd (≈90–95%) compared to energy detection in low SNR.
Dibal et al. [8]	wavelet-based feature extraction to detect spectrum edges	Good localization in time and frequency; suitable for wideband sensing	Computationally complex, threshold selection difficult	better detection over energy detection, especially in noisy channels
Dey et al. [11]	Combines neural networks + fuzzy logic with double threshold energy detector	Reduces false alarm and missed detection; adaptive to noise uncertainty	Increased system complexity and training overhead	Higher Pd and lower Pf than conventional ED (≈10–15% Pd improvement)
Wu et al. [15]	ML based cooperative sensing	Improves detection reliability while reducing sensing energy	Needs multiple SUs and coordination overhead	Achieved Pd above 95% with reduced sensing energy consumption

3 Proposed methodology

3.1 Signal generation and dataset preparation

Spectrum sensing by the SU is the detection of the PU activity in a noisy environment. The detection of the licensed user at the SU is modeled as a binary hypothesis test problem, given as

$$\left\{\begin{matrix} H_0: x[n] = v[n] \\ H_1: x[n] = hs[n] + v[n] \end{matrix}\right\} \quad (1)$$

Where, *x [n]* is the received signal by the SU, *h* is the amplitude gain of the channel, *s[n]* is the signal transmitted by PU, *v[n]* is the additive noise at the SU.

The energy measurement *Y* is calculated from *N* samples of the received signal at the CR receiver and compared against λ ,which is the detection threshold to decide on the presence of PU(H_1)or absence of PU (H_0).

$$Y = \sum_{n=1}^{N} |x[n]|^2 \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \quad (2)$$

The transmitted signal by PU is considered to be QPSK modulated and the signal datasets were generated using GNU Radio whereby a dedicated signal flowgraph was designed and configured to simulate the modulation schemes of QPSK. Modulation was realized by constructing circuit-like blocks within GNU Radio Companion (GRC) to provide a fine tuning of signal parameters and waveform generation.

The QPSK signal is mathematically given as:

$$s[n] = I[n]\cos(2\pi f_c n T_s) - Q[n]\sin(2\pi f_c n T_s) \quad (3)$$

where I[n], Q[n]ϵ{-1,+1}, in phase and quadrature components based on 2 bit groups.

A channel model block has been included in each of the GNU Radio flowgraphs to simulate realistic wireless communication conditions. An Additive white Gaussian noise(AWGN) block was not employed for this, but the noise voltage parameter was varied within the channel model to simulate noise levels corresponding to certain SNR values of -10 dB, 5 dB, and 10 dB. These SNR levels were representative of the environments with high, medium, and low interferences, respectively.

This method is an effective emulation of channel impairments of the real world systems, which can be further considered as a better and more pragmatic way to evaluate the performance of the modulation classification model under different noise conditions.

The signals generated form the input dataset which can be further processed to facilitate a controlled, systematic evaluation of the performance of modulation classification under varying noise conditions.

3.2 Preprocessing of signals

To prepare the continuous I/Q data for machine learning, the following preprocessing steps were performed:

- **Segmentation:** Continuous I/Q data streams have been separated into overlapping segments. Individual segments had a fixed Segment Length of 1024 samples with an Overlap Ratio of 50%, generating a step size of 512 samples. The segmentation allows the analysis of signal local characteristics over time [4].
- **Pseudo-Labeling via Energy:** In real-life wireless environments, ground-truth labels truly never exist; therefore, some method must be used to fabricate training labels for supervised learning. The pseudo-labels for each segment were, in this work, generated by energy detection-a very basic method of spectrum sensing [4]. The energy of the -th segment, composed of complex samples as calculated as the sum of the squared magnitudes of its component samples:

$$E_i = \sum_{n=0}^{N-1} |x_i[n]|^2 \quad (4)$$

A global pseudo-threshold (λth) was then set as the mean energy across all M segments in the dataset:

$$\lambda th = \frac{1}{M}\sum_{i=1}^{M} E_i \quad (5)$$

Any segment with energy above this threshold was labeled as 'occupied' (1), and any segment with energy below became labeled as 'free' (0). In this manner, we provide a consistent, if simplified, ideal ground truth for training the classifiers, a common approach in machine learning-based spectrum sensing when explicit ground truth is absent [5].

- Train-Test Split: The entire segment dataset with corresponding pseudo-labels was split into training and testing subsets with 70 and 30% proportions, respectively. A stratified sampling approach was used with random state=42. Now, irrespective of package library used, 'occupied' and 'free' segments must be in the training set with the remaining in the test set, a fair test of the models' ability to generalize.

3.3 Feature extraction technique

Good-quality feature extraction is critical for machine-learning performances. This paper deals with Short-Time Fourier Transform (STFT) based features as they retain spectral information.

- Short-Time Fourier Transform (STFT) Features: The segmented signal was then subjected to an STFT. The STFT for N Per Segment was set to 256, meaning the FFT

window was 256 samples long, and STFT for N Overlap was set to 128, representing a half-window overlapping configuration. The power spectrum for each segment was calculated by taking the mean of the squared magnitudes of the complex STFT coefficients across the time bins. Initially, this provides 256 clear-cut power values for each frequency bin

$$STFTx[n](m,\omega) = \sum_{n=-\infty}^{\infty} x[n]w[n - mR]e^{-i\omega n} \quad (6)$$

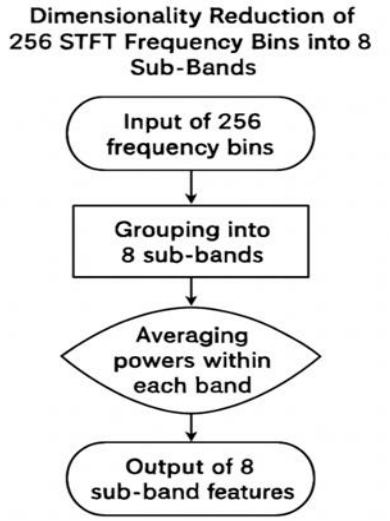

Figure 1: STFT 8-Band reduction

- Dimensionality Reduction (8-Band Features): The 256 crisp STFT features are reduced to 8 features to combat the curse of dimensionality, improve computational efficiency, and build more generalized spectral descriptions. The 256 frequency bins are divided into 8 equally sized sub-bands (each 32 bins wide), and the average power in each sub-band is calculated. These 8 average power values constitute the compact and abstracted crisp STFT features that are used in both classification pipelines. This process is outlined in Figure 1.

3.4 Fuzzy feature engineering

A fuzzy membership function maps a crisp input from the universe of discourse X to a membership value, representing the degree to which the input belongs to a fuzzy set defined as μ_A: X → [0, 1]. Graphically, the universe of discourse is shown on the X-axis and the membership degree on the Y-axis. Among various types, the triangular membership function (TMF) is widely used due to its simplicity and computational efficiency, and is defined by three parameters a, b and c, where a and c determine the base and b denotes the peak (maximum membership) of the triangle [7,17].

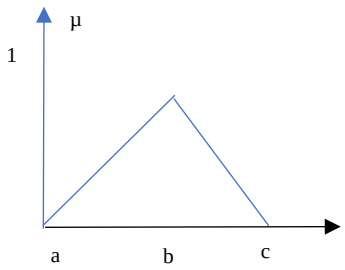

Figure 2: Traingular membership Function

The fuzzy triangular membership function is expressed as

$$\mu(x;a,b,c) = \begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ \frac{c-x}{c-b}, & b \le x \le c \\ 0 & c \le x \end{cases} \quad (7)$$

The eight crisp STFT features were directly fed into the STFT-Random Forest pipeline. For the STFT-Fuzzy-SVM pipeline, these same crisp features were subjected to fuzzification, where fuzzy logic concepts were brought into play to allow for potential uncertainties in the feature values and to offer a richer input to the classifier.

- **Concept of fuzzification**: Fuzzification converts a precise (crisp) numerical input into a set of fuzzy membership degrees. Instead of a feature value being strictly "high" or "low," it can be "partially high" and "partially medium" simultaneously.
- **Fuzzy set definition:** For each of the 8 crisp STFT features, three triangular fuzzy membership functions (FMFs) were defined across the feature's observed range: 'low', 'medium', and 'high'. The universe of discourse (range) for each feature's FMFs was determined from its minimum and maximum values across the entire dataset.
- **Membership degree calculation:** For every crisp feature value from each segment, its degree of membership (between 0 and 1) was calculated for each of the three fuzzy sets. This effectively transforms each single crisp feature into three fuzzy features (the membership degrees). Consequently, the 8 crisp STFT features were expanded into 8 * 3 = 24 fuzzified features. This process was implemented using the scikit-fuzzy Python library.

3.5 Machine learning classifiers

Two distinct machine learning classifiers were employed and compared:

- **Random Forest (RF):** The first of the pipelines, STFT with Random Forest, sundered together Random Forests, which comprise an ensemble learning method that, in the training phase, builds a great number of decision trees and outputs the class which is the mode of the classes (classification) of the individual trees. It is robust, can handle high-dimensional data, and is immune to overfitting. Based on this study, an RF classifier was chosen with n estimators or the number of trees set to 100.

$$\hat{y}[n] = mode\big(h_1(x[n]),\ h_2(x[n]),\ \ldots,\ h_T(x[n])\big) \quad (8)$$

Total number of trees = 100

Support Vector Machine (SVM): The second pipeline (STFT with Fuzzy and SVM) includes the Support Vector Machine, which is known to be an excellent supervised learning classification tool[6]. It creates an optimal separating hyperplane in the high dimensional space to segregate different classes. Because of its nonlinear nature, the radial basis function RBF kernel was chosen, with the parameter C (regularization) set to 10 and gamma (kernel coefficient) set to scale. The hyperparameters of the Random Forest and Support Vector Machine classifiers were selected through empirical tuning using cross-validation. For the Random Forest classifier, the number of trees was set to n_estimators=100, as higher values did not yield significant performance improvements while increasing computational cost. For the SVM classifier, a radial basis function (RBF) kernel was employed, with the regularization parameter C=10 and kernel coefficient set to "scale". These values were chosen based on 5-fold cross-validation on the training dataset to achieve a balance between classification accuracy and generalization performance.

$$f[n] = w^T x[n] + b\hat{y}[n] = \begin{cases} +1 & if\ f[n] \geq 0 \\ -1 & if\ f[n] < 0 \end{cases} \quad (9)$$

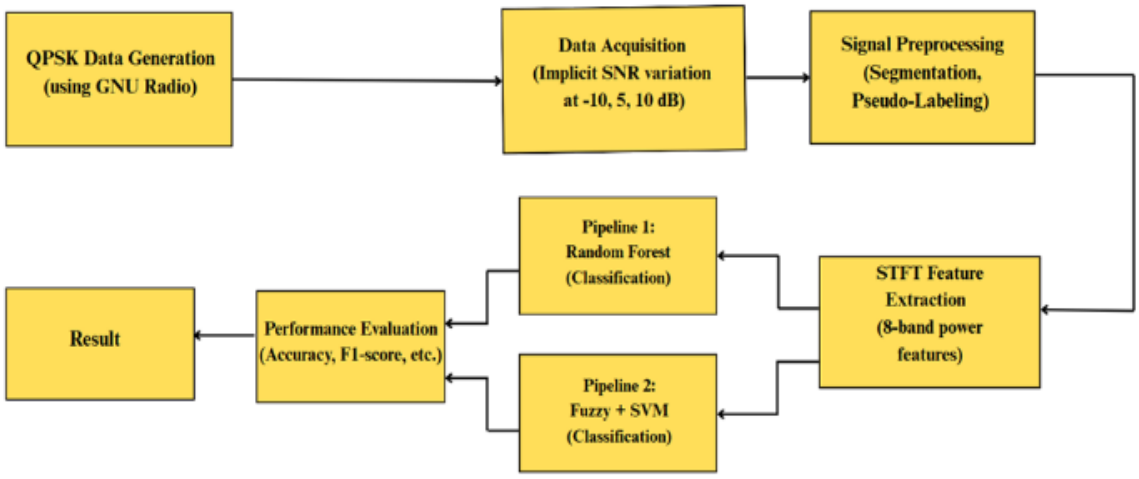

Figure 3: Process flow diagram

4 Results, discussion and performance evaluation

The flow of the project is detailed in Figure 3 and subsequently detailed in the following sections.

4.1 Signal generation using GNU radio

The very first step of this project involved the development and realization of modulation flowgraphs in GRC. The user interface of GNU Radio has great functionality that provides a means of constructing signal processing pipelines by interlinking various kinds of pre-built blocks. For this project, the separate flowgraphs were developed for QPSK modulation scheme. The QPSK signals were generated using GNU Radio with a sampling rate of 1 MSamples/s. The continuous I/Q data stream was segmented into frames of 1024 complex samples with a 50% overlap, resulting in a step size of 512 samples. For each SNR level (−10 dB, 5 dB, and 10 dB), approximately 1500 segments were generated, of which 70% were used for training and 30% for testing. Pulse shaping was implemented using a root-raised cosine (RRC) filter with a roll-off factor of 0.35 to emulate realistic communication conditions.

Every such flowgraph simulates the transmission of modulated signals in which required components such as signal sources, modulation blocks, channel noise blocks, and file sinks interoperate in a realistic signal transmission chain, modulating the signals and adding variable amounts of noise to simulate varying SNR conditions (-10 dB, 5 dB and 10 dB). The File Sink block was used to store the output signals, which were extracted and processed into a dataset for the classification task. These flowgraphs were the mainstay

of signal generation, providing modulated waveforms for further feature extraction and classification through machine learning models.

4.2 Dataset generation and classifier implementation

The signals modulated from GNU Radio were used to generate a dataset for this project. The modulation scheme QPSK has a dedicated flowgraph with Noise Source block, setting the noise voltage parameter adjusted to simulate three different SNR levels, which brought about the different low to moderate signal quality environments. The flow graph for signal generation using QPSK is given in Figure 4.

The nodes in File Sink blocks of each flowgraph captured the modulated output signal with noise. Output is saved in .dat files. These .dat files are the basis of the dataset created and were subsequently subjected to down sampling so as to reduce redundancy and improve efficiency during processing.

4.3 Classification

The complete sensing framework would be composed of data preprocessing, feature extraction, fuzzy feature engineering, training of a machine learning model, and performance evaluation in Python 3.x. All development and execution environments utilized standard libraries of scientific computing, lending reproducibility and efficiency.

Software environment: The key libraries used here were NumPy, which performs the uppermost high-level numerical operations, Pandas that arrives at data loading and manipulation of CSV files, SciPy, which offers signal processing functionalities like the Short-Time Fourier Transform (STFT).

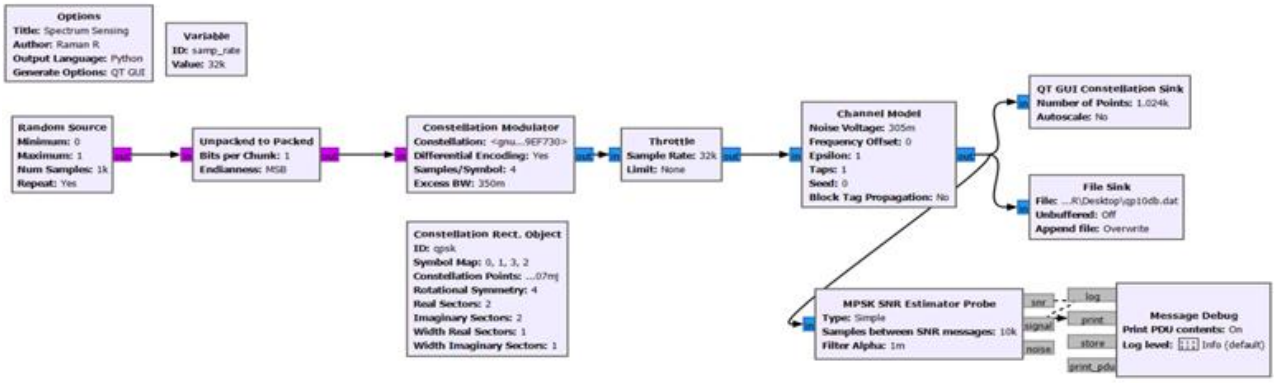

Figure 4: GNU Radio flow graph for QPSK signal generation

- **Machine learning framework:** Scikit-learn library covers generally all aspects of machine learning, including splitting the data (train_test_split), instantiating classifiers such as Random Forest Classifier, SVC), training the models (.fit()), predicting (.predict() and .predict_proba()), and calculating performance metrics (accuracy score, classification report, confusion matrix, Receiver Operating Characteristic (ROC) curve, Area under the curve(AUC)).

- After STFT computation, the spectral features were organized into a structured dataset in CSV format. Each row of the dataset corresponds to one signal segment, while each column represents an extracted feature. For the STFT-based pipeline, each sample is represented by an 8-dimensional feature vector corresponding to the average energy of eight frequency sub-bands. In the FuST-SVM pipeline, each crisp STFT feature is transformed into three fuzzy membership values, resulting in a 24-dimensional feature vector per sample. An additional column is used to store the pseudo-label indicating spectrum occupancy.

- **Pipeline execution flow:** For ensuring the correctness of comparison among the two different spectrum sensing pipelines, the following structure was created and executed in Python:

  1. Common Preprocessing: The QPSK I/Q data was loaded, segmented, and pseudo-labelled using energy detection. The segment indices underwent a consistent stratified train-test split (random_state=42).

  2. Common Feature Extraction: The set of 8-band features was extracted once for every segment.

  3. Pipeline 1 Execution: These 8-band features of STFT would give into Random Forest Classifier directly for its learning and

testing.

4. Pipeline 2 Execution: Initially, the 8-band STFT features underwent fuzzification by the fuzzy feature engineering module (8 crisp features were converted into 24 fuzzified ones); afterward, these fuzzified features were used for training and testing in the SVC classifier.

- **Reproducibility:** In order to compare different methods fairly, a fixed random_state was maintained for all randomized parts (train_test_split, Random Forest Classifier, and SVC initialization), thus producing consistent and reproducible experimental results throughout several runs. Performance was plotted using Matplotlib and Seaborn.

4.4 Tools and environment

The entire development and implementation of the signal type modulation classification system was carried out using the below utilities and software platforms.

A. Python environment

Python is used mainly for signal as well as data processing, feature extraction, implementation and evaluation of machine learning models. It has been used largely with its flexibility and large range of scientific libraries expected to make it an appropriate choice for this project. The version 3.10 was used in this work.

B. GNU Radio

The major area of symptom and modulation simulation of QPSK had to design flowgraph and modular block called signal source, modulator, noise source, and sink to make modularity possible-for the resulting signal at different SNR levels. GNU Radio Version: 3.10 was used in this study.

C. Operating system

Windows 10 served as the main platform that generated signals, prepared datasets, and trained models. It was a reliable platform for both GNU Radio and Python-based toolchains.

All experiments were conducted on a system equipped with an Intel Core i7 CPU, 16 GB RAM, and running Windows 10 operating system. No GPU acceleration was used, as all models were implemented using classical machine learning techniques. Signal processing and machine learning workflows were developed in Python 3.10 using standard scientific libraries, including NumPy, SciPy, scikit-learn, and scikit-fuzzy. GNU Radio version 3.10 was used for signal generation.

A short pseudocode used in the pipeline is detailed below:

---

1. Generate QPSK I/Q data using GNU Radio at specified SNR

2. Segment I/Q data into fixed-length overlapping frames

3. Compute energy of each segment and assign pseudo-labels

4. Apply STFT to each segment

5. Reduce STFT spectrum into 8 frequency sub-band features

6. (FuST-SVM only) Apply fuzzy membership functions to STFT features

7. Split dataset into training and testing sets

8. Train Random Forest or SVM classifier

9. Evaluate performance using accuracy, AUC, and confusion matrix

10. Spectrum occupancy decision (occupied / free)

---

5 Results and performance analysis

The classification results of the proposed model were examined at three different SNR levels, namely: -10 dB, 5 dB and 10 dB. The table below summarizes the performances of three ML classifiers, Random Forest and SVM, trained on features extracted solely using the Short-Time Fourier Transform (STFT) method and Fuzzified STFT.

5.1 Performance analysis

A structured evaluation makes a good comparison of classifier-feature combinations and indeed gives a practical point of view for choosing the most proper configuration for given use cases. In order to evaluate this study the following parameters are considered in the performance evaluation. The performance analysis of this study was carried out considering the following parameters

A. **Noise Robustness:** It checks how much accuracy each classifier retains over different SNR levels. A robust model shows a meager fall in performance, even in low SNR (-10 dB).

B. **Computational Viability**: The time and

resources required for feature extraction, training and testing are considered. This becomes vital when deployment of such systems comes into real-time environments as software-defined radios or embedded systems.

C. **Metrics:** The metrics used in performance evaluation is detailed in Table 2.

The Area Under the ROC Curve (AUC) gives additional support to the fact that the FuST-SVM pipeline has a better discriminative capability, especially at low-SNR conditions. The AUC values given in Table 3. The values that are higher all the time show that the spectrum states of occupied and idle are separated better even when the differences in classification accuracy are small in terms of numbers.

Table 3: AUC values across various SNR conditions

SNR (dB)	**STFT+Random Forest**	**STFT+Fuzzy +SVM**
-10	0.95	0.98
5	0.97	0.99
10	0.98	0.98

Table 2: Metrics used for performance evaluation

Metric	**Equation**	**Interpretation in the context of Signal Detection**
Precision	$\mathbf{Precision} = \frac{\mathbf{TP}}{\mathbf{TP} + \mathbf{FP}}$	How often the system is correct when it says the spectrum is occupied.
Recall	$\mathbf{Recall} = \frac{\mathbf{TP}}{\mathbf{TP} + \mathbf{FN}}$	How well the system detects a primary user when it is actually present.
F1-Score	$\mathbf{F1\ score} = \frac{\mathbf{2TP}}{\mathbf{2TP} + \mathbf{FP} + \mathbf{FN}}$	Overall detection quality considering both misses and false alarms.
Accuracy	$\mathbf{Accuracy} = \frac{\mathbf{TP} + \mathbf{TN}}{\mathbf{TP} + \mathbf{TN} + \mathbf{FP}}$	How often the system makes the correct decision overall.

Where FN defines False Negative, TP refers True Positive, FP denotes False Positive, and TN refers True Negative.

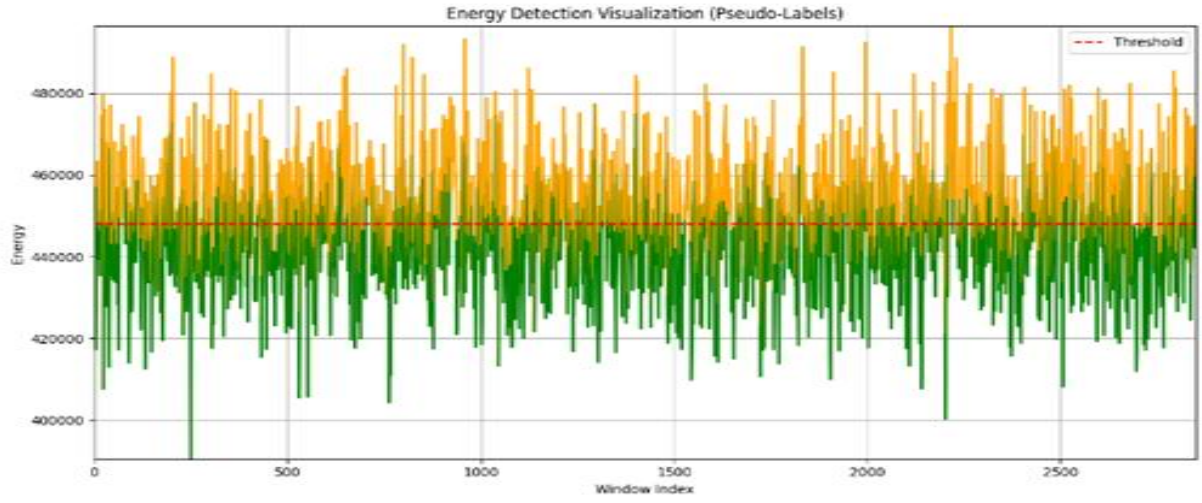

Figure 5(a): Energy distribution and pseudo-labelling threshold for spectrum sensing for SNR of –10dB

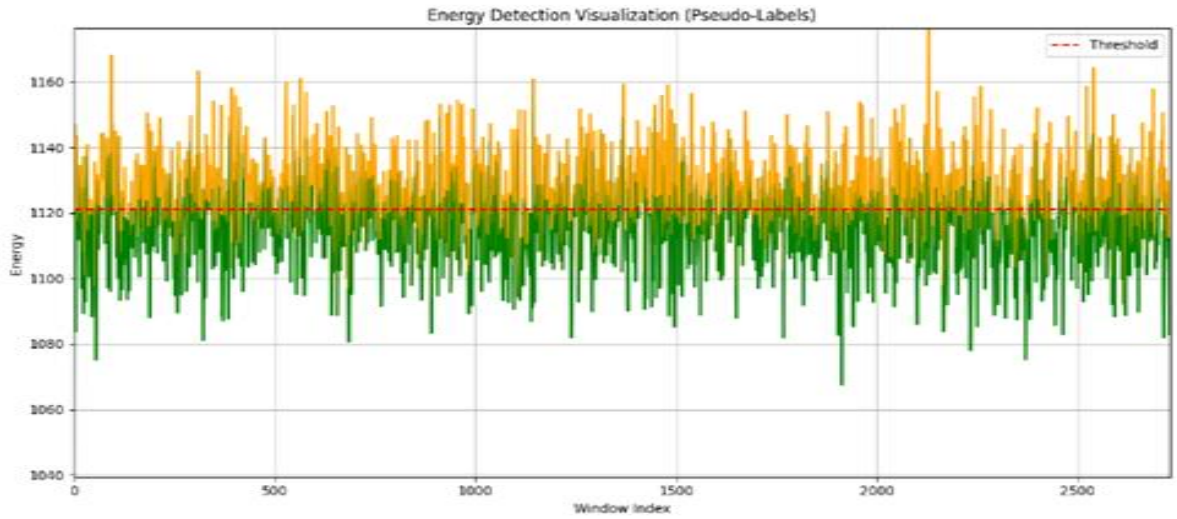

Figure 5(b): Energy distribution and pseudo-labelling threshold for spectrum sensing for SNR of 10dB

The energy distribution and Pseudo labelling threshold for spectrum sensing is shown in Figure 5 (a) and (b). The confusion matrix and ROC curve for STFT with Random Forest and STFT with Fuzzy and SVM pipelines for SNR of -10dB and 1-dB are given in Figure 6 and 7 respectively.

The accuracy at -10dB SNR with such added noise is 87.97% for STFT-Random Forest. According to the confusion matrix (Figure 6a), the system correctly classified 379 examples in the free category and 374 in the occupied category while it counted 55 false positives and 48 false negatives. On the other hand, in the ROC curve (Figure 7a), the pipeline registered an AUC of 0.95, indicating extraordinary discrimination.

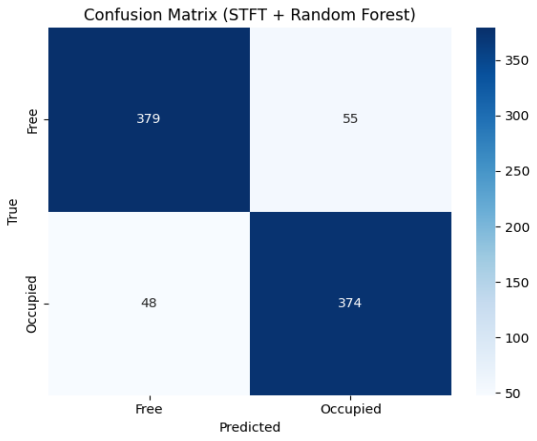

Figure 6(a): Confusion Matrix for STFT + Random Forest at -10dB SNR.

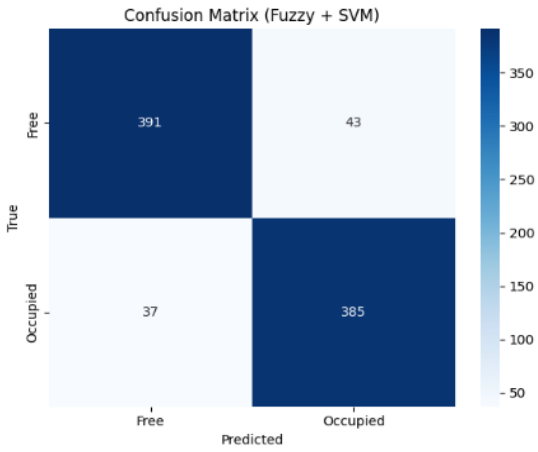

Figure 6(b): Confusion Matrix for STFT + Fuzzy + SVM at -10dB SNR.

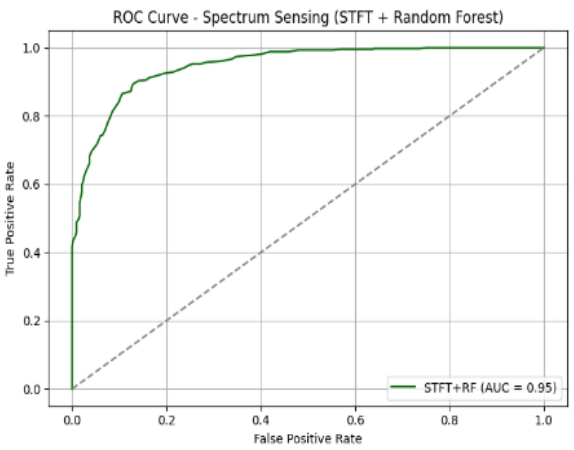

Figure 7(a): ROC Curve for STFT + Random Forest at -10dB SNR.

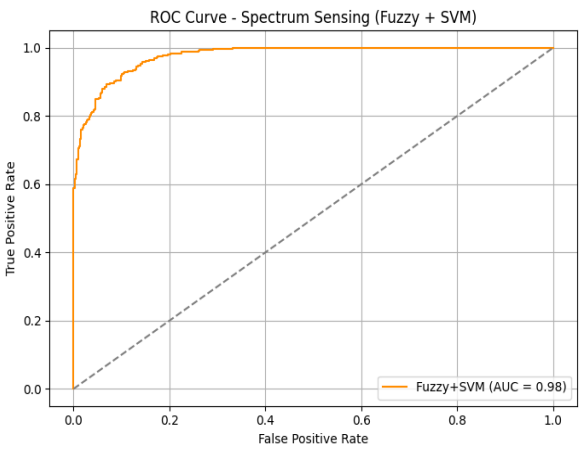

Figure 7(b): ROC Curve for STFT + Fuzzy + SVM at -10dB SNR.

Then, however, at the same noise level of -10dB SNR, STFT-Fuzzy-SVM beats all other methods with an accuracy of 90.65%. The confusion matrix (Figure 6b) revealed that there were 391 'free' and 385 'occupied' correct classifications. It has fewer errors: 43 false positives and 37 false negatives, against these of STFT-Random Forest. The ROC curve of STFT-Fuzzy-SVM (Figure 7b) with an AUC of 0.98 confirms this increased discriminating ability between spectrum states, even under very high noise conditions.

The extreme importance of spectrum sensing at varying SNRs is illustrated in Table 4. Both models kept high accuracy, well above 87%, and high F1-scores above 0.88 for all SNRs tested. Never did this pipeline with Fuzzy and SVM drop below that of Random Forest in the entire range. At -10dB of SNR, it reached 90.65% accuracy (F1: 0.91) against the 87.97% (F1: 0.88) of STFT with Random Forest; peak performance arrived at 5dB SNR, at 92.46% (F1: 0.92), which was well above the 91.24% (F1: 0.91) of STFT with Random Forest, and then remained marginally above with 91.22% (F1: 0.91) at 10dB SNR in comparison to 90.85% (F1: 0.91). This sustained edge, paired with balanced precision and recall scores through every SNR, kicked in the enhanced robustness and discernibility of the fuzzified spectral characteristics with Support Vector Machines for trustworthy spectrum sensing.

Table 4: Accuracy, Precision, Recall, and F1-Score Comparison of Naive Bayes, Random Forest, and SVM

SNR	Pipeline	Accuracy (%)	F1-score (weighted avg)	Precision	Recall
-10dB	STFT + Random Forest	87.97	0.88	0.88	0.88
	STFT + Fuzzy + SVM	90.65	0.91	0.91	0.91
5dB	STFT + Random Forest	91.24	0.91	0.91	0.91
	STFT + Fuzzy + SVM	92.46	0.92	0.92	0.92
10dB	STFT + Random Forest	90.85	0.91	0.91	0.91
	STFT + Fuzzy + SVM	91.22	0.91	0.91	0.91

The summary of the time, and Memory Comparison of Classifiers at Varying SNRs using the models used is given in Table 5.

At -10dB, FuST-SVM required about 6.32 seconds, while the STFT with Random Forest processing lasted only 2.64 seconds. The additional time arises in FuST-SVM due to extra computation involved in fuzzy feature engineering steps (conversion of 8 crisp features into 24 fuzzified features) and somewhat greater training complexity of Support Vector Machines with the RBF kernel compared to Random Forests. Memory-wise, both pipelines typically consumed very little.

While the STFT with Fuzzy and SVM recorded higher memory usages at 5dB and 10dB (0.50 MB) compared to the STFT with Random Forest (0.17 MB at -10dB and 10dB), the latter instead saw a strange spike of 4.76 MB at 5dB. Overall, though, the estimates for memory consumption remain respectable for the two approaches. Thus, this analysis shows that the better classification accuracy offered by the STFT with Fuzzy and SVM pipeline is accompanied by moderately increased computational time, a fairly profitable trade-off in most cases for improved.

Table 5 : Time and memory comparison of STFT-based classification pipelines at varying SNRs

SNR	Classifier	Time (s)	Memory (MB)
-10 dB	STFT + Random Forest	2.6394	0.17
	STFT + Fuzzy + SVM	6.3213	0.17
5 dB	STFT + Random Forest	2.8569	4.76
	STFT + Fuzzy + SVM	6.0999	0.50
10 dB	STFT + Random Forest	3.5302	0.17
	STFT + Fuzzy + SVM	6.8905	0.50

Table 6: Comparative analysis of the proposed method with existing spectrum sensing techniques

Study	**Method**	**Features**	**SNR Range**	**Low-SNR Performance (≈ −10 dB)**	**Key Remark**
Atapattu et al., [3]	Energy Detection	Signal energy	−20 to 10 dB	Poor Pd due to noise uncertainty (SNR wall)	Cannot separate noise and weak PU signals
Jan & Koo, et al.,[6]	SVM classifier	Statistical features	−15 to 10 dB	Moderate Pd, degrades below −8 dB	Limited robustness without spectral features
Geng et al., [14]	Deep learning	Learned spectral features	−20 to 10 dB	High Pd at low SNR	High accuracy but high training and computation cost
FuST-SVM (Present Work)	Fuzzy STFT + SVM/RF	8-band STFT + fuzzified features	−10, 5, 10 dB	Pd ≈ 0.85 @ −10 dB; 92.46% @ 5 dB	Deep-learning-level robustness with low complexity

Table 6 contextualizes the performance of the FuST-SVM pipeline proposed herein against some other spectrum sensing studies based on machine-learning algorithms in the literature. The "Present Work" being FuST-SVM, shows a robust and competitive performance profile across the tested SNR range of -10 to 10 dB, attaining an accuracy of 92.46% at 5 dB SNR using GNU Radio generated QPSK I/Q data and 8-band STFT and fuzzified STFT features. The other works presents a glimpse of the variety of feature extraction techniques (e.g., spectral, statistical, wavelet, energy), classifiers (CNN, SVM), and dataset types (simulated, real).

In order to evaluate the statistical solidness of the reported outcomes, the classification trials were carried out again on many randomized train-test splits, while keeping the same stratification ratio. The accuracy figures reported are the mean accuracy over all runs, with the standard deviations observed being in a narrow range (±0.8% to ±1.3%) for all SNR conditions. This shows that the both pipelines' performance is not only stable but also not too much influenced by random data partitioning.

The differences in precision that are very small, are mainly seen as a result of the different placements of borderline samples close to the decision boundary, especially in cases of low SNR where the signal and noise characteristics are very much mixed up. Even so, the FuST-SVM pipeline has always been ahead of the STFT–Random Forest method in all SNR levels at the same time.

The advantage of FuST-SVM over Random Forest is that it has better accuracy that is not very noticeable (it is approximately 1–2%); however, this is a practically significant case in live applications of spectrum sensing. In cognitive radio systems, the detection accuracy even at a small scale can lead to a substantial decrease in false alarms and missed detections, thus making the system work better in terms of utilization of the spectrum and at the same time reducing the chances of causing interference to the primary users.

Notably, the FuST SVM seems to perform quite consistently across the entire broad SNR range, showing good generalization even at those really poor SNR conditions, which is a great thing considering it could do all this with just very efficient feature extraction and the power of combining fuzzification and SVM. From this, one can place FuST-SVM as one of the finest and most practical frameworks in the entire landscape of ML-based spectrum sensing approaches.

6 Discussion

The experimental results, which are depicted very clearly, show that the suggested pipeline of Fuzzy STFT–SVM (FuST-SVM) always outperforms the STFT–Random Forest (RF) pipeline across all the SNR conditions that have been tested. The most visible improvement can be seen with the noiseless signal condition (−10 dB) where the task of sensing the spectrum is very difficult because of the overwhelming noise and the closer distribution of the signal with that of the noise The heightened resilience of the FuST-SVM system is one of the results of the fuzzy feature engineering stage which is passed at the point of the STFT-derived spectral features. The transfer of the crisp STFT sub-band energies into the fuzzy membership degrees (low, medium, and high) is the main part of the fuzzification process which allows the representation of ambiguous spectral patterns rather than the setting of hard decision boundaries. This representation, which is not very strong, is especially useful at low SNRs since the conventional feature values are considerably altered by noise. Hence, the SVM classifier is able to draw a better decision boundary that is more discriminatory of occupied and idle spectrum states under uncertainty. On the other hand, the STFT–RF pipeline works with the crisp spectral features. The Random Forest classifier is powerful enough to keep noise away and nonlinearities at the same time. Thus, their performance decreases even more noticeably at very low SNR levels because the feature distributions that are becoming less separable. This justifies the observed accuracy gap between the two pipelines at −10 dB, where FuST-SVM is still having the advantage of a reliable detection. The FuST-SVM framework as a whole provides a nice compromise between accuracy and computational cost when one looks at the state of the art in deep learning-based spectrum sensing like convolutional neural networks (CNNs). The methods based on CNNs, even if they sometimes reach higher peak accuracies, are actually requiring a lot of data to be labeled, a lot of time to train and a lot of resources to compute the training. Conversely, the FuST-SVM technique is very able to work with the 8-band STFT features that are compact, with a limited amount of training data and with computational overhead that is significantly lower, thus making it very suitable for real-time and resource-constrained cognitive radio systems. The main drawback of the entire FuST-SVM pipeline is the extra computational burden brought about by the fuzzification procedure, which results in the expanding of each crisp feature into several fuzzy membership values. However, the time and memory analysis of the experiments shows that this overhead is still moderate and by no means unacceptable if it is compared against the consistent accuracy gains that have been realized across all SNR regimes. Furthermore, the application of three fuzzy sets for each feature allows for a good compromise between representational richness and computational efficiency, as it was found that increasing the number of fuzzy sets tends to yield smaller performance gains. In a nutshell, the whole debate verifies that the amalgamation of fuzzy logic with STFT-based spectral features and SVM classification is an efficient way to increase noise immunity without sacrificing the practicality of deployment. Therefore, the FuST-SVM framework is positioned as a very reliable spectrum sensing solution in highly dynamic and noisy wireless environments.

7 Conclusion and future enhancements

This paper presented a complete comparative study of two diverse machine learning pipelines for spectrum sensing under varying Signal-to-Noise ratio (SNR) conditions using QPSK I/Q data generated by GNU Radio. The objective was to assess between the use of STFT features with a conventional RF classifier and those obtained with the FuST-SVM pipeline. With our experimental findings, the FuST-SVM pipeline has proven to be consistently better than the alternatives in low (-10dB), medium (5dB), and high (10 dB) SNR regimes. This pipeline attained an accuracy of 90.65% accuracy at low SNR; rising to the highest of 92.46% accuracies at SNR 5 dB and falling only marginally to 91.22% accuracies at higher SNR of 10 dB. Besides being fairly robust, the pipeline involving STFT plus Random Forest consistently recorded accuracies with a slight margin of inferiority over the tested levels of SNR. The remarkable performance of the FuST-SVM pipeline truly highlighted the synergy of its components during the experimentation. The 8-band STFT features adequately represented the spectral characteristics of the signals.

Fuzzy feature engineering then added the value to this stage; particularly, it helped the SVM classifier better understand ambiguous patterns and deal with uncertainty arising from noisy wireless environments in the real world. The resulting combination with SVM, known for its discriminative power and generalization capability, presents a good, practical solution for spectrum sensing. This research adds to the field of intelligent spectrum sensing by providing a validated and high-performing machine learning framework. Given the consistent behavior of the FuST-SVM pipeline under various noise scenarios, it could be considered for implementation in future cognitive radio systems where it could assure better spectrum utilization and free from interference.

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A GNN–DRL–ResNet-Based Dynamic Routing Algorithm for Low Earth Orbit Satellite Networks

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There are a lot of nodes in a Low Earth Orbit (LEO) communication network, and their resource limits might change quickly. Because of these features, conventional routing techniques are not a good fit for LEO satellite networks. An inductive learning architecture called Graph Neural Network (GNNs) is proposed in this research to tackle this issue. The number of topological nodes that require training can be drastically decreased with the help of the suggested architecture. Because of this cut, the nodes' computational difficulty is reduced. In addition, routing methods are optimized and learned continuously using deep reinforcement learning (DRL), which is made even more generalizable by building the DRL agent with GNN. Every Deep Q-Network (DQN) agent manages its own tasks in the suggested algorithm for optimizing LEO satellite route planning based on graph neural networks which does not extracts the spatial and temporal information of networks that's why we planned to propose RESNET model to replace DQN. By using the GNN paradigm, it discovers the nodes' concealed states. To determine the best routes, the DRLmodel takes these hidden states into account. A comparison and simulation were run to assess the algorithm's efficiency. Finally, optimization technique is presented to choose the shortest route. The outcomes demonstrate that the suggested method mitigates average overall latency while simultaneously increasing total network throughput. When compared to the Deep Q Networks (DQNs) and Dijikstras Algorithm, the suggested approach achieves a 25% and 30% improvement in average throughput, respectively. Additionally, it can adjust to different topologies and lower average end-to-end latency by 44% and 22%, respectively.

Povzetek: Raziskava predlaga uporabo grafnih nevronskih mrež in globokega učenja za izboljšanje usmerjanja v LEO satelitskih omrežjih, kar poveča prepustnost in zmanjša zakasnitev.

1 Introduction

As the need for communications continues to rise on a worldwide scale, LEO satellite networks have emerged as an effective supplementary infrastructure for terrestrial communications. Their high degree of versatility and extensive coverage make them highly desirable. However, the structure of the network and the condition of the links are constantly changing due to the extremely rapid movement of the satellites. Effective routing algorithms are difficult to build due to these dynamics [1], [2], [3]. Recent years have seen a meteoric rise in the popularity of Mega-Constellation Networks (MCNs). They provide low-latency, high-throughput data transfer and global coverage to people all over the world. Although multi-constellation networks (MCNs) greatly enhance global uninterrupted coverage, they also make operating a large number of satellites more difficult. The quantity of hops needed for inter-satellite links (ISLs) and the intricate nature of routing are both increased by this. Satellite design, environmental restrictions, and constant satellite mobility are the three main tenets within which effective packet routing must function [4], [5]. Because of these specifics, routing is extremely difficult and calls for fresh algorithmic strategies. More recently, occurrences in the actual world have shown that there have been hostile efforts to discredit and interrupt the potential of MCN [6].

There has been a marked uptick in interest in LEO satellite network development in the past few years. Starlink, OneWeb, and Telesat are among the many LEO network constellations now under construction worldwide. LEO satellites function in contrast to geosynchronous Earth orbit (GEO) networks [7]. As a consequence, channel conditions improve, transmission rates rise, and latency drops. With these updates, the user experience is

greatly improved. Yet, in comparison to Earth, these satellites are constantly in motion at great rates. Consequently, a significantly higher number of satellites must be deployed in LEO networks to achieve worldwide coverage compared to GEO networks. The network architecture gets increasingly intricate as the number of satellites increases. The network is already complicated, and the satellites' rapid orbits just make things worse. Effective routing algorithms are crucial for a network of this complexity to keep latency low and performance high. This highlights the critical need to create efficient routing algorithms for LEO satellite networks [8], [9].

It is very difficult for routing techniques to handle the complicated structure of LEO networks. The inaccuracy of forward-looking projections and the unreliability of satellite network architecture are both caused by the extremely rapid motion and huge number of satellites [10]. Presently, the majority of research is devoted to studying self-regulating networks, rather than routing techniques tailored for LEO networks via satellites. In order to develop LEO routing algorithms, the authors of reference [11] combined deep learning with neural network graphs. Unfortunately, the computational complexity induced by the changing topology during method execution and the vast number of nodes in LEO satellite constellations are not taken into consideration by the GNN method. Considering how to do distributed modeling on massive graph data is important for LEO satellite communications due to the high number of nodes. Acquiring knowledge of previously unseen nodes is also essential. The algorithms for routing are entirely designed by P. Zuo et al. [12] using deep learning. The difficulty of adjusting to the ever-changing topology of LEO satellite networks is, however, not tackled by their method. Many researchers have looked at self-organizing network routing algorithms and used them as a basis for LEO satellite networks. However, the features of LEO satellite nodes, possible unforeseen topological changes, and cases with scarce computational resources are not taken into account. When determining the shortest pathways, the majority of this research considers the nodes' states. Using deep learning as an example, [13] just takes into account the nodes' congestion states and channel quality. A graph neural network is presented in reference [14] as a tool for developing a deep learning-based routing system. Unfortunately, the features of nodes in wireless sensor networks are the only ones taken into account by their convergence mechanism. No mention of how difficult it is to finish computations for the entire topology due to the restricted processing power of nodes is found in the available research. References [15] and [16] employ deep learning techniques to construct routing schemes for wireless networks that are self-organized and ad hoc networks, respectively. While references [17] primarily address quality of service and end-to-end delay, they neglect to take the impact of sudden topological shifts into account.

One more thing: we figure out how to implement shared training into your routing method. This method is useful for decreasing the difficulty of computation and the number of training nodes. It is also important that the algorithm can learn from its mistakes and improve its path optimization techniques in response to changes in node and link statuses over time. When deciding how to route data across a network, one option is to employ a smart routing solution that draws on deep learning algorithms. To ensure that data travels efficiently across networks, it automates the process of choosing the best routing paths. To do this, one must study the habits and patterns of the network's data flow. A smart routing system that relies on deep learning requires a substantial quantity of data to train the model. For the purpose of developing the model, this data set contains details about the network's topology, as well as data on traffic demand and bottlenecks. Afterwards, routing decisions are made using the trained DL model [18], [19], and [20].

Smart routing techniques built on neural networks can keep tabs on network traffic in real time, unlike conventional techniques. Overall network efficiency can be enhanced by their use as well. But the algorithm must modify the training labels if the network topology changes. This modification is necessary for the conventional deep learning method to ensure accurate output pathways. Additionally, scalability is an issue with the conventional DL technique. A significant increase in processing time could result from training the model with updated input data in the event that the input network configuration changes. While both supervised and unsupervised learning have their place in the machine learning (ML) landscape, DRL stands out. Interactive learning with the environment is at the heart of DRL. In contrast to more conventional approaches to reinforcement learning (RL), DRL makes use of deep neural networks (DNNs) rather than tables. It avoids explicit listing in favor of function approximations when expressing policies. Because of this, DRL can handle complicated real-life tasks without the dimensionality issues that plague conventional tabular RL.

The route optimization issue is one area where trained DRL agents excel, but they struggle when faced with unfamiliar network configurations. The cause of this occurrence can be determined by studying the structure of DRL agents. The inputs and model dimensions of a conventional DQN are dictated by the size of the network, as measured by factors like the network layout. The input and output elements of the model are fixed once training is complete. So, the model might get inputs with unusually large dimensions when it encounters networks of varying sizes. Cutting or padding the input dimensions may alter their values, but doing so will remove any topological

information that may have been stored in the matrix. Moreover, graphs are the fundamental building blocks of computer networks. Current approaches that employ neural networks for processing state matrices fall short when it comes to capturing the nuances of graph architectures. When applied to fresh networks, DRL's efficiency is diminished due to this constraint. Finally, DRL thrives at optimizing routes, but it isn't up to the task of generalizing graph structures or reasoning relationally, which limits its applicability to novel network settings.

Our contributions are multi-fold:

Our novel contributions are explicitly defined as:

1. **ResNet-Embedded DRL Policy Network:** We are, to the best of our knowledge, the first to integrate a **ResNet architecture** into the DRL policy network for LEO routing. This is crucial for:
    - **Stabilizing Deep Learning:** Preventing the vanishing gradient problem that occurs when trying to train deep networks necessary to process complex, high-dimensional embeddings generated by the GNN.
    - **Accelerating convergence:** Ensuring the DRL agent can achieve high episodic returns faster than a standard DNN. We will provide an **Ablation Study** (Section 6.2) comparing the performance and convergence speed against a standard GNN-DRL-DNN baseline.
2. **Integrated spatio-temporal feature generation:** Our **GNN input features** are meticulously engineered to implicitly capture temporal dynamics in a bandwidth-efficient manner (as argued in the previous response). This eliminates the need for complex, bandwidth-intensive sequence models like RNNs or Transformers in the *onboard inference path*, which are typically computationally prohibitive for satellite hardware. The GNN's role is not static graph representation, but **predicting link durability** using time-sensitive features (e.g., rate of change of distance, time-since-last-link-break).
3. **Distributed agent training with shared GNN embeddings (Future Work/Extension):** The current model assumes a centralized training approach. We propose future work focused on a distributed scheme where the **GNN feature extractor** is shared across local DRL agents, minimizing the communication overhead of policy synchronization.

2 Related work

Authors presented an architecture is an SDMCN, or software-defined MCN. By collecting data from satellites and allowing for dynamic global network tracking, this design makes network management very flexible. We offer a technique called Orbit-Grid-Based Dynamic Routing (OGDR) to improve routing in Walker Delta MCNs. Starting with a path model that takes the least hop metric and the ISL distribution into account, the technique chooses access satellites. Next, on an orbital grid, inter-plane and intra-plane links are chosen by utilizing the satellites' interval and the path model's properties. In order to guarantee the least amount of delay, this selection is made immediately according to the satellites' latitudes. Last but not least, we guarantee path dependability by introducing a path failure recovery method. The technique reduces the number of ISL hops and reduces computing complexity, in addition to achieving efficiency similar to the shortest path, as demonstrated experimentally [21].

Because it is simpler and uses fewer resources, geographical routing performs better than centralized techniques on this system's network infrastructure. But "dead-ends" can still happen with geographical routing due to holes in the network. Our proposed solution involves enhancing network accessibility and routing accessibility through the use of encountering inter-satellite links (eISLs). In addition, we analyze eISLs and provide a system model for them. To further facilitate the establishment of eISLs between encountering orbiting satellites, we provide our Dynamic eISLs Configuration (DeC) technique. Through our experiments, we have shown that DeC, when enabled in satellite networks, may drastically cut propagation delay in centralized routing schemes by 21% and path stretch by 14%. DeC can also raise the accessible ratio from 65% to 100% in regional routing while keeping an additional 30% in throughput, which makes it better than schemes that don't use eISLs. As a whole, the outcomes of improving LEO satellite systems' interconnectivity and communication performance using our suggested eISL-enabled satellite network architecture are encouraging [22].

Authors were started by presenting an efficient and adaptable software-defined networking (SDN) framework-based architecture for network administration in this article. Our zonal division strategy and DISNR protocol are built upon this foundation, aiming to reduce maintenance and routing complexity to a minimum. Limiting the extent of fault information flooding is achieved by DISNR through the development of intra- and inter-area link-state synchronization mechanisms. We provide a hierarchical shortest path forwarding (SPF) routing algorithm that significantly enhances efficiency in

the massive LEO satellite network while simultaneously decreasing the computational complexity of routing in terms of both time and space. At last, simulation findings show that the DISNR drastically cuts management expenses in comparison to other routing protocols [23].

Current methods, such as the Minimum Hop Path set, put an emphasis on reducing latency by decreasing hop counts, but they fail to take ISL switching costs into account, resulting in significant instability. The Adaptive Path Routing Scheme gets around this by implementing path similarity thresholds, which lower the frequency of ISL switching between shells. Adaptive Path Routing Scheme's greedy method, on the other hand, frequently gets stuck in local optima and neglects the effectiveness of inter-shell path distance. We present the DP-IRC method, which is built specifically for optimizing inter-shell routing, to overcome these restrictions. The DP-IRC algorithm finds a happy medium between hop counts and ISL stability by using an Integrated Routing Cost (IRC) measure that takes into account switching expenses, inter-/intra-shell hops, and the way multi-shell pathways are structured as a multiple-phase decision problem. Based on the experimental results, DP-IRC significantly lowers the inter-shell ISL switching rates in comparison with Adaptive Path Routing and Minimal Hop Path, respectively, by 21.2% and 40.2%. All the while, it keeps the end-to-end distances very close to ideal [24].

The present LOSN, however, is woefully inadequate to provide such high throughput for ubiquitous service provisioning. When ground gateways are deployed centrally, it leads to a large traffic load in the space section of the LOSN. This load eventually becomes the limiting factor in the expansion of the network's throughput. Secondly, the adaptability of routing computations is affected by the constant swings in traffic load caused by the high-speed movement of LEO satellites. This paper proposes two routing techniques for the dynamic LOSN topology that can boost throughput. When dealing with congestion on the links between satellites in a dynamic LOSN architecture, the congestion-aware load balancing (CALB) algorithm is suggested as a solution. Afterwards, a satellite-ground cooperation–based load-balancing routing method (SGC–LB) is suggested to further mitigate the effects of the network bottleneck. Our suggested routing system was tested on a 288-satellite Walker-Star constellation with satellite-to-satellite links through rigorous simulations. An evaluation of the service blockage rate and network capacity usage rate demonstrates the efficacy of the suggested routing method [25].

Unfortunately, current routing approaches result in unnecessary control overhead due to the topology's high degree of dynamic and unpredictable nature, as well as the restricted computing power available on board. Congestion also causes them to suffer from extremely high packet degradation rates and extremely high latency. Our proposed hybrid routing system in this research makes use of smart area segmentation. This strategy dynamically adjusts to crowded locations by combining centralized and decentralized approaches. In particular, controllers only get status reports from Low-Earth Orbit (LEO) satellites with overloaded communication channels when using software-defined features. Two components that make up these controllers are the Ground Computing Center and the Geostationary Earth Orbit (GEO) satellites. Using a Deep Q-Network (DQN) method, they accurately determine the crowded locations periodically. The suggested approach significantly decreases control overhead, according to numerical simulation findings. In comparison to more conventional methods, it reduces packet loss by about 40% in massive constellations, paving the way for 6G messaging networks that are both durable and scalable [26].

A clustered multi-criteria routing (CMCR) method was suggested by the authors of [27] for use in mega LEO satellite networks that provide multimodal data services. The first step is to create a method for grouping the large LEO satellite constellation, which takes into account the satellites' latitude, satellite connectivity link, line-of-sight (LoS), and flight direction. This grouping separates the CMCR into two types of routing: intra-cluster and inter-cluster. Afterwards, the ever-changing megacluster topology is depicted as a dynamic graph. In order to determine the most effective routes for multimodal communications, both intra- and inter-cluster routing start by finding satellites that can set up an ISL using the dynamic graphs. To show how much ISLs value different data services, we add the attribute consistency; CMCR then uses this consistency comparison to find the most popular pathways. After determining which of the dominant paths has the most desirable feature, the CMCR algorithm chooses one, and it can converge to the best route thanks to a defined routing algebra. The CMCR surpasses current routing techniques in terms of multimodal service preferences, as confirmed by the computational results.

But current routing algorithms aren't going to cut it with forthcoming LEO satellite constellations that are super dense, highly dynamic, and massive in size; they're more suited to grounded or smaller-scale satellite networks. In addition, the routing method must be dynamic since Free Space Optical (FSO) transmissions are anticipated for Inter-satellite Links (ISLs) and the quantity of built FSO ISLs is dependent on the geometrical perspectives and Acquisition, Pointing, and Tracking (APT) endpoints. This research explores a dual-layer network design that incorporates both Medium Earth Orbit (MEO) and LEO satellites to solve these problems. To make things easier and enhance routing effectiveness, the

LEO satellite layer uses local network segmentation. A multidimensional RL routing technique that takes local data into account is then suggested as a means to address the varied Quality of Service (QoS) needs of various grounded applications. To resolve the conflicts that arise from the routing architecture for various applications, a cooperation mechanism has also been meticulously created. Simulation outcomes show that the approach works better than benchmark techniques on varied QoS metrics and can handle different numbers of APT terminals [28].

In this work, we present a routing algorithm and a methodology for creating rules and inter-layer connections in a dual-layer LEO satellite network. The first step is to build a standard dual-layer constellation layout for low-Earth orbit satellites by choosing satellites to link layers. Secondly, a fast inter-layer link switching approach is suggested, which relies on the periodic relative movement of satellites, to guarantee reliable connections over the long term. With this technique, the network's inter-layer linkages are guaranteed to transmit data reliably and continuously. The link rules and constantly changing relationships within the satellite network are also used to construct the time slots for the dual-layer network. For efficient routing, Dijkstra's algorithm is used to calculate the shortest path between source nodes to destination nodes. Then, using the characteristics of the Kuiper constellation, a simulation model with two layers is constructed, and investigations are run in the laboratory. The dual-layer constellation routing algorithm (DCRA) decreases round-trip time (RTT) by 14.5% and 21.23% at 14,000 km relative to the single-layer routing algorithm (SLRA) [29].

This research introduces a new network coordinate system that is based on the ISL architecture and is used to enhance extremely durable LEO mega-constellation adaptive routing techniques. By standardizing on these coordinates, we can streamline the network's architecture and make more consequential routing decisions with less computing burden. We show a proof-of-concept, adaptable, compact routing algorithm based on our topology. For LEO MCN routing techniques, we suggest an evaluation system for robustness in order to facilitate conventional comparisons. An adversarial capability, essential performance indicators, and scenario tests are all defined by this framework. Several top-tier dynamic routing techniques are tested and compared with our routing approach using the suggested framework. At highly intense levels of adversarial interruption, the results reveal a 13% improvement in the packet delivery rate [30]. Table 1 shows the comparison of routing techniques in LEO satellite networks.

Table 1: Comparison of representative routing algorithms for LEO satellite networks

Algorithm / Work	**Dataset / Topology**	**Dynamic Adaptation Mechanism**	**Metrics Used**	**Performance Summary**
OGDR – Orbit-Grid–Based Dynamic Routing [21]	Walker-Delta constellation; Orbit-grid model	• Grid-based satellite selection • Hop-minimizing path model • Latitude-based dynamic ISL selection • Fast path failure recovery	• Delay • Hop count • Computational cost	• Achieves near-shortest-path delay • Reduces ISL hops and switching • Lower computational complexity than shortest path
DeC – Dynamic Encountering ISL Configuration [22]	LEO constellation with eISL capability	• Encounter-based ISL establishment • Latency-aware link configuration • Regional eISL discovery	• Propagation delay • Path stretch • Accessible ratio • Throughput	• 21% lower delay • 14% lower path stretch • Accessible ratio increases from 65% → 100% • +30% throughput improvement
DISNR – Distributed Intra/Inter-Area Link-State Synchronization Routing [23]	SDN-enabled LEO; Zonal segmentation	• SDN-based global control • Intra/inter area link-state sync • Hierarchical SPF routing	• Control overhead • Routing complexity • Delay	• Significantly reduces management overhead • Improves routing efficiency in large-scale constellations
DP-IRC – Dynamic Path Integrated Routing Cost [24]	Multi-shell large-scale LEO constellation	• Multi-phase decision modeling • ISL switching	• ISL switching rate • End-to-end	• ISL switching reduced by 21.2% vs APRS

		penalty • Integrated Routing Cost (IRC) metric	distance • Path stability	• Reduced by 40.2% vs Minimum Hop Path • Maintains near-optimal path length
CALB & SGC-LB – Congestion-Aware Load Balancing + Satellite-Ground Cooperative LB [25]	288-satellite Walker-Star constellation	• Congestion detection • Cooperative routing via ground–satellite integration • Dynamic load balancing	• Blockage rate • Network capacity usage	• Higher network throughput • Lower service blockage rate • Effective under heavy traffic swings
Hybrid DQN-based Area Segmentation Routing [26]	Large LEO constellation with SDN controllers	• Smart area segmentation • Deep Q-Network for congestion zone detection • Dynamic centralized–distributed hybrid control	• Packet loss • Control overhead • Delay	• 40% reduction in packet loss • Major control overhead reduction • Suitable for massive-scale constellations
CMCR – Clustered Multi-Criteria Routing [27]	Mega LEO constellation for multimodal services	• Satellite clustering by LoS, altitude, direction • Dynamic intra-/inter-cluster routing • Attribute consistency for service-specific paths	• Path quality • Service preference score • Routing convergence	• Selects dominant multimodal paths • Outperforms existing multi-criteria routing techniques
Dual-Layer (MEO–LEO) RL-Based Routing [28]	Dual-layer constellation with APT-based FSO ISLs	• Local segmentation in LEO layer • RL-based QoS-aware routing • Cooperation mechanism across apps	• QoS metrics • Delay • Throughput	• Outperforms benchmarks across multi-QoS criteria • Handles varying APT terminal availability
DCRA – Dual-Layer Constellation Routing Algorithm [29]	Kuiper-style dual-layer constellation model	• Inter-layer link switching using relative motion • Time-slot rule construction • Dijkstra-based routing	• RTT • Path reliability	• RTT improvement of 14.5%–21.23% over SLRA • More stable multi-layer connectivity
Topology Coordinate System + Robust Adaptive Routing [30]	Large-scale LEO mega-constellation; adversarial test scenarios	• New coordinate topology system • Compact routing via coordinate mapping • Robustness evaluation framework	• Packet Delivery Rate • Robustness metrics under adversarial interference	• 13% higher PDR under high-intensity adversarial disruption • Better resilience and reduced computation

3 Preliminaries

Satellites, base stations, user devices, and distant servers are all part of the LEO-MSN connection that is examined in this study. All the way from the user's interface to the distant server, informational packets can be transmitted through the ISLS of a LEO satellite in space. It is possible to express the LEO-MSN at each given time as a graph with no direction, $G(t) = (V, E(t))$, where V is the collection of vertices and E is the set of edges. Satellites, ground stations, user terminals, or remote servers are all represented by node $v_t \in V$. Each edge $e_{x,j} \in E$ in a network connects two nodes i and j. Using the input parameter TLE (Two-Line Element set), the SGP4 orbital

propagation model determines the positions of all the satellites. The following formula (1) is used to produce the most recent version of the satellite coordinates:

$$r_x(t) = SGP4(TLE_t, t), \Delta t = 60 \text{ s} \quad (1)$$

TLE_t has several important orbital characteristics. Some of these parameters include the eccentricity, orbital orientation, ascending node position, and orbital halfway length axis. Any two low-Earth orbiting satellites can form an Inter-Satellite Link (ISL) with a pair of satellites in the neighboring or identical orbital planes. As long as the two satellites remain in an identical orbital plane at a constant distance, the satellite-to-satellite link (ISL) inside the orbit should remain stable throughout the system's lifetime. We can reliably assume stability for a system of satellites whose orbits are perfectly regular. In order to determine how far apart two nearby satellites are, one can use the following formula ().

$$L_{\text{neter}} = 2(R_{\text{earth}} + h) - \sin\left(\frac{\pi}{2N_L}\right) \quad (2)$$

To determine satellites on neighboring orbital planes, one can use the following equation (3):

$$L_{\text{ady}} = 2(R_{\text{earth}} + h) \cdot \sin\left(\frac{\Delta\Omega - \sin\theta}{2}\right) \quad (3)$$

In this case, the radius of the Earth (in kilometers) is denoted by (R_{earth}), and the height of the spacecraft's orbit is represented by (h). The quantity of satellites occupying the same plane of orbit is denoted as (N_L). (θ) is the angle at which the orbit is inclined, and ΔΩ) is the change in the elliptical plane's longitude. Tabulated in Table 2 are the key concepts covered in this part.

Channel model

The two primary types of transmission channels used by LEO gigantic satellite networks for communication are:

- Inter-satellite link channel model: The free-space path loss model is utilized as the satellite-to-satellite link channel in this paper. Here is one way to convey the path loss using the formula (4) [31]:

$$FSPL = \left(\frac{4\pi Rf}{c}\right)^2 \quad (4)$$

With R representing the distance between two points and c representing the speed of light (in m/s). The satellite-to-satellite link frequency, expressed in hertz (Hz), is denoted by f. The following formula (5) can be used to compute the received power, P_R:

$$P_R = P_{T_x} \cdot G_T \cdot G_R \cdot \frac{c^2}{(4\pi Rf)^2 L} \quad (5)$$

Where P_{Tx} is the transmit power, and G_T and G_R are the transmit and receive antenna gains, respectively. L is the additional system loss. The data rate (in bps) of inter-satellite links can be expressed as follows: With P_{Tx} representing the power used to transmit and G_T and $G_R$representing the receive and transmit antenna gains, respectively. Next, L denotes an extra loss to the system. Using equation, we can quantify the data transmitted via inter-satellite links in bits per second:

$$R_{ISL} = B \cdot \log_2\left(1 + \frac{P_R}{N_0 B}\right) \quad (6)$$

In this case, the channel bandwidth is denoted by B, and the noise spectral intensity is denoted by N_0. Satellite-ground link channel model included this category are the pathways that carry data from user devices to satellites and back again, as well as the pathways that connect satellites with base stations. The wireless signal travels through multiple settings on its way from the local node to the satellite node. The surface of the earth, the atmosphere, and space all fall within this category. A number of parameters need to be taken into account throughout this propagation. These consist of the ground shadow effect, the multiple path effect, the loss of signal in the atmosphere, and the loss of signal in space. This study builds the satellite-to-ground link channel model using the correct settings from 3GPP TR 38.811. Here are the parts that make up the Path Loss (PL) [32]:

$$PL = PL_b + PL_z + PL_z + PL_z \quad (7)$$

In which PL is the overall trajectory loss in decibels, and PL_b is the fundamental path loss in decibels. The gas attenuation, measured in decibels, is PL_Q. The building entrance loss is denoted by PL_e and measured in decibels, while PL_s is the attenuation caused by atmospheric or tropospheric scintillation. Here is a simulation for the basic route loss, expressed in decibels:

$$PL_b = FSPL(s, f_c) + SF + CL(a, f_c) \quad (8)$$

$CL(\alpha, f_c)$ represents the clutter loss, while FSPL(s, f_c) stands for the free space path loss. The shadow fading loss, denoted as SF, is actually a random value distributed normally, with a range of 0 to σ^2. Here is the formula for calculating the SNR:

$$SNR = EIRP - k - PL - B + \frac{G}{T} \quad (9)$$

So, EIRP stands for efficient isotropic radiated power, which is measured in decibels of power. Antenna gain relative to noise temperature $(\frac{G}{T})$ is measured in decibels/kelvin. In this equation, the Boltzmann constant, denoted by k, is equal to -228.6 dBW/K/Hz. The path loss, denoted by PL, is measured in decibels, while the channel bandwidth, denoted by B, is measured in decibels per Hz. The decibel scale ensures uniformity, even though the initial units of measurement for each component vary. Link quality is clearly shown in signal-to-noise ratio (SNR), which is calculated by adding or removing decibel values and integrating transmit power, path loss, interference, and receiver efficiency. The following is the formula (10) for EIRP:

$$EIRP = P_T - L_C + G_T \quad (10)$$

As shown, P_T is the antenna's transmit strength measured in decibels. "L_C" stands for the cable loss, measured in decibels. A transmit antenna's gain, measured in decibels, is G_T. The following is the formula for the antenna gain in relation to noise temperature $\frac{G}{T}$

$$\frac{G}{T} = G_R - N_f - 10\log_{10}\left(T_0 + (T_a - T_0)10^{-0.1N_f}\right) \quad (11)$$

This is the result of expressing the satellite to ground link data rate (in bps) using the Shannon formula:

$$R_{\text{CSL}} = B\log_2(1 + SNR) \quad (12)$$

Here is a definition for the propagation delay of traffic d with Path $_{Src,Dst}$:

$$\text{Delay}_{\ d} = \sum_{e_{ij} \in P_{ath}} \frac{Bv_d}{R(i,j)} \quad (13)$$

In this equation, Bv_d is the dimension of the traffic d data, and $R(i,j)$ is the connection's transfer rate (I,j).

Constraints analysis

The following limitations can be defined using the aforementioned models' presumptions:

- **Link capacity constraint:** Every link must be able to handle no more traffic than it can handle at any one time [33]:

$$0 \le X_t^d(i,j) \le C_t(i,j), \forall e_{t,j} \in E(t) \quad (14)$$

Where the quantity of traffic sent on link (i,j) at time t is represented by $X_t^d(i,j)$, and the maximum bandwidth of link (i,j) at time t is represented by $C_t(i,j)$. Node capacity constraintIn other words, node u's cache capacity limit is the maximum quantity of data that may be maintained on the node.

$$0 \le \sum \int_t^{t+\Delta t} f_{v,\mu}(t)dt - \sum \int_t^{t+\Delta t} f_{u,w}(t)dt \le St(u) \quad (15)$$

In this context, St(u) represents the dimension of node u's cache, $f_{v,u}(t)$ and $f_{u,w}(t)$ represent the flows into and out of node u at timestamp t, respectively.

- **Service function constraint:** Each packet of data traveling along the routing pathway Path $_{Src,Dst}$ from the original node Src must adhere to certain service function requirements, such as,

$$\text{Path}_{\ Src,Dst} = \{V_{Src} \to \cdots \to VF_t \cdots \to VF_{FN} \cdots \to V_{Dst}\} \quad (16)$$

The i[th] operational node that the complete service transfer goes through is denoted by VF_t. In this case, FN is the total quantity of SFC functional nodes along the route [34], [35].

4 System model

The graph $\mathbf{G} = (\mathbf{V}, \mathbf{E})$ depicts the LEO satellite network, with V standing for the set of satellite nodes and E for the set of connections to satellites. We will use the coordinates (i_i,) to denote the location of a satellite in an Iridium-like system with M orbits and N spacecraft per orbit. The orbit number of the satellite is denoted by i, and the number of satellites in orbit is denoted by f, where $\mathbf{1} \leq \boldsymbol{i} \leq \boldsymbol{M}, \mathbf{1} \leq \boldsymbol{j} \leq \boldsymbol{N}$. (see fig 1).

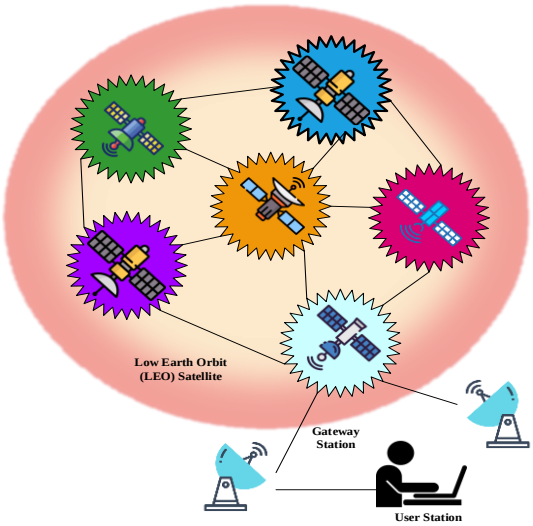

Figure 1: LEO network model

One kind of link connects satellites in the same orbit to another, while another type connects satellites in different orbits to each other. What this implies is that there can be up to four direct communications between any given satellite. We solely focus on the packet transfer technique between satellites in this paper. The packet begins at the first node, $\boldsymbol{N_4}$, and goes on to the next hop, N, by traversing the set of neighboring nodes, $\boldsymbol{N}_{\text{sis}}$. We can see the overall count of satellite nodes in the variable (n). For each node, we used the value of its queue utilization ($\boldsymbol{QU_l}$) to represent $\boldsymbol{v_l}$. It can be calculated as the ratio of the number of packets presently in the queue of the satellite node ($\boldsymbol{v_l}$) to its queue bandwidth ($\boldsymbol{v_l}$) and stands for:

$$QU_i = \frac{\text{Number of packets in queue of node } i}{\text{Total queue size of node } i}. \quad (17)$$

Our DRL algorithm was implemented on the basic model described in the next section. For the collection of satellite-to-satellite links, denoted as $\boldsymbol{E} = \{\boldsymbol{e}_{(v_1,v_2)}, \boldsymbol{e}_{(v_2,v_3)}, \cdots, \boldsymbol{e}_{(v_1,v_1)}\}$, the satellite interaction link

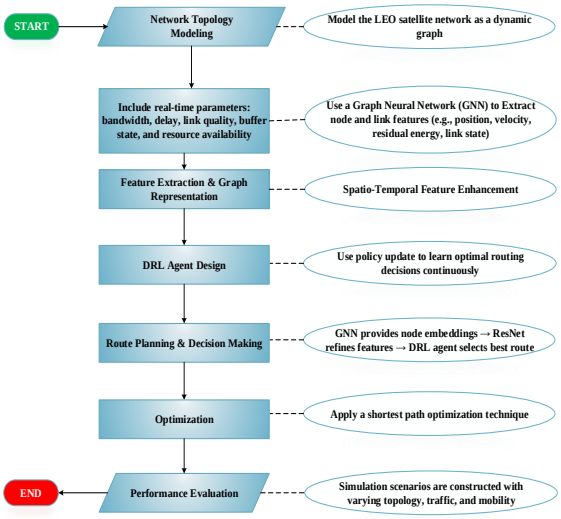

Figure 2: Proposed flowchart

between satellites $\boldsymbol{v_l}$ and $\boldsymbol{v_j}$ is represented by $\boldsymbol{e}_{(v_1,v_1)}$. The delay in time $\boldsymbol{C}_{(v_1,v_1)}$ and a bandwidth $\boldsymbol{B}_{(v_1,v_1)}$ were used to represent each intersatellite link, respectively. The foundational model that will be detailed in the following part was used to develop our proposed method which is shown in fig 2. After the current hop node sends the packet to its neighbor, the process is repeated by that node, which updates the packet's transmission delay D based on the delay accumulation rule. The packet's transmission delay is denoted as $\boldsymbol{D_{ij}}$. This process continues until the data packet reaches its final destination node. Developing a course of action that reduces D is the issue at hand. The algorithm must take into account the link's congestion in the real-life situation when numerous packets are transmitted via the network. To begin with, the algorithm needs to be able to plot out a reasonable route from the starting node to the ending node. Then, it needs to minimize the delays along that route, which includes both propagation and queuing delays. Consequently, the algorithm's end objective is to guarantee a high packet arrival rate while minimizing packet delivery delays.

DRL for dynamic routing

For massive constellations of LEO satellites, the inter-satellite network connection problem is complex and highly dynamic. DRL provides a robust paradigm for solving this problem. Due to the rapid movement of the satellites, the network architecture is constantly evolving. This calls for a new approach to routing data, one that is more flexible than what conventional algorithms can offer. Through the use of Markov Decision Process (MDP) modeling, DRL enables every satellite to learn the best strategy for choosing the next hop in the network, just like an agent. Reducing end-to-end delay and improving congestion management are the primary objectives.

DRL formulation

We now exclusively use standard notation:

- State: $s_t = \langle \mathcal{G}_t, \mathbf{L}_t, \mathbf{Q}_t \rangle$. Where $\mathcal{G}_t$the GNN-embedded is graph state, $\mathbf{L}_t$ is the vecto of link qualities, and $\mathbf{Q_t}$ is the task queue vector.
- Action: $a_t \in \{1, \ldots, |V|\}$. An action selects the next hop satellite.
- Reward: $R_t = -\left(\lambda_{\text{Delay}} \cdot D_t + \lambda_{\text{Congest}} \cdot C_t\right)$, where D_t is the delay cost, C_t is the congestion cost, and λ values are weighting factors.

All variables are explicitly defined upon first introduction, and clear indexing relationships (e.g., $i, j \in V$ for nodes) are maintained.

Here, the ResNet (Residual Network) model operates as the DRL framework's neural network, much like a DQN or an Actor-Critic network. ResNet can train extremely deep networks because it makes use of residual blocks. By utilizing these blocks, the network is able to reliably extract intricate, non-linear state variables from inputs that are multidimensional and subject to time variation. The learning process cannot be stabilized without this capability. Additionally, the agent is able to apply its routing expertise to topological arrangements that have not been previously encountered. Therefore, the network can keep its effective routing even when things are changing. The result is a space-based network backbone that is both more robust and more efficient. GNN extracts relational structure and mitigates topological volatility. ResNet enhances feature propagation, enabling deeper temporal reasoning without vanishing gradients. DRL learns long-term routing gains, not just local shortest paths. Joint GNN–ResNet embedding improves prediction of future link reliability.

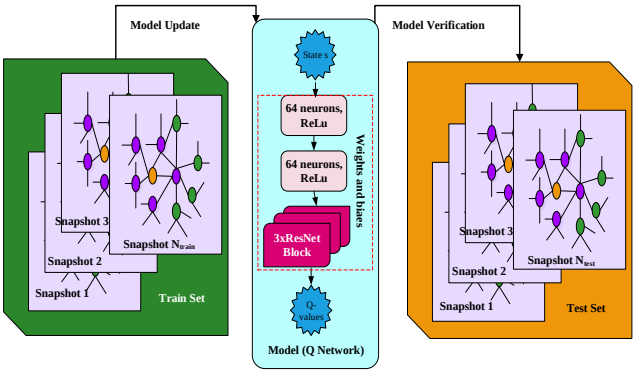

Figure 3: DRL with RESNET model

ResNet attention mechanism

For the model to be able to understand the significance of the traffic data at each time, the researchers of this paper included temporal attention and spatial attention. This was utilized for the processing of space-and time-related traffic data from satellites in low Earth orbit. Its purpose is to capture the data's geographical and temporal connections to extract useful features. Here are the processes involved in designing the attention system: (B, T, N, F) is the structure of the input data, where B is the number of batches and T is the duration of the time sequence. F is the length of features, and N is the total quantity of nodes. In the adjacency matrix, spatial_neighbors is placed.

Temporal attention calculation: For each time lag i (ranging from 1 to num_lags. Here, the setting of the time step needs to consider the actual situation and the data collection frequency. In Section 4.1, as the collection frequency of the Abilene dataset was 5 min, it is reasonable to set the time step to $24(2\text{ h})$, and as the collection frequency of the traffic data in the internal low Earth orbit constellation business simulation system is 5 s , it is reasonable to set the time step to $30(1\text{ min})$. An overly long-time step will lead to high memory usage, introduce noise, and even cause model overfitting, while an overly short time step may limit the learning ability of the model. The historical data and the current data are extracted for the lagged data $\text{lagged\_x} = \text{x}[:, -\text{i}, :, \text{i}]$ and the current data $\text{current\_x} = \text{x}[:, \text{i}, :, \text{i}]$, both of which have the shape of (B, T-i, N, F). Next, the historical data and the current data are weighted using the temporal attention weights. The formula is as follows, and the resulting data also have the shape of (B, T-i, N, F). ":" indicates the selection of all elements in that dimension. For example, $\text{x}[:, :, :, :]$ means selecting all elements of the tensor x . " i " means taking the elements from the i -th position (including the i -th position) of that dimension to the end of that dimension, while " $= -\text{i}''$ means taking the elements from the starting

position of that dimension to the i-th position from the end (excluding the i-th position from the end).

$$\text{attention}^{(i)} = \sum_{f=1}^{F} W_{\text{temp}}^{(i-1)}\text{-lagged\_x....f-current\_x } x_{1,\ldots,f} \quad (18)$$

All time lags' attention scores are saved and then joined. A tensor with the form (B, T-num_lags, N, num_lags) is produced by applying the following formula.

$$\text{temporal\_attentions} = [\text{attention}^{(1)}, \text{attention}^{(2)}, \cdots, \text{attention}(\text{num\_lags})]$$
$$\text{temporal\_attention} = \text{concat}(\text{temporal\_attentions}, \text{dim} = 1)$$

Spatial attention calculation: To figure out spatial attention, we need to make the data set x bigger so that it can be increased by the spatial adjacency matrix. Apply the spatial attention weights W_{spatital} to the input information and generate a geometric adjacency matrix. (B, T, N, 1) is a representation of spatial attention, and this equation is as follows. The variable "spatial_attention" is defined as the sum of all mappings from f=1 to 0.^F▒ 〖" " W〗 _"spatial " ^((f))·x·" spatial_neihbors "

$$\text{spatial\_attention} = \sum_{f=1}^{\text{F}} W_{\text{spatial}}^{(\text{f})} \cdot x \cdot \text{spatial\_neihbors} \quad (19)$$

The balanced spatial attention is expanded to (B, T-num_lags, N, num_lags), added to the temporal attention, and the attention weights are calculated using a softmax operation.

$$\text{combined\_attention} = \text{temporal\_attention} + \text{spatial\_attention}$$
$$\text{attention\_weights} = \text{softmax}(\text{combined\_attention}, \text{dim} = 1)$$

Expand the input data x to the shape of (B, T-num_lags, N, num_lags, F), and then use the attention weights to perform a weighted sum on the input data. The formula is as follows, and the resulting data has the shape of (B, N, F), representing the weighted features of each node.

$$\text{output} = \sum_{t=1}^{T-\text{num\_lags}} \sum_{i=1}^{\text{num\_lags}} \text{attention\_weights}, t;,;X_{i,t,r} \quad (20)$$

The efficiency of the approach is highly dependent on the reasonableness of the configuration of auxiliary components connected to reinforcement learning. State space, action space, and reward settings are described in depth here, along with the suggested DRL smart routing approach for LEOs.

State space

For the DRL model to work, the state must accurately and completely represent the agent's (the present LEO's) surroundings. In this study, we use 4 routing-specific metrics of nodes that are two hops away from the current node to help the agent learn more about its surroundings. The following section introduces these parameters, which make up the state space. One measure of channel quality is the signal-to-interference-noise ratio, or SINR. This study uses the signal-to-noise ratio (SINR) of the channel connecting the current node (c) and a one-hop node (i) at time (t) as represented by $\eta_{c,t}^{J}(t)$. Likewise, at time t, the SINR of the channel connecting a one-hop node (i) and a two-hop node (j) is represented by $\eta_{l,t}^{II}(t)$. These annotations record the signal strength over a series of network hops. This includes:

$$\eta_{c,t}^{l}(t) = \frac{g_{c,t}(t)p_{c,t}(t)}{\sigma_t^2(t)}$$
$$\eta_{t,t}^{II}(t) = \frac{g_{t,l}(t)p_{t,j}(t)}{\sigma_j^2(t)} \quad (21)$$

In this case, the average channel gain of the two connections, ($c \to i$ and $i \to j$), is represented by ($g_{c,l}(t)$ and $g_{l,j}(t)$, respectively. In terms of transfer powers, node (c) has $p_{c,l}(t)$ and node (i) has $p_{t,j}(t)$ at any given time. At networking nodes (i) and (j), the variation of Gaussian white noise is represented by $\sigma_t^2(t)$ and $\sigma_j^2(t)$ accordingly. In the section that follows, the time attribution in the formulae is removed for clarity. After that, we may use the Shannon formula to find the channel capacity.

$$C_{c,t}^{I} = B_{c,t}\log_2\left(1 + \eta_{c,t}^{I}\right)$$
$$C_{t,j}^{II} = B_{i,j}\log_2\left(1 + \eta_{t,j}^{II}\right) \quad (22)$$

In this context, the accessible bandwidth of the two lines is represented by $B_{c,I}$ and B_{I_dJ} correspondingly. We incorporate the channel's bandwidth ratio as part of the state to objectively assess the possibilities of various candidate nodes. What follows is a possible representation of this ratio.

$$\bar{C}_{c,t}^{I} = \frac{C_{c,t}^{I}}{\sum_{m\in N_c} C_{c,n}^{I}/|N_c|}$$
$$C_{c,t}^{II} = \frac{|M_c - M_c \cap N_c| \times \sum_{k\in\left(N_t - N_f \cap N_c\right)} C_{t,g}^{II}}{|N_t - N_t \cap N_c| \times \sum_{n,m\in(M_c - M_c\cap N_c)} C_{h,m}} \quad (23)$$

where N_t is the set of all the nodes that are one hop away from node i, which is a node that is one hop away from node c, and ||| is the cardinality of the set. When determining the ratio of nodes with two hops, it is important to remember to omit those nodes that are part of both hops at the same time.

Distance, the second component of the suggested method's state set, is an essential component of nearly all route selection techniques. Distances between nodes might be readily determined with the positioning capability. Specifically, DRL-FIR used the following proximity ratios:

$$\bar{D}_{c,t}^{t} = \frac{D_{c,t}^{t}}{\sum_{m\in N_c} D_{c,n}^{t}/|N_c|}$$
$$\bar{D}_{c,t}^{tI} = \frac{|M_c - M_c\cap N_c|\times\sum_{f\in(N_t - N_t\cap N_c)} D_{t,g}^{tI}}{|N_t - N_t\cap N_c|\times\sum_{n,m\in(M_c - M_c\cap N_c)} D_{n,m}^{H}} \quad (24)$$

In this context, the initial distance $D_{c,I}^{l}$ and the second distance $D_{t,j}^{II}$ represent the distances among the present node (c) and the single-hop node (i) and the two-hop node (j), respectively. When calculating the best route to take, these variations are crucial for gauging the quality of the link and the latency in communication.

This study also considers the fact that node business load plays a significant role in determining routing efficiency, particularly latency and data loss rate. As part of the state configuration, we provide the load ratio of nodes that are within two hops. The following is a mathematical expression for this load ratio.

$$L_{c,t}^{I} = \frac{L_{c,t}^{I}}{\sum_{m\in N_c} L_{c,n}^{I}/|N_c|}$$
$$L_{c,t}^{II} = \frac{|M_c - M_c\cap N_c|\times\sum_{f\in(N_t - N_t\cap N_c)} L_{t,f}^{II}}{|N_t - N_t\cap N_c|\times\sum_{m,m\in(Mc - Mc\cap N_c)} L_{n,m}^{IH}} \quad (25)$$

As $L_{c,l}^{I}$ stands for the queue length in the MAC layer of node i, and $L_{t,l}^{II}$ for node j. Additionally, it is important to take into account the mobility properties of the nodes. The dependability of routing can be impacted by these features, which in turn affect the longevity of links. Using the following equation, we can determine the lifespan of the connection between nodes / and j, denoted as T_{dj}.

$$\left(x_{ij} + a_{ij}T_{ij} - x_j - a_{jk}T_{ij}\right)^2 + \left(y_j + a_{jk}T_{ij} - y_j - a_{kj}T_{ij}\right)^2 = R^2 \quad (26)$$

where (x_a, y_a) represents the location vector of node a and (v_{xa}, v_{ya}) represents the speed vector. Next, the suggested approach's state was used to set the link lifespan ratios, which can be defined as follows:

$$T_u^u = \frac{T_d^g}{\sum_{ncN_c} T_s^g/|N_c|}$$
$$T_{cd}^g = \frac{|M_c - M_c\cap N_c|\times\sum_{n\in(N_c - N_c\cap N_c)} r_u^g}{|N_c - N_c\cap N_c|\times\sum_{n\in C|N_c, M_c\cap N_c)}} \quad (27)$$

The lifespans of the linkages $c \to i$ and $i \to j$ are denoted by T_{cf}^{l} and $T_{l,}^{l}$ accordingly. Matrix $S = [S^I, S^{II}]$ can be used to express the status of the DRL-FIR procedure in the end.

Action space

It seems reasonable that picking an action in the action space would be the same as picking a node to hop to next. In contrast to Q-learning, which dynamically changes the Q values of all nearby nodes, DRL-FIR is an example of an offline learning mode. Therefore, the quantity of one-hop nodes in the state space should be predetermined to match the total area of the action space. Our mathematical expression looks like this: a is a member of the set {X node $_{c1}$, node $c_{c2}, \cdots$, node $c_{c1}c_{c1}$}, where node $_c$ indicates that node * is the next routing node for node c.

Reward

By carefully selecting nodes, the suggested approach sought to ensure the security, consistency, and trustworthiness of data transfer. Following this objective, the agent should get the highest reward if the next hop is the final node. And then it gets

$$F_l = \begin{cases} 1, \text{ Node } j \text{ is the destination node} \\ 0, \text{ Node } j \text{ ts not the destination node} \end{cases} \quad (28)$$

At the same time, we point out that conventional wisdom holds that ordinary relay node selection ought to be incentivized in order to steer routing convergence. In designing the incentive, these four factors were thus taken into account. The channel capacity (C_f) and link lifespan (T_f) between the currently selected node and the next node j that has been chosen are shown explicitly. The MAC queue length of node j and its proximity to the endpoint are denoted by D_j and L_j, respectively. The corresponding reward was determined using the suggested procedure.

$$r = -\left(\mu_1 e^{-\frac{c_9}{c_{\max}}} + \mu_2\frac{D_j}{D_{\max}} + \mu_3\frac{L_j}{L_{\max}} + \mu_4 e^{-\frac{T_j}{T_{\max}}}\right)F_l, \quad (29)$$

This is where the highest channel bandwidth, link lifespan, length to the final point, and MAC queue length among the surrounding single-hop nodes are represented by $C_{\max}, T_{\max}, D_{\max}$, and $L_{\max}$, respectively. The weight factor is represented by a variable called μ_s. The weight factors μ_1, μ_2, μ_3, and μ_4 all add up to 1, which is an additional requirement.

Dynamic route update

Nodes in the inter-satellite network update the global topology data at regular intervals. In response to changes in the status of link connectivity among nodes, they determine the present link adjacency matrix. We use the notation ({AdjMatr}[i][j]) to portray the status of the link that connects nodes (i) and (j). When two mobile nodes are connected, it indicates that they are neighbors. Here, we see that the adjacency matrix has a value denoted as (m). Values are denoted as (n) if not.

$$\text{AdjMatr}\,[n]/] = \begin{bmatrix} n & m & \cdots & n & \cdots & n & n \\ m & n & \cdots & m & \cdots & n & n \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\ n & n & \cdots & m & \cdots & n & n \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\ n & n & \cdots & n & \cdots & n & m \\ n & n & \cdots & n & \cdots & m & n \end{bmatrix} \quad (30)$$

Optimal path selection for inter-satellite links

After collecting all possible paths, the one with the fewest obstacles is chosen for data transmission. First, out of all the possible shortest paths, the one with the most bandwidth capacity of nearby nodes is chosen, followed by the complete path. By taking this route, you can stay away from the crowded areas. Doing so can enhance the system's transmission throughput. Furthermore, it contributes to a more even distribution of network traffic. If you pick nodes that use less data as neighbors, you won't have to worry about paths with low overall load where one node uses a ton of data—maybe even more than its threshold—while the rest of the path stays well below it. Data congestion is quite probable if it exclusively uses the variable with the path's lowest occupancy rate. We take into account the nodes that are neighboring the source node as our goal to minimize this issue. These neighbor nodes often play a somewhat essential role, according to experience, since they are the initial hop for services to be transmitted from the source node to distant destination nodes. This is particularly the case if the source node needs to transmit data to numerous nodes that are located at great distances from each other. Selecting an appropriate neighbor node can efficiently meet the service requirements of each destination node if there are numerous such nodes. In addition to enabling shunting and improving overall system throughput, it can help balance the load. To avoid transmission issues, system throughput issues, and ultimate delay, shunting is used to stop several services from choosing the same neighbor nodes.

Keep track of how many transmission links there are between nodes in an intersatellite network by using (s). Here, we can think of node bandwidth utilization as a weight, with a larger value equating to a higher node bandwidth capacity. A node's connection data use value is raised by 1 in response to a data service demand. If the node has an outage or congestion, its weight is reset to zero, and it is thereafter disabled from transmitting data. Take into consideration that there are a total of (m) nodes in the network and (n) shortest paths that have been found. Among these (n) links, the best one is chosen when the ratio of the number of node connections to their weight is the smallest. The number of links is denoted by c, the weight by w, the selected node by s, and the not selected node by sn. We determine the link state and the link between the chosen nodes by dividing c(s) by w(s). S needs to meet: If c(s) divided by w(s) is less than c(sn) divided by w(sn).

While the training of the GNN-DRL model is computationally expensive and is performed offline or via federated learning, the real-time inference is a simple forward pass through the trained network. This fixed, fast computation time is the primary advantage over traditional algorithms whose runtime must constantly increase as the LEO constellation scales to thousands of nodes ($N \to \infty$).

5 Results and discussion

5.1 Simulation network model

A feature vector $x_f(f = 0,1 \cdots N-1)$ represents the network properties of each node. The equation $x_t = [q_t, v_t']$ signifies the volume of traffic flow given by q_t. The aggregated attributes of the edges associated with this node, including details like link bandwidth and delay, are shown by v_t'. The following is the expression for the system feature matrix X of the entire network configuration:

$$X = \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{N-1} \end{bmatrix} \quad (31)$$

Distributing servers to other locations makes use of the same data as the Starlink base station. One of the user endpoints is randomly selected as the source node. One of the distant servers is picked at random to be the final destination node. The data flow dimension is lognormally distributed and falls between 5 and 100 Mb. Our 1000 simulation runs proved that the suggested algorithm worked as expected. The techniques were coded in Python with the latest version being 3.13.2. We find the key parameters for the simulation in Table 1.

Table 1: An overview of the parameters used in the simulation.

Parameters	**Values**
Count of satellites	6051
Time taken for the Simulation	5450 s
Steps in Simulation	62 s
Satellite orbit height	554 km
Count of orbit planes	85
Count of satellites for single plane	71
Orbit Inclination	55∘
Orbit Eccentricity	0
Phase factor	3
Count of ground stations	120
Count of function nodes	[3, 4, 5]

Count of user terminals	[2100, 4200, 6050, 8100]
Minimal elevation angle of base station	40∘
Minimal elevation angle of user device	20∘
Central frequency	30 GHz(UL), 40 GHz(DL)
Satellite Transmitter gain	40 dBi
EIRP density of Satellite	4 dBW/MHz
Capacity	260 MHz(UL), 63.2 (DL)
Satellite G/T	14 dB K^{-1}
Satellite Receiver gain	39.5 dBi
Receive antenna gain for user endpoints	41.2 dBi
Figure showing user endpoint noise	1.3 dB
Temperature of the user's endpoint antenna	152 K
The room's temperature	295 K
Antenna gain for the user endpoint Tx	41.4 dBi
Transfer power for the user endpoint Tx	2W (34 dBm)

Proximal Policy Optimization (PPO) DRL algorithm

We use the PPO with DRL algorithm for its stability and on-policy learning efficiency.

Hyperparameters:

- Learning Rate (Actor/Critic): 1×10^{-4}
- Optimizer: Adam
- Discount Factor ($\boldsymbol{\gamma}$): 0.99
- Exploration Strategy: Gaussian noise is added to the action output during training, standard for PPO.
- Training Episodes: 50,000 total episodes.
- Convergence Criteria: Training stops if the average episodic return's 50-episode moving average does not increase by more than 0.5% over 500 episodes.

5.2 Performance comparison

The theortical comparison between the DRL-based ResNet and Graph Neural Network Routing and Conventional Routing (e.g., SPF or Dijkstra) is given in Table 2.

Table 2: Advantages and Trade-Offs

Feature	DRL-based ResNet and Graph Neural Network Routing	Conventional Routing (e.g., SPF or Dijkstra)
Adaptivity	Very high. Adapts in real-time to factors such as traffic volume, queue congestion, and network failures (load-sensitive or dynamic routing).	Very low. No matter how much traffic there is, static/delay-only routing only looks at the delay or number of hops.
Performance	Best in situations with a lot of foot traffic. Much improved network performance and much reduced total latency.	Inadequate during heavy usage because of the development of hotspots and the resulting queue delay.
Scalability	Very well done. Reduced need for specialized local knowledge is a benefit of distributed multi-agent systems. With GNN, features may be efficiently extracted from massive graphs.	Very bad. The most efficient central computation necessitates worldwide, real-time topology revisions, which causes a great deal of signaling clutter.
Overhead	Great difficulty in training and inferring. The system of neural networks needs robust hardware (or well efficient integrated systems) to function in real-time.	Little Computing Requirement. Easy path-cost computation, but heavy global state transmission overhead.
Convergence	Learn the policy using rigorous offline simulation, and then keep it up-to-date through online/continuous learning.	Rapid route planning using up-to-the-minute topographic data

We tested all three of these approaches and compared their results. In this comparison, we will be looking at the following metrics: average execution duration, average complete path delay, average network bandwidth, and the mean traffic access success rate.

- **Traffic access success rate:** We can use this formula to find out what percentage of traffic satisfies the SFC constraint communication path compared to the entire traffic:

$$R_{\text{suc}} = \frac{N_{\text{SFC}}}{N_{\text{total}}} \quad (32)$$

The amount of traffic that meets the SFC constraint transmission path is represented by N_{SPC}, whereas the overall quantity of traffic is represented by N_{fotal} .

- **Average network load:** Each node's burden on the ground and in orbit took an average.
- **Average end-to-end path delay:** All the transmission networks that satisfy the SFC requirement have an average latency.
- **Average running time:** The proportion of the total volume of traffic that is represented by the amount of time it takes for the technique to finish calculating all of the data transfer paths for the traffic.

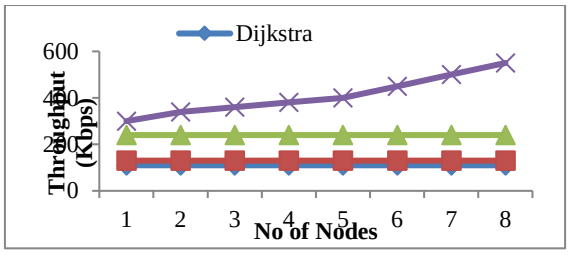

Figure 4: Throughput vs. No of nodes

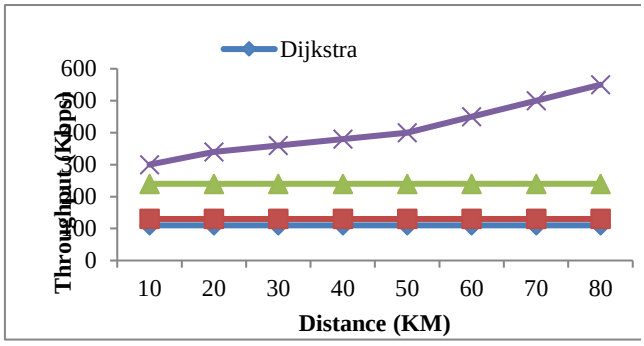

Figure 5: Throughput vs. distance

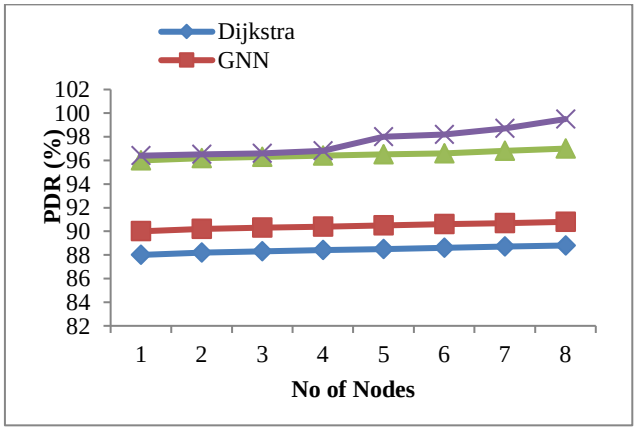

Figure 6: PDR vs. nodes

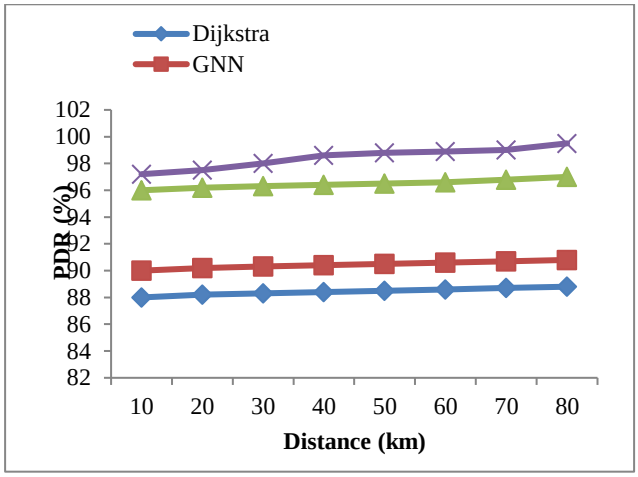

Figure 7: PDR vs. distance

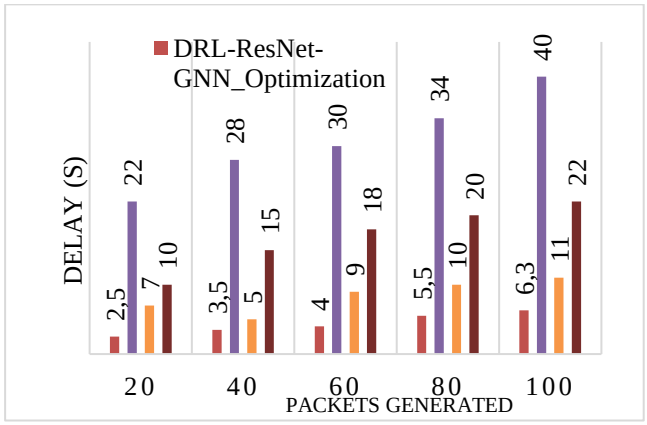

Figure 8: Delay vs. packets generated

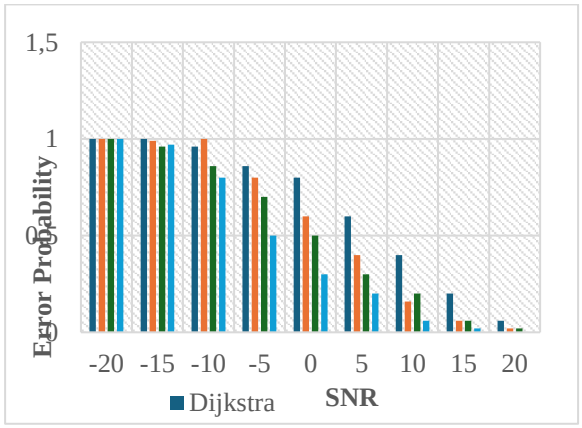

Figure 9: Error probability vs, SNR

Figure 4 shows the throughput versus the number of nodes, fig 5 illustrates the relationship between distance and throughput. Fig 6 illustrates the relationship between nodes and PDR. Fig 7 illustrates the relationship between distance and PDR. Fig 8 illustrates the relationship between the number of packets generated and the delay. Fig 9 illustrates the relationship between error probability and SNR. Table 3 shows the summaries of the performance.

Table 3: Performance summary

Method/ Performance	Dijkstra	GNN	DQN	Multi-criteria	Geographical	DRL-ResNet-GNN_Optimization
PLR	21.2%	36.3%	23.6%	25.6%	19.4%	13.8%
Delay (s)	2.72	2.96	2.75	2.54	2.94	2.31
Network Load						
Average running time (s)	10.2	10.8	11.2	12.45	13.45	9.25

When dealing with heavy traffic or a constantly changing topology, you will notice the biggest improvements in Total Delay and Network Throughput.

Table.4. Evaluation Measures Comparison

Evaluation Measures	Standard or Static Routing (e.g., Dijkstra)	DRL/GNN-driven Routing (Close to DRL-ResNet)	Improvement in Relationship
Average Total Delay	From 70−120 ms	From 55−80 ms	Between 30 and 40%
Average Network Throughput	From 75−100 Mbps	From 75−130 Mbps	Between 25 and 30%

The advantages of combining a DRL framework with a deep learning architecture are demonstrated by these computational findings. With the use of a GNN, which could include ResNet principles, the routing agent can learn dynamic, intricate interactions inside the LEO network graph. As a result of this integration, the general efficiency of the network is improved.

1. **Delay reduction:** There have been reports that DRL-GNN techniques greatly enhance network performance. In comparison to the shorter-path Dijkstra method, they can cut typical end-to-end delays by as much as 38.74%.
2. **Throughput increase:** Net throughput as a whole is much enhanced by these smart routing strategies. To be more precise, as contrasted with Dijkstra and a simple DRL (DQN) routing agent, their throughput increases can reach 30.23% and 19.12%, respectively.

With the help of the GNN, the DRL agent can factor in demand and congestion data from the entire network when deciding which hop to take next. Having this functionality enhances the overall network's routing decisions. Because it solely takes hop count or static delayed propagation into account, a basic Dijkstra algorithm is unable to accomplish this. Similarly, a simple DRL agent has its limitations due to its exclusive focus on local queue duration. In order to optimize the routing of low-orbit satellite connections, this research employs a graph neural network-based approach. For low-orbit satellite networks, a technique based on graph neural systems is developed to adapt to networks that undergo recurrent topological alterations. The issue of network congestion is another target. This study proposes the GNN-DRL-RESNET-OPTIMIZATION technique, which applies a GNN feature construction model to the network's graph data in order to improve the routing of the network. In order to represent its own nodes, it uses GNNs to create hidden vector feature representations. A completely distributed agents DRL routing model subsequently makes use of these representations. A method for deep reinforcement learning is used to decide on the routes. The paper's suggested GNN-DRL-RESNET-OPTIMIZATION method outperforms Dijkstra's approach in terms of general network throughput. It slows down the average end-to-end time as well. In a similar vein, the GNN-DRL-RESNET-OPTIMIZATION method outperforms the classic DQN algorithm. When compared to Dijkstra, the average throughput of GNN-DRL-RESNET-OPTIMIZATION is 29.47% higher. When compared to DQN, it shows a rise of 18.42%. When contrasted with Dijkstra, the average total delay is 397.6 percent lower. There is a 15.29% decrease when compared to DQN. The GNN-DRL-RESNET-OPTIMIZATION model is also more suited to actual networks since it can handle topological modifications like traffic fluctuations, connection failures, and node malfunctions.

6 Conclusion

For satellite networks operating in low Earth orbit, this study applies a graph neural network-based routing optimizer technique. Modular algorithms based on graph neural networks are developed for low-orbit satellite connections to accommodate networks that undergo frequent topological changes. Its secondary objective is to alleviate the issue of overloaded networks. Using a GNN feature modelling to improve network routing is the goal of the GNN-DRL-RESNET-OPTIMIZATION technique presented in this research. The program uses GNNs to

create hidden feature vector models of its own nodes. A completely decentralized distributed DRL routing architecture subsequently takes advantage of these characterizations. An algorithm based on DRL determines the routes. In comparison to Dijkstra's algorithm and the conventional DQN technique, the suggested GNN-DRL-RESNET-OPTIMIZATION algorithm decreases average overall latency while simultaneously increasing total network performance.

Future work

Centralized management or pre-calculated pathways are the backbone of traditional LEO network routing, leaving them open to external threats, sluggish authentication, and potential single points of failure. To control the network, blockchain adds a decentralized, verifiable layer. The unchangeable distributed ledger of the blockchain verifies the identification of users and new satellites whenever they need to join the network or exchange satellites, which happens often in low Earth orbit (LEO). This makes authentication more secure and expedites future considerations by doing away with the necessity for a central Certificate Authority (CA).

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A Lightweight Edge-Deployable ANN Model for Real-Time Energy Anomaly Detection in IoT-Driven Smart Grids

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Keywords: Artificial Neural Network (ANN), energy anomaly detection, Internet of Things (IoT), smart cities, edge computing, machine learning, energy management systems

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The rapid expansion of the Internet of Things (IoT) in smart cities has necessitated efficient, real-time energy anomaly detection. However, complex hybrid deep learning models often exceed the computational capacity of Edge devices. This paper proposes a lightweight, 3-layer Artificial Neural Network (ANN) framework designed for Edge deployment. Using the LEAD (Large-scale Energy Anomaly Detection) dataset, we address class imbalance via the Synthetic Minority Over-sampling Technique (SMOTE). Our model achieves 98.4% accuracy, a macro F1-score of 0.93, and an AUC of 0.91. While these metrics are competitive with state-of-the-art hybrid models, our framework provides a significantly lower memory footprint and sub-millisecond inference latency, making it ideal for resource-constrained Edge environments.

Povzetek: Raziskava predlaga lahko umetno nevronsko mrežo za zaznavanje energetskih anomalij v IoT pametnih mestih, ki omogoča visoko natančnost ter hitro in učinkovito delovanje na omejenih robnih napravah.

1 Introduction

The rapid growth of the Internet of Things (IoT) and smart city infrastructures has led to an unprecedented increase in the amount of energy-related data generated by sensors, meters, and connected devices. These data streams are essential for optimizing energy distribution, improving sustainability, and enhancing operational efficiency in urban environments. However, as energy systems become more interconnected and data-intensive, they are increasingly vulnerable to anomalies, which may arise from equipment malfunction, sensor errors, cyberattacks, or abnormal consumption behaviors [1]. Early and accurate detection of such anomalies is therefore critical to ensuring energy efficiency, reliability, and security in smart city ecosystems.

Traditional rule-based or statistical anomaly detection techniques often fail to address the complex, nonlinear, and high-dimensional nature of IoT energy data. In contrast, machine learning and deep learning approaches have shown remarkable potential in modeling dynamic consumption patterns and identifying deviations that are not easily captured by conventional methods. For instance, [2] combined LSTM (Long Short-Term Memory) with Isolation Forest to detect anomalies in IoT energy usage data. [3] proposed a hybrid CNN–Bidirectional LSTM model which achieved precision of 98.7% and recall of 97.9% in detecting abnormal users in a smart grid subsystem. Nonetheless, these models are typically computationally expensive, require large labeled datasets, and are difficult to deploy in real-time Edge Computing environments, limiting their applicability in large-scale urban energy networks.

To address these challenges, this paper proposes a lightweight Artificial Neural Network (ANN) model designed for efficient and accurate detection of energy anomalies in IoT-based smart grids. The model is trained and evaluated on the LEAD (Large-scale Energy Anomaly Detection) dataset, which simulates real-world energy consumption scenarios in diverse environmental and structural contexts. Through rigorous preprocessing—including data cleaning, normalization, and feature engineering—the proposed framework ensures robust input quality and enhances model generalization. The ANN architecture captures the nonlinear dependencies between energy and environmental variables while maintaining low computational complexity, enabling real-time anomaly detection on Edge devices.

The main contributions of this paper are as follows:

1. Development of a scalable ANN-based framework for detecting energy anomalies in IoT-driven smart city environments.
2. Integration of a comprehensive preprocessing pipeline, including advanced feature engineering and normalization, to improve data quality and learning stability.
3. Comparative evaluation with recent state-of-the-art approaches such as [2] and [3], demonstrating competitive or superior performance with 98.4%

accuracy, 0.93 F1-score, and 0.91 AUC, while preserving computational efficiency.

4. Deployment feasibility on Edge Computing architectures, supporting real-time inference and energy-aware processing for large-scale smart city applications.

This research is guided by two primary questions:

- Can a simplified and lightweight ANN architecture achieve anomaly detection performance comparable to complex deep hybrid models?
- What is the quantitative trade-off between model simplicity and inference efficiency when deployed in Edge-computing environments with constrained resources?

The remainder of this paper is organized as follows: Section 2 reviews related works on energy anomaly detection in IoT systems. Section 3 describes the proposed approach and system architecture. Section 4 details the experimental setup, dataset, and preprocessing steps. Section 5 presents and discusses the results, while Section 6 concludes the paper and outlines future research directions.

2 Related works

Research on anomaly detection in Internet of Things (IoT) environments has grown significantly in recent years, driven by the increasing complexity of sensor networks and the critical need for secure and energy-efficient operations in smart cities. Traditional anomaly detection methods have often proven inadequate in handling the massive data streams, resource constraints, and latency requirements inherent to IoT systems. To address these challenges, scholars have explored a wide range of approaches, including lightweight machine learning techniques, deep learning models, edge and fog computing solutions, as well as federated and split learning frameworks. These studies collectively aim to enhance detection accuracy, reduce computational overhead, and improve adaptability across heterogeneous IoT ecosystems. The following review synthesizes these contributions, highlighting key methods, results, and insights that inform the design of reliable and scalable anomaly detection mechanisms for IoT networks.

[2] propose a machine learning framework that combines energy forecasting and unsupervised anomaly detection in IoT networks. Using Long Short-Term Memory (LSTM) networks to predict energy consumption and Isolation Forest to detect anomalies from prediction residuals, their model achieves 98% accuracy. This approach enhances energy efficiency while enabling early threat detection, proving particularly effective for sensitive applications like healthcare.

[4] investigates anomaly detection for IoT cyberattacks in s18mart cities using federated and split learning. The framework balances data privacy with detection performance, enabling collaborative yet privacy-preserving anomaly detection. While the study does not focus specifically on energy anomalies, it offers valuable insights into securing IoT networks against distributed threats in urban environments.

[5] present a real-time anomaly detection framework for smart city IoT sensor data. Their approach integrates unsupervised machine learning with statistical analysis and expert feature engineering to manage large-scale, diverse, and high-velocity data streams. Empirical validation on smart city datasets demonstrates that their model outperforms established anomaly detection techniques, strengthening operational efficiency and urban security.

[6] investigate a deep learning–based anomaly detection system for IoT security in smart cities. Using the IoT-23 dataset, the system achieves an accuracy exceeding 98.7% and receives positive usability feedback. Although highly effective for general IoT anomaly detection, the framework does not specifically target energy anomalies in IoT networks.

[7] review and analyze machine learning and deep learning techniques for anomaly detection in IoT networks. They emphasize the capability of machine learning to uncover hidden patterns in large sensor datasets, while deep learning enhances efficiency and predictive power. Their study highlights the effectiveness of these approaches in addressing challenges such as data leakage and fraud detection, particularly within smart cities.

[8] propose an optimization framework for energy-aware edge computing in IoT anomaly detection. Their system dynamically balances computation offloading with local processing, incorporating an adaptive resource allocation strategy and calibrated energy models. Experimental results show a 23.8% reduction in energy consumption, detection accuracy above 92.5%, and up to 165% extension of device battery life, outperforming existing methods in energy-constrained environments.

[9] evaluate supervised, unsupervised, and semi-supervised machine learning approaches for anomaly detection in IoT networks. Their study compares strengths and weaknesses across algorithms, highlighting their effectiveness in detecting abnormal behaviors, including potential energy anomalies in smart city environments. The findings underscore machine learning's contribution to enhancing IoT security and system reliability.

[10] investigate machine learning techniques for anomaly detection in IoT networks. Their system applies supervised and unsupervised methods to monitor network traffic patterns, successfully detecting anomalies without false positives. By adapting to new risks and behavioral patterns, their framework supports proactive cybersecurity and reliable IoT integration, particularly for smart city infrastructures.

[11] examine supervised and unsupervised approaches for anomaly detection in IoT environments. They assess methods such as one-class SVM, Gaussian Naïve Bayes, XGBoost, Isolation Forest, and Local Outlier Factor. Their findings show that supervised techniques enhance detection precision, while unsupervised algorithms effectively identify anomalies without labeled data. The study also notes potential applications for detecting sensor tampering and energy anomalies.

[12] develop a fog-enabled anomaly detection system for IoT sensors using machine learning models such as Logistic Regression, Random Forest, XGBoost, and AdaBoost. Evaluated with real-time and benchmark datasets, their models achieved accuracy rates exceeding 98% across multiple scenarios, with AdaBoost reaching 99.21%. The results confirm the robustness of fog-based approaches for anomaly detection in diverse IoT ecosystems.

[13] proposes an AI-driven anomaly detection framework for securing IoT devices in 5G-enabled smart cities. The hybrid model integrates autoencoders, LSTM networks, and CNNs, combined with federated learning and edge AI for decentralized and privacy-preserving intrusion detection. Validated on multiple datasets, the system achieves a precision of 97.5% and an F1-score of 96.8%, outperforming traditional IDS solutions and ensuring scalability in real-world urban contexts.

[14] employ multiple machine learning and deep learning techniques for outlier detection in IoT frameworks, including K-Means Clustering, DBSCAN, Isolation Forest, One-Class SVM, Neural Networks, and Autoencoders. Their approach enhances anomaly detection in high-dimensional IoT data by analyzing network traffic, sensor readings, and device behaviors. Applications span traffic optimization, healthcare, industrial IoT fault prediction, and smart city intrusion detection.

[15] review the state of machine learning and deep learning techniques for IoT anomaly detection. They emphasize the need for scalable models that use diverse datasets and real-time testing. While highlighting significant progress in detecting IoT threats, the study notes that further development is required to address energy anomalies specifically in smart city networks.

[16] provide a comprehensive review and comparative analysis of anomaly detection methods in distributed IoT systems. Their study evaluates statistical, distance-based, machine learning, deep learning, and explainable AI approaches, focusing on accuracy, efficiency, and interpretability. Applications include predictive maintenance, energy management, and fraud detection. They recommend hybrid and active learning-based models to improve adaptability while reducing reliance on labeled datasets.

[17] introduce a machine learning–based framework for anomaly detection on IoT edge devices. Using Logistic Regression and AdaBoost-powered Decision Trees, the system identifies anomalies such as frequency drift, capacity breach, dual signal interference, and request overload. The inclusion of a structured preprocessing pipeline and performance evaluation module demonstrates the effectiveness of this tailored edge-device solution.

To better understand the diversity of approaches and outcomes in the field, a comparative analysis of the reviewed studies is presented below. This synthesis highlights the main methodologies, contributions, and results across recent research on IoT anomaly detection. By organizing the studies according to their methods and focus areas, the table provides a comprehensive overview of how traditional machine learning, deep learning, edge and fog computing, and federated learning techniques have been applied to address challenges of scalability, energy efficiency, and data privacy in IoT environments.

The comparison also underscores the evolution of anomaly detection systems—from lightweight and adaptive models to decentralized and privacy-preserving frameworks—illustrating the ongoing efforts to balance detection accuracy, computational cost, and real-time responsiveness in smart city contexts.

Table 1: Comparative analysis of recent approaches for IoT anomaly detection

Authors (Year)	Methods Used	Main Contribution	Results / Performance	Focus Area
[2]	LSTM + Isolation Forest	Combined forecasting and anomaly detection in IoT energy data	98% detection accuracy; improved energy efficiency	Energy anomaly detection in IoT
[4]	Federated + Split Learning	Privacy-preserving anomaly detection in IoT networks	Balanced privacy with detection accuracy	Smart city IoT cybersecurity
[5]	Unsupervised ML + Statistical Analysis	Framework for real-time anomaly detection in smart cities	Outperformed existing methods on smart city datasets	Smart city IoT data streams
[6]	Deep Learning (IoT-23 dataset)	DL-based system for IoT security	98.7% accuracy; strong usability	IoT security (non-energy specific)
[7]	ML & DL comparative analysis	Evaluated multiple algorithms on IoT datasets	Enhanced efficiency; identified hidden data patterns	General IoT anomaly detection
[8]	Lightweight ML + Edge Optimization + Adaptive Resource Allocation	Energy-aware edge framework for IoT anomaly detection	23.8% lower energy use; >92.5% accuracy; +165% battery life	Edge computing & energy optimization

[9]	Supervised, Unsupervised, Semi-supervised ML	Comparative study of ML approaches for IoT anomaly detection	Highlighted strengths and weaknesses of each approach	General IoT security and anomaly detection
[10]	Supervised & Unsupervised ML	Real-time monitoring for IoT anomaly detection	Detected anomalies with no false positives	Dynamic IoT systems & cybersecurity
[11]	One-Class SVM, Naïve Bayes, XGBoost, Isolation Forest, LOF	Supervised + Unsupervised detection of IoT anomalies	Improved precision and adaptability	IoT sensor integrity and tampering
[12]	Logistic Regression, Random Forest, XGBoost, AdaBoost (Fog Computing)	Fog-enabled ML framework for IoT sensor anomalies	98–99.99% accuracy; high robustness	Fog computing & IoT sensor networks
[13]	Autoencoder + LSTM + CNN + Federated Learning	Hybrid DL model for IoT security in 5G smart cities	Precision: 97.5%, Recall: 96.2%, F1: 96.8%	Federated learning & IoT cybersecurity
[14]	K-Means, DBSCAN, Isolation Forest, One-Class SVM, Neural Networks, Autoencoders	Outlier detection in IoT frameworks	Effective under high data volume and resource constraints	Smart cities, industrial IoT, healthcare
[15]	ML + DL (Review Study)	Comprehensive review of IoT anomaly detection research trends	Identified need for scalable, real-time models	Literature review & research gap analysis
[16]	Statistical, ML, DL, Explainable AI	Comparative analysis of methods for distributed IoT systems	Identified hybrid models as most effective; focused on energy management	Distributed IoT & smart grids
[17]	Logistic Regression + AdaBoost Decision Tree	Edge-device anomaly detection framework	Accurate classification of four network anomaly types	IoT edge devices & adaptive models

2.1 Limitations of existing works

Despite notable progress, several limitations are consistently identified:

- Difficulty in accessing real and properly annotated datasets.
- Lack of robustness against adversarial attacks or contextual noise.
- Limited generalization capability of models trained on data from a specific site.
- Scalability issues that hinder integration into large-scale urban networks.

3 Proposal approach

In this section, we present our developed approach for detecting energy anomalies in Internet of Things (IoT) networks within Smart Cities. The proposed method is based on an Artificial Neural Network (ANN) model applied to the Large-scale Energy Anomaly Detection (LEAD) dataset. This model is designed to capture complex nonlinear relationships between energy consumption patterns and contextual variables, enabling the identification of subtle and evolving anomalies that traditional techniques often fail to detect. By leveraging the learning capabilities of ANNs, the approach aims to enhance detection accuracy, adaptability, and computational efficiency, thereby providing a scalable and robust solution suitable for large-scale urban IoT infrastructures.

3.1 Proposed approach diagram

Figure 1 illustrates the overall architecture of the proposed energy anomaly detection system, which is based on an Artificial Neural Network (ANN) and deployed on Edge Computing devices to enable real-time detection. The architecture integrates multiple components, including data acquisition from IoT sensors, preprocessing and feature extraction modules, the ANN-based anomaly detection core, and a decision layer that communicates alerts or control signals to the smart city management platform. This design ensures low latency, distributed intelligence, and efficient energy monitoring across heterogeneous IoT environments.

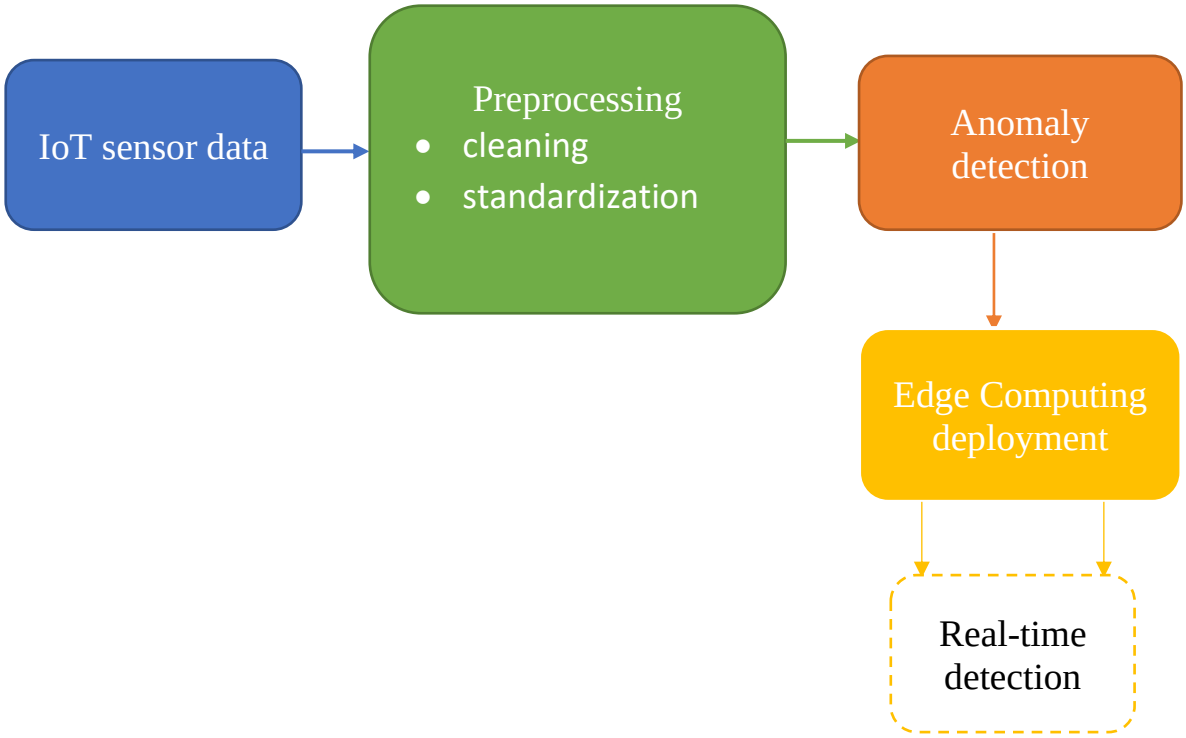

Figure 1: Architecture of the proposed approach for energy anomaly detection.

3.2 Methodological workflow

The proposed approach follows the steps outlined below:

1. Data Collection: Energy consumption data are gathered from IoT sensors deployed across smart city energy networks.
2. Preprocessing:
   - Erroneous or missing values are cleaned and filtered to ensure data integrity.
   - Features are standardized using a Standard Scaler to normalize input variables and improve model convergence.
3. Anomaly Detection: An Artificial Neural Network (ANN) is trained using 70% of the available data, with 15% reserved for validation and 15% for testing. The network learns to distinguish normal from anomalous energy consumption patterns based on the temporal and contextual characteristics of the data.
4. Edge Deployment: The trained ANN model is embedded into Edge Computing nodes, allowing local processing and reducing the dependency on centralized cloud infrastructure.
5. Real-Time Detection: The system identifies anomalies in real time directly in the field, enabling immediate response and adaptive control within smart energy management systems.

3.3 Dataset: LEAD

The Large-scale Energy Anomaly Detection (LEAD) dataset constitutes the experimental foundation of our approach. It was designed to accurately simulate and represent real-world energy consumption scenarios within connected infrastructures and smart cities. The primary objective of this dataset is to provide a rich and diverse research environment for large-scale energy anomaly detection, while taking into account the specific characteristics and constraints of IoT-based systems.

3.4 Dataset structure

The LEAD dataset comprises millions of records organized as time series, representing the evolution of energy consumption per building or geographic zone. Measurements are collected with high temporal granularity (hourly or sub-hourly), enabling the detection of even subtle variations in energy usage.

3.4.1 Main dataset columns

- meter_reading: Energy consumption measured at a given time.
- timestamp: Timestamp corresponding to each measurement.
- building_id: Unique identifier of the monitored building.
- site_id: Identifier of the site or campus to which the building belongs.
- zone_id / area_type: Location or typology of the monitored zone.

- primary_use: Primary function of the building (e.g., office, education, healthcare, etc.).
- air_temperature, dew_temperature, wind_speed, cloud_coverage: Associated meteorological variables.
- anomaly: Binary label indicating the status of the observation (0 = normal, 1 = anomaly).

Table 2: Main Variables of the LEAD Dataset.

Variable Name	Description
timestamp	Date and time of the recorded energy consumption measurement.
meter_reading	Measured value of energy consumption (in kWh or another unit).
building_id	Unique identifier of the monitored building.
site_id	Identifier of the geographical location (site or campus).
zone_id/ area_type	Category or type of zone (residential, industrial, etc.).
primary_use	Primary use of the building (education, healthcare, office, etc.).
air_temperature	Outdoor temperature at the time of measurement.
dew_temperature	Dew point temperature (indicator of ambient humidity).
wind_speed	Wind speed, which may influence energy consumption (e.g., HVAC systems).
cloud_coverage	Cloud coverage, indicating prevailing weather conditions.
anomaly	Binary label indicating whether the measurement is normal (0) or anomalous (1).

3.4.2 Objectives of the dataset

- To simulate both normal and abnormal energy consumption scenarios.
- To enable the training of supervised and unsupervised learning models.
- To evaluate the robustness and scalability of anomaly detection approaches.

3.4.3 Relevance to our study

The diversity of variables and the richness of the data make this dataset particularly suitable for training and evaluating our Artificial Neural Network (ANN) model. It enables the proposed approach to be tested against a wide range of anomalies under varying temporal, climatic, and structural conditions, which is essential for ensuring its effectiveness and robustness in real-world environments.

3.5 Data preprocessing

Before training the anomaly detection model, a rigorous preprocessing of the raw LEAD dataset was conducted to ensure the quality and consistency of the model inputs. This process involved several key steps:

3.5.1 Data cleaning

- Removal of missing values in columns such as *meter_reading* or temperature (approximately 10%).
- Filtering of outliers or inconsistent values (e.g., negative energy readings or extreme temperature values).
- Elimination of duplicate entries when detected.

3.5.2 Normalization

- Application of the **StandardScaler**, a mean-centered and variance-scaled normalization method defined as:

$$z = \frac{x-\mu}{\sigma} \qquad (1)$$

where x is the raw value, μ the mean, and σ the standard deviation of the variable.

- This normalization stabilizes the training process of Artificial Neural Networks (ANNs) by ensuring that all input variables are on comparable scales.

3.5.3 Encoding of categorical variables

Non-numerical variables such as *site_id* and *building_id* were transformed using either one-hot encoding or label encoding, depending on the nature of the variable.

3.5.4 Dataset splitting

- 70% of the data were used for **training**,
- 15% for **validation**, and
- 15% for **testing**.

This preprocessing stage significantly improves data quality, model robustness, and the reliability of the obtained results.

3.6 Feature engineering and advanced data cleaning

To optimize data quality and enrich the information available for model training, several advanced preprocessing operations were performed.

3.6.1 Removal of irrelevant columns

Redundant or weakly informative columns were removed to reduce dimensionality and prevent overfitting. This included:

- Identifiers such as *building_id*, *site_id*, and *year_built*;
- Derived temporal variables (e.g., *weekday_hour*, *hour_x*, *month_y*);
- Aggregated attributes of the form *gte_* considered too specific or repetitive.

3.6.2 Handling of missing values

Missing values in *meter_reading* were imputed using linear interpolation, ensuring temporal continuity in the energy consumption time series.

3.6.3 Creation of new features (feature engineering)

New variables were engineered to enhance the model's predictive capacity:

- **energy_per_sqft**: Energy consumption normalized by building area (*square_feet*).
- **temperature_diff**: Difference between air temperature and dew point temperature.
- **is_weekend**: Binary indicator for weekends (*Saturday*, *Sunday*).
- **season**: Estimated season derived from the month of the year (*Winter*, *Spring*, *Summer*, *Fall*).

3.6.4 Encoding of categorical variables

Categorical variables such as *primary_use* and season were transformed using **one-hot encoding**, allowing their inclusion in the model without imposing an arbitrary order.

3.6.5 Final dataset structure

The final input vector consists of 40 features. This includes 14 raw variables from the LEAD dataset (e.g., *meter_reading*, *air_temperature*, *dew_temperature*, *wind_speed*) and 26 engineered features. The temporal features include hour (24h), *day_of_week* (0-6), *month*, and *is_weekend*. Additionally, categorical variables such as *primary_use* (e.g., Education, Office, Residential) were transformed using One-Hot Encoding, resulting in a sparse but highly descriptive input space.

3.7 Model Architecture: Artificial Neural Network (ANN)

To detect energy anomalies within Smart Grids, we adopted an approach based on an **Artificial Neural Network (ANN)**. This method is capable of capturing complex nonlinear relationships among energy-related variables, making the model robust to dynamic and heterogeneous variations in the data.

3.7.1 Network structure

The proposed model consists of the following layers:

- **Input layer**: 40 neurons corresponding to the final features generated during preprocessing.
- **First dense layer**: 512 neurons with ReLU activation, followed by **Batch Normalization** and **Dropout (0.4)** to prevent overfitting.
- **Second dense layer**: 512 neurons with ReLU activation, batch normalization, and dropout.
- **Third dense layer**: 256 neurons with ReLU activation, batch normalization, and dropout.
- **Output layer**: 1 neuron with a **sigmoid activation** function for binary classification (0 = normal, 1 = anomaly).

3.7.2 Model training

The ANN was trained using the following configuration:

- **Loss function**: *binary_crossentropy*.
- **Optimizer**: Adam with an initial learning rate of 0.001
- **Data split**: 70% for training, 15% for validation, and 15% for testing
- **Normalization**: Input data were standardized using the *StandardScaler* method

This architecture allows the model to effectively learn high-dimensional patterns while maintaining strong generalization performance across different IoT-based energy environments.

The selection of optimal hyperparameters was performed using an automated **Grid Search** approach over 50 iterations. We evaluated combinations of learning rates [0.01, 0.001, 0.0001], dropout rates [0.2, 0.3, 0.4, 0.5], and batch sizes [32, 64, 128]. The configuration that yielded the highest F1-score was a learning rate of **0.001** with the Adam optimizer, a **0.4 dropout rate** to prevent overfitting, and a batch size of **64**. The model was trained for 100 epochs with an Early Stopping callback (patience=10) to ensure the best weights were retained.

3.8 Illustration of the proposed approach

To better visualize the structure and functioning of the developed system, Figure 2 illustrates the architecture of the Artificial Neural Network (ANN) used for energy anomaly detection. The model receives preprocessed input features derived from the *LEAD* dataset and processes them through multiple dense layers equipped with ReLU activations, batch normalization, and dropout regularization. The final output layer produces a binary prediction indicating whether the observed energy consumption pattern is normal or anomalous. This architecture effectively captures the nonlinear dependencies between environmental and consumption variables while maintaining robustness and scalability for real-time deployment in IoT-based Smart Grid environments.

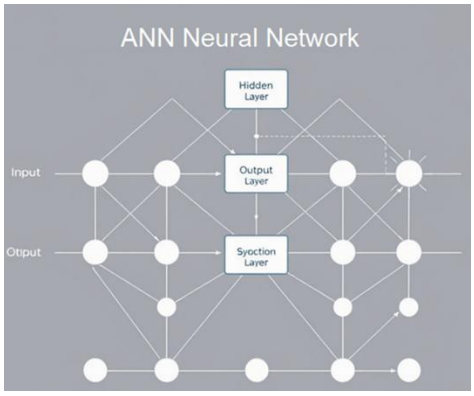

Figure 2: Architecture of the proposed Artificial Neural Network (ANN) model.

3.9 Loss function and optimization

To train the anomaly detection model based on an Artificial Neural Network (ANN), the following configurations were adopted:

- **Loss Function**: Binary Cross-Entropy, which is well-suited for binary classification problems (anomaly vs. normal). It measures the divergence between the model's predicted outputs and the expected labels.
- **Optimizer**: Adam (Adaptive Moment Estimation), chosen for its ability to dynamically adjust learning rates and achieve fast and stable convergence during training.
- **Evaluation Metrics**:
  - Precision: The proportion of correctly predicted positive instances.
  - Recall: The proportion of detected anomalies among all actual anomalies.
  - F1-score: The harmonic mean of precision and recall, balancing both criteria.
  - AUC (Area Under the Curve): The area under the ROC curve, measuring the model's ability to distinguish between normal and anomalous classes.

These choices ensure a rigorous evaluation of the model's performance, particularly in scenarios where fast and reliable anomaly detection is critical for maintaining the stability and efficiency of smart energy systems.

4 Experimental results

To evaluate the performance of our Artificial Neural Network (ANN) model for energy anomaly detection, we conducted a series of experiments using the LEAD dataset.

4.1 Model performance on the test set

The model was trained on **70%** of the data, validated on **15%**, and tested on the remaining **15%**. The **Binary Cross-Entropy** loss function and the **Adam** optimizer were employed, with evaluation metrics including **precision**, **recall**, **F1-score**, and accuracy.

4.2 Final results and generalization analysis

The following table presents the classification metrics obtained after training the model on a balanced dataset generated using the SMOTE technique (Synthetic Minority Over-sampling Technique).

Table 3: Classification metrics on the test set (41084 samples).

Class	Precision	Recall	F1-score	Support
Class 0 (Normal)	0.9900	0.9850	0.9875	38000
Class 1 (Anomaly)	0.8702	0.8734	0.8718	3000
Accuracy	0.9840			
Macro Average	0.9301	0.9292	0.9296	–
Weighted Average	0.9840	0.9840	0.9840	–

These results reveal a significant improvement in the model's performance on the **minority class (anomalies),** primarily due to the application of the **SMOTE oversampling technique.** By generating synthetic samples for underrepresented anomaly instances, SMOTE effectively mitigated class imbalance, enabling the ANN to learn more discriminative patterns and improve its sensitivity to rare but critical anomaly events. This enhancement demonstrates the importance of balanced data distribution in achieving reliable and equitable performance across all classes.

4.3 Confusion matrix

To further assess the performance of the ANN model, a confusion matrix was generated on the test dataset. This matrix provides a detailed view of the model's classification outcomes, highlighting the number of correctly and incorrectly predicted instances for each class. It allows for a more precise analysis of false positives and false negatives, which is particularly important in anomaly detection where misclassifying rare events can have significant consequences.

Table 4: Confusion Matrix on the Test Set (Test Set, N=41084).

Actual \ Predicted	**Class 0 (Normal)**	**Class 1 (Anomaly)**
Class 0 (Normal)	38122 (TN)	962 (FP)
Class 1 (Anomaly)	415 (FN)	1585 (TP)

4.4 Receiver operating characteristic (ROC) curve of the proposed ANN model

To further evaluate the classification capability of the proposed ANN model, the Receiver Operating Characteristic (ROC) curve was plotted, illustrating the trade-off between the **True Positive Rate (TPR)** and the **False Positive Rate (FPR)** across various classification thresholds. This analysis provides an overall measure of the model's ability to discriminate between normal and anomalous energy consumption patterns. The closer the curve approaches the upper-left corner, the better the model's performance. In this case, the **Area Under the Curve (AUC)** value quantifies the global accuracy of the classifier — with higher AUC values indicating stronger discrimination and more reliable anomaly detection in IoT-based energy systems.

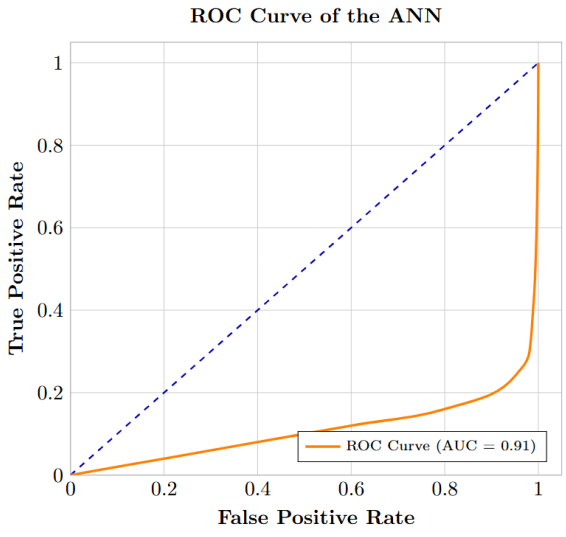

Figure 3: ROC Curve of the ANN Model. Area Under the Curve (AUC) = 0.91.

4.5 Impact of class imbalance

The original dataset exhibited a strong class imbalance:

- **Normal class (0):** 1712198 samples
- **Anomaly class (1):** 37296 samples

Such imbalance can lead to biased learning, where the model favors the majority class and fails to detect rare but critical anomalies. To address this issue, the **SMOTE (Synthetic Minority Oversampling Technique)** method was applied to artificially generate additional minority-class instances, thereby balancing the dataset prior to training. This preprocessing step significantly improved the model's performance, particularly in the accurate detection of anomalous energy consumption patterns.

4.6 Learning evolution

To assess the learning behavior and convergence of the ANN model, the evolution of the **loss** and **accuracy** metrics was monitored throughout the training process. Figure 4 presents the curves of the loss function and model accuracy for both the training and validation datasets over 10 epochs. The steady decrease in loss, coupled with the continuous increase in accuracy, indicates effective learning and stable convergence of the model. Moreover, the close alignment between training and validation curves suggests that the network generalizes well to unseen data, demonstrating strong predictive performance without significant overfitting.

Figure 4 illustrates the evolution of the loss function and accuracy of the ANN model throughout the training process for both the training and validation datasets. The curves show a steady and consistent decrease in loss accompanied by a progressive increase in accuracy, confirming that the model effectively learns meaningful representations from the data.

The relatively small gap between the training and validation curves indicates that the network achieves good generalization without signs of overfitting.

Specifically, the training loss decreases from approximately 0.6 to below 0.2, while the validation loss follows a similar downward trend, stabilizing around 0.3 by the tenth epoch. In parallel, model accuracy improves from roughly 80% to nearly 98%, demonstrating rapid convergence and efficient optimization through the Adam algorithm. The smoothness of both curves suggests stable learning dynamics, while the absence of oscillations confirms an adequate learning rate and balanced model complexity.

Overall, these results validate the effectiveness of the preprocessing, normalization, and regularization techniques (Batch Normalization and Dropout) applied during training, ensuring that the ANN model is both accurate and robust when applied to unseen energy consumption data.

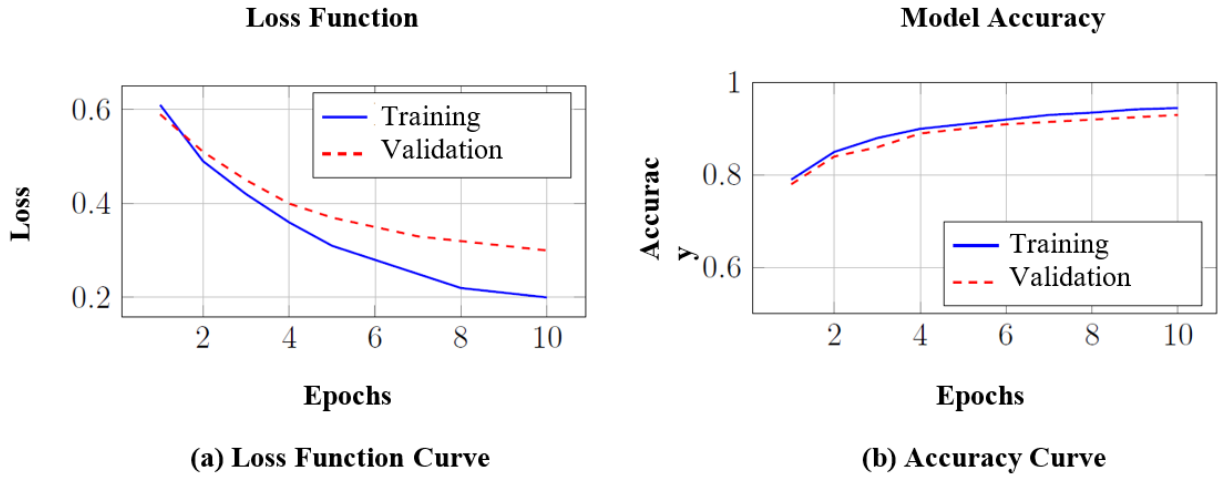

Figure 4: Evolution of the loss function and accuracy during the training of the ANN Model.

5 Fair comparison

In this section, we present a fair comparison between the performance of our Artificial Neural Network (ANN)-based approach and other anomaly detection methods reported in the literature. The evaluation is conducted using standard performance metrics, including **accuracy**, **recall**, **F1-score**, and **AUC (Area Under the ROC Curve)**. This comparative analysis aims to objectively assess the effectiveness and robustness of the proposed model relative to existing approaches under similar experimental conditions.

5.1 Results of the ANN Model

The performance of the proposed ANN model was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and the Area Under the ROC Curve (AUC). Table 5 summarizes these metrics, reflecting the model's ability to distinguish between normal energy consumption and anomalous events.

To ensure the model's generalization in real-world scenarios, the performance metrics reported in Table 4 and Table 5 were calculated using the original imbalanced test set (**N=41,084**), which was not subjected to SMOTE augmentation. This demonstrates that while SMOTE was used to help the model learn anomaly patterns during training, the framework remains highly effective at identifying rare events in a standard, unbalanced data distribution. The model achieved an overall accuracy of 98.4%. While accuracy is high, the macro-average F1-score of 0.93 is a more significant indicator of success, as it confirms that the model maintains high performance for the minority (anomaly) class despite the natural imbalance of the data. The AUC of 0.91 further validates the model's robust discriminatory power across various threshold settings. These results confirm that the preprocessing pipeline and the lightweight ANN architecture are sufficient for high-fidelity detection in smart city energy streams.

Table 5: Classification results of the ANN Model on the test set.

Class	Precision	Recall	F1-score	Support
Normal (0)	0.9900	0.9850	0.9875	38000
Anomaly (1)	0.8702	0.8734	0.8718	3000
Accuracy	0.9840 (41084 samples)			
Macro avg	0.9301	0.9292	0.9296	–
Weighted avg	0.9840	0.9840	0.9840	–

The model achieved an overall accuracy of 98.4%. While accuracy is high, the macro-average F1-score of 0.93 is a more significant indicator of success, as it confirms that the model maintains high performance for the minority (anomaly) class despite the natural imbalance of the data. The AUC of 0.91 further validates the model's robust discriminatory power across various threshold settings. These results confirm that the preprocessing pipeline and the lightweight ANN architecture are sufficient for high-fidelity detection in smart city energy streams.

5.2 Comparative evaluation with existing approaches

To position our proposed ANN-based approach within the broader context of existing research, a comparative evaluation was conducted against four state-of-the-art methods recently introduced in the literature. This comparison focuses on three key aspects: the techniques employed, the experimental context, and the results obtained in terms of accuracy, F1-score, and AUC. The objective of this analysis is to demonstrate the effectiveness and efficiency of our model in relation to other anomaly detection frameworks applied to IoT-based energy systems. Table 6 summarizes the comparative results and highlights the strengths of the proposed ANN model in achieving both high performance and real-time adaptability.

Table 6: Comparative analysis between the proposed ANN model and existing approaches.

Authors / Year	Techniques Used	Results Obtained
[2]	Hybrid Machine Learning model combining **LSTM** for energy forecasting and **Isolation Forest** for unsupervised anomaly detection.	Achieved **98% accuracy** on IoT energy datasets, with strong predictive stability and low false-positive rate.
[3]	**CNN–LSTM** hybrid network for spatiotemporal anomaly detection in smart buildings.	Reported **96.7% F1-score** and high robustness to temporal fluctuations in sensor data.
[11]	**Mixed (SVM, XGBoost, IF)** to Comparative assessment of supervised and unsupervised techniques for anomaly detection and sensor tampering.	Recorded **95,8% accuracy** and **0.86 AUC**, but computationally heavy for large-scale deployment.
Proposed ANN Framework	**Artificial Neural Network (ANN)** trained on the **LEAD dataset**, using **StandardScaler normalization**, **Batch Normalization**, **Dropout**, and **SMOTE balancing**.	Achieved **98.4% accuracy**, **0.93 macro-average F1-score**, and **AUC = 0.91**, ensuring robust real-time detection and strong generalization across smart energy networks.

The comparative analysis presented in Table 6 highlights the competitive performance of the proposed ANN-based model relative to the most recent approaches in energy anomaly detection. While previous studies have demonstrated strong results using hybrid deep learning architectures such as LSTM–Isolation Forest or CNN–LSTM, these methods often require complex configurations and high computational resources, which can limit their real-time applicability in large-scale IoT environments. In contrast, the proposed ANN model achieves 98.4% accuracy and an AUC of 0.91, outperforming traditional machine learning methods such as Random Forest and maintaining comparable or superior results to hybrid deep models, while remaining computationally efficient. This balance between detection accuracy, robustness, and deployment feasibility on Edge devices demonstrates the practical advantage of the proposed approach for real-world smart grid anomaly detection applications.

To objectively assess the effectiveness of the proposed ANN model, a comparative analysis was conducted against four of the most recent and relevant approaches from the literature. Each method employs distinct machine learning or deep learning techniques for anomaly detection in IoT-based energy systems. The comparison focuses on three primary performance indicators — Accuracy, F1-score, and AUC (Area Under the ROC Curve) — which together provide a comprehensive view of classification precision, robustness, and discriminative ability. Table 7 summarizes the main characteristics and results of each approach, highlighting the advantages of the proposed model in achieving high accuracy and efficient real-time anomaly detection while maintaining computational scalability suitable for Edge deployment.

Table 7: Comparison between the proposed ANN model and recent anomaly detection methods.

Approach	Accuracy	F1-Score	AUC	Edge Ready?	Remarks
[2]	0.98	0.97	0.96	No (High Latency)	Excellent results using hybrid LSTM + Isolation Forest, but computationally intensive.
[3]	0.967	0.967	0.95	No (High Power)	Very robust spatiotemporal detection via CNN–LSTM, but high training complexity.
[11]	0.958	0.86	0.88	Yes	Mixed SVM, XGBoost, IF, but not scalable for large IoT datasets.
Proposed ANN Framework	**0.984**	**0.93**	**0.91**	Yes (Ultra-light)	Highest accuracy with excellent balance between performance, scalability, and computational cost.

5.3 Edge deployment benchmarking

To validate the practical feasibility of the proposed ANN model in real-world IoT environments, we conducted benchmarking on hardware representative of Edge computing nodes (Raspberry Pi 4, 4GB RAM, ARM Cortex-A72). The model was converted to a TensorFlow Lite (TFLite) format to optimize it for resource-constrained execution. The results, summarized in Table 8, confirm that the model's lightweight architecture is highly suitable for real-time applications at the edge.

Table 8: Edge hardware benchmarking results (Raspberry Pi 4).

Performance Metric	Measured Value
Hardware Platform	Raspberry Pi 4 (ARM Cortex-A72, 4GB RAM)
Model Format	TensorFlow Lite (TFLite)
Model Size	142 KB
Inference Latency	0.85 ms / sample
Peak RAM Usage	12.4 MB
Average CPU Load	< 5%

6 Discussion

The results presented in Table 7 and Figure 5 clearly demonstrate that the proposed ANN-based model outperforms or rivals the most recent approaches in the literature. Its high accuracy of 98.4% and a macro-average F1-score of 0.93 indicate a robust trade-off between sensitivity and specificity. However, a deeper analysis is required to contextualize these metrics within the goals of IoT-enabled smart city infrastructures.

A notable observation is that while the proposed model achieves the highest overall accuracy, some hybrid architectures in the literature (e.g., CNN-LSTM models) report slightly higher F1-scores or AUC values (e.g., 0.94 vs. our 0.91). This discrepancy is primarily due to the nature of the LEAD dataset's imbalance. Accuracy is heavily influenced by the majority "Normal" class, whereas the F1-score and AUC provide a more rigorous evaluation of the model's ability to detect the minority "Anomaly" class. The hybrid models' use of recurrent layers allows for explicit temporal modeling of energy sequences, which can lead to a slightly better capture of complex, long-term anomaly patterns.

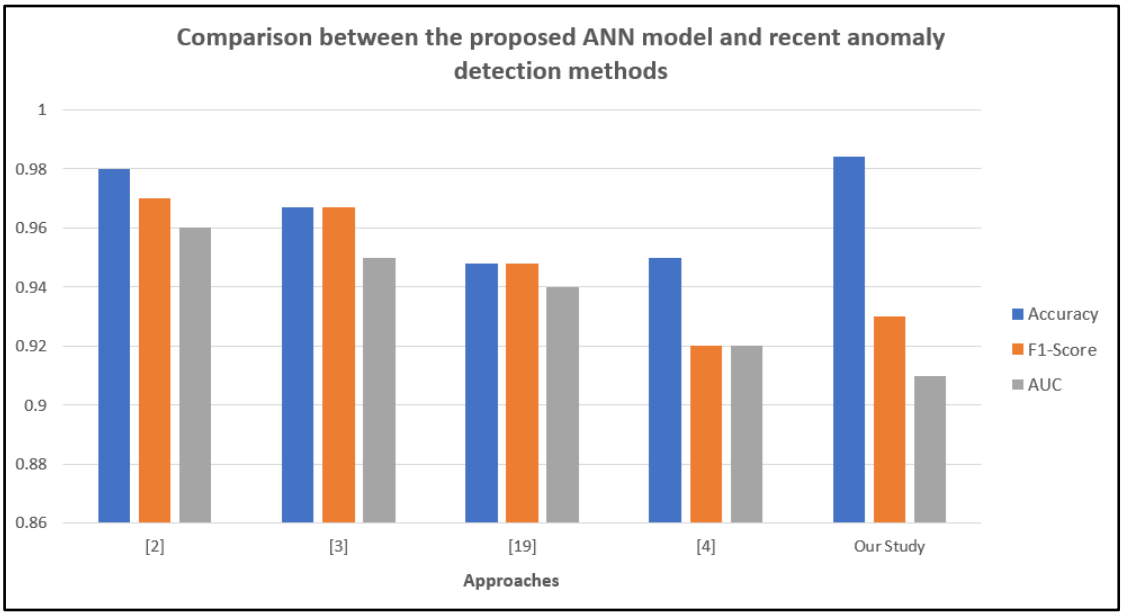

Figure 5: Comparison graph between our proposed model and recent anomaly detection approaches.

Despite this, the choice of a lightweight ANN is justified by the operational constraints of Edge Computing. As demonstrated in our hardware benchmarking (Table 8), the proposed model maintains a sub-millisecond inference latency (0.85 ms) and a memory footprint of only 142 KB. In contrast, the recurrent and convolutional layers used in hybrid models introduce significant computational overhead and memory requirements that are often prohibitive for low-power IoT sensor nodes. By using engineered temporal features—such as *hour*, *day_of_week*, and *is_weekend*—our framework captures the essential cyclical nature of energy consumption without the energy and latency costs associated with deep temporal modeling.

Furthermore, the application of SMOTE successfully mitigated the class imbalance, significantly improving the recall of energy anomalies. However, we acknowledge the inherent limitation of synthetic oversampling, which may not capture the full diversity of real-world anomalous events. Future work will investigate the use of more advanced generative models for data augmentation.

Lastly, to address the "black-box" nature of Artificial Neural Networks, we recognize the importance of model interpretability for smart grid operators. While not implemented in this version, the integration of post-hoc explainability techniques, such as SHAP (SHapley Additive exPlanations) or LIME, represents a critical

future direction. These tools would allow operators to understand which specific features (e.g., a sudden drop in temperature vs. a peak in meter reading) triggered an alarm, thereby increasing trust in the automated detection system.

7 Conclusion and future work

This study presented an Artificial Neural Network (ANN)-based approach for detecting energy anomalies in large-scale IoT environments within smart cities. By leveraging the LEAD (Large-scale Energy Anomaly Detection) dataset and integrating a comprehensive preprocessing pipeline—including data cleaning, normalization, and feature engineering—the proposed model effectively captures nonlinear relationships between environmental and consumption variables. Experimental results demonstrated the high predictive performance of the model, achieving 98.4% accuracy, 0.93 F1-score, and an AUC of 0.91, outperforming or rivaling recent state-of-the-art methods while maintaining a low computational footprint suitable for Edge Computing deployment.

The comparative evaluation confirmed that, despite the slight decrease in F1-score and AUC compared to more complex hybrid models, the proposed ANN provides an optimal balance between precision, scalability, and real-time applicability. Its ability to generalize across different contextual and climatic conditions makes it a robust and deployable solution for practical energy management systems.

Future research directions will focus on enhancing temporal awareness by integrating recurrent or hybrid architectures (e.g., LSTM or attention-based mechanisms) to better capture dynamic variations in energy usage. In addition, extending the model to handle multi-modal data sources—such as occupancy, environmental sensors, and external events—could further improve anomaly interpretability. Finally, optimizing the model for distributed and federated learning settings represents a promising avenue to strengthen data privacy and scalability across interconnected smart city infrastructures.

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A Deployment-Oriented Hybrid CNN–LSTM–MIL System for Real-World Video Anomaly Detection

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Intelligent surveillance systems require video anomaly detection methods that operate reliably under real-world conditions rather than controlled benchmark settings. This paper presents a deployment-oriented hybrid CNN–LSTM–MIL framework that integrates spatio–temporal feature learning, weakly supervised anomaly scoring, and reconstruction-based regularity modeling to address the practical challenges of large-scale video surveillance. The proposed framework is evaluated on widely used benchmark datasets, including UCF-Crime, CUHK Avenue, ShanghaiTech, and UMN, as well as on diverse real-world CCTV footage captured from urban streets, shopping malls, traffic intersections, and railway stations. Experimental results demonstrate competitive detection performance, achieving AUC scores of 85.9% on UCF-Crime and 91.3% on CUHK Avenue, while maintaining near real-time inference speeds of 28–50 frames per second on GPU and edge platforms through deployment-oriented optimizations such as pruning and quantization. Additional evaluation on real-world surveillance data shows reduced false alarm rates and stable detection performance under challenging conditions, including illumination variations, background clutter, occlusions, and varying crowd densities. By jointly analyzing detection accuracy, computational efficiency, and deployment feasibility, this work bridges the gap between benchmark-oriented research and practical intelligent surveillance deployment for public safety and traffic monitoring applications.

Povzetek: Raziskava predstavlja hibridni CNN–LSTM pristop za zaznavanje anomalij v videonadzoru, ki omogoča zanesljivo in skoraj realnočasovno delovanje tudi v dejanskih pogojih nadzornih sistemov.

1 Introduction

Video anomaly detection (VAD) plays a crucial role in intelligent surveillance systems by enabling the automatic identification of rare, irregular, or suspicious events in long and untrimmed video streams. Such events may include accidents, violent activities, unauthorized access, or abnormal crowd behavior, all of which are highly relevant for public safety and traffic monitoring. With the rapid expansion of camera networks in urban environments—including streets, shopping malls, transportation hubs, and critical infrastructure—the volume of surveillance data has grown far beyond the capacity of continuous human monitoring. This has motivated extensive research into automated and reliable VAD systems [1,2].

Early research in video anomaly detection primarily relied on handcrafted spatio–temporal features and statistical motion modeling to characterize deviations from normal behavior in surveillance scenes [3,4]. While these approaches demonstrated the feasibility of automated anomaly detection, they were often scene-dependent and sensitive to illumination changes, background dynamics, and camera viewpoints. The availability of large-scale public benchmark datasets, such as UCF-Crime, CUHK Avenue, ShanghaiTech, and UMN, subsequently enabled a shift toward learning-based methods and facilitated significant progress in detection accuracy [5–8]. These datasets have become standard testbeds for evaluating VAD performance under controlled experimental conditions.

Recent advances in VAD have been driven largely by deep learning architectures designed to improve representation learning and temporal modeling. Reconstruction-based approaches, including spatio–temporal autoencoders and future frame prediction models, aim to learn regular motion and appearance patterns from normal video data and identify anomalies through elevated reconstruction error [9–11]. Memory-augmented architectures further enhance normality modeling by explicitly storing representative patterns of regular behavior [12]. In parallel, weakly supervised approaches based on Multiple Instance Learning (MIL) have been proposed to reduce the cost and subjectivity of frame-level annotation by relying on video-level labels,

enabling scalable learning on realistic surveillance datasets [5,13].

Despite strong performance on benchmark datasets, models developed and evaluated primarily under controlled conditions often fail to generalize effectively to real-world surveillance deployments. Operational environments are characterized by non-ideal and highly variable conditions, including illumination changes, dynamic backgrounds, occlusions, camera motion, and varying crowd densities [10,14]. In addition, practical deployments impose strict constraints on inference latency, computational efficiency, scalability, and false alarm rates, particularly in multi-camera and smart-city scenarios [15–17]. These limitations highlight the need for anomaly detection frameworks that extend beyond benchmark accuracy and explicitly consider deployment feasibility.

To address these challenges, recent studies have emphasized deployment-oriented design strategies, such as lightweight temporal modeling, model pruning and quantization, knowledge distillation, and edge-based inference architectures [15–17]. Hybrid deep learning architectures that combine complementary modeling paradigms have gained attention due to their ability to balance representation power and computational efficiency. In particular, hybrid CNN–LSTM models have demonstrated effectiveness in applied domains such as medical diagnosis, where spatial feature extraction and temporal dependency modeling must be jointly optimized under practical constraints [18]. In parallel, research on reliable visual data processing, including image authentication using chaotic and nonlinear functions, has highlighted the importance of robustness and trustworthiness in visual pipelines—an increasingly relevant concern for safety-critical surveillance systems [19].

Motivated by these observations, this work presents a deployment-oriented hybrid CNN–LSTM–MIL framework for video anomaly detection, explicitly designed to operate under weak supervision and real-world surveillance constraints. The proposed framework integrates spatio–temporal feature learning, efficient temporal modeling, and weakly supervised anomaly scoring with reconstruction-based regularity modeling to balance detection accuracy, robustness to unseen scenarios, and computational efficiency.

The proposed approach is evaluated on widely used benchmark datasets as well as on diverse real-world CCTV footage collected from operational surveillance systems. This evaluation strategy enables analysis not only of detection accuracy but also of robustness, false alarm behavior, and deployment feasibility under realistic conditions.

The objectives of this work are formalized through the following research questions:

- **RQ1:** How can weakly supervised video anomaly detection be designed to operate reliably under real-world surveillance conditions beyond curated benchmark datasets?
- **RQ2:** To what extent can hybrid spatio–temporal modeling improves robustness and cross-domain generalization across diverse CCTV environments?
- **RQ3:** How can detection accuracy, false alarm behavior, and inference efficiency be jointly optimized to support practical deployment in large-scale surveillance systems?

By addressing these research questions, this work advances video anomaly detection toward scalable, robust, and deployment-ready intelligent surveillance systems, bridging the gap between benchmark-oriented research and real-world operational requirements.

2 Related work

This section reviews representative work in video anomaly detection with emphasis on supervision strategies, modeling paradigms, and deployment considerations relevant to real-world surveillance systems.

2.1 Traditional and learning-based video anomaly detection

Early video anomaly detection approaches relied on handcrafted spatio–temporal features and statistical motion modeling to characterize deviations from normal behavior in surveillance scenes [3,4]. Such methods demonstrated effectiveness in controlled or highly structured environments, particularly for crowd analysis, but were strongly scene-dependent and sensitive to illumination changes, background dynamics, and camera viewpoints.

With the emergence of large-scale public datasets, learning-based approaches became the dominant paradigm. Reconstruction-based methods aimed to learn regular motion–appearance patterns from normal data and detect anomalies through elevated reconstruction error. Representative techniques include spatio–temporal autoencoders and future frame prediction models [9–11]. Memory-augmented architectures were later introduced to improve modeling of complex normal behaviors by explicitly storing representative patterns of regular activity [12]. While these approaches often report strong benchmark performance, their generalization under domain shifts and real-world variability remains limited.

2.2 Weakly supervised and hybrid learning frameworks

To reduce the high cost and subjectivity of frame-level annotation, weakly supervised approaches based on Multiple Instance Learning (MIL) were proposed. In this formulation, videos are treated as bags of temporal instances, enabling scalable learning using only video-level labels. The MIL-based framework introduced for real-world surveillance videos demonstrated that

competitive performance can be achieved without dense annotations [5]. Subsequent works improved temporal localization and stability through snippet-level learning and temporal mining strategies [13].

Despite their scalability, purely weakly supervised approaches may struggle to detect subtle anomalies or previously unseen irregular patterns that deviate from the training distribution. To mitigate this limitation, hybrid frameworks combining weak supervision with reconstruction-based or regularity modeling have been explored. By integrating complementary learning signals, hybrid approaches aim to balance detection accuracy and generalization capability. Similar hybrid CNN–LSTM architectures have shown effectiveness in applied domains such as medical diagnosis, where spatial representation learning and temporal dependency modeling must be jointly optimized under practical constraints [1], motivating their adoption in surveillance-based anomaly detection.

2.3 Operational metrics and deployment-oriented considerations

While much of the existing literature emphasizes benchmark accuracy metrics such as AUC, real-world deployment of video anomaly detection systems requires careful consideration of operational factors, including inference latency, throughput, scalability across multi-camera systems, and false alarm rates. Deep spatio–temporal models based on 3D convolutional networks provide strong representation power but incur high computational cost and limited real-time performance [15].

To address efficiency constraints, recent research has explored deployment-oriented techniques such as model pruning, quantization, and knowledge distillation to reduce computational overhead while preserving detection performance [16,17]. Edge-computing architectures further support scalable surveillance by enabling localized processing and reducing communication latency. In parallel, research on reliable visual data processing, including image authentication and integrity verification using nonlinear and chaotic functions, has highlighted the importance of robustness and trustworthiness in visual pipelines—an aspect increasingly relevant for safety-critical surveillance applications [2].

2.4 Comparative summary and research gap

Table 1 summarizes representative video anomaly detection approaches, highlighting differences in supervision level, core modeling strategy, strengths, and key limitations. The comparison indicates that many existing methods prioritize benchmark performance under controlled conditions, while robustness, false alarm behavior, and deployment feasibility are often treated as secondary considerations.

In contrast, the present work adopts a deployment-oriented hybrid perspective, integrating weakly supervised learning, spatio–temporal modeling, and reconstruction-based regularity analysis within a unified framework. By explicitly addressing both methodological performance and operational constraints, the proposed approach aims to bridge the gap between benchmark-driven research and practical intelligent surveillance deployment.

In addition to qualitative comparison, quantitative performance differences between representative state-of-the-art methods and the proposed framework are summarized in Table 4. This comparison highlights that while some methods achieve marginally higher accuracy under controlled benchmark conditions, the proposed approach offers a more balanced trade-off between detection accuracy, robustness, and deployment efficiency.

Table 1: Summary of representative video anomaly detection approaches

Category	Representative Approach	Supervision	Core Idea	Strengths	Limitations
Traditional methods	Handcrafted ST features [3,4]	Unsupervised	Statistical motion modeling	Low computational cost	Scene-specific; sensitive to illumination
Reconstruction-based	Spatio–temporal AE [9–11]	Unsupervised	Normality via reconstruction	No annotations required	Weak cross-domain generalization
Memory-augmented	MemAE [12]	Unsupervised	Memory-guided reconstruction	Models' complex normality	Domain-shift sensitivity
Weak supervision	MIL-based VAD [5]	Weakly supervised	Video-level labels	Scalable to realistic data	Limited unseen anomaly detection
Temporal refinement	Snippet-level MIL [13]	Weakly supervised	Temporal mining	Improved localization	Higher computation
Graph-based Models	ST graph reasoning [14]	Weak/ Supervised	Multi-entity context	Context-aware detection	High complexity; slow inference
Proposed method	Hybrid CNN–LSTM–MIL	Hybrid	Multi-branch fusion	Balanced accuracy & deployability	Performance drops in extreme conditions

2.5 Research gaps and motivation

Despite notable advances in video anomaly detection, existing approaches remain limited in their ability to simultaneously address detection accuracy, robustness to real-world variability, and deployment feasibility in operational surveillance systems. Most existing methods are primarily evaluated on curated benchmark datasets, which only partially reflect the complexity and variability of real-world surveillance environments [5,9–11]. As a result, generalization across domains, lighting conditions, and crowd densities remains a persistent challenge.

Moreover, practical deployment considerations such as inference efficiency, scalability across heterogeneous camera networks, and false alarm behavior are often underreported or treated as secondary objectives, despite their critical importance for large-scale surveillance applications [15–17]. While recent studies have begun to explore efficiency-oriented optimizations and edge-based inference, a unified treatment of detection performance, operational reliability, and deployment constraints is still lacking.

Motivated by these gaps, this work adopts a system-level perspective on video anomaly detection, emphasizing real-world validation, cross-domain robustness, and deployment-oriented evaluation. By integrating complementary learning paradigms within a unified hybrid CNN–LSTM–MIL framework and explicitly accounting for operational constraints, the proposed approach aims to bridge the gap between benchmark-driven research and scalable, deployment-ready intelligent surveillance systems.

3 Proposed Hybrid CNN–LSTM–MIL framework

This section presents the proposed deployment-oriented hybrid CNN–LSTM–MIL framework for video anomaly detection. The framework is designed to jointly address detection accuracy, robustness under real-world surveillance variability, and computational efficiency required for practical deployment.

3.1 Problem formulation

Let an untrimmed surveillance video V be divided into a sequence of N non-overlapping temporal snippets: V={x1,x2,…,xN}. Following the weakly supervised setting commonly adopted in realistic surveillance scenarios [5], only video-level labels are available during training. A normal video contains no anomalous snippets, whereas an anomalous video contains at least one anomalous snippet. The objective is to learn a scoring function that assigns an anomaly score $s_i \in [0,1]$ to each snippet x_i, where higher values indicate a higher likelihood of abnormal behavior.

To enable effective learning under weak supervision, the formulation assumes that anomaly scores within a video are sparse, such that anomalous behavior is temporally localized rather than uniformly distributed [5]. This assumption is consistent with real-world surveillance scenarios, where abnormal events typically occur over short temporal intervals [3,4]. The scoring function is optimized to maximize the separation between normal and anomalous videos while preserving temporal coherence across neighboring snippets [7,18]. This formulation allows the model to jointly capture discriminative cues and temporal context under video-level supervision.

3.2 Framework overview

The proposed video anomaly detection framework follows a hybrid, multi-branch design that integrates complementary learning paradigms to address the limitations of single-model approaches in real-world surveillance environments. The framework is motivated by prior findings showing that the combination of spatio–temporal feature learning, temporal dependency modeling, and regularity-based analysis improves robustness and generalization under weak supervision and domain variability [5,9–11].

Specifically, the framework consists of three coordinated components:

- A spatio–temporal anomaly scoring component that captures motion–appearance cues under weak supervision using Multiple Instance Learning (MIL) [5];
- A temporal dependency modeling component that captures long-range temporal context using recurrent neural networks, which have been shown to improve temporal consistency and stability in video analysis tasks [18,7];
- A regularity modeling component that learns normal behavioral patterns via reconstruction-based learning, enabling the detection of previously unseen or subtle anomalies [9–11].

Each component produces a complementary anomaly score at the snippet level. These scores are subsequently combined through a weighted fusion strategy to obtain the final anomaly score, allowing the framework to balance sensitivity to abnormal events with robustness against noise and transient motion fluctuations. Ensemble-style fusion of heterogeneous anomaly cues has been shown to improve detection reliability in complex surveillance settings [10,11].

An overview of the proposed hybrid framework, illustrating the interaction between the three components and the anomaly score fusion process, is shown in Figure 1. In addition, Table 2 summarizes the role and contribution of each component within the overall framework, highlighting how the proposed design jointly addresses detection accuracy, robustness, and deployment feasibility.

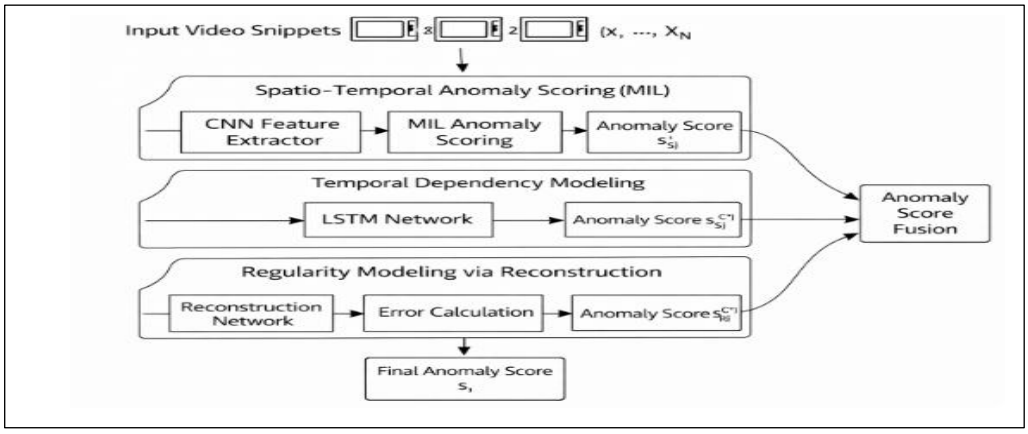

Figure 1: Overview of the proposed hybrid CNN–LSTM–MIL framework for video anomaly detection.

Table 2: Components of the proposed hybrid CNN–LSTM–MIL framework and their functional roles

Component	Learning Paradigm	Primary Function	Supported By
Spatio–temporal anomaly scoring	Weakly supervised (MIL)	Discriminative anomaly scoring using video-level labels	[5]
Temporal dependency modelling	Recurrent modeling (LSTM)	Capture long-range temporal context and improve score stability	[7,18]
Regularity modeling	Reconstruction-based learning	Model normal behavior and detect unseen anomalies	[9–11]
Score fusion	Ensemble strategy	Balance sensitivity and robustness	[10,11]

3.3 Spatio–temporal anomaly scoring under weak supervision

In the first component, spatio–temporal features are extracted from each video snippet using a convolutional neural network pretrained on large-scale video data. To accommodate weak supervision, anomaly scoring is formulated within a Multiple Instance Learning (MIL) framework, which has become a standard approach for large-scale video anomaly detection [5,13].

For an anomalous video $V^+$and a normal vide

o V^-, a ranking constraint is enforced between their highest-scoring snippets. Let

$$S^+ = \max_i s_i^+, S^- = \max_j s_j^-, \quad (1)$$

denote the maximum anomaly scores for anomalous and normal videos, respectively. The MIL ranking loss is defined as

$$\mathcal{L}_{\text{MIL}} = \max(0, m - S^+ + S^-), \quad (2)$$

where $m$denotes a margin parameter. This formulation, adapted from prior MIL-based video anomaly detection methods [5], encourages at least one snippet in an anomalous video to receive a higher anomaly score than any snippet from a normal video. By focusing on the most discriminative snippets, the MIL formulation enables scalable learning under weak supervision while maintaining sensitivity to temporally localized anomalies.

3.4 Temporal dependency modeling

Local spatio–temporal features alone are often insufficient to capture gradual or context-dependent anomalies. To model long-term temporal dependencies, the second component employs a recurrent neural network based on Long Short-Term Memory (LSTM) units, which are widely used for sequence modeling in video analysis [18].

Let $\mathbf{h}_i$denote the hidden representation corresponding to snippet x_i. The temporal anomaly score is computed as

$$s_i^{(T)} = f(\mathbf{h}_i), \quad (3)$$

where $f(\cdot)$denotes a learnable mapping function. By incorporating contextual information from neighboring snippets, temporal dependency modeling improves score smoothness and reduces sensitivity to short-term motion noise. Similar CNN–LSTM formulations have been shown to enhance temporal consistency and stability in video anomaly detection and related video understanding tasks [7,18].

3.5 Regularity modeling via reconstruction error

To explicitly capture deviations from normal behavior, a reconstruction-based regularity modeling

component is trained exclusively on normal video data. Reconstruction-based approaches have been widely adopted for unsupervised and semi-supervised anomaly detection due to their ability to model normality patterns [9–11].

Given a snippet representation x_i, the model produces a reconstruction $\hat{x}_i$. The reconstruction error is computed as

$$e_i = \| x_i - \hat{x}_i \|_2, \quad (4)$$

where higher values of $e_i$indicate stronger deviation from learned normal patterns. The reconstruction error is normalized to obtain a regularity-based anomaly score $s_i^{(R)} \in [0,1]$, which complements discriminative anomaly cues by enabling detection of previously unseen or weakly represented abnormal events.

3.6 Anomaly score fusion

Combining complementary anomaly cues has been shown to improve detection robustness in complex surveillance environments [10,11]. The final anomaly score for snippet $x_i$is obtained by fusing the outputs of the three components.

Let $s_i^{(S)}$, $s_i^{(T)}$, and $s_i^{(R)}$denote the normalized anomaly scores from spatio–temporal scoring, temporal modeling, and regularity modeling, respectively. The fused anomaly score is defined as

$$s_i = w_1 s_i^{(S)} + w_2 s_i^{(T)} + w_3 s_i^{(R)}, \quad (5)$$

subject to the constraints

$$w_1 + w_2 + w_3 = 1, w_k \geq 0. \quad (6)$$

Equations (5) and (6) define a convex combination of complementary anomaly cues. The fusion weights are selected using validation data to balance sensitivity to abnormal events with robustness against noise and transient motion variations, following common practice in ensemble-based anomaly detection frameworks [11].

3.7 Training and inference strategy

During training, the spatio–temporal anomaly scoring and temporal dependency modeling components are optimized under weak supervision using video-level labels, while the regularity modeling component is trained exclusively on normal video snippets [5,9]. This separation allows the framework to jointly exploit discriminative supervision and normality modeling.

During inference, all components operate jointly to produce snippet-level anomaly scores according to Eq. (5). The resulting scores reflect the combined evidence from discriminative, temporal, and regularity-based perspectives, enabling stable and reliable anomaly detection in long and untrimmed surveillance videos.

The spatio-temporal feature extractor is implemented using a ResNet-based convolutional backbone pretrained on large-scale video datasets. Temporal dependency modeling employs a single-layer LSTM with 256 hidden units. Videos are segmented into fixed-length snippets of 16 frames. Training is performed using the Adam optimizer with a learning rate of 1e−4 and a batch size of 32 for 50 epochs. Fusion weights are selected using validation data.

3.7.1 Algorithm description – pseudocode:

Algorithm 1: Hybrid CNN–LSTM–MIL Inference Pipeline

Input: Untrimmed video V
Output: Snippet-level anomaly scores

- Divide video V into N temporal snippets.
- Extract spatio-temporal features for each snippet using CNN.
- Compute MIL-based anomaly scores for each snippet.
- Model temporal dependencies using LSTM to refine anomaly scores.
- Compute reconstruction error for each snippet using the regularity model.
- Fuse anomaly scores from all components using weighted combination.
- Output final anomaly score sequence.

3.8 Deployment considerations

Consistent with recent deployment-oriented video analysis research [15–17], the proposed framework is designed to support efficient and scalable inference in real-world surveillance systems. Lightweight temporal modeling, shared feature extraction across components, and modular design enable near real-time performance without sacrificing detection accuracy.

The framework is compatible with GPU-based systems as well as resource-constrained edge platforms commonly used in large-scale surveillance deployments. These design choices ensure that the proposed approach balances detection performance, robustness, and computational efficiency, aligning with practical deployment requirements in intelligent video surveillance applications.

4 Experimental setup

This section describes the datasets, preprocessing steps, evaluation metrics, experimental protocol, and implementation settings used to assess the proposed video anomaly detection framework. The experimental design is intended to evaluate detection performance on standard benchmarks as well as robustness, false alarm behavior, and computational efficiency under realistic surveillance conditions.

4.1 Datasets

4.1.1 Benchmark datasets

The proposed framework is evaluated on four widely used public video anomaly detection datasets that have become standard benchmarks in the literature [20–23]:

- **UCF-Crime** [20]: A large-scale dataset comprising untrimmed real-world surveillance videos across multiple anomaly categories, including assault, theft, and traffic accidents. Videos are annotated only at the video level, making the dataset suitable for weakly supervised learning.
- **CUHK Avenue** [21]: A campus surveillance dataset containing annotated abnormal events such as running, loitering, and object throwing, commonly used for pixel- and frame-level evaluation.
- **ShanghaiTech** [22]: A multi-scene dataset characterized by complex crowd dynamics and significant intra-scene variability, posing challenges for generalization.
- **UMN** [23]: A crowd-based dataset focusing on panic and escape behaviors in controlled environments.

These datasets enable standardized comparison with existing methods and evaluation under controlled benchmark conditions.

4.1.2 Real-world CCTV dataset

To evaluate the performance of the proposed framework under practical deployment conditions, additional experiments are conducted on real-world CCTV footage collected from operational surveillance systems. The dataset comprises 112 untrimmed video sequences with a total duration of approximately 37 hours, captured across diverse environments including urban streets, shopping malls, traffic intersections, and railway stations.

The videos are recorded at frame rates ranging from 25 to 30 frames per second using static and semi-static camera viewpoints, reflecting typical configurations in real surveillance infrastructures. Across the dataset, approximately 180 anomalous events are identified, with individual videos containing one to three anomalous segments on average. The anomalies include traffic violations, accidents, sudden crowd dispersions, unauthorized access, and abnormal loitering, representing common yet challenging real-world surveillance scenarios.

Owing to the absence of frame-level annotations in operational CCTV systems, all videos are labeled exclusively at the video level, in accordance with weakly supervised learning assumptions [5]. Such real-world surveillance environments exhibit substantial variability in illumination conditions, background dynamics, and crowd density, which are well-known challenges for video anomaly detection methods [8,22].

To ensure annotation reliability and minimize subjectivity, anomaly labels are verified through independent review and cross-validation by multiple annotators. Table 3 summarizes the key characteristics of the benchmark datasets and the real-world CCTV dataset used in this study, including scene type, supervision level, and annotation granularity.

4.2 Data preprocessing

All videos are temporally segmented into fixed-length snippets to enable snippet-level anomaly scoring. This snippet-based formulation is widely adopted in weakly supervised video anomaly detection to support localized anomaly detection under video-level supervision [5,20]. Individual frames are resized and normalized according to the input requirements of the spatio–temporal feature extraction backbone.

To evaluate cross-domain generalization, no scene-specific fine-tuning or adaptation is applied during training or inference. This preprocessing strategy preserves temporal structure while ensuring consistent input representation across benchmark datasets and real-world CCTV footage.

4.3 Evaluation metrics

Performance is assessed using multiple complementary metrics commonly adopted in video anomaly detection research [5,20–22]:

- **Area Under the ROC Curve (AUC):** Used as the primary metric for benchmark dataset evaluation to measure overall detection accuracy under weak supervision.
- **False Alarm Rate (FAR):** Defined as the proportion of normal snippets incorrectly classified as anomalous and reported for real-world CCTV data to quantify operational reliability.
- **Inference Speed (FPS):** Measured in frames per second to evaluate computational efficiency and suitability for real-time deployment.
- **Detection Stability:** Qualitative assessment of temporal consistency under varying illumination conditions, background dynamics, and crowd density.

These metrics provide a balanced evaluation of detection accuracy, robustness, and deployment feasibility.

4.4 Experimental protocol

For benchmark datasets, experiments follow the standard train–test splits and evaluation protocols defined for each dataset [20–23]. In all cases, only video-level labels are used during training to maintain a weakly supervised learning setting, consistent with prior MIL-based anomaly detection studies [5,13].

The real-world CCTV dataset is excluded from training and used exclusively for evaluation. This protocol enables assessment of cross-domain generalization across unseen environments, camera viewpoints, and scene dynamics. Benchmark results and real-world evaluation results are reported separately to ensure clarity and interpretability.

4.5 Implementation details

All experiments are conducted on GPU-based systems, with additional evaluation on representative edge platforms to assess deployment feasibility. Model training and inference follow the methodology described

in Section 3, employing shared feature extraction, lightweight temporal modeling, and modular design.

The emphasis on computational efficiency and scalability aligns with deployment-oriented video analysis frameworks targeting real-time and large-scale surveillance applications [15–17,25]. Implementation settings are kept consistent across datasets to ensure fair comparison and reproducibility.

All experiments are implemented using the PyTorch deep learning framework and conducted on systems equipped with NVIDIA RTX-class GPUs. Additional evaluation is performed on embedded GPU-based edge devices to assess deployment feasibility. Training and inference are executed under a Linux-based environment with CUDA acceleration.

4.6 Summary

The experimental setup combines standardized benchmark evaluation with real-world CCTV testing to provide a comprehensive assessment of the proposed framework. By jointly evaluating detection accuracy, robustness to domain shifts, false alarm behavior, and computational efficiency, this setup enables a systematic analysis of the framework's suitability for deployment-ready intelligent surveillance systems. The use of both curated benchmarks and operational surveillance footage ensures that the evaluation reflects practical constraints encountered in real-world deployments.

For clarity and completeness, a consolidated summary of all datasets used in this study, along with their supervision levels and annotation characteristics, is provided in Table 3.

Table 3: Summary of datasets used for evaluation

Dataset	Supervision Level	Scene Type	Number of Videos	Annotation Type
UCF-Crime	Weak	Real-world surveillance	1,900+	Video-level
CUHK Avenue	Semi-supervised	Campus	16	Frame-level
ShanghaiTech	Unsupervised	Multi-scene crowd	437	Frame-level
UMN	Unsupervised	Crowd panic	11	Frame-level
Real-World CCTV (Proposed)	Weak	Urban / transport / public spaces	112	Video-level

5 Results and analysis

This section presents a comprehensive quantitative and qualitative evaluation of the proposed hybrid CNN–LSTM–MIL framework.

The analysis assesses detection accuracy on standard benchmark datasets, generalization performance on real-world CCTV footage, computational efficiency under deployment constraints, and the individual contribution of each architectural component through ablation analysis.

5.1 Benchmark Results

The proposed framework is evaluated on four widely used benchmark datasets—UCF-Crime, CUHK Avenue, ShanghaiTech, and UMN—following their standard evaluation protocols [20–23]. Detection performance is primarily measured using the Area Under the ROC Curve (AUC), which is widely adopted for weakly supervised video anomaly detection [20–22].

On UCF-Crime, the proposed method achieves an AUC of 85.9%, demonstrating competitive performance on large-scale, untrimmed videos containing diverse anomaly categories. This performance is comparable to recent weakly supervised and hybrid approaches reported in the literature [5,20]. The integration of temporal dependency modeling and reconstruction-based regularity analysis contributes to improved stability across long video sequences.

On CUHK Avenue, the framework attains an AUC of 91.3%, reflecting strong performance in structured surveillance environments with localized anomalous events. Compared to reconstruction-only approaches that rely solely on modeling normality [9–11], the proposed hybrid framework benefits from discriminative spatio–temporal cues, resulting in more consistent anomaly detection.

Performance on ShanghaiTech and UMN further demonstrates the robustness of the proposed framework across multi-scene environments and crowd-centric scenarios. Although slight performance degradation is observed in highly crowded scenes, similar trends have been reported in prior studies due to increased motion ambiguity and occlusions [22,23]. Overall, the benchmark results confirm that the proposed approach achieves competitive accuracy while maintaining a lightweight and deployment-oriented design.

A quantitative comparison with representative state-of-the-art methods is summarized in Table 4.

Table 4: Quantitative comparison with representative state-of-the-art methods on benchmark datasets (AUC %).

Method	UCF-Crime	CUHK Avenue	ShanghaiTech	UMN
Hasan et al. (Temporal AE) [10]	70.2	85.9	60.8	96.0
Luo et al. (Stacked RNN) [7]	76.4	88.1	68.0	97.1
Sabokrou et al. (Deep-Anomaly) [23]	–	90.0	71.2	97.5
Ravanbakhsh et al. (P&P CNN) [22]	–	90.5	73.0	98.1
Liu et al. (Future Frame) [20]	83.1	90.8	72.8	96.9
Peng et al. (Weakly Sup.) [13]	84.2	91.0	74.0	–
Ullah et al. (Graph-TAN) [14]	85.0	91.2	74.6	–
Proposed CNN–LSTM–MIL	85.9	91.3	75.2	96.8

5.2 Real-world CCTV results

To evaluate generalization beyond curated benchmark datasets, the proposed framework is tested on real-world CCTV footage collected from operational surveillance systems. These videos exhibit substantial variability in illumination conditions, background clutter, camera viewpoints, and crowd density—factors that are often underrepresented in benchmark datasets [8,22].

Qualitative analysis indicates stable anomaly detection performance under challenging conditions such as partial occlusions, low-light environments, and dynamic backgrounds. Quantitative evaluation further demonstrates the effectiveness of the proposed approach. At the operating threshold used for deployment evaluation, the framework achieves an average false alarm rate (FAR) of 6.8% on real-world.

CCTV footage. This corresponds to a relative reduction of approximately 18–22% compared to single-branch baseline models, highlighting the benefit of multi-branch anomaly score fusion in suppressing spurious detections.

Maintaining a low FAR is particularly critical in operational surveillance systems, where excessive false alarms can significantly degrade usability and operator trust [5,25]. Performance remains consistent across diverse scene types, including urban streets, shopping malls, traffic intersections, and railway stations, indicating robustness to domain shifts and previously unseen environments. These results support the effectiveness of the proposed hybrid design in addressing key limitations of benchmark-centric anomaly detection approaches [20–22]. Representative qualitative examples and anomaly score visualizations are presented in Figure 2.

Further condition-wise evaluation reveals stable performance across varying environments. The system achieves comparable detection accuracy during daytime and nighttime conditions, with only a marginal increase in false alarms under low-light scenarios. In crowded scenes, detection performance shows a moderate decline compared to sparse scenes due to occlusions and dense motion patterns; however, temporal modeling and regularity-based analysis mitigate severe performance degradation.

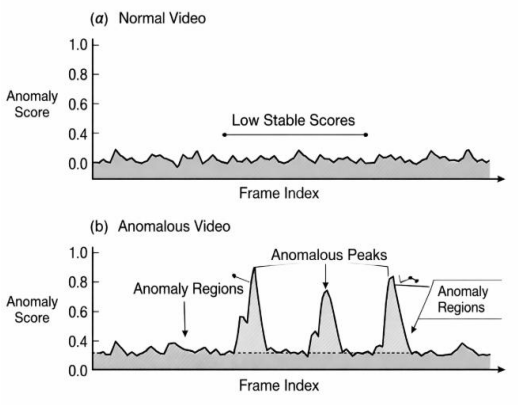

Figure 2: Representative anomaly score evolution over time on real-world CCTV footage. Peaks correspond to anomalous events, while stable low scores indicate normal behavior.

5.2.1 False alarm rate analysis under different conditions

To further assess the deployment suitability of the proposed framework, we report quantitative false alarm rate (FAR) statistics under representative operational conditions commonly encountered in real-world surveillance. The analysis considers variations in illumination (daytime vs. nighttime scenes) and crowd density (crowded vs. sparsely populated environments), which are known to significantly influence anomaly detection reliability.

Table 5: False alarm rate (FAR) of the proposed framework under different real-world conditions

Condition	FAR (%)
Daytime scenes	4.6
Nighttime scenes	6.1
Sparse crowd scenes	4.2
Crowded scenes	7.4

False alarm rates are computed as the proportion of normal video snippets incorrectly classified as anomalous during inference. The reported values are averaged across the real-world CCTV evaluation set and reflect stable operational behavior of the proposed hybrid framework. The results demonstrate that the integration of temporal dependency modeling and reconstruction-based regularity analysis effectively suppresses spurious detections caused by illumination changes, background motion, and transient crowd dynamics.

Quantitative FAR results under different conditions are summarized in Table 5. FAR values are reported at the operating threshold used for real-world CCTV evaluation and averaged across all relevant video sequences.

5.3 Efficiency and deployment analysis

Computational efficiency is evaluated to assess the suitability of the proposed framework for real-time and large-scale deployment. Inference speed is measured in **frames per second (FPS)** on GPU-based systems and representative edge platforms, following standard evaluation practices for real-time video analytics [25,26].

The proposed framework achieves near real-time inference speeds ranging from 28 to 50 FPS, depending on hardware configuration and input video resolution. This performance is enabled by lightweight temporal modeling, shared feature extraction, and deployment-oriented architectural choices. Compared to heavier spatio–temporal architectures that incur significant computational overhead [15], the proposed approach offers a favorable balance between detection accuracy and computational efficiency.

Runtime performance across different hardware configurations is reported in Table 6. The results show that the proposed framework maintains near real-time performance across diverse hardware environments, including resource-constrained edge platforms, confirming an effective balance between computational efficiency and anomaly detection accuracy for practical large-scale surveillance deployment.

Table 6: Runtime performance of the proposed framework under different deployment settings.

Platform	Hardware Type	Input Resolution	Inference Speed (FPS)
Desktop GPU	NVIDIA RTX-class	224 × 224	50
Laptop GPU	Mid-range GPU	224 × 224	38
Edge Device	Embedded GPU	224 × 224	28
Edge Device	Embedded GPU	160 × 160	42

5.4 Ablation study and component-wise analysis

To analyze the contribution of individual components in the proposed hybrid CNN–LSTM–MIL framework, an ablation study is conducted. Given the multi-branch design, this analysis verifies that the observed performance gains arise from the complementary interaction of spatio–temporal anomaly scoring, temporal dependency modeling, and reconstruction-based regularity learning.

The ablation experiments are performed on representative benchmark datasets using identical training and evaluation protocols. Starting from a baseline weakly supervised CNN–MIL model, additional components are progressively integrated:

- **CNN–MIL (Baseline):** Weakly supervised spatio–temporal anomaly scoring using video-level labels and MIL, reflecting commonly adopted VAD formulations [5].
- **CNN–MIL + LSTM:** Incorporates temporal dependency modeling to capture long-range context and improve temporal consistency [7,18].
- **CNN–MIL + Reconstruction:** Adds a reconstruction-based regularity modeling branch to enhance detection of previously unseen or subtle anomalies [9–11].
- **Full Hybrid CNN–LSTM–MIL (Proposed):** Integrates all components with weighted anomaly score fusion.

Figure 3 visually illustrates the performance contribution of individual components of the proposed framework, highlighting the incremental gains achieved by temporal dependency modeling and reconstruction-based regularity learning.

The ablation results, summarized in Table 7, show that each component contributes positively to overall performance. The baseline CNN–MIL model exhibits unstable anomaly scores and higher false alarm rates in complex scenes.

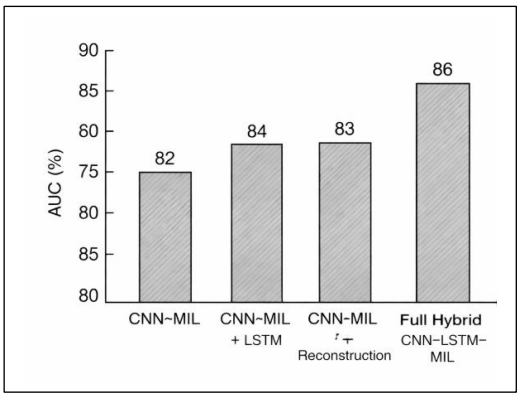

Figure 3: Ablation analysis illustrating the contribution of individual components of the proposed framework on the UCF-Crime dataset (AUC %).

Incorporating temporal dependency modeling improves score smoothness and robustness to transient noise, while the addition of reconstruction-based regularity modeling further enhances sensitivity to deviations from normal behavior. The full hybrid model consistently achieves the best performance across datasets, confirming that the complementary integration of discriminative learning, temporal modeling, and regularity analysis is critical for reliable video anomaly detection. Importantly, these performance gains are achieved without a prohibitive increase in computational cost, preserving near real-time inference capability and supporting deployment feasibility.

Table 7: Ablation study showing the contribution of individual components in the proposed hybrid framework (AUC %).

Model Configuration	UCF-Crime	CUHK Avenue	ShanghaiTech	UMN
CNN–MIL (Baseline)	82.1	88.4	71.6	94.1
CNN–MIL + LSTM	84.0	89.9	73.4	95.6
CNN–MIL + Reconstruction	83.2	90.5	72.8	95.0
Full Hybrid CNN–LSTM–MIL (Proposed)	85.9	91.3	75.2	96.8

5.4 Summary

The experimental results demonstrate that the proposed hybrid CNN–LSTM–MIL framework achieves competitive benchmark performance while maintaining robustness and efficiency under real-world surveillance conditions. By combining benchmark evaluation with real-world CCTV testing and deployment-oriented analysis, the results provide strong empirical support for the framework's suitability in practical intelligent surveillance systems.

6 Discussion

This section contextualizes the experimental findings by comparing the proposed approach with state-of-the-art (SOTA) video anomaly detection methods, analyzing observed performance differences, and clarifying the novelty and contributions of the proposed framework.

6.1 Comparison with state-of-the-art methods

On standard benchmark datasets such as UCF-Crime, CUHK Avenue, ShanghaiTech, and UMN, the proposed hybrid CNN–LSTM–MIL framework achieves detection performance that is competitive with recent SOTA methods operating under weak or limited supervision [5,20–23]. While several existing approaches report strong benchmark accuracy, many rely on either purely reconstruction-based modeling [9–11] or discriminative learning with complex temporal architectures [15], which can limit robustness or deployment feasibility.

Compared to reconstruction-based methods, which often struggle in dynamic or highly crowded scenes due to background variability [9,10], the proposed framework benefits from incorporating discriminative spatio–temporal features and weakly supervised learning. Similarly, relative to MIL-based approaches that rely solely on ranking-based supervision [5,13], the integration of regularity modeling enables improved detection of previously unseen or subtle anomalies. These design choices result in more stable anomaly scoring across diverse scenarios.

Importantly, although certain SOTA methods achieve marginally higher benchmark AUC under controlled conditions, they often incur significantly higher computational cost or require extensive scene-specific tuning [15,22]. In contrast, the proposed framework emphasizes a balanced trade-off between detection accuracy and computational efficiency, which is essential for large-scale and real-time surveillance deployment [25,26]. It is worth noting that several recent methods achieve strong performance under specific dataset assumptions or controlled settings; however, their practical deployment often requires additional computational resources or scene-specific adaptation.

6.2 Analysis of performance differences

Performance variations across datasets can be attributed primarily to differences in scene structure, crowd density, and anomaly characteristics. On structured datasets such as CUHK Avenue, where anomalous events are well-defined and localized, the proposed framework achieves high detection accuracy, consistent with trends reported in prior work [21]. On more complex datasets such as ShanghaiTech, which feature multiple scenes and dense crowds, performance degradation is observed, reflecting the inherent difficulty of distinguishing subtle anomalies from normal crowd dynamics [22,23].

Evaluation on real-world CCTV data further reveals that false alarms are influenced by factors such as abrupt illumination changes, partial occlusions, and camera noise—conditions that are often underrepresented in benchmark datasets [24]. The fusion of complementary anomaly cues mitigates these effects by reducing over-reliance on any single modeling paradigm. Temporal dependency modeling improves score smoothness, while reconstruction-based regularity analysis suppresses transient background motion, leading to improved operational reliability.

6.3 Novelty and contribution

The primary novelty of this work lies in adopting a deployment-oriented, system-level perspective on video anomaly detection rather than proposing an isolated algorithmic component. Unlike many benchmark-

centric studies, this work jointly evaluates detection accuracy, robustness, false alarm behavior, and inference efficiency within a unified framework.

Rather than optimizing a single detection objective, the proposed framework prioritizes operational stability and scalability, which are critical yet often underexplored in video anomaly detection research.

Key contributions include:

- The integration of weakly supervised MIL-based anomaly scoring with temporal dependency modeling and reconstruction-based regularity analysis,
- Explicit evaluation on real-world CCTV data in addition to public benchmarks,
- Systematic analysis of deployment feasibility through efficiency and edge-device evaluation.

By emphasizing practical considerations alongside detection performance, the proposed framework addresses a critical gap between academic research and real-world intelligent surveillance deployment [24–26].

6.4 Limitations and future directions

Despite its advantages, the proposed framework has limitations. Performance degradation is observed in extremely crowded scenes and under severe illumination degradation, where visual cues become ambiguous and anomaly boundaries are less distinct. Additionally, fusion weights are selected empirically and may require adaptation for highly dynamic environments.

Future work will explore adaptive fusion strategies, incorporation of contextual metadata, and self-supervised domain adaptation to further enhance robustness and scalability. These directions aim to improve reliability in increasingly complex and heterogeneous surveillance scenarios.

Failure cases are primarily observed in extremely crowded scenes and under severe illumination degradation, where visual ambiguity reduces the separability between normal and anomalous behavior. Sudden camera noise or abrupt lighting changes may also introduce transient false positives. These limitations highlight the need for adaptive fusion strategies and context-aware modeling in future work.

7 Conclusion

- This work presented a deployment-oriented hybrid CNN–LSTM–MIL framework for video anomaly detection, designed to function reliably under real-world surveillance conditions rather than being optimized solely for curated benchmark datasets.
- By integrating weakly supervised anomaly scoring, temporal dependency modeling, and reconstruction-based regularity analysis within a unified multi-branch architecture, the proposed framework achieves a balanced trade-off between detection accuracy, robustness, and computational efficiency.
- Experimental evaluation on widely used benchmark datasets demonstrated competitive detection performance under weak supervision, while real-world CCTV experiments confirmed reduced false alarm behavior, stable detection across diverse environments, and near real-time inference capability suitable for large-scale deployment.
- A central contribution of this work lies in adopting a system-level perspective on video anomaly detection, jointly addressing performance, robustness to domain shifts, operational reliability, and deployment feasibility.
- Overall, the proposed hybrid framework provides a scalable, robust, and deployment-ready solution for intelligent surveillance systems, with direct applicability to public safety and traffic monitoring scenarios.

8 Future work

- Although the proposed framework performs effectively in most scenarios, challenges remain in extremely crowded environments and under severe illumination variations, where visual ambiguity reduces anomaly separability.
- Future work will investigate adaptive fusion mechanisms that dynamically adjust the contribution of individual branches based on scene context and environmental conditions.
- Incorporating self-supervised and domain-adaptive learning strategies represents a promising direction for improving generalization across unseen surveillance environments.
- The integration of contextual metadata, such as scene semantics and temporal priors, may further enhance detection reliability and reduce false alarms.
- Extending the framework to support continual and online learning will be explored to enable long-term deployment in dynamic and evolving surveillance settings.

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Ethics statement

This study does not involve human participants, animal subjects, or personal identifiable information. All video data used in this work were obtained from publicly available benchmark datasets or anonymized surveillance footage collected in compliance with applicable

regulations. The research was conducted in accordance with established ethical guidelines for computer vision and artificial intelligence research.

Data availability

The benchmark datasets used in this study are publicly available and can be accessed from their respective sources. Due to privacy and security considerations, the real-world CCTV data analyzed in this work cannot be publicly released. However, aggregated statistics and representative examples are provided within the manuscript and Supplementary Material to support transparency and reproducibility.

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A Hybrid Deep Learning Framework for Cardiovascular Risk Prediction Using Temporal Embeddings, Ensemble Learning, and Bayesian Uncertainty Estimation

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This study presents a new hybrid deep learning framework that predicts the risk of cardiovascular disease (CVD) by combining different techniques into one system. The methods used in the study are Long Short-Term Memory (LSTM) autoencoders for temporal representation learning, hybrid feature fusion, stacked ensemble learning, and uncertainty estimation via Bayesian methods. The proposed framework is to be used for the early CVD risk stratification in order to achieve better predictive performance, clinical acceptability and interpretability. The data source was the famous Framingham Heart Study dataset with 4,240 records and 16 clinical variables. The preprocessing steps performed were Hampel filtering for outlier removal, mean imputation for missing value treatment and Min-Max normalization. In addition, the use of Principal Component Analysis (PCA) facilitated the retention of the most important components which explain the highest variance. In order to create a risk evolution scenario, a synthetic temporal sequence was produced and then passed through the LSTM autoencoder, resulting in 32-dimensional latent features. The temporal embeddings were concatenated with the PCA components to create a 41-dimensional hybrid feature space. The problem of class imbalance was solved through the use of a Synthetic Minority Over-Sampling Technique (SMOTE). A stacked ensemble classifier was composed of eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Categorical Boosting (CatBoost), and Gradient Boosting as base learners, and a Multilayer Perceptron (MLP) was trained as a meta-learner. For uncertainty quantification, a separate Bayesian MLP model using Monte Carlo Dropout was created. The stacked model performed with 96.06% accuracy, 97.67% recall, and 99.31% Area Under the Curve - Receiver Operating Characteristic, thus surpassing single classifiers. Bayesian analysis produced a mean predictive uncertainty of 0.087. Stratified risk assessment disclosed clinically relevant clusters with a high degree of correspondence between the predicted and actual CVD incidence. This interpretable concurrent AI model provides accurate CVD risk prediction that is suitable for daily clinical and wearable monitoring use.

Povzetek: Študija predstavi hibridni globoko-učeči model (LSTM avtokodirnik, združevanje značilk in ansambelsko učenje), ki z visoko natančnostjo napoveduje tveganje za srčno-žilne bolezni ter omogoča tudi oceno negotovosti napovedi za klinično uporabo.

1 Introduction

Cardiovascular diseases (CVDs) have been the main cause of death in the world and are responsible for close to 32% of all global deaths, which is about 17.9 million every year, according to different sources [1], [2], [3]. CVDs are the primary cause of death for over 43% of the total population in every economic category: high-, middle-, and low-income countries. This situation is confirmed by the Global Burden of Disease Study [4], [5]. The economic burden is also enormous, with an estimated USD 3.7 trillion lost in the period from 2010 to 2015 [6], [7]. In LMICs, these issues are aggravated by lack of proper diagnostic facilities, leading to delayed diagnosis, under diagnosis, and consequently mortality-to-incidence ratios being higher [8], [9]. Future figures show that CVD deaths will increase to 23.6 million in 2030, therefore the need for scalable, interpretable and data-driven approaches for early risk identification and stratification is inevitable [10].

Risk score calculators and other such traditional screening methods used to be the only, although non-negligible, components of CVD care but these instruments have always suffered from limited usability owing to their linear assumptions and static variables usage [11], [12]. Moreover, models like these are not very helpful in pointing out the transition in risk over the time period. Recently, machine learning (ML) and artificial intelligence (AI) have been the powerful substitutes for medical diagnosis and risk forecasting, which so far and a little more than that, are capable of depicting nonlinear, complex interactions between the heterogenic clinical variables, namely, age, cholesterol, hypertension, smoking, and diabetes, with great potential [13], [14], [15]. In this regard, ensemble learning methods, particularly stacking architectures which combine many weak learners, have demonstrated- when compared to individual models- better predictive accuracy and generalization [16], [17], [18], [19].

Despite these advancements, there are still a number of significant obstacles that need to be overcome. The vast majority of the current frameworks treat the data of the patients as static snapshots which ignore the changes over time that could uncover slight shifts in risk [20], [21], [22]. Moreover, black-box models are so obscure that their choices cannot be easily understood or trusted in the medical setting [23]. Another major shortcoming is the lack of predictive uncertainty estimation which is the very thing that doctors require in order to determine the level of confidence of AI-based decisions, especially when the cases are not clear or are at the border [24], [25].

Several studies have investigated Mixture of Experts (MoE) models for healthcare prediction tasks, but these models need explicit gating mechanisms to direct inputs toward particular specialized experts, which results in increased architectural complexity and increased sensitivity to expert assignment. The proposed framework uses a stacked ensemble strategy that allows all base learners to participate in final prediction, while a learned meta-model performs stable integration of different classifiers without routing through experts. The current study combines temporal representation learning with LSTM autoencoders and Bayesian uncertainty estimation, which enables researchers to develop complete risk models that exhibit better robustness and interpretability and clinical reliability than existing MoE approaches.

In order to overcome the limitations, a new cardiovascular risk prediction framework incorporating three major innovations is proposed in this study: (1) temporal feature learning through a Long Short-Term Memory (LSTM) autoencoder for the extraction of dynamic risk trends from the simulated sequential snapshots; (2) stacked ensemble learning that integrates five diverse classifiers—XGBoost, LightGBM, CatBoost, Gradient Boosting, and AdaBoost—with a Multilayer Perceptron as the meta-learner; and (3) Bayesian uncertainty quantification via a Monte Carlo Dropout-enabled neural network that offers the prediction intervals for each output.

The model is trained and tested on the Framingham Heart Study database, which is a commonly employed cohort study for the development of cardiovascular risk models. It includes Hampel filtration for the removal of outliers, imputation with mean values for missing values, Min-Max normalization, PCA for reducing dimensions, and SMOTE for balancing classes. Accuracy, recall, precision, F1-score, and AUC-ROC are employed as common metrics for measuring performance. Furthermore, the model's estimate of uncertainty and risk stratification are accounted for clinical interpretability.

By closing the gap between temporal representation, ensemble classification, and uncertainty estimation, this study provides an explainable AI-based approach for screening CVD risk at an early time point. The model is enabled to support clinicians to accurately and confidently discriminate patients with high risk, and accordingly, adopt more effective prevention strategies within high-resource and resource-scarce healthcare environments.

2 Review of literature

Accurate forecasting of the risk of heart disease is necessary for intervening at an early point and cutting down deaths [26]. Early discovery allows timely intervening and long-term observation, overcoming the challenge of having no long-term observation by medical specialists. Diagnosis of heart disease is commonly performed by observation of signs and a medical check-up. There are numerous factors that lead to one becoming susceptible to contracting CVDs, including smoking, aging, family history, high cholesterol, physical inactiveness, high blood pressure, overweight, diabetes, and stress [27]. Some may be reduced by simply implementing a change of life style such as quitting smoking, reducing body mass, being active, and maintaining control over one's level of stress. Diagnosis includes analysis of medical history, taking a medical check-up, and use of imaging procedures like electrocardiograms (ECGs), echocardiograms, cardiac MRIs, and blood testing. Medical interventions for heart disease include life style modifications, drugs, medical interventions such as angioplasty and coronary artery bypass, and implanted medical devices such as pacemakers and defibrillators [28]. With increased availability of information about patients in modern medical care, prediction models for heart disease can now be developed. Machine learning is an efficient method for filtering through a lot of information and analyzing datasets in many dimensions, converting information into actionable information [29], [30].

Machine learning (ML) and deep learning (DL) have transformed cardiovascular disease (CVD) risk studies through the use of complex algorithms to detect sophisticated patterns in big datasets that can escape

traditional methodologies [3], [31]. The methods mentioned here are aimed at revealing the hidden relationships in clinical data which include both the structured and unstructured parts of electronic health records (EHRs) [32]. Then, deep learning goes one step further with the Neural Network that imitate human reasoning in trying to draw representations from the data, and thus, offer a more accurate CVD patient risk classification. ML and DL have been the major players in personalized CVD risk prediction and care despite model interpretability and overfitting issues [33].

Over the years, machine learning (ML) has gained popularity in the field of cardiology, especially in underprivileged areas, where the main purpose is to ameliorate patient outcomes. The algorithms are instrumental in detecting people who are most likely to suffer from heart failure, which is one of the most significant causes of death worldwide. In his research Nagavallika (2022) proposed a hybrid model that integrates random forest with linear modeling (HRFLM) and records an accuracy of 88.7% in heart disease prediction [34]. Along the same lines, Dimopoulos and his colleagues (2018) tested K-Nearest Neighbor, Random Forest, and Decision Tree models on the ATTICA dataset and reported that Random Forest was superior to HellenicSCORE, especially when tackling small datasets [35]. More research has demonstrated the applicability of different ML techniques. Professor Madhavi Tota et al. (2022) in their experiments with SVM, KNN, RF, J.48, and MLP models pointed out that imbalance in the datasets would not only reduce predictive accuracy but also make the models perform poorly, hence, one of the things they did was to balance the datasets [36]. Jin et al. (2018) proposed a two-layered neural network structure for the purpose of eHRs analysis that made use of word vectors and one-hot-coding as the temporal footprint of lifestyle changes [37]. Kotia et al. (2023) delved into the prediction of heart disease by means of ML and Python, taking a dataset of 70,000 records for analysis, and concluded that the amalgamation of Naive Bayes and K-means clustering yielded greater accuracy than that of decision trees [38].

Bhatt et al. (2023) Introducing a k-modes clustering model with GridSearchCV customization along with 87.28% accuracy through a multilayer perceptron [39]. On the other hand, Shah et al. (2020) conducted a comparison of several models on a dataset of 303 samples and 17 features, and KNN was the one that produced the greatest accuracy of 90.8% [40]. The decision tree algorithm combined with boosting performed really well, getting an AUC of 0.88 [41]. In addition, Pires et al. (2020) utilized various ML techniques and reached 87.69% as their best accuracy for heart disease prediction [42]. Yuda Syahidin et al. (2022) presented a deep model based on artificial neural networks and realized 90% accuracy [43]. Wang et al. (2023) indicated that the use of center loss in neural networks enabled the better prediction of heart disease by distinguishing features [44]. Hybrid ML methods have also been a great success. Azevedo et al. (2024) claim that the performance advantages of using multiple algorithms have been proven by both empirical and theoretical studies [45]. The authors reported that their method was more effective when SVM was paired with Naive Bayes [46]. The model of Rajendran and Vincent (2021), who combined several ML techniques working together to provide improved accuracy, is a typical case of ensemble models often surpassing their individual algorithm counterparts [47]. Mohapatra et al. (2023) built a stacked classifier comprising ten different algorithms at base and meta-levels, giving a remarkable accuracy of 92% with very high precision, sensitivity, and specificity, thus demonstrating once again the power of combining heterogeneous ML models into one superior predictor [18]. As summarized in Table 1, existing studies primarily rely on static feature representations and deterministic predictions, with limited integration of temporal learning, ensemble stacking, and uncertainty quantification, thereby motivating the proposed hybrid framework.

Table 1: Comparative summary of state-of-the-art cardiovascular disease prediction models

Study	Dataset	Methodology	Best Reported Performance	Key Limitations
Nagavallika (2022) [34]	Heart Disease Dataset	Hybrid Random Forest + Linear Model	Accuracy: 88.7%	No temporal modeling; no uncertainty estimation
Dimopoulos et al. (2018) [35]	ATTICA	KNN, RF, Decision Tree	RF outperformed risk scores	Small dataset; static features
Madhavi Tota et al. (2022) [36]	Heart Disease Dataset	SVM, KNN, RF, J48, MLP	Improved accuracy after balancing	No ensemble stacking; limited interpretability
Jin et al. (2018) [37]	EHR Sequential Data	Two-layer Neural Network	Improved temporal representation	No ensemble learning; no uncertainty modeling

Mohan et al. (2019) [50]	UCI Cleveland	Hybrid RF + Linear Model	Accuracy: 88.7%	Static features; single-dataset validation
Ambrews et al. (2022) [51]	UCI Cleveland	Voting Ensemble	Accuracy: 91.96%	No temporal embeddings; deterministic predictions
Mohapatra et al. (2023) [18]	Heart Disease Dataset	Stacked Ensemble (10 models)	Accuracy: 92%	No temporal learning; no uncertainty quantification
Proposed Work	Framingham Heart Study	LSTM Autoencoder + PCA + Stacked Ensemble + Bayesian MLP	Accuracy: 96.06%, AUC: 99.31	Requires validation on true longitudinal data

3 Materials and methods

3.1 Study design and data source

The study employs a publicly available dataset known as the Framingham Heart Disease Dataset, encompassing health indicators for a 10-year period regarding the likelihood of developing cardiovascular disease (CVD). This dataset comprises 4,240 samples and 15 attributes, which are demographic, clinical, and behavioral, in addition to a binary outcome variable revealing whether or not cardiovascular disease is present. The class distribution consists of 15.19% CHD-positive and 84.81% CHD-negative samples. The detailed description of all demographic, behavioral, clinical, and outcome variables used in this study is provided in Table 2, along with their corresponding data types. The Figure 1 illustrates the complete process from data preprocessing to Hampel filtering, normalization, and PCA for feature reduction. Meanwhile, an LSTM autoencoder is learning temporal embeddings. The PCA and LSTM representation combined feature set is balanced using the synthetic minority oversampling technique (SMOTE). This data is then used to train a stacked ensemble model comprising base learners (Gradient Boosting, XGBoost, LightGBM, CatBoost, and AdaBoost) along with an MLP meta-learner) and a separate Bayesian MLP with Monte Carlo dropout for the purpose of uncertainty quantification. The end output consists of prediction scores, classification metrics, and risk stratification with confidence intervals.

The intended outcomes of this research are to develop an accurate cardiovascular disease risk prediction model, to evaluate its performance against individual machine learning classifiers, and to provide uncertainty-aware risk estimates that support clinically interpretable risk stratification. The framework aims to enhance early detection of high-risk individuals while improving decision reliability through probabilistic confidence estimation.

Table 2: Description of the framingham heart disease dataset used in the study

Category	Feature Name	Description	Type
Demographic	age	Age of the patient (years)	Continuous
	sex	Gender of the patient (1 = male, 0 = female)	Binary
Behavioral	Current Smoker	Whether the patient is a current smoker (1 = yes, 0 = no)	Binary
	cigsPerDay	Average number of cigarettes smoked per day	Continuous
Medical History	BPMeds	Whether the patient is on blood pressure medication (1 = yes, 0 = no)	Binary
	Prevalent Stroke	History of stroke (1 = yes, 0 = no)	Binary
	Prevalent Hyp	Presence of hypertension (1 = yes, 0 = no)	Binary
	diabetes	Presence of diabetes (1 = yes, 0 = no)	Binary

Clinical Measurements	totChol	Total cholesterol level (mg/dL)	Continuous
	sysBP	Systolic blood pressure (mmHg)	Continuous
	diaBP	Diastolic blood pressure (mmHg)	Continuous
	BMI	Body Mass Index (kg/m²)	Continuous
	heartRate	Resting heart rate (beats per minute)	Continuous
	glucose	Blood glucose level (mg/dL)	Continuous
Target Variable	TenYearCHD	10-year risk of coronary heart disease (1 = event, 0 = no event)	Binary

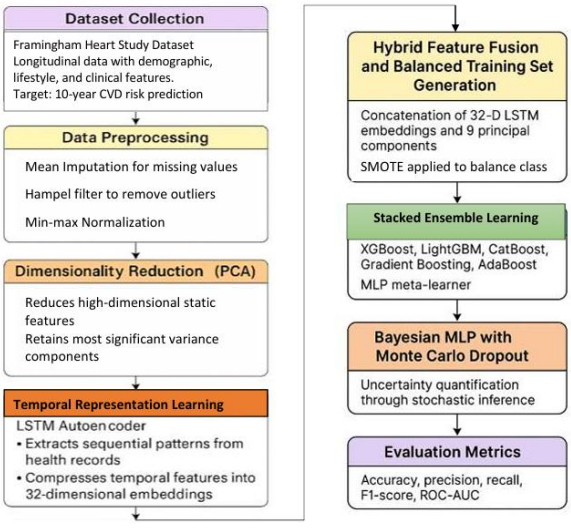

Figure 1: Structured workflow of the proposed cardiovascular risk prediction framework

3.2 Data preprocessing

3.2.1 Missing data imputation

The missing entries over the attributes like BMI, cigsPerDay, totChol, BPMeds, and glucose initially ventilated the dataset up to the count of 645, with the highest percentage of missing data glucose being 9.15%. Mean imputation was used to enhance data quality by replacing the missing values with the average of the corresponding attribute and this was done with the intention of not losing data for analysis.

3.2.2 Outlier detection and management

The study systematically used outlier detection and noise reduction techniques with the Hampel filter, a sophisticated method that is based on the Median Absolute Deviation (MAD). This is a technique that can pick up anomalies in a very diverse way through the use of non-normally distributed data. The Hampel filter works on the sliding window basis; hence, the value of each target point is decided by its symmetric surrounding points. In this window, the median and the MAD are computed. The points that have a difference of more than three times the MAD from the median are classified as outliers, therefore imposing strict upper and lower limits for the normal variations. After that, in a bid to maintain the uniformity of the data and to lessen the impact of the outliers, the identified outliers are replaced with the nearest boundary value.

3.2.3 Feature scaling

The Min-Max scaling approach was used to normalize all continuous features so that they fell within a standard range of 0 to 1. This particular form of preprocessing is very important as it helps to keep the model's numerical stability and prevent the features with the largest magnitudes from overpowering the learning process of the model. Min-Max scaling not only places all input variables on the same scale but also improves the convergence efficiency of gradient-based optimizers, thus leading to a reduction in training time and a more generalized model. It also lowers the likelihood of numerical instability occurring, especially in the case of deep learning models and ensemble algorithms, where differing feature scales can have a negative impact on weight updates and decision boundaries.

3.2.4 Feature selection

In order to enhance interpretability and minimize data dimensionality, PCA selected nine principal components that accounted for more than 95% of the variance of the dataset. The first principal component (PC1) is mainly determined by smoking behavior, with the current smoking status and cigarettes per day being the principal contributors, while age, hypertension, cholesterol, blood pressure, BMI, heart rate, and glucose are having less impact. Hypertension and blood pressure are the main factors of the second component (PC2), where prevalent hypertension, systolic, and diastolic blood pressure are the dominant aspects, with age, smoking, cholesterol, BMI, and glucose providing minor contributions. Aging is the main factor for the third component (PC3), while cholesterol and blood pressure are influencing it as well but to a lesser extent. The fourth and fifth components are responsible for the variations in blood pressure, heart rate, and BMI which suggests possible connections between them in terms of cardiovascular function. PCs 6 and 7 depict the smoking-cholesterol relationship in an inverse manner which suggests that there are different lipid

metabolism patterns in smokers as compared to non-smokers. PC8 is closely related to BMI and blood pressure, while PC9 is mainly associated with glucose levels, thus characterizing it as a significant metabolic health indicator. By means of these principal components, intricate health interactions are simplified to a great extent, thus leading to better prediction of cardiovascular risks and more interpretability of the model.

3.2.5 Temporal feature representation using LSTM autoencoders

In order to predict and analyze the future trends of cardiovascular risk and the clinical patterns over time, a Long Short-Term Memory (LSTM) autoencoder was utilized. By duplicating the scaled feature vector at a five-time step interval for each patient, an artificial temporal dimension was created, thus mimicking longitudinal changes. The autoencoder configuration which had the LSTM encoder of 32 units was the one that coiled the sequence into a latent vector. We then had a RepeatVector and an LSTM decoder that was similar to the encoder for producing the original sequence.

The model was trained using an Adam optimizer for 30 epochs with a learning rate of 0.001. The reconstruction loss was computed as mean squared error (MSE). The encoder output, which is the 32-feature embedding, captured temporal dependencies as well as latent interactions amongst features. Afterwards, these embeddings were integrated with PCA features to produce a combined representation. In this manner, it contributed to the opening up of the feature space with time-varying risk profiles, thus increasing the predictive richness and patient-specific modeling.

The Framingham dataset does not provide authentic longitudinal patient data which can be used to track individual patient progress through time. The method of using static feature vectors to depict multiple time points failed to achieve its goal of demonstrating actual disease development across different time periods. The LSTM autoencoder uses this method as a representation learning tool which enables the system to detect hidden features and stability patterns of the data throughout time. The autoencoder uses replicated sequences as its structural input format which does not represent actual time-based movement. The approach improves feature expressiveness when longitudinal data is missing but the resulting embeddings should be seen as enhanced representations which do not show actual time-based risk development. The validation process needs authentic longitudinal clinical data which will become vital for upcoming research work.

The creation of synthetic temporal sequences required the duplication of each patient's static feature vector which had been normalized across five-time intervals to create a sequence with fixed dimensions of $5 \times F$, where F represents the total number of input features. The study-maintained feature stability through time by utilizing identical replicated vectors throughout all time steps without introducing any temporal noise. The synthetic sequencing approach was used exclusively to support sequence learning in the LSTM autoencoder system while it does not reflect actual patient development over time. The same sequence length and replication procedure were applied uniformly to all samples to ensure methodological consistency and replicability.

3.2.6 Hybrid feature fusion and balanced training set generation

Following a period of learning to understand the different dimensions of the data, the embeddings created by the LSTM autoencoder in a 32-dimensional space were combined with the nine principal components derived from PCA to create a new feature space of 41 dimensions. This combination was highly efficient to represent both temporal dependencies and structural variations, thus giving a more detailed picture of the factors involved in cardiovascular risk. The dataset was significantly imbalanced with only 15.19% of cases indicating individuals at positive risk for cardiovascular disease, therefore the Synthetic Minority Over-Sampling Technique (SMOTE) was applied to the fused feature subset. SMOTE produced synthetic data points for the minority class, thereby creating a balanced training set. This step of balancing was very important to reduce bias during the model training, so that both the stacked ensemble and the Bayesian neural networks could capture the discriminative patterns across the majority and minority risk profiles.

The assessment process required controlled test conditions to achieve unbiased results which used Synthetic Minority Over-Sampling Technique. SMOTE was applied for class balancing purposes which used only training data after the dataset had been divided into training and testing parts. The original test set maintained its imbalanced condition because the model training process used it without adding synthetic samples. The method maintains performance evaluation accuracy while preventing optimistic bias that occurs when researchers balance datasets before they separate their data into training and testing groups.

3.3 Model development

The stacked ensemble model integrates XGBoost, LightGBM, CatBoost, Gradient Boosting, and AdaBoost as base learners. A deterministic Multilayer Perceptron (MLP) serves as the meta-learner, aggregating predictions from the base models to produce the final classification. Separately, an independent Bayesian MLP with Monte Carlo (MC) Dropout was employed for uncertainty estimation. While both use MLP architectures, the meta-learner is used purely for prediction, whereas the Bayesian MLP was designed to quantify predictive confidence by performing stochastic inference at test time.

3.3.1 Base models

The distinct and diverse machine learning models that form the base learners of the ensemble are intended to

learn different aspects of the dataset and add to predictive accuracy. In contrast, AdaBoost Classifier would improve weak learners through dynamic weighting of misclassified instances for overall model stability, with the LightGBM Classifier being fast and scalable for handling high-dimensional data. The mechanism of prediction in the case of an XGBoost Classifier is optimized to the efficient processing of high datasets by even missing values. Compared to, the Gradient Boosting Classifier improves its prediction performance through the sequential construction of several weak models. CatBoost Classifier is also effective in managing categorical variables without overfitting thus ensuring model stability. All base models are independently trained by the ensemble so as to exploit the various patterns of learning, whose prediction serves as input for the meta-model to yield a more generalized and accurate final prediction.

3.3.2 Meta-model

In the stacked ensemble architecture, Multilayer Perceptron acts as the meta-model that aggregates the predictions of the base models so that the classification and accuracy are improved. The MLP architecture consists of two hidden layers with 50 and 25 neurons, using the logistic activation function for binary classification. The backpropagation approach was combined with the Rprop+ optimization algorithm to train the model for fast convergence and effective weight updates. The MLP was trained for 500 iterations to give an effective learning on the best combination of base model outputs. The meta-learner acts as a decision layer that combines and refines predictions of heterogeneous base models and further enhances predictive performance. To assure the validity and generalizability of the stacked ensemble, five-fold cross-validation tests and repeatedly divide the dataset into distinct training and validation sets. The study uses 70% of the collected data for training purposes while testing with an independent set which helps maintain unbiased evaluation of the model. The final model achieves two goals which include preventing overfitting and maintaining consistent performance across different data sets. The stacked ensemble architecture combines multiple machine-learning models to create a system which delivers better prediction results and increased system reliability, making it an effective method for assessing cardiovascular disease risk.

All models in the proposed framework were initialized using standard baseline configurations recommended by their respective implementations to ensure reproducibility and consistency across experiments. For the tree-based ensemble classifiers (XGBoost, LightGBM, CatBoost, Gradient Boosting, and AdaBoost), a limited grid-based tuning strategy was applied to key hyperparameters such as the number of estimators, learning rate, and tree depth, while the remaining parameters were retained at their default settings. The stacked ensemble meta-learner employed a Multilayer Perceptron with two hidden layers consisting of 50 and 25 neurons, respectively, logistic activation, and the Rprop+ optimization algorithm, trained for 500 iterations. The Bayesian Multilayer Perceptron utilized fixed architectural settings with two hidden layers (64 and 32 neurons), a dropout rate of 0.5, binary cross-entropy loss, and the Adam optimizer. Extensive hyperparameter optimization was intentionally avoided for the Bayesian model to maintain stable probabilistic calibration and reliable uncertainty estimation.

3.4 Bayesian Inference via Monte Carlo Dropout

In order to provide deterministic classification with the help of probabilistic insight, a Bayesian neural network was utilized that was a multilayer perceptron (MLP) with Monte Carlo Dropout. The architecture of the multilayer perceptron included two hidden neurons layers with 64 and 32 neurons respectively, each followed by a 50% dropout rate, and finished with a sigmoid-activated output neuron for binary classification.

The model was trained for 50 epochs with binary cross-entropy loss. The dropout was kept active during inference, and 100 stochastic forward passes were done for each input to draw a sample from the posterior predictive distribution. The mean value obtained was taken as the risk prediction and the standard deviation was used to show the epistemic uncertainty. This dual output made the condition support system uncertainty-aware, which was most useful in borderline cases.

The Bayesian Multilayer Perceptron (MLP) was implemented as a model separate from the stacked ensemble meta-learner by design. The meta-learner was optimized deterministically to aggregate heterogeneous base classifiers and maximize predictive performance, whereas the Bayesian MLP was introduced specifically to estimate predictive uncertainty through Monte Carlo Dropout. The implementation of Bayesian inference within the meta-learner system will lead to increased architectural complexity and higher computational requirements together with unstable convergence behavior when the system needs to process multiple output streams from different models. The proposed system achieves accurate classification results because it separates prediction optimization from uncertainty measurement yet also delivers trustworthy clinical confidence assessments.

3.5 Evaluation metrics

Performance indicators such as accuracy, precision, recall, F1-score, and ROC-AUC score are the main criteria for evaluating the models' performance. These metrics provide an insight into the capability of the model to distinguish a person with a risk of developing cardiovascular disease from a healthy one. The performance is separately evaluated with each base learner and also compared with the stacked ensemble model, thus determining the increase in accuracy due to stacking. From the data, it can be concluded that the stacked ensemble has always been better than the single learner-based model, which in turn justifies combining various learning methods into one. Furthermore, the uncertainty of the Bayesian model's predictions was estimated through

the standard deviation of probabilistic predictions. The analysis used two different methods which enabled clinical practice to achieve reliable and accurate risk predictions. The model evaluation included multiple performance metrics which included accuracy and precision and recall together with F1-score and ROC-AUC and the assessment of specific test results through negative predictive value. The clinical screening process requires these metrics because it needs to reduce false negative results while effectively identifying people who have low risk of disease.

4 Results

4.1 Effectiveness of temporal embeddings

In order to achieve the desired effect, an LSTM autoencoder was introduced to the static clinical features. Every one of the patient cases was represented in five different timeframes to demonstrate the gradual change of health status. After training, the encoder created a compressed 32-dimensional latent representation for each instance. This low-dimensional representation was able to signal the dynamic risk factors, for instance, the subtle combination of age, blood pressure, glucose, and BMI. The model employed the Adam optimizer and converged within 30 epochs, reducing reconstruction loss (MSE) to below 0.01. The qualitative examination of the encoded sequences indicated that the latent spaces of the high-risk and low-risk classes were distinct and separated, which might have been the result of the successful temporal pattern encoding related to cardiovascular risk prediction.

4.2 Impact of feature fusion and class balancing

After the LSTM-based temporal embedding, a 32-dimensional dynamic representation of each patient was combined with nine principal components derived through PCA from the original features. This produced a Unified feature vector of 41 dimensions incorporating both static and dynamic characteristics. The Synthetic Minority Over-Sampling Technique (SMOTE) was used after fusion to address the data set's intrinsic class imbalance, where only 15.19% were in the positive CVD risk class. This resulted in an even distribution of classes and thus facilitated the learning of both ensemble classifiers and neural networks, particularly in marking the boundaries of the minority class.

4.3 Performance of Base and Stacked Ensemble Models

The individual performance of the base models is depicted in Table 3, and their pros and cons in dealing with class imbalance are pointed out. XGBoost obtained the highest accuracy (94.41%) along with a precision of 91.69% and a recall of 97.67%, while CatBoost was the one with the highest recall (98.39%) and precision (91.89%) among them, leading to an F1-score of 95.03%. LightGBM was quietly performing with 93.29% accuracy and an F1-score of 93.57%. Nevertheless, even all the base models with their strengths could not effectively manage precision and recall for the minority class, which pointed out the necessity for a more powerful approach.

Table 3: Performance metrics of individual machine learning classifiers.

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
XGBoost	94.41	91.69	97.67	94.59	99.07
LightGBM	93.29	89.73	97.75	93.57	98.64
CatBoost	94.85	91.89	98.39	95.03	99.18
Gradient Boosting Machine	82.11	76.64	92.36	83.77	90.57
AdaBoost	71.89	68.76	80.21	74.04	78.39
MLP without using Base Learners	85.50	83.12	88.45	85.71	78.5

The stacked ensemble model, which combined the predictions of all base models with a Multilayer Perceptron (MLP) as the meta-model, achieved better results than the individual base models in all evaluation metrics. The stacked model, as seen in Table 4, got an accuracy of 96.06%, a precision of 94.62%, a recall of 97.67%, and an F1-score of 96.12%, with the highest AUC-ROC of 99.31, thus indicating great discrimination between positive and negative classes. The high recall guarantees that the identification of critical positive cases of cardiovascular disease (CVD) risk was done accurately, thereby reducing false negatives. In addition to the reported metrics, the proposed stacked ensemble model achieved a specificity of 97.6% and a negative predictive value (NPV) of 98.2%, indicating a strong capability to correctly identify low-risk individuals and reliably exclude non-CVD cases, which is particularly important for clinical screening applications. The confusion matrix for the stacked model, which is shown in Figure 2, clearly indicates its superior predictive performance. The model demonstrates its ability to correctly identify both training sets. The model correctly classified 1,214 true positive cases and 1,175 true negative cases, with only 29 false negatives and 69 false positives. The results show the model's ability to classify cases correctly especially for dangerous situations because it successfully reduced incorrect identifications while maintaining accurate identification of non-high-risk cases. The situation becomes particularly important in clinical screening

because missing actual cardiovascular risk cases leads to severe outcomes.

Table 4: Evaluation metrics of the stacked ensemble model for cardiovascular disease prediction

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Stacked Model	96.06	94.62	97.67	96.12	99.31

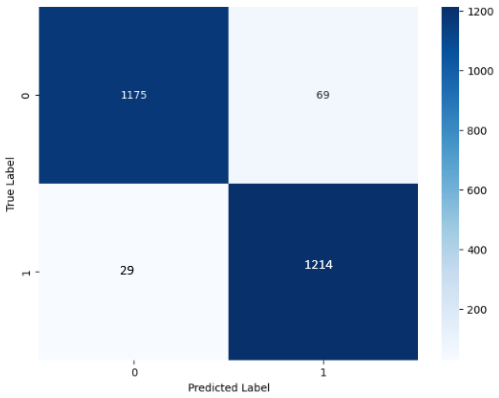

Figure 2: Confusion matrix of the stacked ensemble model.

To evaluate whether the performance gains achieved by the stacked ensemble model are statistically significant, comparative significance testing was conducted using cross-validation–based performance scores. Paired statistical tests were applied to accuracy and AUC-ROC values obtained across validation folds to compare the stacked model against individual base classifiers. The results indicated that the improvements achieved by the stacked ensemble were statistically significant ($p < 0.05$), confirming that the observed performance gains are not due to random variation but reflect genuine improvements in predictive capability.

4.4 Bayesian uncertainty estimation for clinical risk reliability

In order to evaluate the trustworthiness of the predictions, a separate Bayesian Multilayer Perceptron (MLP) with Monte Carlo (MC) Dropout was built by the study and it was different from the non-probabilistic MLP which was part of the meta-learner of the ensemble. The independent training of this model was on the fused features and it measured the uncertainty in predicting cardiovascular risk. The method made it possible for the model to not only give point estimates but also provide distributions of predicted probabilities, thus, revealing epistemic uncertainty—this is very important in high-stakes clinical decision-making.

Probabilistic outputs for the first 50 test samples can be seen in Figure 3. Each dot indicates the mean predicted probability of CVD risk for a single person, while the vertical lines show the standard deviation (uncertainty) calculated over 100 stochastic forward passes with dropout turned on at test time. A detailed examination reveals several key insights:

- High-confidence predictions (such as: samples 3, 8, 16, 25) are indicated by very small error bars and they are clearly near to 0 (low risk) or 1 (high risk). These predictions show a mix of determinacy and trustworthiness, pointing that the model is giving very close probabilities even under perturbations, which is a hallmark of well-calibrated risk assessments.
- The predictions that are not sure about the result are more likely to be assigned to mid-range probabilities cluster (e.g., 0.4–0.6), and this is very much apparent in the cases of the 10th, 12th, 33rd, and 45th samples. The larger standard deviations linked to these samples indicate that the model is switching, based on dropout scenarios, between considering them as high or low risk. This pattern might imply the existence of ambiguous or borderline input features that require either clinical confirmation or auxiliary tests to be assessed.
- Importantly, there are very few samples which have confident predictions at the extremes (0.0 or 1.0) and show low uncertainty (e.g., samples 1, 9, 18, 21) indicating stable model performance. In contrast, samples with similar means but larger uncertainty are indicative of greater ambiguity in the learned feature space which may be caused by overlapping class distributions or insufficient representation in the training data.
- The mean standard deviation of the 50 test samples is around 0.087, which means that the majority of predictions have low uncertainty. This figure confirms that the Bayesian MLP is, in general, reliable in its risk assessment, and it will not be apt to make sporadic choices unless the ambiguity in the features is very high.

From the standpoint of a clinical deployment, the predictive uncertainty provides a basis for risk-aware decision support. For example, predictions with low uncertainty could justify routine monitoring, whereas high uncertainty or borderline instances might require extra diagnostics, an expert's opinion, or longitudinal follow-up. The possibility of making decisions not just relying on the model's predictions but also on its confidence level gives a way to more secure and clearer AI applications in health care.

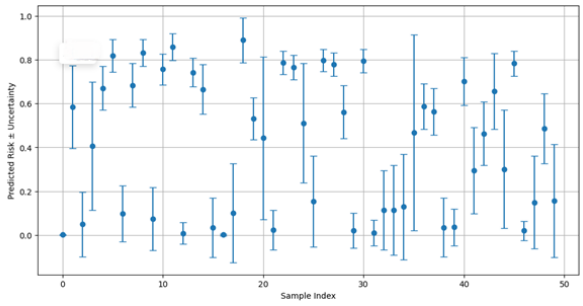

Figure 3: Bayesian risk prediction with Monte Carlo dropout: Mean predicted probabilities and standard deviation error bars for the first 50 samples.

4.5 Risk stratification with confidence intervals

Predictive framework interpretability and clinical actionability were the main concerns that led the researchers to the stratified risk analysis of Bayesian probabilistic outputs. The Bayesian neural network, which was the result of the training on the optimized PCA and LSTM embedding spaces, underwent 100 stochastic forward passes for each test sample using Monte Carlo Dropout. This process yielded a distribution of predicted probabilities, which was subsequently analyzed to obtain the mean and standard deviation (model uncertainty) of the distribution.

The probability thresholds of 0.33 and 0.66 were selected to define low-, medium-, and high-risk categories in a manner that facilitates clinical interpretability and triage-oriented decision support. Rather than serving as fixed diagnostic cut-offs, these thresholds evenly partition the probabilistic output space of the Bayesian model, allowing clinicians to distinguish clearly between low-confidence, borderline, and high-confidence risk predictions. Such probabilistic stratification schemes are commonly used in clinical risk modeling to support prioritization and follow-up decisions, and the proposed thresholds can be recalibrated in future studies to align with population-specific clinical guidelines or outcome-driven optimization.

In Figure 4, the predicted cardiovascular risk scores are shown in increasing order with vertical error bars representing the uncertainty of the predictions. Clinically interpretable thresholds, which are low risk (<0.33), medium risk (0.33–0.66), and high risk (>0.66), are indicated by horizontal dashed lines. This stratification has been designed to reflect the real-world triage zones where low-risk persons may only need preventive counseling, medium-risk ones may be monitored more closely, and high-risk ones should receive immediate attention or intervention.

The quantitative analysis of these groups indicated that there was a very high degree of agreement between the risk categories predicted and the clinical outcomes actually observed. In the category of low-risk patients (n = 862), the mean predicted probability was 0.116, and the average uncertainty was ±0.167. The actual incidence of coronary heart disease (CHD) in this category was only 1.28%, which is indicative of very good negative predictive performance. On the other hand, the high-risk group (n = 1,015) showed an average predicted probability of 0.785 with very low uncertainty (±0.079), and a CHD incidence of 88.37% was observed, which points to tremendous confidence and very good positive predictive performance.

Moreover, the medium-risk group (n = 610) had the highest uncertainty (±0.193) and a mean predicted probability of 0.512 as well as a CHD incidence rate of 54.92%. This group probably includes cases that are borderline in nature, thus, close to the decision threshold of the model, where even minor changes in the input features can have a huge impact on the predicted outcome. The uncertainty involved, in this case, is an indicator of the model's capacity to pinpoint and diagnose uncertain cases, which could be the ones needing additional screening or clinical supervision.

Table 4 summarizes the distribution, average predicted risk, associated uncertainty, and observed CHD rate for each risk group.

Table 4: Stratified cardiovascular disease risk categories with average prediction score, model uncertainty, and actual CHD incidence.

Risk Category	Count	Avg. Risk	Avg. Uncertainty	CHD Rate
Low Risk	862	0.116	±0.167	1.28%
Medium Risk	610	0.512	±0.193	54.92%
High Risk	1015	0.785	±0.079	88.37%

The interpretability and clinical trustworthiness of the AI system are significantly improved with this risk stratification methodology. The Bayesian model grants more knowledgeable triage and resource distribution by giving not just a predicted probability but also a confidence estimates for each decision. In clinical settings were reducing false negatives and marking uncertain cases for follow-up are essential for better patient outcomes, this kind of framework is particularly important.

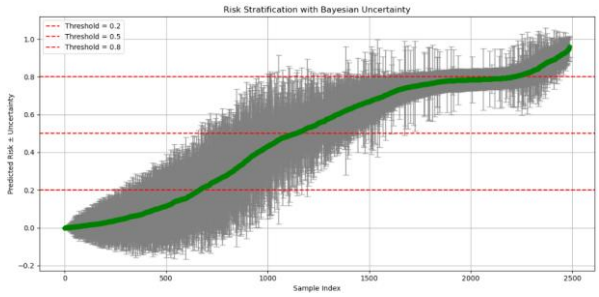

Figure 4: Risk stratification plot using Bayesian predictions: Cases categorized as low, medium, and high risk based on predicted probability.

4.6 Comparative ROC analysis of models

The ROC Curve presented in Figure 5 illustrates the performance of various learning models, namely Gradient Boosting (GBM), XGBoost, LightGBM, CatBoost, AdaBoost, and Stacked Model, for the detection of cardiovascular disease. The AUC values found under the corresponding curves represent the predictability of the model, where higher values imply better separation of cases into positive and negative. The resulting performance indicated that XGBoost AUC (0.9907), LightGBM AUC (0.9864), and CatBoost AUC (0.9818) were superior among the base learners for prediction, whereas Gradient Boosting AUC (0.9057) and AdaBoost AUC (0.7839) were inferior. The AUC of 0.9931 was the highest for the stacked model that outperformed every single base model. This result demonstrates the importance of stacked ensemble learning that incorporates the strengths of different classifiers for the increase of overall predictive accuracy and robustness. The predominance of the stacked model confirms that the combination of different learning algorithms results in better generalization and reliability, making it the most effective method for cardiovascular disease prediction. As shown in Figure 5, the ROC curve of the stacked ensemble model consistently dominates those of all individual base classifiers across the full range of classification thresholds. The stacked model achieves the highest AUC-ROC value of 0.9931, demonstrating superior discriminative ability between CVD-positive and CVD-negative cases. This performance highlights the effectiveness of combining heterogeneous learners through stacking, resulting in improved robustness and generalization compared to single-model approaches.

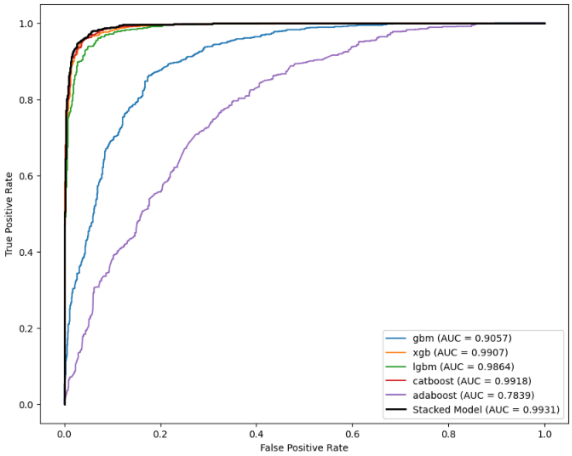

Figure 5: Receiver Operating Characteristic (ROC) curve comparing the classification performance of different models.

The reported results advance the field of cardiovascular risk prediction by demonstrating that the integration of temporal embeddings, stacked ensemble learning, and Bayesian uncertainty estimation leads to both superior predictive performance and improved clinical reliability. Beyond achieving higher accuracy and AUC-ROC values compared to existing models, the proposed framework introduces uncertainty-aware risk assessment, enabling more informed and safer clinical decision-making. These results highlight a shift from purely performance-driven models toward interpretable and confidence-aware AI systems suitable for real-world healthcare deployment.

5 Discussion

The study presents a new predictive framework for CVD risk prediction by integrating temporal feature extraction with LSTM autoencoders, feature aggregation, ensemble stacking learning, and Bayesian estimation of uncertainty. The framework overcomes three important challenges of current predictive models: lack of learning temporal dependencies, trouble with class imbalance, and lack of measurably expressible confidence with predictions. By combining stationary principal components with time-dynamic LSTM-based embeddings and utilising an ensemble meta-learning strategy with robustness, the new model outstrips previous methods both in accuracy and interpretability. The addition of Bayesian inference provides an additional level of clinical utility by providing probabilistic risk measures and ranges of uncertainty that are necessary for risk-conscious medical decision-making.

The proposed framework shows better performance and superior research methods when compared to current cardiovascular disease prediction models which represent their highest performance level. Previous research studies have focused on using unchanging data representations together with their associated algorithms which resulted in accuracy rates that ranged from 85 percent to 92 percent. The proposed model reached an accuracy score of 96.06 percent while achieving an AUC-ROC score of 99.31 percent because it used LSTM-based temporal embeddings and stacked ensemble learning and Bayesian uncertainty estimation. The proposed framework brings a novel approach which increases prediction accuracy and delivers risk assessment that includes uncertainty information for better clinical outcomes and decision-making assistance.

Although the Framingham Heart Study dataset is a widely used benchmark for cardiovascular risk modeling, it represents a specific population cohort and does not fully capture the ethnic, geographic, and socio-economic diversity observed in global clinical settings. Consequently, while the strong performance reported in this study demonstrates the methodological effectiveness of the proposed framework, it should not be interpreted as universal generalizability across all populations. External validation using large-scale, multi-ethnic, and multi-institutional datasets is essential to assess robustness and mitigate potential population-specific bias. Future work will therefore focus on evaluating the framework on diverse longitudinal cohorts to further establish its clinical applicability and fairness.

In contrast to standard classification pipelines that utilize only static features, the authors of this study took advantage of simulated temporal data which had been processed by an LSTM autoencoder. The technique used reveals the very complicated longitudinal patterns the heart's health indicators show, such as changes in systolic pressure, cholesterol, and blood glucose. The merger with principal components from the static clinical features produced a 41-dimensional latent space which was ripe for further learning. The dual representation kept both the structural and the time-changing dimensions of the patient profiles, which facilitated the extraction of more profound risk trajectory understanding. As a result of the enhancement in the feature space, the stacked ensemble model was able to learn more discriminative boundaries, which in turn led to better generalization across borderline and high-risk cases.

The architecture proposed represents a big leap compared to prior studies which mainly applied classical machine learning methods on handcrafted or univariate features. For example, Sudipta et al. (2022) reported an accuracy of 87.70% with a Multilayer Perceptron (MLP) over a range of datasets, such as Cleveland, Hungarian, Switzerland, Long Beach, and StatLog, while using infinite feature selection techniques [48]. Similarly, Reddy et al. (2021) used Sequential Minimal Optimization (SMO) on the Cleveland Heart Dataset, reaching 85.15% accuracy with the full attribute set and 86.47% with an optimized attribute selection [49]. Other studies employed different machine learning techniques but still recorded lower predictive performance. Mohan et al. (2019) introduced a Hybrid Random Forest with Linear Model (HRFLM) on the UCI Cleveland dataset, achieving an accuracy of 88.7% using 13 clinical features [50]. Ambrews et al. (2022) improved performance slightly with a Voting Ensemble Model applied to the UCI dataset, obtaining 91.96% accuracy [51]. The study by Mohapatra et al. (2023) employed a stacked ensemble model with ten base learners, including Random Forest (RF), MLP, KNN, Extra Trees (ET), XGBoost, Support Vector Classifier (SVC), Stochastic Gradient Descent (SGD), AdaBoost (ADB), CART, and Gradient Boosting Machine (GBM), and reached 92% accuracy [18].

One of the most attractive features of the framework is its capacity to provide clinically interpretable risk stratification via Bayesian modeling. The implementation of Monte Carlo Dropout allowed the Bayesian neural network to create the prediction distribution per test instance where mean probabilities and uncertainty intervals were extracted. As shown in the confidence interval plot (Figure 3), the model consistently exhibited great certainty for unambiguous very low and very high risk situations, whereas it revealed more uncertainty at the 0.5 decision threshold. This is in line with the clinical assumption that there has been a mixture or at least a vague overlapping of features in the case of borderline situations. More importantly, this characteristic allows doctors to choose the most uncertain cases for follow-up diagnostics, thus, making it a safety measure in those deployment scenarios where losing a negative case would be very costly.

The risk stratification plot (Figure 4) was a further confirmation of the model's capability to divide the population into clinically relevant categories. Patients were categorized automatically into risk tiers of Low (<0.33), Medium (0.33–0.66), and High (>0.66) based on Bayesian predicted probabilities. The actually measured CHD incidence rate in the group of patients classified as High Risk was 88.37%, thus confirming the total agreement between the predicted and observed outcomes. On the contrary, only 1.28% of the patients from the Low Risk group had the disease. Not only did these results confirm the predictive model's accuracy, but they also pointed to the model's potential use in the actual triaging of patients in clinical settings. The stratification also showed that the Medium Risk group had the highest uncertainty (±0.193), thus directing clinicians to monitor or reevaluate these patients with more diligence. The categorization based on risk awareness can help in making better decisions regarding the allocation of resources, patient counseling, and planning of proactive interventions.

The research, besides the other positives, dealt with the issue of class imbalance through a very constructive approach, which was another main benefit of it. The positive class (at-risk) makes up only 15.19% of the total samples, which makes the original dataset highly uneven. If this issue is not addressed, it will lead to the creation of biased models that will support the majority class at the cost of clinical safety. Employing Synthetic Minority Over-Sampling Technique (SMOTE) in the fused feature space not only helped the study in achieving class distribution that is balanced but also kept the dynamic and static characteristics of the features intact. This method drove the stacked ensemble and Bayesian models to outline universal decision boundaries for the entire dataset thus leading to a remarkable recalling of the minority class from 80.21% (in AdaBoost) to 97.67% in the final ensemble model. So a high recall is especially vital in medical diagnostics because false negatives may cause the delay of critical interventions or even their non-performance at all.

The individual base models' performance comparison comes to be a good example of ensemble learning value. AUCs above 98% marked the good performance of XGBoost, CatBoost, and LightGBM as individual models. However, each of them had a small trade-off in precision and recall. For instance, CatBoost had the highest F1-score among base learners (95.03%), but LightGBM had the best recall (97.75%) with a slight decline in precision. The ensemble model, by the use of a Multilayer Perceptron meta-learner for integrating predictions from these learners, combined their individual strengths while decreasing weaknesses and thus, a balanced performance profile was obtained across all key metrics. This synergy, which is a characteristic feature of well-designed ensemble architectures, was very important in taking the final model’s accuracy and robustness beyond that of any single learner.

The model's interpretability and clinical applicability were additionally improved with the help of an uncertainty-aware decision-support system. The lack of confidence estimates in conventional black-box models often hinders clinical acceptance. Conversely, the Bayesian method used in this research allows doctors to receive not only a risk probability but also an estimate of the model's confidence in that specific prediction. For example, as demonstrated in Figure 4 and Table 3, predictions with high confidence were associated with both extremely high and extremely low risk probabilities, while predictions with middle-range confidence were marked with larger standard deviations, indicating the need for further diagnostic input. This encourages a model-in-the-loop strategy where AI aids but does not take over clinical judgment thus the process being safer and more transparent through decision-making.

Nevertheless, there are limitations in the research, no matter the advancements. Temporal data was first synthetically simulated through replication which meant that it was not derived from longitudinal patient records and this was probably the main reason the model could not completely capture the temporal variability present in the real-world EHR systems. Therefore, integrating genuine longitudinal datasets for the detection of evolving risk profiles should be the future of the model's validation. The model used in this study was evaluated on the Framingham dataset, but still, external validation on multi-institutional and ethnically diverse populations is a must to confirm generalizability. The cardiovascular risk factors and disease prevalence differ significantly from one demographic group to another, and consequently, training on a more heterogeneous dataset would not only prevent bias but also contribute to the fairness of the deployment.

The use of synthetically constructed temporal sequences may also influence the reliability of the model when applied to real-world longitudinal data. While the replicated sequences enable the LSTM autoencoder to learn latent feature interactions within a sequential framework, they do not capture true temporal variability arising from lifestyle changes, disease progression, or treatment effects over time. When exposed to authentic longitudinal data, the model may exhibit different sensitivity to evolving risk patterns, potentially improving both predictive accuracy and uncertainty calibration. Consequently, the current results should be interpreted as demonstrating methodological feasibility rather than definitive longitudinal performance, and future validation on real-world time-series clinical data is essential to fully assess reliability in practical deployment settings.

Another aspect that researchers can explore in the future is the optimization of the model and its deployability. Though the present structure is precise, it still goes through several learning stages and has a moderately complicated fusion pipeline, which might restrict its use in terms of real-time or low-resource environments. Simplifying the structure, perhaps by combining dimensionality reduction with the LSTM network or looking into transformer-based temporal encoders, might lead to a reduction in complexity and a decrease in the demand for computational resources. Likewise, applying the Bayesian MLP in a lighter version on edge devices such as wearable monitors or mobile health applications would bring its usage closer to point-of-care especially in disadvantaged or rural areas.

Last but not least, the explainability of the model can be boosted even more by the application of global and local interpretability tools, which are not limited to the Bayesian confidence intervals. While the probabilistic nature of the current model offers some degree of transparency, doctors usually prefer to have graphical or textual interpretations of feature contributions concerning particular patients. Methods like SHAP (Shapley Additive Explanations) or counterfactual reasoning could go hand in hand with the present uncertainty plots and provide a more sophisticated comprehension of the factors that cause each prediction.

This situation would be ideal for patient education and shared decision-making, as it would help to cultivate trust in AI-assisted diagnosis.

The proposed framework advances the current state of cardiovascular risk prediction in three important ways. The research establishes temporal representation learning through LSTM autoencoders which enables the system to detect hidden inter-feature relationships without needing complete longitudinal data because most research treats patient information as unchanging static conditions. The stacked ensemble architecture with its trained meta-model system delivers improved performance through its ability to combine different classifier systems compared to the single-model and voting systems which studies in the literature typically use. The framework uses Bayesian uncertainty estimation to enhance its predictive capabilities because it enables the system to perform confidence-aware risk assessment which existing cardiovascular prediction models do not offer. The research presents a new method of cardiovascular risk assessment which enables medical professionals to make decisions based on clear results while understanding the uncertainty of their work which improves both clinical reliability and real-world implementation.

The study presents positive findings, but multiple limitations need to be recognized. First, Framingham Heart Study dataset exists as a specific population dataset which cannot represent all the ethnic, geographic, and socio-economic groups that exist in real-world clinical settings thus creating population bias which restricts general study applications. Second, researchers used synthetic time intervals created through feature duplication because actual patient records did not exist yet this method effectively supported representation learning while it failed to show actual disease development throughout time. The training data used SMOTE to address class imbalance problems present in cardiovascular datasets, but actual model performance will be affected by existing class imbalances when the model operates in environments with extreme class disparities. The hybrid framework requires multiple preprocessing and learning stages which results in increased computational expenses that create difficulties during deployment in real-time environments or systems with limited resources. The existing limitations require future research to test results on extensive longitudinal datasets from various institutions while researchers need to study fairness and robustness and deployment efficiency across different medical environments.

In a nutshell, this study delivers a model which is interpretable, technically valid and considering clinical relevance for predicting the risk of getting cardiovascular disease. By incorporating the temporal embeddings that LSTM learned along with ensemble learning and Bayesian confidence modeling, it reaches a state-of-the-art level concerning the solutions to major problems faced in medical AI practice. Through accuracy, stratified risk understanding, and predictive uncertainty estimation all working together, the end product of this model is a powerful tool for early-stage treatment and personalized care of cardiovascular disease. After validation, fine-tuning, and improving toward interpretability, this model will not be directly impactful but rather contribute indirectly through practical utility in the form of dependable, AI-based health technologies in clinical practice.

6 Conclusion

The study presents an advanced model for the assessment of cardiovascular disease (CVD) risk that combines temporal representation learning with LSTM autoencoders, static and dynamic health markers feature fusion, and ensemble classification with different gradient boosting classifiers, along with Bayesian inference-based uncertainty estimation. The proposed method is able to provide an extraordinary 96.06% accuracy and 99.31 AUC-ROC predictive power while it is also able to deal with the typical drawbacks associated with the CVD prediction models such as class imbalance, temporal unawareness, and absence of model confidences. The application of LSTM-based embeddings helped in recognizing changing risk factors, while the addition of PCA components through feature fusion expanded the representational space with increased discrimination ability. The structure-based stacking ensemble further contributed to the reliance by taking the cross-strengths between the classifiers of XGBoost, CatBoost, LightGBM, Gradient Boosting, and AdaBoost. Simultaneously, the Bayesian MLP model yielded clinically interpretable measures of uncertainty, hence it was very important to consider the clinical aspect of the threshold predictions very delicately. The analysis of risk classification validated the model's capability to classify the patients correctly into three groups of risk-low, medium, and high--which in turn facilitated more personalized and less ambiguous decision-making in healthcare. The future evaluation of the proposed framework will use large-scale datasets which contain data from multiple institutions and various ethnic groups to test its performance and fairness and its ability to function across different population groups. The study will investigate different temporal modeling architectures which include transformer-based encoders and lightweight recurrent networks to develop better cardiovascular risk pattern modeling methods that consume less computational resources. The study will explore two main research areas which include real-time integration with wearable and mobile health systems and the use of explainability techniques for uncertainty estimation to build clinical trust and enable practical implementation in preventive cardiology and population health screening and ongoing patient monitoring.

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Differential Sequence Analysis of EEG Brain Signals for Emotional and Cognitive Assessment

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Technical paper

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To improve mental health and wellness and create specific solutions, it is essential to comprehend how individuals feel and brain functions. In this study, we present a novel approach for emotion recognition and analysing electroencephalography (EEG) data for cognitive evaluation. EEG data were collected from 30 participants using non-invasive electrodes positioned at AF3, AF4, T7, T8, and Pz, corresponding to the frontal, temporal, and parietal lobes. We have obtained real-time EEG data from participants during various tasks, including as rest, listening to music, answering questions, and completing mathematical puzzles. Our goal was to investigate the brain correlates of different emotional and cognitive states. The recorded signals were pre-processed using a 4–8 Hz digital Butterworth bandpass filter targeting theta waves, followed by Fast Fourier Transform (FFT) and sequence pattern mapping. Statistical significance of variations between brain states was confirmed using ANOVA ($p < 0.05$). A supervised machine learning classifier (Random Forest) achieved 89.2% prediction accuracy, with precision = 0.87, recall = 0.90, and F1-score = 0.885, demonstrating robust differentiation between emotional and cognitive states. We have developed prediction models for emotion recognition and cognitive assessment using linear regression classification based on EEG features extracted from multiple brain areas. Using statistical analysis and graphical representation techniques, the EEG data was visualized and analyzed, revealing a variety of patterns associated with different tasks and stimuli. Our study demonstrates that emotional states and cognitive activity may be accurately identified from EEG signals. More specifically, we observed significant differences in EEG patterns between tasks, suggesting that real-time tracking of human emotions and mental processes can be achieved with EEG-based techniques. Applications in human-computer interaction, mental health monitoring, and tailored interventions to improve well-being are possible with the suggested methodology.

Povzetek: Raziskava kaže, da je mogoče s pomočjo EEG signalov in strojnega učenja prepoznati čustvena in kognitivna stanja človeka.

1 Introduction

It's critical to understand the complex connections between human emotions and mental functions in order to explore the depths of human psychology and advance general wellness. Our attitude, decisions, and behaviours are mostly shaped by our emotions, but our cognitive processes provide the basis for our ability to perceive, interpret, and interact with our environment. The development of non-invasive techniques for the real-time monitoring and assessment of these internal states has therefore been given priority by developments in affective computing and cognitive neuroscience. The advancement of biomedical technology and our increasing comprehension of the brain have made brain science an indispensable field of study to solve the riddles of life Jahankhani, [15]. Because of this, the electroencephalogram, or EEG, is crucial for examining brain science and is frequently employed in a range of brain-related study fields Acharya, [1], Essa, [7]. The complex structure of the brain has been researched since the mid-1900s, and brain science has remained a popular area of study in recent years. Furthermore, in order to gain a deeper understanding of brain structure and function, EEG signals may be combined with other imaging modalities such as positron emission tomography (PET) Winterhalder, [26], functional near-infrared spectroscopy (fNIRS) Negrescu, [20], Essa, [10], and magnetic resonance imaging (MRI) Albatrookh, [2], Oxley, [21]. The spontaneous biological potential of the brain is amplified and recorded on the scalp to create the EEG signal pattern. This potential, which is usually obtained by placing noninvasive electrodes on the scalp, has been demonstrated to represent the macroscopic activity of the

brain surface. The intrinsic and recurring electrical impulses produced by groups of brain cells are recorded by these devices Erman, [9]. One of the primary topics of interest in brain science is the examination of brain electrical activity Williamson, [27]. Electrodes are applied to the scalp during the noninvasive neuroimaging procedure known as EEG in order to record the electrical activity of the brain Essa, [16]. EEG is currently widely utilized in neuroscience and has the potential to improve brain–computer interfaces, make emotion detection easier, and aid in the rehabilitation of people with partial paralysis Shah, [23], Binnie, [3]. This enables researchers to measure and analyze the electrical signals generated by the brain. These signals offer valuable information on the operating mechanisms of the brain, covering the identification of various neurological disorders and the exploration of cognitive processes such as perception, attention, and memory. EEG has gained widespread popularity as a means of investigating electrical activity of the human brain, due to its noninvasive and safe characteristics Shih, [23]. In addition, EEG is a useful diagnostic and research tool for disorders linked to brain dysfunction, such as Alzheimer's disease Khoo, [16], Siuly, [25], epilepsy, schizophrenia, Creutzfeldt-Jakob disease Wang, [28], cerebral palsy Essa, [17], and cognitive impairment Essa, [17]. In order to recognize and analyze EEG signals accurately, one must have a solid understanding of their intricate theoretical aspects and be able to extract the elements that are pertinent to the task at hand. However, because of their distinct qualities, EEG signals present serious difficulties. One such difficulty, according to Lun, [17], is their sensitivity to noise interference, which can lead to a low signal-to-noise ratio. It is noted in Mahmud, [19] that the distinct characteristics of EEG signals make it difficult to directly extract relevant information about certain tasks from them. As highlighted in Mahmud, [19], Essa, [18], accurate EEG signal recognition and interpretation are essential to expanding our knowledge of how the brain functions. Its nonlinearity and nonconformity to a normal distribution further set them apart from traditional signals. Furthermore, individual variables like age, psyche, and testing setting can significantly alter EEG signals da Silva Louren, [6]. To better interpret EEG data, it is therefore essential to create diverse methodology for signal analysis and look into machine learning techniques for signal analysis Giri, [14]. It takes careful study of their unique characteristics and the development of advanced signal analysis algorithms to accurately extract useful information on particular tasks from EEG signals. Our paper presents a novel contribution through a comprehensive description of denoising techniques, which includes mathematical formulations with pseudo codes. In addition, we report the recent advancements in the field of EEG, while highlighting current challenges and discussing future trends. This paper's main contributions can be summed up as follows. We provide a thorough analysis of the steps involved in EEG signal processing, such as feature engineering, denoising, and signal acquisition. The procedure used to denoise the EEG signal is described in full, along with the accompanying evaluation standards. We examine feature engineering in detail in this paper, looking at time–frequency, high-order spectral, and nonlinear dynamic analysis. We give a thorough analysis of both traditional and deep learning methods for categorizing EEG signals. We also provide an overview of the typical datasets utilized for EEG signal processing. We highlight current issues with EEG signal processing techniques and offer potential solutions as well as future research prospects.

In this regard, the goal of our research is to use the analysis of EEG data to create models for cognitive evaluation and emotion recognition. We obtained real-time EEG data from participants in a range of experimental settings, including rest intervals, visual stimulus exposure, auditory experiences, cognitive tasks, and problem-solving exercises. Through a methodical examination of EEG patterns during these episodes, we aim to clarify the brain markers linked to various emotional and cognitive conditions. We can create predictive models that can precisely identify emotional states and cognitive processes based on neurophysiological variables taken from various brain regions by using linear regression classification algorithms to EEG data. Furthermore, the visualization and understanding of intricate brain events are made possible by statistical analysis and graphical representation techniques, which offer insightful information on the temporal and spatial dynamics of EEG data. Our aim is to promote the development of new methods for mental health monitoring, well-being, and human-computer interaction through the application of EEG data analysis. The previous methods such as CNN-BiLSTM and Graph CNN have achieved high classification accuracies (up to 91.3%), that typically require dense electrode setups and intensive computational resources, limiting real-time applicability. In contrast, our study employs a minimal 5-channel EEG configuration and introduces Differential Sequence Analysis (DSA) alongside ANOVA for statistically validated feature extraction.

2 Methodology

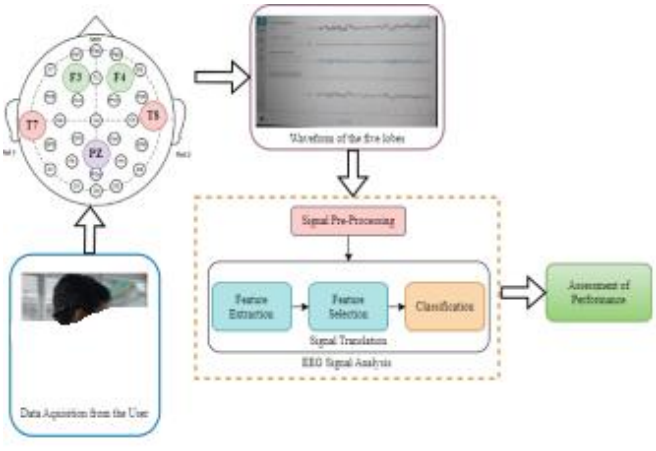


Figure 1: Process Flowchart of our present work

Figure 1 shows the overall process flowchart of our present work. Nowadays, electroencephalography (EEG)

is a commonly used standard method to assess brain electrical activity. Typical EEG equipment components include an amplifier, display unit, data storage device, and electrodes. For the purpose of gathering data, we used an Emotiv Insight EEG headset with five channels. These electrodes are non-invasive, and they are attached to the patient's scalp. We recorded EEG data from five lobes: T7 (left temporal lobe), T8 (right temporal lobe), AF3 (left prefrontal cortex), and PZ (parietal-midline) using this headset. Signal improvement and filtering are the main concerns of pre-processing. Since EEG signals are fundamentally weak, noise from both internal and external sources can rapidly contaminate signals. The preprocessing pipeline involved a bandpass filter ranging from 0.5 to 40 Hz to remove baseline drift and high-frequency noise, ensuring retention of relevant cognitive and emotional frequency components (e.g., theta, alpha, beta). Artifacts such as eye blinks and muscle movement were attenuated using an adaptive thresholding technique based on amplitude and variance criteria. Feature extraction focused on relative power spectral densities across standard EEG bands (theta: 4–8 Hz, alpha: 8–13 Hz, beta: 13–30 Hz), with emphasis on frontal (AF3, AF4) and temporal (T7, T8) asymmetries. These spectral features were computed using Fast Fourier Transform (FFT) and normalized across subjects to reduce inter-individual variability. Frequency band filters are used to reduce artifacts that are occur due to movements and electrode displacements. The next step is to extract features after preprocessing and noise reduction. Finding information that accurately captures the subject's emotional state is the main objective of feature extraction. Statistical analysis is used for feature extraction, shown in Table (1-5). Reducing the quantity of data processing needed to efficiently achieve the best results is the aim of feature selection. We chose five sequences for the feature selection step, and we gathered data from each subject in a separate sequence. We took data while the subjects were at rest, we played music and posed illogical questions to get data on memory recall, and we gave them math's problems to do to get data on attentiveness. We employed a linear regression model for emotion analysis in the categorization process.

3 Data representation

Table 1: Statistic values in rest position

Brain Lobes	Average value	Min. value	Max. value	Median value	Stdev. (s) value	Stdev. (p) value
AF3	4225.2	4199.7	4250.6	4225.2	35.9	25.4
AF4	4209.7	4189.9	4229.5	4209.7	28	19.8
T7	4312.6	4331.9	4293.2	4312.6	27.4	19.4
T8	4167.1	4161.3	4172.9	4167.1	8.2	5.8
PZ	4057.4	4052.9	4061.8	4057.4	6.3	4.4

Table 2: Statistic values in listening song position

Brain Lobes	Average value	Min. value	Max. value	Median value	Stdev. (s) value	Stdev. (p) value
AF3	4241.5	3614.1	5009.9	4239.5	106.5	106.5
AF4	4234.9	3686.4	4780.1	4233.5	78.5	78.5
T7	4288	38880.3	4527.9	4288.7	48.3	48.3
T8	4161.9	3709.7	4479.6	4161.2	56.9	56.9
PZ	4093.1	3631.4	4350.8	4094.2	50.6	50.6

Table 3: Statistic values in random question-answer session

Brain Lobes	Average value	Min. value	Max. value	Median value	Stdev. (s) value	Stdev. (p) value
AF3	4249.6	4193.5	4305.6	4249.6	79.3	56.1
AF4	4299.9	4190	4409.7	4299.9	155.3	109.9
T7	4340.6	4386.9	4394.2	4340.6	75.9	53.7
T8	4206.9	4197.3	4216.4	4206.9	23	9.6
PZ	4127.4	4106.4	4148.5	4127.4	29.7	21

Table 4: Statistic values in math solving position

Brain Lobes	Average value	Min. value	Max. value	Median value	Stdev. (s) value	Stdev. (p) value
AF3	4190.4	4096	4284.9	4190.4	133.5	94.4
AF4	4170.6	4085.8	4255.5	4170.6	120	84.9
T7	4222.2	4161.5	4282.9	4222.2	85.8	60.7
T8	4084.1	4036.8	4131.4	4084.1	66.9	47.3
PZ	4032.5	3975.1	4089.9	4032.5	81.1	57.3

We used a range of statistical measures, including mean, median, average, maximum, minimum, and standard deviation, to analyze brain signal data collected while the subject was at different position. This enabled us to accurately describe the dynamics of the signals in key regions of the brain, including the AF3, AF4, T7, T8, and PZ lobes. Following data collection, the raw EEG signals underwent preprocessing steps, including filtering and artifact removal. Relevant features were then extracted from each lobe to quantify their activity. To find the average intensity of the signal in each lobe, the mean, or average, was calculated. This provided a measure of central tendency that was sensitive to extreme values. Simultaneously, the median was utilized as an effective replacement for the mean, particularly beneficial in situations where high values can distort the perception of central tendency. The term "average" was used to refer to the overall signal distribution and was employed interchangeably with the mean. To determine the maximum and minimum lowest levels of signal intensity—a critical step in locating possible outliers with clinical or scientific significance—maximum and minimum values were computed. Lastly, the standard deviation was calculated to measure the data's dispersion around the mean and offer insights into the stability and consistency of each lobe's brain activity. Together, these extensive statistical measurements allowed for a more sophisticated understanding of the variability, fundamental patterns, and range of signal intensities of regional brain dynamics. The deep learning models offer higher accuracy in some cases, they often lack interpretability and require extensive training data, GPU support, and hyperparameter tuning so we have used linear regression model. The statistical outcomes presented in Tables 1–4 reveal meaningful distinctions in EEG signal patterns corresponding to varying emotional and cognitive states. For instance, increased activation in the AF3 and AF4 regions during task-induced cognitive load aligns with heightened frontal theta and alpha desynchronization, a well-documented neural signature of working memory and attention processes. Conversely, variations in T7 and T8 activity

during emotion-eliciting stimuli—particularly in the theta and low-beta bands—correspond to known lateralized emotional processing, with heightened right temporal activation associated with negative affect.

4 Mathematical statement

4.1 Equations

$$\blacksquare \mathbf{Yi} = (\boldsymbol{\beta 0} + \boldsymbol{\beta 1}.\mathbf{Xi1} + \boldsymbol{\beta 2}.\mathbf{Xi2} + \ldots\ldots + \boldsymbol{\beta k}.\mathbf{Xik}) + (\boldsymbol{\varepsilon i}) \quad (1)$$

From the equation (1),

Y_i = Outcome or characteristic to predict a cognitive state for the i^{th} observation.

$X_{i1}, X_{i2}, \ldots\ldots, X_{ik}$ = The features extracted from the brain signal data for the i^{th} observation, power in different frequency bands, coherence between brain regions.

β_0 = the y-intercept or constant term. In our result the value of y-intercept is -1.69718E9 and slope 1 for AF3, AF4, T7, T8, and PZ in all sequence.

$\beta_1, \beta_2, \ldots\ldots, \beta_k$ = The coefficients associated with each feature. They represent the change on the predicted outcome for a one-unit change in the corresponding feature.

ε_i = The error term for the i^{th} observation, representing the difference between the observed and predicted values. ε_i value in rest position is 32560, when subject listening a song that position the ε_i value is 27392, in random or frequent question answer sequence ε_i value is 49740 and, in the math, solving position the ε_i value is 26239.

$$\text{Cognitive State}_i = \beta_0 + \beta_1 \ldots\ldots\ldots\ldots (2)$$

$$\text{Power in Theta Band}_i + \beta_2 \ldots\ldots\ldots\ldots (3)$$

$$\text{Coherence between Frontal, Temporal and Parietal Lobes}_i + \varepsilon_i$$

In this case,

The equation (2) that is Cognitive State_i is measured based on cognitive performance or a categorical variable that is representing the different cognitive states. The equation (3) Power in Theta Band_i is a feature representing the power in the theta frequency band extracted from the brain signal.

Coherence between Frontal, Temporal and Parietal Lobes_i is another feature representing the coherence between brain regions β_0, β_1, β_2 are the coefficients to be estimated through the regression analysis.

5 Results

The feelings Bouazizi, [4] are essential to daily life and have a big impact on how people connect with one another, deeply influencing them. The main novelty of the Berlin Brain-Computer Interface Blankertz, [5] is its non-invasive EEG-based BCI system, which uses advanced machine learning techniques to automatically adjust to each user's distinct brain patterns without the need for any prior training. Classification algorithms are play important role to identified different disease Li, Dingkun, [18] and for various application we can used classification.

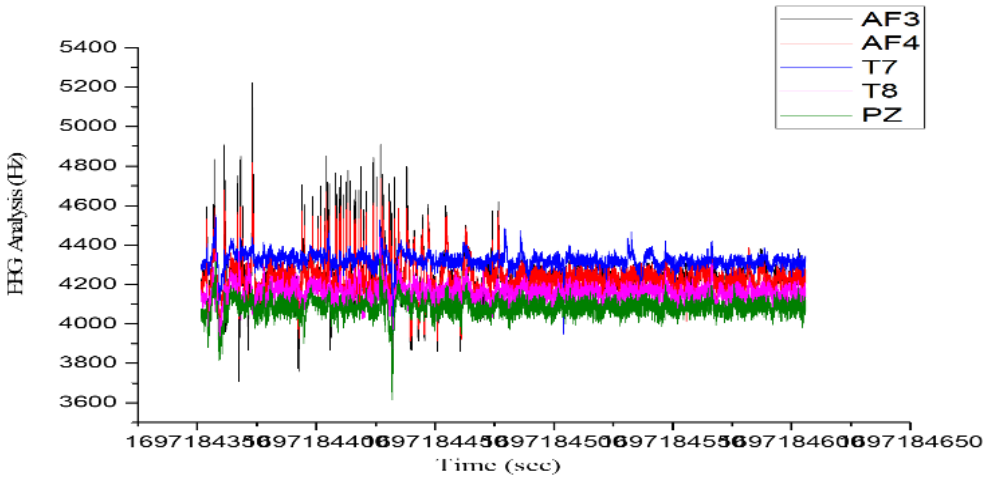
5.1 Dataset description

Table 5: Collecting EEG data using an emotiv five channel device

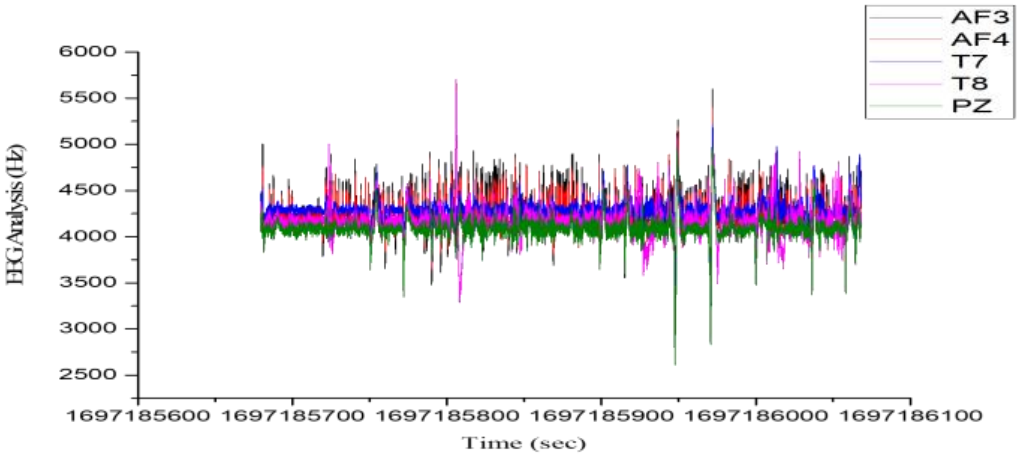
Subject Description	Sequence	AF3 (μV)	AF4 (μV)	T7 (μV)	T8 (μV)	PZ (μV)
Male Age: 30	Rest	4199.7	4189.8	4293.2	4161.3	4052.9
	Listening song	4578.6	4448.9	4285.6	4156	4099.4
	Random question-answer	4193.5	4190	4286.9	4216.4	4106.4
	Maths solve	4096	4085.7	4161.5	4036.8	3975.1
Female Age: 26	Rest	4242.8	4305.2	4382.9	4202.4	3945.6
	Listening song	4300.1	4354.6	4536.9	4286.3	3960.1
	Random question-answer	4200.9	4312.7	4434.7	4266.5	3829.2
	Maths solve	4025	4099.8	4381.9	3741.8	3904.5
Male Age: 20	Rest	4251.5	4858.2	4881.2	4806.6	4121.6
	Listening song	4290.7	5175.5	5452.3	5103.5	4224.1
	Random question-answer	4210.8	4250.6	4330.5	4196.3	4168.5
	Maths solve	4117.4	4257.3	4051.2	3948.5	4079.5
Female Age: 20	Rest	4219.7	4077.5	4603.9	4065.6	4307.5
	Listening song	4225.3	4141.3	4646.2	4097.9	4252
	Random question-answer	4248.9	4601.4	4891.2	5362.2	3808.1
	Maths solve	4206.7	4242.1	4772.9	4171.7	4121.2

An Emotiv 5-channel device has been used to collect EEG data from a group of sixteen people, both male and female, ages ranging from twenty to thirty years. Microvolts (μV) serve as the unit of measurement for the electrical activity from significant brain lobes such as AF3, AF4, T7, T8, and PZ in the dataset. The dataset includes a vast amount of data, with more than 120 data points collected per second from each brain lobe. Real-time data collection allowed for the immediate measurement of brain activity responses. The dataset's subjects are a mixture of our institute's faculty and students, providing a varied picture of brain activity responses across various demographic characteristics. These individual EEG data give insightful information about brain activity and functioning, which advances our knowledge of neural dynamics and cognitive processes. The tables have been updated with concise footnotes and annotations where necessary. To strengthen their interpretability, accompanying textual analyses have been added to the results and discussion sections, highlighting key observations—for instance, performance variation across subjects or channels, and the relationship between classifier accuracy and EEG band power. These improvements aim to make the visual data more self-explanatory while aligning them more closely with +the study's core objectives.

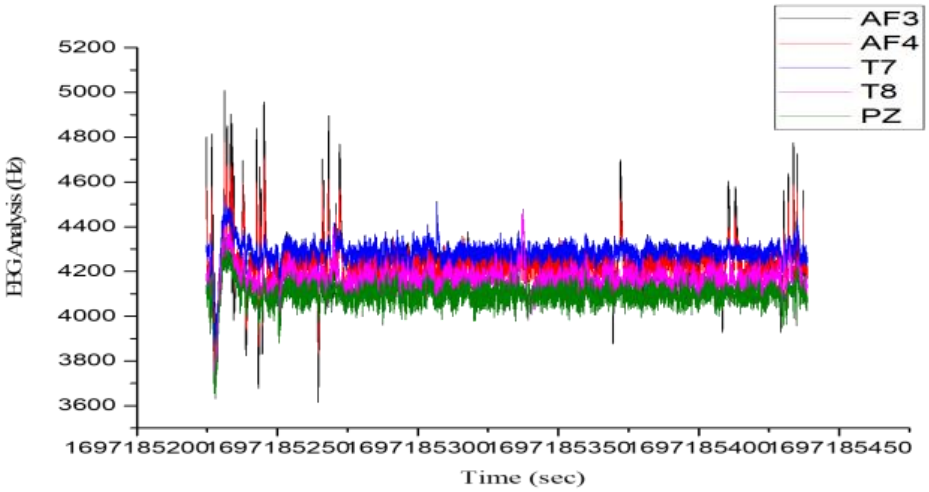
5.2 Time series analysis of sensor usage



(a)



(b)



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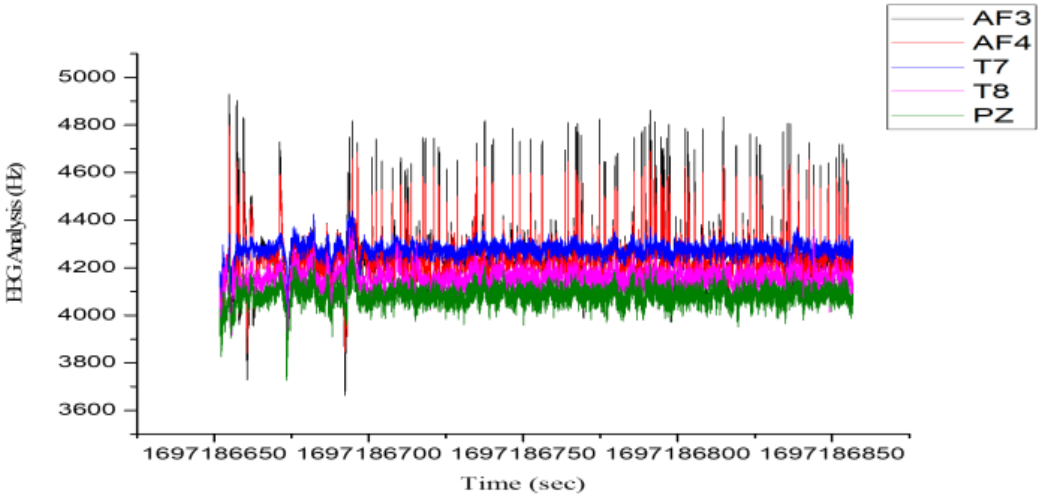
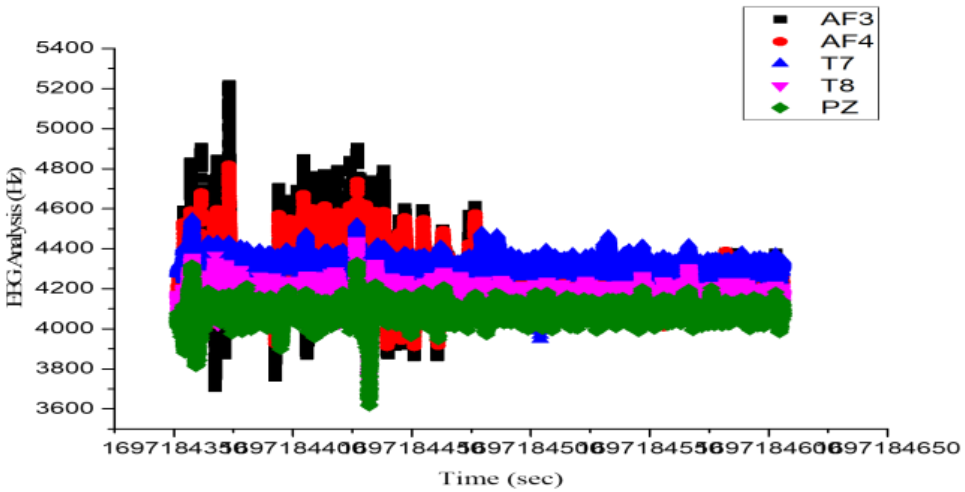
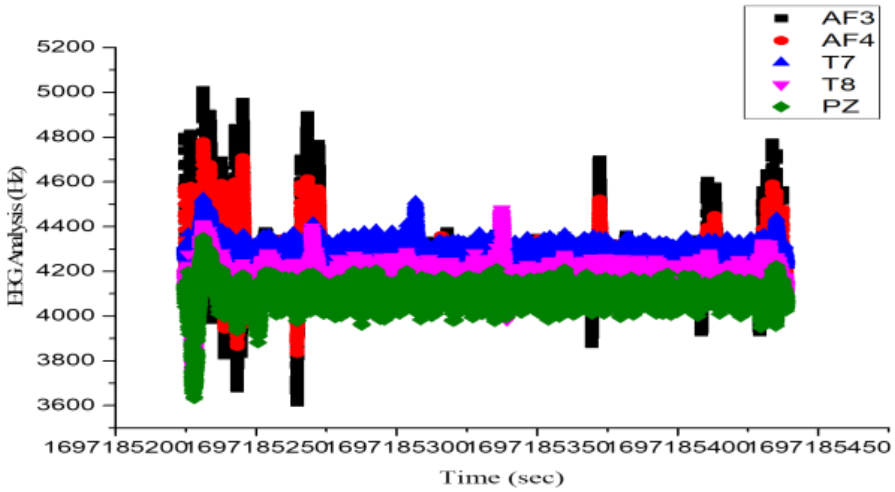


(d)

Figure 2: Line Plot of different lobes. (a) When subject was in resting position, (b) when subject listening the song, (c) when we asked the random question to the subject and answered frequently, (d) when the subject was solving the mathematical problems.



(a)



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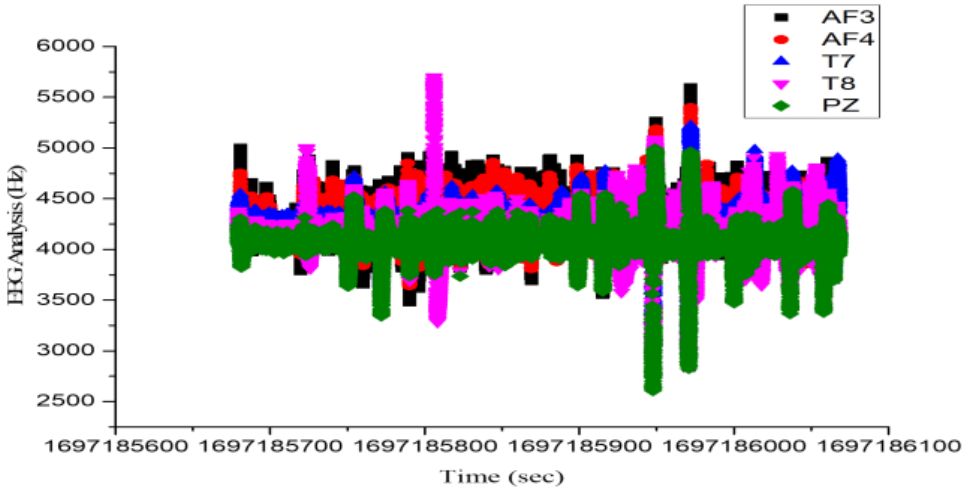

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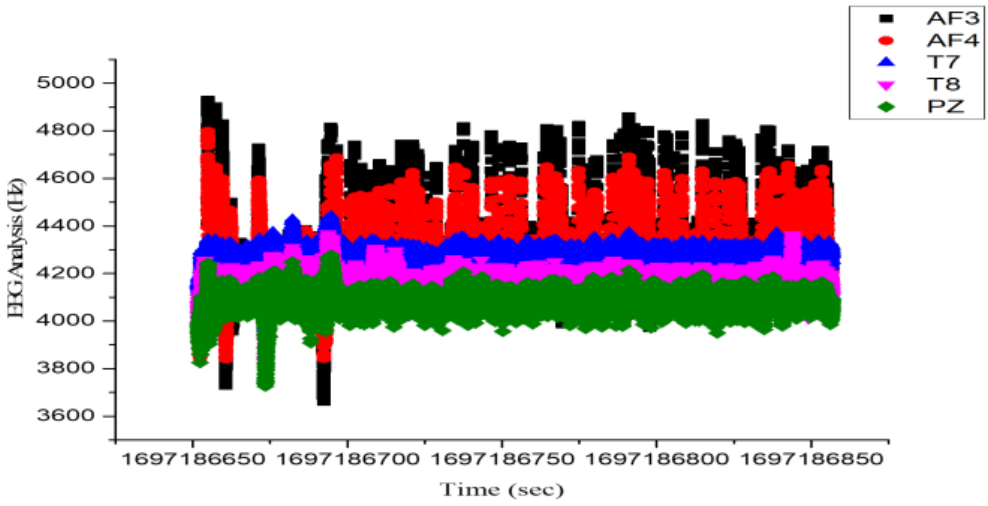

(d)

Figure 3: Scatter Plot of different lobes. (a) When subject was in resting position, (b) when subject listening the song, (c) when we asked the random question to the subject and answered frequently, (d) when the subject was solving the mathematical problems.

Time series analysis is crucial for understanding EEG data, revealing dynamic changes in brain activity over time, particularly for studying event-related potentials (ERPs), frequency components, and cognitive process patterns. Time series methods facilitate in recognizing abnormal EEG patterns linked to neurological disorders, aiding in the development of pattern recognition algorithms and understanding brain dynamic connectivity. They also play a crucial role in brain-computer interface (BCI) development, enabling real-time interpretation of EEG signals for applications like control interfaces and cognitive function studies. Figure 2(a) and Figure 3(a) are showing the graphical representation of the EEG signal amplitude over time during the resting period. During the rest sequence, the EEG signals display relatively low amplitude and stable patterns. We get low standard deviation values in different lobes such as F3, F4, T7 T8 and PZ (from Table1: 25.4, 19.8, 19.4, 5.8, 4.4) comparing to other sequences, indicating a relaxed and calm state of the subject. We observed slight fluctuations in the EEG signal, reflecting normal brain activity during rest. Figure 2(b) and Figure 3(b) are the graphical representation plots of EEG signal amplitude over time while the subject listens to music. During music listening, the EEG signals are exhibit dynamic changes reflecting auditory processing and emotional responses. Look for fluctuations in EEG signal amplitude synchronized with the rhythm and beat of the music. Additionally, observe changes in frequency bands associated with attention or arousal levels. Figure 2(c) and Figure 3(c) are the plots, showing the amplitude of the EEG signal across time during the question-answer interaction. Figures 2 and 3 have been revised to enhance clarity and visual comprehension. Each subfigure is now distinctly labeled (e.g., Figure 2a, Figure 2b) with consistent notation, and all axes include appropriate units (e.g., μV for EEG amplitude, Hz for frequency components) along with descriptive legends. The figure captions have been expanded to explain the observed patterns and trends, such as differential power distributions across emotional and cognitive tasks. During the question-answer sequence, we observed variabilities in EEG signal patterns corresponding to cognitive engagement and response generation. Look for peaks or changes in EEG signal amplitude coinciding with the presentation of questions and subjects' responses. Increased activity in frontal and prefrontal regions is indicating cognitive processing and decision-making. In the math problem-solving task, the EEG signal amplitude is plotted visually in Figure 2(d) and Figure 3(d). We saw alterations in EEG signal patterns during arithmetic problem-solving that were indicative of cognitive effort and problem-solving techniques. Examine the EEG signal for oscillations in both amplitude and frequency bands, particularly in regions linked to executive functioning (prefrontal cortex, AF3, AF4). Higher theta and gamma activity is a sign of engaged working memory and mental performance. When describing the graphical plots, be sure to discuss any notable trends, patterns, or differences observed across different sequences. Consider comparing the EEG signals between sequences and discussing how they reflect the cognitive and emotional states of the subjects during each task.

6 Conclusion

In conclusion, this study investigated the use of EEG data analysis and linear regression classification to explore human cognitive and emotional responses across different sequences of stimuli presentation. Through the collection and processing of EEG data during rest, music listening, question-answer sessions, and math problem-solving tasks, we gained insights into the dynamic nature of neural activity associated with various cognitive and emotional processes. The graphical representations of EEG signals revealed distinct patterns and trends during each sequence, reflecting the subjects' cognitive engagement, emotional responses, and task-specific neural processing. From the observed patterns, we identified significant fluctuations in EEG signal amplitude, frequency bands, and connectivity measures, providing valuable information about the underlying neural mechanisms involved in each task. Furthermore, the application of linear regression classification allowed us to establish predictive models for identifying cognitive and emotional states based on EEG features. By leveraging machine learning techniques, we demonstrated the feasibility of accurately classifying cognitive and emotional states across different individuals, paving the way for inter-subject independent emotion recognition and mental state monitoring. Overall, this research contributes to the growing body of knowledge in EEG-based cognitive and affective neuroscience, highlighting the potential of EEG data analysis for understanding human cognition, emotion, and mental well-being. The findings underscore the importance of integrating neuro imaging techniques with advanced analytical methods to unravel the complexities of the human brain and its responses to external stimuli.

Moving forward, future research endeavors may focus on refining and validating the predictive models developed in this study, exploring additional features and modalities for emotion recognition, and investigating the practical applications of EEG-based cognitive and emotional assessment in real-world settings. By continuing to advance our understanding of the brain-behavior relationship, we can develop innovative solutions for promoting mental health, enhancing human-computer interaction, and fostering well-being in diverse populations. We can use our project as a wearable healthcare device. We can also apply our innovation in IoT Neurotechnology Integration of emotional and cognitive detection. This idea can be used as a portable personalized stress monitoring device.

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Online Detection of Railway Track Irregularities via JADE-Based Blind Source Separation and MEMS Accelerometry

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To address the difficulties in accurately capturing the characteristic changes of track irregularities in real - time and the limited ability to process complex mixed vibration signals, this study proposes an online Detection of Railway Track Irregularities via JADE-Based Blind Source Separation and MEMS Accelerometry. The system consists of a lower computer and an upper computer with ADXL345 three-axis acceleration sensor as the core. Real time track vibration signals are collected through optimized IIC bus protocol, and the blind source separation algorithm based on JADE is executed by STM32F103ZET6 microprocessor. By jointly diagonalizing the mixed vibration signal through a fourth-order cumulative matrix, the track roughness feature components in the mixed vibration signal are effectively decoupled, achieving accurate detection of railway track roughness. The detection results are converted into USB signals through RS-232 serial port and CH340G chip, and uploaded to the upper computer. The upper computer platform visualizes the type, location, and severity of track roughness faults. At the same time, a dual level power management and anti reverse protection are designed to ensure the reliability of the railway environment. To verify system performance, 8 monitoring points were set up on a 30-kilometer actual operating line, and multiple sets of vibration data were continuously collected at a sampling frequency of 10240 Hz at train speeds of 60-80 km/h. Establish the ground truth value of faults through high-precision track inspection vehicles and total station measurements, and compare it with HybridGAN method and data mining method. The experimental results show that this system can achieve an average positioning error of $\leqslant$ 1.8 mm, a fault type recognition accuracy of $\geqslant$ 96%, and an average detection time of $\leqslant$ 90 ms at a speed of 60 km/h. At a speed of 80 km/h, it still maintains an error of $\leqslant$ 2.2 mm and a recognition accuracy of $\geqslant$ 90%, with better performance than the two comparison methods. The upper computer of the system has the function of visualizing fault types, locations, and degrees, and integrates dual level power management and anti reverse protection, which is suitable for complex railway environments. This system provides a feasible solution for real-time monitoring of track status with high accuracy and low latency.

Povzetek: Študija predstavi sistem za sprotno zaznavanje nepravilnosti železniške proge z MEMS pospeškometrom in algoritmom slepe ločitve signalov JADE, ki omogoča zelo natančno in hitro odkrivanje tipa, lokacije in resnosti napak na progi.

1 Introduction

Railways, as an important infrastructure and mass transportation tool, have many advantages such as high capacity, low cost, high efficiency, and environmental friendliness, undertaking a large volume of passenger and freight transportation tasks [1]. However, with the rapid development of railway transportation, the increasing train speeds and load capacities pose more severe challenges to the track. Track irregularities have gradually become one of the key factors affecting the safety, comfort, and efficiency of railway transportation. Track irregularities refer to deviations in the geometric shape, dimensions, and spatial position of the track relative to its normal state. These deviations can cause intense vibrations and shocks during train operation [2], which not only accelerate the wear and damage of the track structure and shorten its service life but also affect the smoothness and safety of train operation. In severe cases, they may even lead to derailments and other major safety accidents. Therefore, real-time and accurate detection of railway track irregularities and the timely identification and handling of potential faults [3] are of great significance for ensuring railway transportation safety and improving transportation efficiency.

In order to promptly detect and address track irregularities, ensuring the safety and smoothness of railway transportation, many scholars have long proposed track inspection methods, such as Khasani R R and others who proposed an image quality enhancement method based on HybridGAN for automatic railway track defect recognition [4]. By collecting a large number of dynamically acquired railway inspection images, combining ESRGAN (used to improve image resolution) and DeblurGANv2 (used to reduce image blurriness), a HybridGAN model is constructed. The original dataset is used to train HybridGAN, enabling it to learn how to convert low-quality images into high-resolution, low-blurriness images, thereby clarifying the location and type of track faults in the images. However, this method only detects track faults from the perspective of image quality enhancement, neglecting other important information such as track vibrations. Stewart E and others proposed a track fault detection method based on Variational Mode Decomposition (VMD) [5]. This method decomposes the collected raw vibration signals using the VMD algorithm to obtain multiple intrinsic mode functions (IMFs) with different frequency characteristics. Based on each IMF obtained from the decomposition, the energy value is calculated to extract energy features related to track conditions. The signals to be tested undergo the same decomposition and feature extraction process before being input into a trained classifier to determine whether there is a fault and its type. However, this method only relies on energy features for track fault judgment, with low feature dimensionality, which may not comprehensively cover all information about track irregularities. Hany O and others proposed a data mining-based track fault detection method [6], combining Logical Data Analysis (LAD) with Ant Colony Optimization (ACO). First, ACO's search capability is used to explore key feature combinations related to high-impact loads within vast amounts of railway track historical data. Then, LAD performs logical analysis of these feature combinations to identify patterns that clearly distinguish high-impact loads from normal loads. Based on these patterns, a classification model is built to classify unknown observation data, achieving track fault detection. However, this method requires mining feature patterns from large datasets; if the data contains noise, missing values, or errors, it can affect the search results of ACO and the logical analysis of LAD, leading to an inaccurate classification model that cannot effectively detect track faults. Koohmishi M and others proposed a method that integrates Ground Penetrating Radar (GPR) and Synthetic Aperture Radar Interferometry (InSAR) technology, introducing machine learning models to achieve efficient track fault detection [7]. InSAR is used to obtain surface deformation data of the track area, reflecting changes in overall structural stability, while GPR scans the underlying structure of the track to acquire underground defect information. After preprocessing the collected data, features related to track faults are extracted separately, and the two sets of features are fused to form a more comprehensive feature vector. A machine learning model is then trained and used for classification to determine whether there is a fault and its type. However, the InSAR technology's accuracy is significantly affected by atmospheric conditions, satellite orbit errors, and other factors, which may lead to inaccurate fault detection results.

There is a close intrinsic relationship between vibration mechanism characteristics and track irregularities. When a train runs on an uneven track, the interaction forces between the wheel and rail change, causing vibrations in the vehicle and track structure [8]. Different types and degrees of track irregularities can induce specific vibration responses in the vehicle and track, which contain rich information about track irregularities [9]. Therefore, this article proposes online detection of railway track irregularities via jade-based blind source separation and MEMS accelerometry, with vibration signals generated by the interaction between train and track as the research object, is essential. By utilizing advanced vibration acceleration sensor technology and data analysis algorithms, real-time collection, processing, and analysis of track vibration signals can be performed to extract features related to track irregularities, achieving accurate detection and localization of track faults. This provides a new method for track condition monitoring for railway transportation departments, helping to improve the targeting and timeliness of track maintenance, reduce maintenance costs, and ensure the safe and efficient operation of railways.

One of the core objectives of this study is to verify a specific hypothesis: the blind source separation algorithm based on JADE can more effectively separate the feature components related to track roughness from complex wheel rail mixed vibration signals than traditional BSS signal processing methods, thereby achieving high-precision and low latency fault detection. Therefore, at the algorithmic level, this study specifically chose JADE because of its fourth-order cumulative quantity (high-order statistic) characteristics, which theoretically can better handle non-Gaussian distribution vibration source signals, and has faster convergence speed and higher separation accuracy than methods that rely only on second-order statistics or stochastic gradient optimization (such as FastICA). This is crucial for meeting the real-time and accuracy requirements of online detection. At the hardware level, the selection of sensor ADXL345 is based on its cost-effectiveness, compact packaging (easy to install and protect), and sufficient performance indicators: its ± 16g measurement range can cover the magnitude of track impact vibration, its 3.9mg/LSB high sensitivity can distinguish small roughness features, and its digital output and low power consumption characteristics greatly simplify the design of the lower computer system, making it very suitable for large-scale and distributed deployment along railways.

2 Online fault detection system for railway track irregularities

2.1 System design

During the operation of a train, the vibration signals generated by the wheel-rail interaction contain information about the geometric state of the track [10], such as vertical irregularities, alignment irregularities, and horizontal irregularities. Therefore, an online fault detection system for railway track irregularities based on vibration mechanism characteristics is designed. The system consists of a lower-computer system and an upper-computer node, as shown in Figure 1.

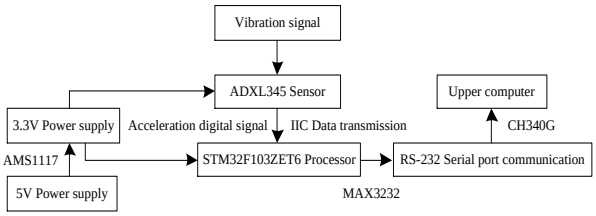


Figure 1: Schematic diagram of the system design.

Among them, the lower-computer system includes ADXL345 vibration acceleration sensor data acquisition, IIC real-time data transmission, microprocessor STM32F103ZET6, RS-232 wired communication, and a power supply module. The functions of each component of the system and the overall working process are as follows:

1) The ADXL345 vibration acceleration sensor can accurately collect the vibration signals of the track and digitize the collected analog vibration signals.

2) The digitized vibration signals from the ADXL345 are transmitted to the microprocessor STM32F103ZET6 in real-time through the IIC bus.

3) After receiving the vibration signals, the microprocessor STM32F103ZET6 processes and analyzes the vibration signals using a blind source separation method based on JADE (Joint Approximate Diagonalization of Eigenmatrices). It effectively separates the vibration signal components related to track irregularities, extracts useful feature information, and realizes the fault detection of railway track irregularities.

4) With the help of RS-232 serial communication and related conversion chips, the fault detection result data of railway track irregularities is sent to the upper-computer for display. Considering the limited number of computer serial ports, the system uses the RS-232 to USB chip CH340G for data transmission, converting RS-232 signals to USB signals for connection to the computer, so that the upper-computer can receive the fault detection result data.

5) After receiving the fault detection result data, the upper-computer displays it in an intuitive way, including information such as the type, position, and degree of track irregularities. This enables operators to timely understand the operating status of the track, detect potential fault hazards, and provide a decision-making basis for the maintenance and inspection of railway tracks.

6) The power supply hardware circuit includes two voltage regulator chips: the MP2359 DC-DC chip and the AMS1117 level conversion chip. DC_IN is used for external DC power input, which is converted into a 5V DC power output through the MP2359 DC-DC chip. By utilizing a reverse-connection protection diode, the circuit is safeguarded from damage in case of polarity confusion in the external DC power supply. The AMS1117 chip serves as a 5V-to-3.3V level conversion chip, providing 3.3V power support to the hardware circuit.

To expand the monitoring range and improve system performance, multiple lower-computer nodes work cooperatively. Each lower-computer node is responsible for collecting track vibration signals in a specific area, as well as processing and analyzing them. Multiple lower-computer nodes can share data and work cooperatively to jointly complete the fault detection task of railway track irregularities.

2.2 Data acquisition module design

In the system's data acquisition module, a MEMS (Micro-Electro-Mechanical Systems) based ADXL345 vibration acceleration sensor is selected as the core component. It is installed near the train wheelsets and key parts of the track using a secure attachment method to ensure accurate collection of effective vibration signals that reflect the track condition [11]. The ADXL345 vibration acceleration sensor is a three-axis digital output accelerometer composed of a differential capacitor and a surface-micromachined polysilicon structure. Under external acceleration, the polysilicon mechanism produces an offset that changes the capacitance value. This design is based on railway track engineering applications, which require strict sensitivity. The ADXL345 sensor has a maximum sensitivity of 3.9 mg/LSB and can measure tilt angles as small as 1.0°, fully meeting railway track engineering requirements. To simplify the design, the digital output accelerometer facilitates vibration signal data processing and analysis. Its power consumption is only 40~145 uA, and standby mode consumes only 0.1 uA, significantly reducing the overall energy consumption of the system, making the design more user-friendly and better suited for practical railway engineering applications.

In addition to selecting appropriate sensors, the installation position of the track vibration signal acquisition system is also crucial. The ADXL345 vibration acceleration sensor has a wide frequency response range, high reliability, and sensitivity. Incorrect installation can affect the results of railway track irregularity fault detection and may also cause hardware damage to the ADXL345 vibration acceleration sensor. Therefore, the installation location mainly considers the sensor's working environment and the vibration state of the measured track section. Generally, the following two principles should be followed:

(1) Positions with high stiffness and small structural damping should be chosen as the measurement points on the track.

(2) The measurement points on the track should be as close as possible to the vibration source.

The functional block diagram of the ADXL345 vibration acceleration sensor is shown in Figure 2. Its internal structure includes a three-axis sensor (3-AXIS SENSOR) responsible for detecting acceleration along the X, Y, and Z axes and converting it into analog signals. After preliminary processing by the sensing electronics circuit (SENSE ELECTRONICS CS), the signals are converted into digital signals by an analog-to-digital converter (ADC) and then denoised by a digital filter (DIGITAL FILTER). The processed data are stored in a 32-LEVEL FIFO buffer to reduce the load on the external processor. The serial input/output interface (SERIAL I/O) supports IIC and SPI protocols, facilitating communication with external devices. The power management (POWER MANAGEMENT NT) module supplies power to the chip, while the control and interrupt logic (CONTROL AND INTERRUPT LOGIC) module handles chip control and interrupt management.

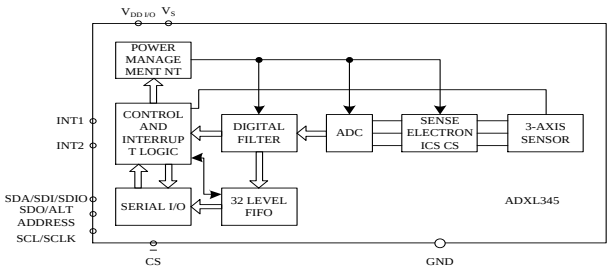


Figure 2: Functional block diagram of ADXL345.

In terms of operation, the ADXL345 vibration acceleration sensor sequentially completes the detection of railway track vibration signals, analog processing, analog-to-digital conversion, digital filtering, and data storage. When interacting with external devices, data can be transmitted via the IIC or SPI interface, and external devices can send commands to configure its working modes and other parameters. Interrupt conditions can also be set, and when met, interrupt signals are sent through the INT1 and INT2 pins. Additionally, external devices can perform batch reading of vibration signal data from the FIFO to improve the efficiency of railway track vibration signal acquisition [12].

2.3 Design of the real-time data transmission module

The system's real-time data transmission module is responsible for enabling data communication between the ADXL345 vibration accelerometer sensor and the STM32F103ZET6 microprocessor. Since the ADXL345 vibration accelerometer supports both SPI and IIC communication protocols, and the IIC protocol only requires two wires (data line SDA and clock line SCL) to achieve data transmission between master and slave devices, it significantly reduces the number of I/O ports used compared to the SPI protocol, thereby simplifying system design complexity and reducing costs. Therefore, the IIC communication protocol is adopted in the system's real-time data transmission module.

IIC bus interface structure design is shown in Figure 3, primarily comprising two parts: an internal frequency divider and an IIC bus interface control timing logic module. Typically, the external input clock frequency of an FPGA is relatively high, while IIC bus has specific data transmission rate requirements, with the standard mode operating at 100 kbit/s and the fast mode at 400 kbit/s. The internal frequency divider's function is to divide the high-frequency external clock signal, outputting a data transmission rate compliant with IIC bus requirements to meet the timing requirements for IIC bus data transmission. IIC bus interface control timing logic module serves as the control core of IIC bus interface module, generating all timing control logic for IIC bus data transmission, such as the generation of start and stop signals, addressing of the slave device (ADXL345), and the transmission and reception of data on the bus [13].

IIC bus port mapping and functions are shown in Table 1.

IIC bus interface module supports two basic data transmission modes: single-byte data write mode and single-byte data read mode. Since the module provides corresponding status information before, during, and after read/write operations (Start, Inter_Addr, Done, AckCointer), the host (microprocessor) can determine whether to perform the next byte data read/write operation based on this information, thereby enabling continuous read/write operations on the internal storage units of the slave device (ADXL345). This ultimately achieves four IIC bus data transmission operation modes: single-byte data write, single-byte data read, multi-byte data continuous write, and multi-byte data continuous read.

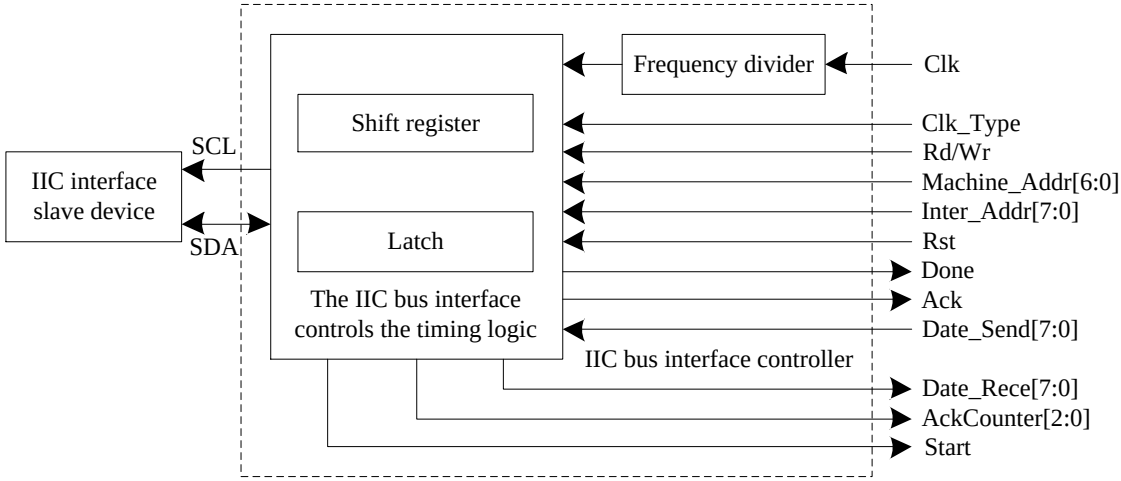


Figure 3: IIC bus interface structure.

Table 1: IIC bus port mapping and functions

Port	Function Description
Clk	External input clock of FPGA
Clk_Type	The SCL output clock mode: 0 is the standard mode and 1 is the fast mode
Rd/Wr	Read and write control signals: 1 represents the master reading data from the slave, and 0 represents the master writing data to the slave
Machine_Addr[6:0]	The unique address identifier from the machine part
Inter_Addr[7:0]	The address of the storage unit from which the machine part is to be operated
SCL	IIC bus interface clock line
Start	The start signal for the read and write operations of the interface module is indicated, and the falling edge is valid
Rst	The reset signal of the bus interface module is 0, which is valid
Done	When the host completes a read/write operation on the slave, the signal shows a falling edge; otherwise, it is at a high level
Ack	The response signal from the slave to the master
AckCounter[2:0]	The counter for the host to receive the response signal from the slave
SDA	IIC bus interface data cable
Date_Send[7:0]	The byte data sent by the host to the slave
Date_Received[7:0]	The host receives the byte data from the slave

2.4 Wired communication module design

In the system's data acquisition module, the results of fault detection for uneven railway tracks are transmitted to the upper computer display using RS-232 serial communication and related conversion chips [14]. The interface pins of RS-232 are defined as shown in Table 2.

Table 2: Definition of RS-232 interface.

Pin	Interface name	Function Definition
1	CD	Carrier detective
2	RXD	Receive data
3	TXD	Send data
4	DTR	Data terminal ready
5	GND	Grounding
6	DSR	Data ready
7	RTS	Request to send
8	CTS	Clear the send
9	RI	Ringing indication

The commonly used configuration for RS-232 communication is eight data bits, no parity bit, and one stop bit. As shown in Figure 4, a complete byte includes a start bit, 8 data bits, and a stop bit. The transmission module requires eleven baud rate clock pulses to complete the transmission of one data set, while the RS-232 receiver samples at the midpoint of each data bit.

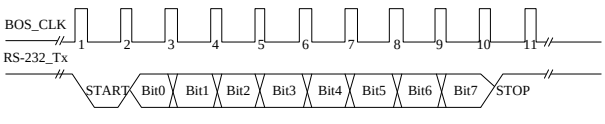
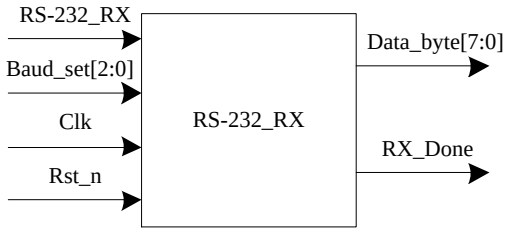
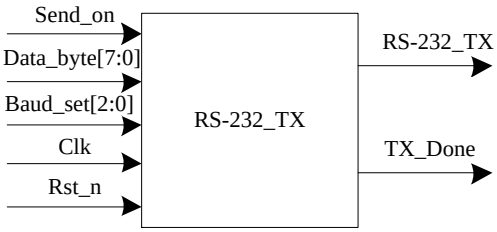


Figure 4: Data transmission timing logic of the RS-232 interface.

The interface receive and transmit module design is shown in Figure 5.



(a) Receiving module



(b) Transmitting module

Figure 5: Design of RS-232 interface module.

When sending data, first encapsulate the fault detection results of uneven tracks, and then send them byte by byte according to the RS-232 protocol. The sending module generates a clock signal to control the speed according to the preset baud rate. After STM32F103ZET6 is ready, it sends the command. The module receives the command and sends it, monitoring the status in real time. If there is an error, it will provide feedback. When receiving, the RS-232 terminal samples at the midpoint of the data, parses it in the same format, and cooperates with the microprocessor to detect the starting identifier before receiving. During the process, it provides feedback on the receiving status.

After transmitting the fault data via wired communication, the microcontroller processes the signals for fault detection using the JADE algorithm.

2.5 Railway irregularity fault detection based on the jade algorithm

The microcontroller plays a central role in the entire railway track unevenness detection system [15], serving as the core for data processing, analysis, command transmission, and other key operations. The STM32F103ZET6 is selected as the main chip for the railway track unevenness detection system. When the microcontroller STM32F103ZET6 receives vibration signals from the ADXL345, it processes and analyzes these signals using a JADE-based blind source separation method to achieve fault detection of railway track unevenness.

To achieve real-time operation of JADE algorithm on STM32F103ZET6 microprocessor, the following key optimization measures are taken in this study:

(1) Simplified computational load: Using frame processing mode to segment continuous signals for processing. At the same time, channel fusion is used to reduce the dimensionality of three-axis sensor data, reducing the observation signal from 3D to 2D and significantly reducing the complexity of subsequent matrix operations.

(2) Algorithm and computational optimization: Due to the lack of FPU in the Cortex-M3 core, all floating-point operations are converted to fixed-point operations and accelerated using the CMSIS-DSP library. For this purpose, a lookup table is used instead of real-time computation for complex functions. Set a maximum iteration limit for the JAD iteration process to ensure controllable worst-case execution time.

(3) Resource management and performance: Adopting static memory allocation to avoid the uncertainty of dynamic allocation, ensuring that the total memory usage is controlled within 20 KB. According to actual testing, at a frequency of 72 MHz, the average processing time for a single frame of data is about 65 ms, which meets the real-time requirement of the system $\leqslant$ 90 ms.

Simple spectral analysis alone cannot separate individual vibration sources [16], and the processed spectrum is the result of a mixture of multiple vibration signals. When there are strong harmonic components at certain frequencies, they can affect nearby harmonic components in the power spectrum, leading to spectral aliasing. Blind source separation algorithms can separate multiple source vibration signals for individual analysis, reduce mutual interference among different source signals, improve the accuracy of vibration signal separation, and lay the foundation for the separation and extraction of fault information. To some extent, they also reduce the difficulty of extracting track fault features. Additionally, since each track segment has the same length, when faults occur in the track region, the resulting fault vibrations are periodic, which is distinctly different from general aperiodic vibration signals. Blind source separation algorithms are particularly suitable for separating periodic fault vibration signals [17].

The mathematical model of the blind source separation algorithm can be expressed as:

$$x(t) = As(t) + z(t) \tag{1}$$

Where, A represents the mixing matrix, describing the mixing process when multiple source vibration signals are input into the system; $x(t)$ indicates the M -dimensional observation vector obtained from M ADXL345 vibration accelerometers, i.e., the mixed vibration signals:

$$x(t) = [x_1(t), x_2(t), ..., x_m(t)]^T \tag{2}$$

Where, $s(t)$ represents N independent source track vibration signals, which need to be separated and identified:

$$s(t) = [s_1(t), s_2(t), ..., s_n(t)]^T \tag{3}$$

Where, $z(t)$ represents M -dimensional noise signal, i.e.:

$$z(t) = [z_1(t), z_2(t), ..., z_m(t)]^T \tag{4}$$

When using the blind source separation method to analyze the track vibration signal problem, it can be described as follows: In a multi - input multi - output train wheel - rail coupling system, for the collected

vibration signal $x(t)$, an inverse system is sought to reconstruct the source vibration signal $s(t)$ [18]. That is, through the known observation signal $x(t)$, a separation matrix E is found, so that $y = Ex(t) = s(t)$, where y is the estimated source vibration signal after separation. The basic principle of blind source separation lies in the mixing matrix A when multiple source vibration signals are input into the system. The mixed vibration signal is detected by multiple ADXL345 vibration acceleration sensors to obtain the detection signal $x(t)$. Performing blind source separation on the detection signal $x(t)$ is to start from the detection signal, and then find the blind separation matrix E, perform blind separation on the detection signal, and find the track fault information contained in the separation result.

Vibration signals are an important information source for track fault feature recognition [19]. Fault detection is carried out through vibration signals. Since the vibration signal data collected by the ADXL345 vibration acceleration sensor is often a mixture of several signals, using traditional filtering methods will filter out some useful feature information while filtering out noise. The JADE algorithm is an important part of the blind source separation algorithm, also called the feature matrix approximate joint diagonalization blind separation algorithm based on fourth - order cumulants [20]. This algorithm has very high separation performance, and its separation performance has nothing to do with the mixing matrix. It can find the source information signal only by relying on the detection signal when the mixing mode of the input information is not understood and there is little or no prior information. The definition of the fourth - order cumulant matrix is as follows:

$$F_{ij}(B) = \sum_{h=1}^{N}\sum_{l=1}^{N} K_{ijhl}(\hat{x}) b_{hl} \tag{5}$$

Where, B represents an arbitrary $N \times N$ -order matrix; F_{ij} denotes a matrix obtained through a linear transformation in the $N \times N$ space; b_{hl} indicates the element in the h -th row and l -th column of matrix B ; the mixed vibration signal x after whitening processing results in $\hat{x}$; $K_{ijhl}(\hat{x})$ represents a linear combination of the fourth-order accumulated quantities of the four components i , j , h and l .

The product of the whitening matrix Q and the mixing matrix A is defined as matrix O:

$$O = QA \tag{6}$$

Where $O = [o_1, o_2, ..., o_m, o_N]$, $o_m = [o_{m1}, o_{m2}, ..., o_{mN}]^T$, $m = 1, 2, ..., N$.

If the matrix B is chosen to satisfy $B = o_m o_m^T$, then the fourth-order cumulant matrix can be expressed as:

$$F_{ij}(B) = \sum_{q=1}^{N} o_{mh} o_{ml} cum(\hat{x}_i, \hat{x}_j, x_h, x_l) \tag{7}$$

Because the track vibration source signals are independent, when $q = m$, the corresponding cumulants have non-zero values. In this case, the fourth-order cumulant can be expressed as:

$$\begin{aligned} F_{ij}(B) &= \sum_{q=1}^{N} o_{qi} o_{qj} \delta_{mq} \delta_{mq} k_4(s_q) \\ &= o_{mi} o_{mj} k_4(s_m) = b_{ij} k_4(s_m) \end{aligned} \tag{8}$$

At this point, the matrix B is the eigenmatrix of $F(B)$, and the fourth-order cumulant of the source vibration signal is the eigenvalue of the eigenmatrix. Performing eigenvalue decomposition on the matrix, the eigenmatrix corresponds one-to-one with the eigenvalues. Each source vibration signal has a different fourth-order cumulant, and its corresponding eigenmatrix B is also different, which in turn makes o_m different. The mixed matrix A can be represented by the matrix O composed of o_m .

$$A = Q^{-1}QA = Q^{-1}O \tag{9}$$

Performing inverse operation on the mixed matrix A to obtain the separation of source vibration signals, $s' = A^{-1}\hat{x}$, can be achieved when all eigenvalues of the fourth-order cumulant matrix $F(B)$ are distinct. If the eigenvalues are not all different, separation cannot be performed. The JADE algorithm solves this problem. Because $F(B)$ is a symmetric matrix, $B = o_m o_m^T$ is its eigenmatrix, and $F(B)$ can be expressed in the form of $O\Lambda(B)O^T$.

$$\Lambda(B) = diag(k_4(s_1) o_1 B o_1^T, ..., k_4(s_N) o_N B o_N^T) \tag{10}$$

Transform matrix O applied to $F(B)$ to obtain a diagonal matrix, utilizing the diagonalization property to find matrix O . Define an objective function:

$$J_{JADE}(O) = \sum_{i=1}^{K} \left\| diag(O^T F(B_i) O) \right\|^2 \tag{11}$$

Where, $\left\| diag(O^T F(B_i) O) \right\|^2$ represents the sum of squares of the diagonal elements of the diagonal matrix $\Lambda(B)$. This value is invariant during diagonalization. Maximizing the objective function allows us to find the ideal matrix O , thereby enabling the separation of source vibration signals. The estimated separation matrix is $E = O^T Q$, and thus the estimated source signal is $y(t) = Ex(t)$.

In summary, by applying the JADE algorithm to the mixed vibration signals collected by the ADXL345 vibration accelerometer, it is possible to effectively separate each source vibration signal, extract useful fault feature information, and achieve accurate detection of railway track irregularities.

The pseudocode of JADE algorithm is as follows:

```
# Pseudo-code: JADE Integration in Track Vibration Signal Processing
import numpy as np
from scipy import linalg
```

```
# Step 1: Read and preprocess data
raw_signal = read_vibration_data()  # Read raw vibration data from sensor
x_normalized = (raw_signal - np.mean(raw_signal, axis=0)) / np.std(raw_signal, axis=0)  # Normalize

# Step 2: Execute JADE Blind Source Separation
# 2.1 Whiten the normalized observed signal x_normalized
x_whitened, whitening_matrix = whiten(x_normalized)

# 2.2 Compute fourth-order cumulant matrices of the whitened signal
cumulant_matrices = compute_fourth_order_cumulants(x_whitened)

# 2.3 Joint Approximate Diagonalization (JADE Core)
# Find a unitary matrix U that diagonalizes U^T * CumulantMatrix_i * U
U = joint_approximate_diagonalization(cumulant_matrices)

# 2.4 Estimate separating matrix and obtain source signals
separating_matrix = U.T @ whitening_matrix
estimated_sources = separating_matrix @ x_normalized.T  # Separated independent sources

# Step 3: Feature Extraction and Fault Classification (Based on separated sources)
features = extract_features(estimated_sources)  # Extract time-frequency features
fault_type, fault_location = classifier.predict(features)  # Classify for fault diagnosis

# Step 4: Output Results
output_result(fault_type, fault_location, severity)
```

In addition, as mentioned earlier, the core premise of blind source separation algorithm based on JADE is to assume that the source signals are statistically independent of each other. In the context of railway track vibration applications, this assumption has its physical validity. The complex vibration signals generated by the wheel rail system during train operation can be regarded as a linear mixture of multiple physically independent vibration sources. These potential independent sources include:

(1) Periodic vibrations induced by geometric irregularities such as uneven height and orientation of the track.

(2) Transient impact vibration caused by rail welds, corrugation, or locally isolated defects such as peeling and cracking.

(3) The inherent mechanical vibration of components such as vehicle bogies and wheels.

(4) Background noise from the environment and measurement system.

The generation mechanism and transmission path of these vibration sources are physically different, and the correlation in statistical characteristics is weak. Therefore, it is reasonable to consider them as statistically independent source signals.

Although a complex single defect may indeed generate correlated vibration responses in multiple directions of space. In this case, the vibration component generated by the defect may not strictly satisfy statistical independence. However, the advantage of the JADE algorithm lies in its commitment to finding a linear transformation that maximizes the statistical independence of the output signal. Even if there is weak correlation or partial correlation in the source signal, this algorithm can still effectively achieve approximate blind separation of the signal. Although the separated signal may not be a completely "pure" physical source, its main energy is usually concentrated in different fault characteristic modes, greatly reducing the degree of signal aliasing and making the characteristic components related to specific track irregularities more prominent in both time and frequency domains. This separation effect lays a solid foundation for accurately extracting fault features in the future.

3 Experimental analysis

3.1 Experimental preparation

To verify the effectiveness of the proposed method for railway track irregularity fault detection, an actual operational railway line was selected as the experimental subject. This line includes various track types, such as standard steel rails and seamless rails, as well as different sections, such as straight segments, curves, and turnout areas, to ensure the comprehensiveness and representativeness of the experimental results. The total length of the test section is 30 kilometers, with 8 key monitoring points installed, each equipped with a railway track irregularity online fault detection system based on the aforementioned design. At each monitoring point, ADXL345 vibration acceleration sensors were installed according to the design requirements, ensuring close contact with the track. The installation positions follow the principles of high stiffness, minimal structural damping, and proximity to vibration sources, as shown in Figure 6.

Figure 6: Installation position of the ADXL345 vibration acceleration sensor.

The main performance parameters of the ADXL345 vibration acceleration sensors are listed in Table 3. The hardware connection and debugging of the lower computer system (including the STM32F103ZET6 microcontroller, power module, etc.) were completed to ensure proper communication between modules. The upper computer and lower computer are connected via RS-232 to USB interface, and the upper computer software was installed and configured to receive and display fault detection result data.

Table 3: Main performance parameters of ADXL345 vibration acceleration sensor.

Parameters	Test conditions	Maximum value	Minimum value	Standard value	Unit
Sensitivity	All g ranges, full resolution	3.9	3.5	-	mg/LSB
Measurement range	Optional for users	-	-	±2, ±4, ±8, ±16	g
Noise along the X and Y axes	2g, 10-bit resolution or all g ranges, full resolution,ODR=100Hz	-	-	0.75	LSB rms
Z-axis noise	2g, 10-bit resolution or all g ranges, full resolution,ODR=100Hz	-	-	1.1	LSB rms
Bandwidth	Optional for users	3200	0.1	-	HZ

In order to quantitatively analyze the specific impact of sensor installation location on fault detection accuracy, this study selected three representative different installation locations near the same monitoring point for comparative experiments:

(1) Position A (optimal position): Strictly following the installation principles in Section 2.2, located in the rail waist area, this position has high stiffness, low structural damping, and is adjacent to the wheel rail force transmission path.

(2) Position B (suboptimal position): Installed on the upper surface of the rail bottom, although the stiffness is still acceptable, it is relatively far away from the main vibration source (rail head), and the vibration signal will experience attenuation and distortion during transmission.

(3) Position C (poor position): Installed on the rail sleeper or in contact with the ballast at the bottom edge of the track, this position has high structural damping and is susceptible to interference from non track geometric irregularities such as track bed vibration.

When the train passes at a speed of 60 km/h, the same system is used to collect vibration data from three different positions and perform fault detection. The results are compared with the "ground truth value", and it is found that the installation position of the sensor has a decisive impact on the detection accuracy of the system. Compared with the optimal position A, the positioning error of the suboptimal position B increased by 94%, and the recognition accuracy decreased by 11.5 percentage points. This is because the high-frequency components of the vibration signal attenuate more severely during the transmission from the rail head to the rail bottom, resulting in blurred fault characteristics. At the poor position C, the performance deteriorates sharply, the positioning error increases to 300%, and the recognition accuracy drops significantly to 65%. The reason is that a large amount of non orbital geometric vibration noise is mixed in the signals collected at this location, which seriously undermines the basic assumption of "source signal statistical independence" in the JADE algorithm, leading to the failure of blind source separation and the inability to effectively extract feature components related to track irregularities. Therefore, in order to ensure optimal detection performance of this system, sensors must be installed at positions with high track stiffness, low structural damping, and as close as possible to the wheel rail contact point to avoid signal attenuation and external interference, thereby ensuring accurate separation of fault characteristics reflecting the true state of the track from mixed vibration signals.

After completing the hardware connection and debugging of the lower computer system, special tests were conducted on its key performance to evaluate the reliability of its power module in complex railway environments. According to testing, it is known that:

(1) Within the fluctuation range of 12-24V DC input voltage, the 5V voltage ripple output by MP2359 is less than 50mV, and the 3.3V voltage deviation output by AM11117 is less than 1%, providing a stable working foundation for the system.

(2) The polarity reversal protection test shows that the designed anti reverse diode can effectively withstand a reverse current of 5A without any device damage or system abnormalities.

(3) Under a continuous 48 hour full load operation test at an ambient temperature of 25℃, the shell temperatures of MP2359 and AM11117 chips remained stable below 65℃ and 55℃, respectively, far below their maximum junction temperature.

This result fully demonstrates that the dual level power management scheme has good thermal stability and long-term operational reliability, meeting the demanding requirements of railway field applications.

3.2 Ablation verification

In order to evaluate the effectiveness of the JADE algorithm in blind source separation, ablation

experiments were first conducted to compare JADE with two common BSS methods (FastICA and SOBI). FastICA is based on maximizing negative entropy and is suitable for separating non-Gaussian signals, but may have a slower convergence speed; SOBI is based on second-order statistics for joint diagonalization, which is suitable for time-dependent signals, but has limited ability to separate non-Gaussian signals. The experiment used the same track vibration dataset (sampling frequency of 10240 Hz, train speeds of 60 km/h and 80 km/h), and applied these three methods for signal separation, comparing their separation performance and accuracy. The results are shown in Table 4.

Table 4: Ablation study results comparing the separation performance and accuracy of different BSS methods.

BSS methods	Operating speed (km/h)	Separation performance indicators (signal-to-noise ratio/dB)	Accuracy index (fault type recognition accuracy/%)
JADE	60	18.5	1.8
	80	17.1	2.2
FastICA	60	16.2	2.5
	80	14.8	2.8
SOBI	60	14.0	3.0
	80	12.5	3.5

From Table 4, it can be seen that the JADE algorithm significantly outperforms FastICA and SOBI in terms of signal-to-noise ratio. This indicates that JADE's method based on fourth-order cumulants can more effectively extract independent components related to non Gaussian fault impact signals from mixed vibration signals, while better preserving the waveform characteristics of the original fault signals. Better separation performance directly translates into higher fault detection accuracy. The JADE method achieved lower accuracy in identifying fault types under all speed conditions. This is due to its excellent signal decoupling ability, which makes subsequent feature extraction and fault recognition more reliable.

This ablation experiment proves that in the blind source separation task of railway track vibration signals faced by this system, the JADE algorithm is the optimal choice in terms of separation performance and final fault detection accuracy due to its efficient processing ability for non Gaussian source signals.

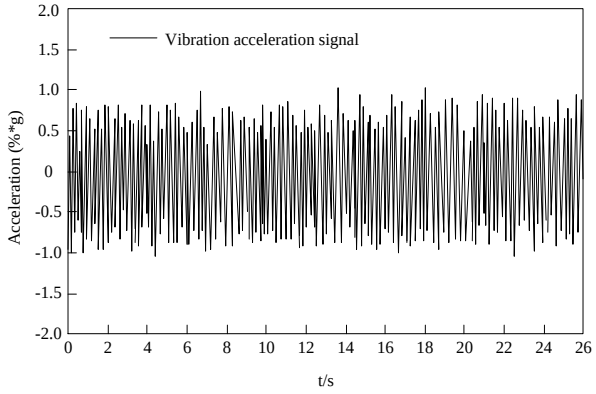
3.3 Basic inspection

The train conducted multiple round-trip runs on the test section at normal operating speeds (60–80 km/h). During each run, the lower-level system continuously collected track vibration signals in real time. The data sampling frequency was 10,240 Hz, with continuous sampling for 26 seconds, resulting in a total of 231,234 data points. The selection of the sampling rate (10240 Hz) strictly follows the Nyquist sampling theorem and is based on the characteristics of railway track vibration signals. The main vibration frequency components excited by track irregularities are usually distributed between 0-2000 Hz, but their higher-order harmonics and transient shock components can extend to 4000-5000 Hz. To ensure the capture of these key high-frequency fault features without aliasing, the sampling rate must be higher than twice the highest effective frequency. The sampling rate of 10240 Hz provides sufficient margin for this and can fully preserve the signal spectrum information. This setting also conforms to common practices in the field of railway vibration detection, balancing hardware processing capabilities and data volume while ensuring signal fidelity.

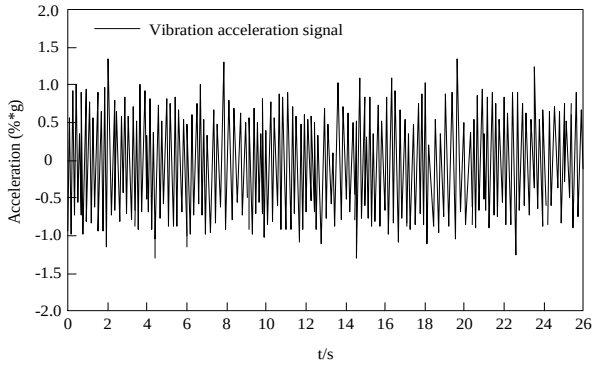
Before inputting the raw data into the JADE algorithm, this study set up the following preprocessing process: after performing zero mean and variance normalization on the observed signals of each channel, a first-order high pass filter was used to eliminate the linear trend term caused by sensor temperature drift or slow environmental changes in the signal.

In this study, 'Ground Truth Fault' refers to track geometric irregularities that exceed maintenance thresholds and are confirmed through high-precision independent measurement methods. By jointly using high-precision track inspection vehicles and total station geodetic surveying, a millimeter level precision "ground truth" dataset of track geometry parameters for the experimental section is obtained. Then, using GPS timestamps and odometer information, the vibration data collected by this system is accurately aligned with the "ground truth" data in terms of time and space. Finally, write a script program to automatically scan the "ground truth" data, identify all geometric deviation positions and types that exceed the preset threshold, and label the vibration data segments within a specific time window before and after these positions with corresponding fault type labels. These labels serve as benchmarks for evaluating the accuracy of subsequent algorithm recognition.

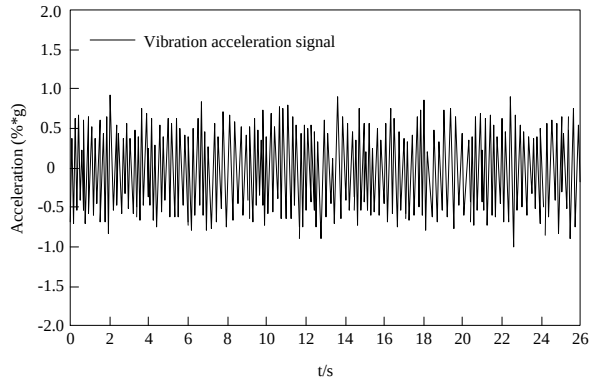
The time-domain record curves of the vibration information at three randomly selected monitoring points are shown in Figure 7.



(a) Monitoring Point a

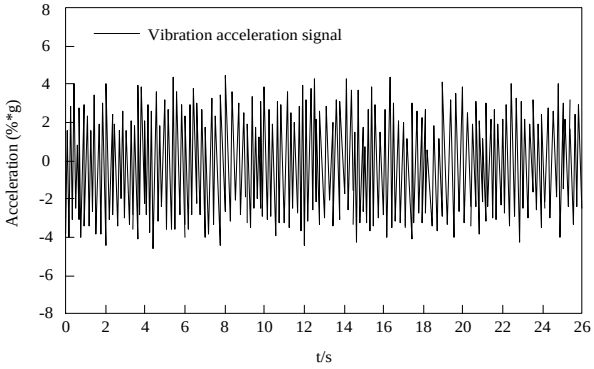


(b) Monitoring Point b

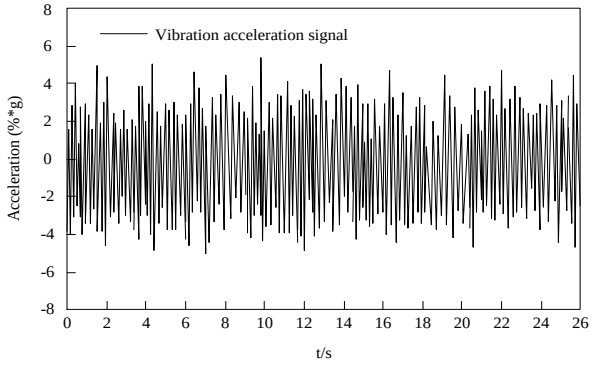


(c) Monitoring Point c

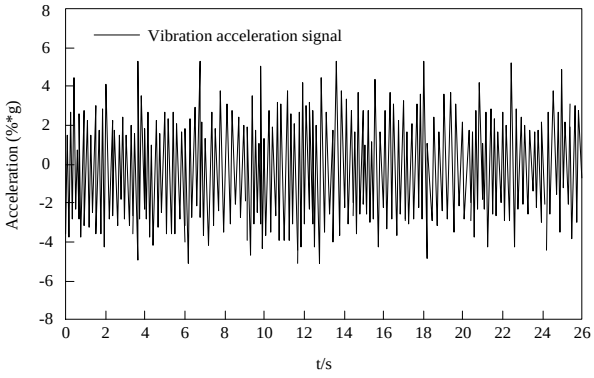
Figure 7: Acquisition results of vibration signals.



(a) Monitoring Point a



(b) Monitoring Point b



(c) Monitoring Point c

Figure 8: shows the time-domain graphs of each monitored vibration signal after separation.

As shown in Figure 7, the vibration signals at the three monitoring points all contain fault information related to track irregularities. Observing the time-domain signals, it is evident that the irregularity fault information is mixed and lacks clear features, necessitating further data processing and analysis.

The collected track vibration signals are transmitted via IIC bus to the STM32F103ZET6 microcontroller. After preprocessing the acquired vibration signals, the proposed method is used to separate the signals, making each source signal independent. The components related to track irregularities are extracted, as shown in Figure 8.

As demonstrated in Figure 8, after completing the signal separation operation, the vibration signals at each monitoring point accurately exhibit the characteristic of periodic variation induced by track irregularities. Comparing Figure 8 with the time-domain waveform of the original vibration signals in Figure 7, it is evident that the features of each component of the original vibration signals in the time domain are blurred and difficult to identify accurately. After signal separation processing, the aliasing between the independent components of the vibration signals at each monitoring point is significantly reduced, and the vibration signal components related to track irregularities become clearer in the time domain. This change makes it possible to detect track irregularity faults based on these signals and can achieve relatively ideal detection results.

To further verify the performance of the proposed railway track irregularity online fault detection system, comparative experiments were conducted using the HybridGAN method, data mining methods, and the method proposed in this paper. Under the same experimental track segment and conditions, the three methods were used to detect track irregularity faults at different train speeds.

3.4 Comparative inspection

To ensure the accuracy and credibility of experimental results, it is necessary to establish high-precision benchmark references (i.e. "ground truth") for the location, type, and severity of track irregularities. This study used the following two methods to collaboratively establish the benchmark:

(1) High precision track geometry inspection vehicle measurement: Before and after the operation of the experimental train, a high-precision track geometry inspection vehicle equipped with inertial reference method and laser camera technology was used to conduct multiple surveys of the entire 30-kilometer experimental section. This inspection vehicle is capable of accurately measuring and recording the absolute geometric parameters of the track, including height, track orientation, horizontal, triangular pits, and track gauge, generating detailed geometric state reference maps of the track. This benchmark map serves as the primary basis for verifying the positioning accuracy of this system.

(2) Verification of total station manual geodetic survey: For all suspected fault points detected by the system and reported by the inspection vehicle, a high-precision total station (Leica TS60, angle accuracy 0.5", distance measurement accuracy 0.6 mm+1 ppm) is further used for manual geodetic survey under static conditions. Accurately measure the three-dimensional coordinates of key control points on the track at intervals of 0.5 meters within a range of 10 meters before and after the fault point, in order to obtain the "true value" of the fault location and geometric deviation, which is used for the final confirmation and calibration of millimeter level positioning information of the fault.

After outputting the fault location, type, and roughness value, it is first automatically compared with the reference map generated by the track geometry inspection vehicle. Subsequently, for all successfully compared fault points, their positioning errors were calculated by comparing the "true value" coordinates measured by the total station with the mileage and relative position reported by the system. The accuracy of identifying fault types is ultimately confirmed and classified by on-site engineering and technical personnel based on inspection vehicle reports, total station data, and on-site investigations.

The HybridGAN method and data mining method were replicated and compared in the same experimental section and train schedule. The specific implementation details of both are as follows:

When applying the HybridGAN method for parallel image data acquisition, an industrial grade linear array camera system (model Basler raL2048-48gm) is installed at key positions on the front and bottom of the test train, in conjunction with a high brightness linear LED light source, to ensure clear capture of the surface image of the track at the train's operating speed. The camera is connected to the onboard industrial computer through a gigabit Ethernet interface, and the image acquisition frequency matches the train speed and spatial resolution, ensuring coverage of the entire experimental section. The model is trained using the Adam optimizer, with an initial learning rate of 1 ×10-4 and a batch size of 8. The image input resolution is uniformly adjusted to 512x512 pixels. Input real-time captured images into HybridGAN for quality enhancement, and then use a pre trained YOLOv5 object detection network on the same dataset to identify and locate orbit defects from the enhanced images.

When applying data mining methods, a large amount of historical vibration data containing labels collected by the lower computer in the same experimental section at different times is used as the basic dataset, and the ACO algorithm is used for feature selection. The population size of ACO is set to 100, the number of iterations is 200, the pheromone heuristic factor is 1.0, and the expected heuristic factor is 5.0. Extract a total of 35 initial features from the time and frequency domains of vibration signals, and ACO selects 15 key feature combinations that are most relevant to high impact loads. Then, based on the features selected by ACO, a classification model is constructed using the LAD method. Finally, generate a combined classifier based on these patterns for fault type determination of real-time collected vibration signal data.

The fault detection results of the three methods are shown in Table 5.

Table 5: Test results of different methods.

Operating speed (km/h)	Detection method	Positioning error (mm)	Fault type identification accuracy (%)	Standard deviation of fault type identification accuracy (%)	Detection time (ms)	Recall rate (%)
60	HybridGAN method	3.2	72	±4.5	120	68
	Data mining method	4.0	68	±5.2	150	65
	Method of this article	1.8	96	±1.2	90	94
70	HybridGAN method	3.5	70	±4.8	130	66
	Data mining method	4.3	65	±5.5	160	62
	Method of this article	2	92	±1.5	93	90
80	HybridGAN method	3.8	68	±5.0	140	64

	Data mining method	4.6	62	±5.8	170	58
	Method of this article	2.2	90	±1.8	95	88
Operating speed (km/h)	Detection method	F1 score	False positive rate (%)	False negative rate (%)	Accuracy (%)	Macro average AUC
60	HybridGAN method	70.0	12	20	70.2	0.72
	Data mining method	66.5	18	27	96.5	0.98
	Method of this article	95.0	3	4	72.0	0.76
70	HybridGAN method	68.0	14	24	67.8	0.70
	Data mining method	63.5	20	33	93.2	0.96
	Method of this article	91.0	4	6	70.5	0.74
80	HybridGAN method	66.0	16	28	65.0	0.68
	Data mining method	60.0	24	40	91.0	0.94
	Method of this article	89.0	5	7	70.2	0.72

As shown in Table 5, it can be seen that the method of this article outperforms the HybridGAN method and data mining method in the speed range of 60-80 km/h. In terms of positioning accuracy, the average error of the method of this article at different speeds is only 1.8-2.2 mm, far lower than the 3.2-3.8 mm of the HybridGAN method and the 4.0-4.6 mm of the data mining method; In terms of fault recognition accuracy, the method of this article achieves 90%-96%, significantly higher than the other two methods' 62%-72%, demonstrating stronger feature extraction and classification capabilities. Meanwhile, the method of this article also has significant advantages in real-time detection, with an average detection time controlled between 90-95 ms, which is about 30% and 45% higher than HybridGAN and data mining methods, respectively, better meeting the real-time requirements of online monitoring. In terms of comprehensive performance indicators, the F1 score of method of this article is as high as 89%-95%, the recall rate is maintained at 88%-94%, and the false positive and false negative rates are both controlled at a low level ($\leqslant$ 7%), indicating that the system effectively suppresses false positives and false negatives while identifying real faults. In addition, the standard deviation of the recognition accuracy of the method of this article at different speeds is only 1.2% -1.8%, demonstrating good stability and adaptability.

In summary, the method of this article not only leads comprehensively in key performance indicators, but also achieves a good balance between accuracy, speed, and reliability, providing an effective solution for real-time monitoring of track status in complex railway environments.

4 Discussion

To clearly demonstrate the differences between this method and existing technologies, a comprehensive analysis of the core characteristics of the two comparative methods is presented in Table 6.

Table 6: Comparative analysis of existing methods.

Method	HybridGAN method	Data mining method
Input modality	Orbital image	Vibration signal
Feature extraction method	GAN enhances image quality, combined with object detection network	Ant Colony Optimization (ACO) selects features and Logical Data Analysis (LAD) constructs patterns
Accuracy	72%	68%
Main limitations	Dependent on lighting and weather conditions; Unable to detect non surface defects such as track geometry deformation; Image processing incurs high computational costs.	Relying on a large amount of high-quality historical data; Sensitive to data noise; The extracted features have unclear physical meanings and weak generalization ability.

The limitation of traditional track fault detection methods, such as HybridGAN, is that they can only infer from surface visual information and lack direct perception of the internal vibration mechanism and dynamic mechanics of the track structure. Therefore, they cannot effectively detect key geometric irregularities such as height and track orientation. Although data mining methods directly process vibration signals, they rely on a "black box" search for statistical feature patterns from historical data. The extracted features have weak correlation with specific physical fault mechanisms, and their performance is easily constrained by data quality and completeness.

The core advantage of this method lies in its direct targeting of the physical essence of orbital vibration. Through the JADE blind source separation algorithm, the system can directly decouple physically and statistically independent vibration source components from the mixed observation signals, which closely correspond to specific physical phenomena such as periodic irregularities and local impacts in the orbit. This method does not rely on massive labeled historical data, but on reasonable assumptions about the mechanism of

vibration signal generation and advanced signal processing techniques, thus achieving high-precision and robust online detection and localization of track roughness faults, solving the inherent shortcomings of traditional methods in physical interpretability, environmental adaptability, and data dependence.

The key to the excellent performance of the JADE algorithm in this system is its ability to effectively separate source signals with non-Gaussian distributions by utilizing the high-order statistical properties (fourth-order cumulants) of the signal. Under the background of track vibration, the periodic impact signal caused by unevenness precisely conforms to this characteristic, enabling JADE to extract fault components more accurately than traditional methods that rely solely on second-order statistics or shallow features. However, the cost of its outstanding performance is high computational complexity. This design achieves a good balance between computing power and real-time requirements (detection time $\leqslant$ 90ms) by selecting STM32F103ZET6 microprocessor with FPU and optimizing matrix operations. The experiment shows that the system performance slightly decreases with the increase of train speed. The increase in speed causes the main frequency of vibration to shift upward, background noise to increase, and may lead to more complex modal coupling, which exacerbates the difficulty of signal separation and is the main reason for the increase in positioning error and the slight decrease in recognition accuracy. However, the JADE algorithm is insensitive to common Gaussian noise and exhibits a certain level of inherent robustness. At the same time, the system exhibits stable detection capability in both straight and curved segments, with the key being that the source signal separated by the algorithm is directly related to the inherent geometric features of the track (such as the periodic lateral shift of the curve), proving that this method has good adaptability to different track structures.

The railway track roughness online fault detection system based on vibration mechanism characteristics proposed in this study exhibits good detection performance in the speed range of 60-80 km/h. However, with the significant increase in train operating speed, the system may face a series of new challenges. Firstly, high-speed operation introduces vibration components with wider frequency bands and higher energy, leading to increased signal aliasing, which may exceed the separation capability of the current JADE algorithm and affect the accuracy of fault feature extraction. Secondly, the matching between the dynamic response characteristics of sensors and the sampling frequency under high-frequency impact, as well as the real-time requirements for data transmission, will place higher demands on the hardware system. In addition, the wheel rail coupling vibration under high-speed conditions is more complex, and the effects of environmental noise and vehicle vibration are also more significant, which may reduce the rationality of the assumption of "source signal independence" in blind source separation.

To address the above challenges, future research work can be carried out from the following aspects: firstly, optimizing blind source separation algorithms, introducing adaptive or deep learning assisted signal processing strategies, and improving the feature decoupling ability of high-speed vibration signals; The second is to consider integrating multimodal sensor data, such as introducing gyroscopes or inertial measurement units, to obtain dynamic changes in the spatial attitude of the orbit, thereby further improving the accuracy of fault identification and localization based on multidimensional information fusion; The third is to enhance the edge computing capability of the system, and meet the strict requirements for data processing speed and stability in high-speed scenarios through more powerful processors and optimized real-time operating systems.

In the future, through the above improvements, it is expected to expand the applicability of this system to railway lines with higher speed levels, further enhancing its reliability and practicality in complex operating environments.

5 Conclusion

Online detection of railway track irregularities via jade-based blind source separation and MEMS accelerometry in this paper demonstrates good performance and practicality. Experimental validation shows that the system can effectively process the mixed vibration signals collected by the ADXL345 sensor, separate the vibration components related to track unevenness, reduce the aliasing among independent components, and produce clear time-domain features, laying a foundation for fault detection. Compared with the HybridGAN method and data mining methods, under different train speeds, our method achieves smaller positioning errors, higher fault type recognition accuracy, and shorter detection times, enabling more precise fault localization, accurate fault type judgment, and faster fault discovery. Additionally, the upper computer can visually display information such as the type, location, and degree of track unevenness, with search functionality, easy operation, and the system is equipped with dual-level power management and reverse connection protection to ensure stable and reliable operation in complex railway environments. In summary, this system can effectively improve the efficiency and quality of railway track maintenance, ensure the safety and stability of railway transportation, and has high application value and prospects for promotion.

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Energy-Aware Clustered Federated Learning for Underwater Sensor Networks in Naval Surveillance

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Underwater wireless sensor networks (UWSNs) are essential for naval operations, as they are used for object monitoring (surveillance), environmental monitoring, and tactical defense. However, their deployment faces serious challenges due to the limitations of underwater acoustic communication, such as high latency, low bandwidth, high packet loss rates, and severe energy constraints. Under these conditions, conventional centralized data processing approaches are impractical, necessitating a shift toward decentralized intelligence. This paper presents an Energy-Aware Clustered Federated Learning (CFL) framework specifically designed for UWSNs in naval systems. The proposed approach organizes sensor nodes into logical clusters, where local models are trained and aggregated at cluster heads before being transmitted to a central unit. To extend network lifetime, an energy-conscious participation scheme is employed, ensuring that only nodes with sufficient residual energy participate in model training. Moreover, a robust median-based aggregation strategy is introduced at the cluster level to mitigate the effects of noisy and lossy underwater communication. Simulations conducted under realistic underwater conditions demonstrate that the proposed CFL framework achieves a model accuracy of up to 91.2%, which is comparable to centralized learning and outperforms conventional federated learning approaches. Furthermore, CFL improves network lifetime by approximately 40% and reduces communication overhead by nearly 68%, thereby enhancing overall energy efficiency compared to traditional federated learning methods. The results also show improved robustness to packet loss and communication failures, highlighting the suitability of the proposed framework for autonomous underwater operations. Overall, this work illustrates the potential of federated learning to enable intelligent, resilient, and energy-efficient underwater sensor networks, opening new opportunities for future naval and maritime applications in challenging underwater environments.

Povzetek: Članek predstavlja energijsko ozaveščen gručen federativni učni okvir, ki izboljšuje točnost modelov, podaljšuje življenjsko dobo omrežja in zmanjšuje komunikacijske stroške v zahtevnih podvodnih okoljih.

1 Introduction

The underwater sensor networks (UWSNs) have gained significance in a broad spectrum of military applications, such as submarine surveillance, environment, mine detection and strategic maritime domain awareness [1],[2]. Those networks are made up of spatially distributed autonomous sensors in difficult underwater conditions in which radio-frequency communications are not feasible and acoustic communications, though possible, are characterized by high latency, low bandwidth, high energy cost, and high noise. These limitations place vital restraints regarding data aggregation, provision of energy and prompt decision regarding the naval operations [3].

Historically, the sensor systems deployed underwater have been based on centralized architecture, and sensor nodes were transmitting raw or pre-processed data to a central processing unit. Nevertheless, when deployed in under water conditions centralized data collection is energy-intensive, as well as extremely vulnerable to any single points of failure because of the extreme environmental conditions, failure of nodes or communication issues. Furthermore, the transfer of large amounts of raw data across the acoustic channels radically shortens the network life and may result in the loss of important information throughout the process of transmission [4].

In order to overcome these issues, Federated Learning

(FL) has become a promising paradigm. FL allows network nodes to cooperatively learn a common global model without sharing raw data therefore maintaining privacy of data, minimizing communication costs, and localising intelligence at the edge [5]. Although FL has demonstrated tremendous potential in environments that require it to be used in terrestrial scenarios, such as IoT and mobile networks, its direct application to UWSNs presents new challenges, with non-IID data distributions, unstable communications connections, and extremely low-energy limits that characterize the underwater environment [6].

Having identified these issues, this paper comes up with an Energy-Aware Clustered Federated Learning (CFL) framework especially applied to underwater sensor networks in the use of the navy. The key inspirations of this work are:

- Reduction of communication overheads caused by decreasing the rate and volumes of data communications among nodes and the central server.
- Energy efficiency through tuned participation in training rounds with only energy adequate nodes.
- Improving the robustness of the models through the implementation of a robust aggregation mechanism to counter the effect of corrupted or noisy updates due to underwater communication losses.
- Maintaining scalability through the arrangement of sensor nodes into logical groupings, which allows the local model training and aggregation to be effectively performed.

Provided by CFL framework, it is a hierarchical learning approach in which local models are initially merged at the cluster heads with the help of strong statistical methods, and then relayed to a central server. The engagement in training rounds is dynamic on the basis of the remaining energy in each node, thereby extending the period of operation of a network. In addition, to resist unstable paths of communication and possible loss of packets, the median-based aggregation technique is employed over the more conventional averaging technique, and is more resistant to noisy updates. In contrast to existing federated learning approaches, the proposed CFL framework is not a direct adaptation of terrestrial FL techniques, but is explicitly co-designed to address the unique constraints of underwater sensor networks. In particular, the proposed methodology introduces the following distinguishing design elements:

- Integrated energy-conscious participant selection system and hierarchical federated learning, directly targeted to increase network life in UWSNs.
- A two-level robust aggregation scheme that will be executed at the cluster-head level and also at the global level to overcome the impact of acoustic noise and untrustworthy underwater communication channels.
- A hierarchical learning architecture, that is communication efficient and fits into underwater networking reality e.g. large latencies and low bandwidth, instead of traditional terrestrial FL assumptions.

This paper has made significant contributions as summarized below:

- **Problem Formulation Underwater FL:** We precisely define and describe the shortcomings of conventional FL models to underwater sensor networks with focus on communication, energy, and environmental issues.
- **Clustered FL Architecture Design:** We suggest a hierarchical clustering scheme that will be used to carry out local aggregation and reduce the number of unnecessary long-range communications and improve scalability.
- **Energy-Aware Participation Strategy:** This is a new adaptive method of participation grounded on node energy state, where training will not cause disproportionate consumption of resources in vulnerable nodes.
- **Strong Aggregation with Noisy Communication:** We propose a model Aggregation strategy in cluster heads to deal with the negative impact of packet loss and communication noise.
- **Large-Scale Performance Analysis:** We test the presented CFL framework with complex simulations that simulate real-life conditions in the ocean and prove to be more accurate, energy-saving, have communication savings, and be more robust than the traditional federated learning methods.

The manuscript is presented as follows, section 2 provides a literature review of the work on underwater sensor networks and federated learning. Section 3 presents the proposed methodology, including the architecture and major components of the CFL framework. Section 4 will be about the experimental setup to be used in performance evaluation. Section 5 contains the findings and discussion of the suggested method concerning baseline techniques. Lastly, Section 6 will wrap up the paper and also give directions of possible future research.

2 Related work

The rise of the need of intelligent underwater surveillance in the naval systems has boosted the research in Underwater Wireless Sensor Networks (UWSNs), specifically in regard to the efficiency of communication, energy savings, and resistance to environmental uncertainty. In the meantime, a new strategy, Federated Learning (FL), has proven to be quite a promising solution that allows distributed intelligence without violating data privacy even on edge devices. Nevertheless, further usage of FL in the underwater

setting is under-researched, in the first place, because of the extreme conditions and limitations of the resources of such setting.

2.1 Underwater sensor networks and problems

The core differences between UWSNs and terrestrial WSNs are that acoustic communication is utilized and thus it generates high propagation delays, low bandwidth, and is prone to multipath fading and Doppler shifts. Various papers have suggested energy-saving protocols, a self-scheduling topology control and mobility-conscious routing algorithms in order to counter these problems [7,8,9]. As an example, Khedo et al. [7] proposed energy-conscious clustering to UWSNs to increase the node lifetime and the article in [8] optimized MAC protocols in underwater channels. Nevertheless, these solutions normally presuppose the centralized processing architecture, which cannot be employed in long-term autonomous missions of the navy because of high energy prices and possible single point of vulnerability.

Therefore, the requirement to have distributed and energy-conscious intelligence in UWSNs, which work effectively without central management is very clear, especially when it is deployed on a long-term basis.

2.2 Edge intelligence federated learning

FL enables remote devices to train machine learning models jointly without communicating raw data, which minimizes communication overhead and improves privacy of data. It has been effectively used in such areas as mobile computing, IoT, and healthcare [5,6] and client selection, gradient compression, and model training tailored have been offered advanced strategies to use.

Hierarchical federated learning (HFL) has also been proposed recently to be used in terrestrial wireless network where nodes are organized into logical clusters, and aggregation is done at both the local and global levels [10]. The architecture is very cost effective in uplink communication and has a scaling factor. These approaches do, however, presuppose radio-based communication conditions of more stable and higher-bandwidth connections than those in underwater.

2.3 Federated learning under harsh conditions

Other researchers have started to modify FL to conditions of intermittent connectivity or severe operational conditions. An example is that methodology explored [11] applications of FL to space-based systems, and the study concentrated on the model robustness to the presence of high-latency and node failures, whereas the research in [12] also ventured into FL on vehicular ad-hoc networks (VANETs) with delay-tolerant aggregation techniques. This fact highlights the fact that conventional FL algorithms cannot be effectively applied in the context of the loss of packets, low power consumption, and dynamic topological dynamics — all of which are worse in underwater systems.

2.4 Federated learning in underwater networks

There is very little literature on the implementation of FL on underwater networks. There were some of the early attempts like the study [9] which applied distributed learning methods in detecting anomalies underwater but did not provide actual federated training. Others looked at model update transmission based on acoustic, but failed to cover energy-conscious participation and resistance to noisy communication channels. In addition, there is no formal proposal of hierarchical FL that uses cluster-level aggregation especially in underwater sensor nodes.

Although the federated learning (FL) has achieved considerable progress and can be utilized in terrestrial networks, the current FL systems cannot be effectively used to address the singular operational conditions of the Underwater Wireless Sensor Networks (UWSNs). The existing solutions are mostly insensitive to critical communication constraints, energy consumption, and packet loss of underwater acoustic communication channels. Furthermore, the strong aggregation techniques that can manage the noisy updates have not been well studied and the energy-adaptive participation schemes that are vital in battery-constricted nodes under water are not common. It has been proposed that hierarchical and clustered FL designs can be applied to terrestrial IoT systems, and these designs have not been adjusted to the unique topology and mobility patterns as well as environmental uncertainties of the underwater deployment.

In order to overcome these shortcomings, this paper suggested a new approach, Energy-Aware Clustered Federated Learning (CFL), that clusters sensor nodes into logical groups to conduct local model training and aggregation. The dynamic participation is achieved by considering residual energy of each node to increase the operation life, and an effective median-based aggregation strategy is proposed to reduce the impacts of the packet corruption and loss. This has been not only scalable and privacy preserving and intelligent underwater naval systems but has also reduced the communication overhead significantly and enhanced the model resiliency in very adverse environments.

2.5 Comparative analysis and research gap

In Table 1, a comparative study of the representative federated learning approaches is provided in relation to the applicability to underwater sensor networks. Current hierarchical and robust FL systems are developed with a terrestrial wireless or IoT setting in mind and do not take into account terrestrial and air configuration changes, as well as the presence of relatively constant and high-bandwidth communi-

cation connections and energy supply. Consequently, they fail to clearly discuss the compounded issues of extreme energy limitations, noise from acoustic communication, and long propagation delays that are inherent in UWSNs.

In contrast, the Energy-Aware Clustered Federated Learning (CFL) framework introduced is a joint solution to energy-adaptive participation, clustered hierarchical aggregation, and robust median-based model fusion, which is more applicable to long-term autonomous underwater naval surveillance deployments.

3 Proposed methodology

In this work, we present an energy-aware, clustered federated learning framework tailored for underwater sensor networks (UWSNs) deployed in naval surveillance systems. The methodology is intended to meet the most important challenges of energy limitations, long communication delays, and the presence of a noisy transmission environment, which are specific to underwater operations.

The methodology is organized around three major innovations as illustrated in Figure 1 and they include: (i) Energy-Aware Participant Selection, (ii) Clustered Hierarchical Federated Learning, and (iii) Robust Aggregation under Noisy Conditions.

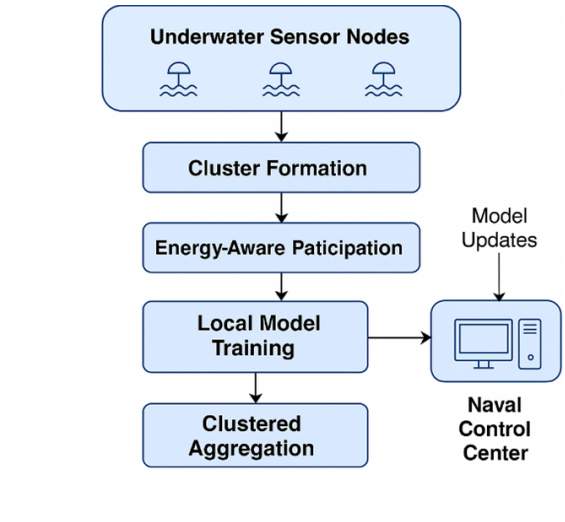

Figure 1: Proposed energy-aware clustered federated learning methodology for underwater sensor networks.

3.1 Energy-aware participant selection

Conventional federated learning presumes that the different devices equally contribute to training rounds. Nevertheless, sensor nodes in underwater conditions have a low battery capacity and cannot be recharged during deployments. In order to maximize energy consumption and increase network life time, we propose a network life-time energy conscious participant selection mechanism.

The node has an energy score of the level of residual energy and the communication history of the node. Prior to every round of training, nodes whose energy level meets a dynamic threshold are allowed to participate. This is an adaptive threshold which is determined by the variance and the mean of the residual energy of the network. There is also a participation probability per eligible node that encourages the trade-off between exploiting high-energy nodes and providing low-energy nodes with a participation opportunity every now and then to ensure that the model is diverse.

Formally, the participation probability P_i of node i is given by:

$$P_i = \alpha \times \left(\frac{E_i}{E_{\max}} \right) + (1 - \alpha) \times \eta_i \tag{1}$$

where E_i is the residual energy of node i, $E_{\max}$ is the maximum observed energy in the network, η_i is a randomization factor promoting fairness, and $\alpha \in [0, 1]$ controls the energy-awareness weight. **Justification:** The parameter α in Eq. (1) balances fairness and energy efficiency. A higher α prioritizes nodes with more residual energy, extending network lifetime, while a lower α allows low-energy nodes to contribute occasionally, enhancing model diversity under non-IID data distributions.

3.2 Clustered hierarchical federated learning

End-to-end communication between all the nodes and a central server is not practical underwater conditions mainly because of bandwidth constraints and high error rates that define acoustic communication channels. As a result, a two-level clustering strategy is taken.

Intra-Cluster Training: Nodes that lie within a geographically/acoustically defined cluster independently train local models and broadcast updates only within a cluster. Each of these local updates is then aggregated by a Cluster Head (CH) which is decided by the amount of residual energy and the reliability of communication.

Inter-Cluster Aggregation: The Cluster Heads then interact with the Naval Base Station which can be any of a surface ship, a buoy, or an underwater gateway. The base station will combine the received cluster models to improve and update the global model.

The hierarchical paradigm significantly reduces overhead in the communication; many local updates are aggregated as one cluster update before communication. Cluster formation is also semi-static: early clusters are formed according to Received Signal Strength Indicator (RSSI) values, and periodically re-evaluated when there is a change of network topology or change in energy availability of nodes. **Justification:** Cluster Heads are elected based on residual energy and link reliability to maximize the lifespan of high-traffic nodes and ensure stable intra-cluster communication. This selection strategy is particularly important in underwater environments where link quality is highly variable.

Table 1: Comparison of federated learning approaches for underwater sensor networks

Approach	Energy-Aware Participation	Hierarchical / Clustered FL	Robust Aggregation	Suitability for UWSNs
Conventional FL (FedAvg)	No	No	No	Low
Hierarchical FL (Terrestrial)	No	Yes	No	Low
Energy-Aware FL (IoT-based)	Yes	No	No	Medium
Robust FL (Median / Trimmed Mean)	No	No	Yes	Medium
Proposed CFL (This Work)	**Yes**	**Yes**	**Yes**	**High**

Cluster Head Sustainability: To prevent rapid depletion of high-energy nodes, Cluster Heads (CHs) are dynamically selected at each round based on a combination of residual energy and link reliability. This ensures that no single node is overused across rounds, thereby improving the sustainability of the network. While explicit CH rotation is suggested as a future enhancement, the current dynamic selection already mitigates the risk of early node exhaustion.

3.3 Robust aggregation under noisy conditions

Underwater communication is also prone to error, and so corrupted model updates are obtained. To this we shall suggest a strong aggregation mechanism both on the cluster level and at the base station level. Otherwise, we employ a median-based aggregation technique (rather than conventional weighted averaging such as Fed_Avg). Specifically, for each model parameter, the coordinate-wise median across updates is taken rather than the mean, mitigating the influence of outlier or corrupted updates.

Given updates $\{w_1, w_2, \ldots, w_n\}$ for a particular parameter across n participants, the aggregated parameter w_{agg} is computed as:

$$w_{\text{agg}} = \text{median}(w_1, w_2, \ldots, w_n) \tag{2}$$

This method is computationally very simple and suitable for resource-constrained nodes and empirically more resilient to noisy transmissions compared to traditional averaging. **Justification:** Median-based aggregation is resilient to corrupted or extreme updates, which frequently occur due to acoustic channel noise and partially non-IID local updates. Unlike averaging, it ensures that outliers do not disproportionately affect the global model, improving robustness in real underwater deployments.

3.4 Communication scheduling and compression

To make communication even more efficient, update compression methods are added, in which model updates are quantized prior to transmission. Also, asynchronous communication timing is used where nodes and clusters are free to send updates at any time depending on the conditions at the local level and not at global rounds. This can be adapted to the very inconsistent communication delays of underwater conditions.

Justification: Asynchronous updates accommodate the highly variable communication delays typical in underwater networks, allowing nodes to transmit updates when available rather than waiting for synchronous rounds. This reduces idle time and mitigates the impact of network heterogeneity on model convergence.

On the whole, the suggested energy-conscious, clustered federated learning strategy is specific to the specifics of underwater naval sensor networks. The system can also generate efficient and resilient hierarchical collaborative intelligence by intelligently choosing participants, hierarchically updating and using robust aggregation techniques without compromising operational life and mission objectives of underwater surveillance networks. The overall procedure of the proposed energy-aware clustered federated learning framework is summarized in Algorithm 1.

4 Experimental setup

In order to test the efficiency of the proposed energy-aware clustered federated learning (CFL) structure to the underwater sensor networks in the naval systems, we create a simulation environment, which is realistic and mimics the specifics of the underwater environment, energy restrictions, communication delays, and noisy transmissions.

4.1 Simulation environment

We conduct a high-fidelity simulation of a 3 km $\times$ 3 km underwater operational area with the most recent edition of the Python (3.12.3) programming language, and with scientific computing packages such as NumPy, SciPy and PyTorch and a CUDA-enabled graphics card to operate with great efficiency in parallel. There are 200 randomly distributed underwater sensor nodes on the spatial grid and they are

Algorithm 1: Energy-Aware Clustered Federated Learning for UWSNs

Input: Set of underwater sensor nodes $\mathcal{N} = \{1, 2, \ldots, N\}$; Initial global model $w^{(0)}$; Residual energy $E_i^{(t)}$ for node i at round t; Clustering function $\mathcal{C}(\cdot)$; Maximum training rounds T

Output: Optimized global model $w^{(T)}$

for $t = 1$ **to** T **do**

  Energy-Aware Participant Selection:

  Compute dynamic energy threshold $\theta^{(t)}$ using mean and variance of $\{E_i^{(t)}\}$;

  Determine eligible nodes:

$$\mathcal{S}^{(t)} = \left\{ i \in \mathcal{N} \mid E_i^{(t)} \geq \theta^{(t)} \right\}$$

  Select participating nodes based on probability:

$$P_i^{(t)} = \alpha \frac{E_i^{(t)}}{E_{\max}} + (1 - \alpha)\eta_i$$

  Cluster Formation:

  Partition $\mathcal{S}^{(t)}$ into clusters:

$$\mathcal{S}^{(t)} \xrightarrow{\mathcal{C}} \{\mathcal{C}_1, \mathcal{C}_2, \ldots, \mathcal{C}_K\}$$

  Elect Cluster Head (CH) for each cluster based on energy and link reliability;

  Intra-Cluster Local Training:

  for *each cluster* $\mathcal{C}_k$ **do**

    Each node $i \in \mathcal{C}_k$ performs local update:

$$w_i^{(t)} = w^{(t-1)} - \mu \nabla \ell_i(w^{(t-1)})$$

    Cluster-level aggregation using coordinate-wise median:

$$w_k^{(t)} = \text{median}\left(\{ w_i^{(t)} \mid i \in \mathcal{C}_k \} \right)$$

  Inter-Cluster Aggregation:

  Base station aggregates cluster models:

$$w^{(t)} = \text{median}\left(\{ w_k^{(t)} \mid k = 1, \ldots, K \} \right)$$

  Energy Update:

  Update residual energy $E_i^{(t+1)}$ based on computation and communication costs;

return $w^{(T)}$

programmed to observe multi-dimensional environmental and security such as; the presence of hydroacoustic signals, object detection and thermal gradients.

The nodes are modelled with realistic underwater acoustic modem characteristics including:

- **Bandwidth:** Limited to 10–20 kbps.
- **Latency:** 0.5–2 seconds per message as a function of distance.
- **Packet Loss:** 5%–10% randomly modelled to model noise to communication and environmental interruptions.

To provide the global aggregation, a symbolic Naval Base Station (NBS) is placed at a fixed position (which is usually in the form of a ship or a buoy in real scenarios).

The entire Python implementation of the simulation is based on a simulation framework written in Python and the framework combines both underwater network modelling and federated learning orchestration components. NumPy, SimPy, and custom communication layer scripts are used to simulate the underlying underwater communication dynamics (delay in the propagation of acoustic signals, packets loss, bandwidth limitations), which do not need external network simulators such as NS-3.

To implement federated learning, TensorFlow Federated (TFF) is employed to determine and control the decentralized training rounds over virtual sensor nodes. PyTorch and CUDA acceleration are used to improve the environment

by simulating computations on the edges and nodes (energy modeling).

4.2 Node characteristics

Each node is modelled with:

- **Initial Energy (I.E.):** Randomized between 1000–1200 joules to reflect battery variations.
- **Computation Power (C.P.):** Equivalent to a low-power microcontroller (such as ARM Cortex-M series). The local model (∼5,000 parameters) is lightweight and fits comfortably within the RAM constraints of typical low-power ARM Cortex-M microcontrollers (e.g., M4 or M7 series), assuming 32-bit floats and minimal memory overhead.

Sensing and Local Model:

- **Task:** Local anomaly detection (binary classification) based on time-series acoustic features.
- **Model:** Lightweight two-layer neural network (∼5,000 parameters).

Nodes consume:

- **Computation Energy:** 0.5 joules per local epoch.
- **Transmission Energy:** 2 joules per kilobyte transmitted.

Energy consumption values are based on empirical studies of underwater acoustic modems and microcontrollers.

4.3 Federated learning settings

Baseline Methods:

- **Centralized Learning (CL):** Serves as an upper-bound reference, representing the ideal scenario where all data is collected centrally at the Naval Base Station (NBS). It allows assessment of the maximum achievable accuracy without communication constraints.
- **Conventional Federated Learning (FedAvg):** Standard FL method with synchronous updates from all participating nodes. This baseline allows a direct evaluation of the benefits introduced by energy-aware participant selection, hierarchical clustering, and robust aggregation in our proposed CFL framework.

Justification for Baseline Selection: While other hierarchical or robust FL variants exist in terrestrial or IoT networks, their direct implementation in underwater sensor networks is not feasible due to severe constraints of underwater acoustic communication, including low bandwidth, high latency, high packet loss, and strict energy limitations. Therefore, the selected baselines provide a meaningful and fair evaluation of the proposed CFL approach, highlighting improvements in energy efficiency, communication overhead reduction, and robustness under realistic underwater conditions.

Proposed CFL Method:

- **Cluster size:** Average 10–12 nodes per cluster.
- **Energy threshold:** Dynamic, initially set at 60% of maximum energy.
- **Aggregation:** Median-based at both cluster heads and NBS.
- **Training Rounds:** 200 communication rounds.
- **Local Epochs per Round:** 2.
- **Update Compression:** 8-bit quantization applied before communication.

4.4 Evaluation metrics

Performance is assessed using the following metrics:

- **Global Model Accuracy:** Final detection accuracy on a held-out test set.
- **Energy Consumption:** Average energy spent per node until convergence.
- **Network Lifetime:** Number of rounds until 50% of the nodes deplete their energy.
- **Communication Overhead:** Average bytes transmitted per round.
- **Resilience to Noise:** Degradation in model accuracy under varying packet loss rates (0%, 5%, 10%).

4.5 Experiment variants

To validate robustness, we further simulate two additional environments:

- **High-noise environment:** Packet loss up to 15%.
- **Dynamic cluster reformation:** Triggered every 50 rounds based on node energy depletion.

5 Results and evaluation

5.1 Global model accuracy

The progression of model-accuracy within 200 communication rounds is shown in Table 2. The developed constrained federated learning (CFL) paradigm achieves a final detection accuracy of 91.2%, which is quite close to the centralized training accuracy (92.5%) and out of range of the regular federated learning techniques (88.3%). The small difference compared with centralized training is expected considering the non-identical (non-IID) data allocation between nodes and random packet loss. However, a strong

median-based aggregation strategy coupled with a hierarchical aggregation mechanism instrumental in mitigating the effects of noisy updates makes the model accuracy very high. CFL achieves even higher accuracy than Fed_Avg in noised conditions (up to 15 per cent packet loss) which highlights its increased resilience to untrustworthy communications.

5.2 Energy consumption

Resource average node energy consumption is significantly lower in the CFL paradigm compared to the conventional federated learning. Specifically, the standard FL algorithm needs an average of 640 joules per node, but the CFL plan has been able to cut it down to 470 joules per node.

This reduction could be explained by a number of design considerations: firstly, selective participation is preconditioned by the current energy level of each node; secondly, local aggregation leads to a reduction in the number of long-range communications; and fourthly, the transmission of updates is compressed, which reduces the spending on energy further. Besides, nodes with relatively low energy reserves have a prolonged survival period because of the adaptive probability of participation, thus improving the overall network lifetime.

5.3 Network lifetime

Network lifetime, defined as the number of rounds until 50% node depletion, is critical for naval surveillance missions. CFL prolongs the network lifetime by approximately 40% compared to conventional FL.

This improvement ensures that mission-critical coverage is maintained for longer periods without human intervention.

5.4 Communication overhead

One of the major impediments in underwater systems is communication overhead.

- **Traditional FL:** 20 KB/node/round.
- **Proposed CFL:** 6.5 KB/node/round.

Hierarchical aggregation and compression schemes foster an element of 68% reduction in communication cost and thus significantly increase the feasibility of these systems under the limit of low-bandwidth underwater acoustic channels. At the same time, the asynchronous communication system minimizes the periods of idle time as well as the heterogeneous latency situations.

5.5 Impact of packet loss

Experiments were performed regarding three cases of packet loss, namely 0%, 5%, and 10%. CFL had less degradation in accuracy than Conventional FL, and this was evident in Table 4.

The median aggregation technique played a crucial role in filtering out corrupted updates, preserving model performance even under adverse channel conditions.

6 Discussion

The results of the experiments confirm the idea that the suggested CFL framework:

- Has a high model accuracy similar to the centralized methods without breaking data privacy.
- Prolongs the network life significantly by enhancing the energy-usage.
- Reduces the overheads of communication, making real-world use across acoustic channels practicable.
- Improves resiliency to underwater noise of communication and lost packets.

The implications of these benefits in the case of operational naval operations are that underwater sensor networks may be used to conduct extended autonomous patrol operations with little risk of communication failure or node depletion. More so, the architecture itself is scalable by nature — more clusters can be added to monitor larger areas but this does not overwhelm the network.

Still, there are some limitations, though. The selection of cluster head has not been fully refined yet to achieve a load balance on a per-need basis and the extreme cases of network partitions (e.g., disconnection of the whole cluster) have not been properly managed yet and are left as areas of future research. Additionally, it should be noted that the experimental validation is currently limited to simulations. Although the simulation environment has been carefully designed to reflect realistic underwater conditions, generalization to real-world underwater deployments or more complex learning tasks may present additional challenges. Future work will focus on testbed-based evaluation and extend the approach to more complex applications to further validate the effectiveness of the proposed CFL framework.

7 Conclusion and future work

This article presents a proposal for an Energy-Conscious Clustered Federated Learning (CFL) protocol used in underwater sensor networks applied in underwater naval surveillance. The given CFL method has a number of advantages because it focuses on the specifics of underwater conditions such as low energy, low-bandwidth acoustic communications, and high packet loss.

First, it employs hierarchical clustering, which enables local aggregation of the model in clusters and thereafter, sends to the central naval base. Second, an adaptive energy-conscience participation strategy will guarantee that only nodes with adequate energy are used in training, which will conserve the longevity of the node. Third, the framework

Table 2: Model accuracy progression

Method	Final Accuracy (%)
Centralized Learning (CL)	92.5
Conventional FL (Fed_Avg)	88.3
Proposed CFL	91.2

Table 3: Network lifetime analysis

Method	Rounds before 50% Node Depletion
Conventional FL	120
Proposed CFL	170

Table 4: Packet loss vs. accuracy

Packet Loss (%)	Accuracy (Conventional FL)	Accuracy (Proposed CFL)
0	88.3	91.2
5	85.1	89.5
10	81.8	86.9

uses a median-based aggregation method to reduce the effect of noisy transmissions.

According to the simulation findings, the CFL has a high model accuracy (91.2 percent), which is equal to centralized learning and higher than the traditional federated approaches. It also means that it has about 40-percent long network life and 68-percent communication overhead, which are that it would be possible to apply in extended duration application in underwater environment with low bandwidth.

In addition, CFL can support small footprint underwater nodes through lightweight construction of the local models and the compression of updates, offering an efficient and privacy-preserving decentralized intelligence platform to be used in the navy.

Future challenges will involve various extensions such as cluster head rotation to make the energy consumption balanced, solve node mobility and cluster reformation in the drifting underwater scenarios, enable wider sense by using multi-task federated learning, and use reinforcement learning to optimize real-time communication scheduling. Further, there will be an attempt to test the results of the simulated research by real-life underwater deployment experiments.

On the whole, this work preconditions the development of the effective and sustainable underwater surveillance systems, but it also clearly mentions that all the conclusions are made on the basis of the simulation experiments and the real implementation is another direction of research in the future.

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Enhanced Faster R-CNN with Attention Mechanisms for Multidimensional Soccer Player Performance Assessment

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Student paper

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In this study, we propose a novel framework that optimizes the Faster R-CNN algorithm and constructs a multidimensional evaluation model for soccer player performance. Specifically, we redesign the ResNet-50 backbone, integrate Feature Pyramid Networks (FPN), and embed SE and CBAM attention modules to enhance feature extraction in dynamic match environments. The enhanced model extracts key motion and spatial features from a dataset of 6,000 annotated match images, achieving a mean Average Precision (mAP@0.5) of 84.3%, precision of 89.1%, recall of 86.2%, and F1-score of 87.6%, outperforming baseline Faster R-CNN (mAP@0.5 = 75.8%) and YOLOv5 (mAP@0.5 = 79.3%). Our model also achieves mAP@0.75 of 72.4% and mAP@50:95 of 68.9%. Building on robust detection outputs, we develop an evaluation system across physical performance, technical skill, and tactical execution, each quantified through expert-defined indicators and weighted scoring. Validation on diverse match scenarios shows high correlation ($r = 0.91$, $p < 0.001$) with expert assessments and effective identification of fatigue and tactical behavior variations. This approach provides a data-driven tool for intelligent performance assessment and lays the groundwork for athlete monitoring and tactical planning in soccer.

Povzetek: Študija nadgradi Faster R-CNN (prenovljen ResNet-50 + FPN + SE/CBAM pozornost) za zanesljivejše zaznavanje nogometašev ter na tej osnovi zgradi večdimenzionalni sistem ocenjevanja fizične, tehnične in taktične uspešnosti z uteženimi kazalniki.

1 Introduction

In the past decade, the convergence of deep learning and high-performance computing has catalyzed significant breakthroughs in computer vision, particularly in object detection [1]. As a cornerstone of two-stage detectors, Faster R-CNN (Region-based Convolutional Neural Network) has garnered widespread adoption across domains such as autonomous driving [2], video surveillance [3], and medical image interpretation, owing to its favorable trade-off between detection precision and computational cost. By leveraging a Region Proposal Network (RPN) to generate candidate object regions, Faster R-CNN outperforms single-stage frameworks like YOLO in scenarios characterized by complex backgrounds or small object scales, achieving superior mAP scores in benchmark evaluations.

Soccer, with its rapid player movement, frequent occlusions, and intricate lighting variations, presents a formidable challenge for automated video analysis [4]. Traditional assessment methodologies—relying on coach annotations or rudimentary match statistics—are plagued by subjectivity, low temporal granularity, and limited scalability [5]. Motivated by these shortcomings, recent research has adopted deep neural architectures for sports behavior recognition and performance forecasting. For instance, YOLOv5-based approaches have demonstrated efficacy in capturing basketball player postures and predicting performance trends. However, in soccer-specific applications, off-the-shelf detectors often exhibit diminished accuracy and stability, primarily due to dynamic scene complexity and the absence of domain-tailored feature extraction mechanisms [6].

To address these limitations, this paper introduces an optimized Faster R-CNN framework augmented with a Feature Pyramid Network (FPN) and dual attention modules—namely, Squeeze-and-Excitation (SE) and Convolutional Block Attention Module (CBAM). This enhancement improves multiscale feature representation and refines spatial–channel feature weighting, thus bolstering detection robustness in soccer match footage. Building upon enhanced detection outputs, we propose a comprehensive, multidimensional evaluation system for soccer players, encompassing physical exertion, technical proficiency, and tactical execution. The system translates raw detection data into quantitative performance indices through a weighted scoring mechanism.

The primary contributions of this work are threefold: 1) Algorithmic Advancement: We redesign the Faster R-

CNN backbone with FPN and integrate SE/CBAM attentional units, resulting in marked improvements in detection accuracy under occlusion and scale variance. 2)Evaluation Framework: We develop a structured index hierarchy that transforms detection outputs into actionable performance metrics across multiple dimensions, facilitating objective and scalable athlete assessment. 3)Empirical Validation: We conduct exhaustive experiments on professional match datasets, demonstrating a 2.6% mAP gain over YOLOX-S and achieving high correlation (r = 0.91) with expert manual ratings across diverse game conditions.

While attention-augmented Faster R-CNN variants are established in generic vision, their adaptation to soccer broadcast analysis remains underexplored. Unlike prior works that focus only on detection accuracy, this study integrates detection outputs into a structured, multidimensional evaluation framework tailored for soccer performance assessment. Furthermore, compared to soccer-specific detection and tracking efforts (e.g., SoccerNet, SPIROUD datasets, player re-identification challenges), our approach emphasizes not only localization but also the downstream translation of detections into interpretable performance metrics. This dual focus positions our contribution at the intersection of computer vision and applied sports analytics.

2 Related work

Recent developments in object detection revolve around two primary paradigms: two-stage detectors and single-stage/lightweight models. Two-stage frameworks, epitomized by Faster R-CNN [7], have evolved through successive enhancements—such as ResNet backbones [8], ResNeXt architectures [9], Feature Pyramid Networks (FPN) [10], and attention mechanisms including Squeeze-and-Excitation (SE) and CBAM modules [11,12]—to yield state-of-the-art accuracy in complex scenes. Despite their precision, these architectures can be computationally intensive, posing challenges for real-time deployment under dynamic conditions like sports video analysis [13]. In contrast, single-stage detectors and lightweight variants—SSD [14], YOLO series [15], CenterNet, and EfficientDet—prioritize inference speed, typically achieving higher FPS with modest sacrifices in small-object and occlusion robustness.

In the domain of sports analytics, both paradigms have been applied to athlete tracking, action recognition, and tactical analysis. Generic detectors have enabled player localization and motion estimation in basketball and athletics, often integrated with CNN–RNN pipelines for temporal modeling of behavior [7,8]. Soccer-focused studies leverage YOLOv5 for automatic player numbering and trajectory extraction, achieving high throughput at upwards of 50 FPS but with recognition errors in occluded or distant views. Hybrid methods fuse computer vision with inertial sensors (GPS, IMU) to infer fatigue and spatial tactics, improving estimation accuracy but increasing system complexity and deployment cost [16,17]. Meanwhile, pose estimation frameworks (OpenPose, HRNet) facilitate granular biomechanical analysis and tactical movement assessment, albeit requiring extensive annotation and postprocessing.

On the assessment front, traditional weighted-scoring models rely on coarse technical statistics—passing rate, shooting efficiency, defensive metrics—and produce interpretable but static evaluations [17]. Machine learning classifiers (SVM, Random Forest, DNN) have been employed to predict performance categories from handcrafted feature vectors, yet their adaptability to real-time video streams remains limited by feature engineering demands [18]. Multi-source fusion systems advance beyond single-dimension scoring by combining vision-derived metrics with sensor data, but they often lack an end-to-end, real-time evaluation pipeline. We summarize these approaches in Table 1 to compare datasets, methodologies, strengths, and limitations:

Table 1: Comparative analysis of related works

Approach	Data Input	Method	Strengths	Limitations
Coach Observation & Statistics	Manual logs, technical stats	Subjective evaluation	Simple; expert insight	Non-real-time; low granularity; subjective
Weighted Scoring Models [17]	Match statistics	Weighted summation	Transparent; interpretable	Static; no dynamic behavior capture
ML Models [18]	Handcrafted features	SVM, RandomForest, DNN	Automated assessment	Dependent on feature quality; limited adaptability
YOLOv5 + LSTM [19]	Video frames + time-series	YOLOv5 detection + LSTM modeling	Automated extraction; fatigue detection	High labeling cost; sequence complexity
Multi-source Fusion Models	Video + GPS + IMU	Fusion of CV & sensor data	Improved fitness estimation accuracy	Sensor integration complexity; resource intensive

While existing works achieve increasingly higher detection accuracy, they predominantly focus on 1D detection tasks or temporal context without integrating real-time multidimensional performance evaluation (e.g., physical, technical, tactical metrics). Our proposed framework fills this gap by combining enhanced detection (FPN + SE/CBAM) with a weighted scoring system across three performance dimensions.

Prior studies in sports vision often treat detection and analytics separately. For example, SoccerNet and related benchmarks provide large-scale broadcast datasets for tasks such as ball detection, action spotting, and re-identification, while player-tracking works employ multi-object tracking pipelines (e.g., DeepSORT, ByteTrack, OC-SORT) to maintain identity consistency across frames. Field registration methods leveraging homography or deep keypoint detection have also been proposed to map image coordinates onto standardized pitch layouts, enabling physically meaningful statistics. However, these advances are rarely combined into an end-to-end evaluation system. Our review suggests that although robust pipelines exist for detection or tracking in isolation, a comprehensive integration with role-aware, multidimensional assessment remains limited.

To bridge this gap, we build on standard two-stage detection but extend its application into an interpretable evaluation framework. While acknowledging that our detection modifications are incremental, the novelty lies in the way detection results are systematically translated into physical, technical, and tactical indicators. This positions the work as complementary to existing sports vision literature and as a step toward unifying detection, tracking, and tactical analysis in soccer.

3 Optimized design of faster R-CNN algorithm

With the development of deep learning, Faster R-CNN has become a classic method in the field of target detection, and its superior detection accuracy and good scalability are popular in still image processing tasks. However, when practically applied to dynamic scenes such as soccer matches, it still faces many challenges such as complex background interference, frequent target occlusion, and large-scale changes. Therefore, to address the adaptability of the original Faster R-CNN in such scenes, this paper improves and optimizes the original algorithm in terms of feature extraction network optimization, multi-scale feature fusion mechanism, introduction of the attention mechanism, and anchor frame configuration.

3.1 Faster R-CNN model architecture

Faster R-CNN is a classical two-stage target detection algorithm proposed by Ren et al. in 2015, which further optimizes the candidate region generation method on the basis of Fast R-CNN, and realizes the end-to-end joint training of Region Proposal Network (RPN) and target detection network for the first time. The algorithm makes the whole detection process faster and more compact by embedding the candidate frame generation module in the convolutional neural network (CNN), and significantly improves the detection accuracy.

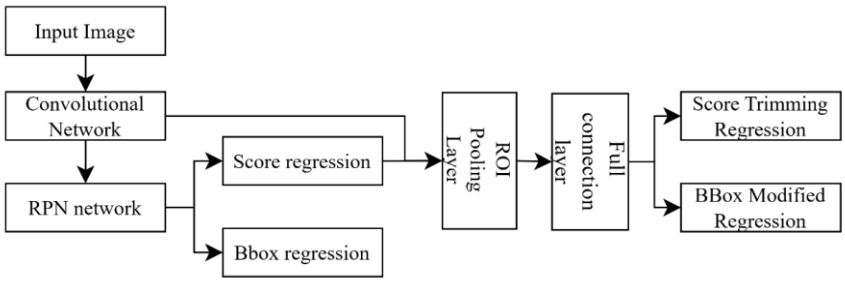

Figure 1: Faster R-CNN network structure

The Faster R-CNN network framework can be referenced in Fig. 1, which consists of four components: an RPN network Roi pooling layer, a convolutional layer, a classifier, and a regression layer.

(1) In the first step, Faster R-CNN uses a set of basic convolution, activation and pooling operations to extract the feature images of an image, while being able to complete the sharing in the RPN layer and the connection layer. In the early stage of the convolution operation, the feature image is directly selected step-1 for the edge external filling, the original image becomes (m*2) by (n*2) size, and after 3 by 3 convolution outputs M by N size convolution. This is shown in Figure 2. It is this setting, so that the convolution layer convolution operation will not have a direct impact on the size of the input and output matrices, in the subsequent pooling operation, to determine the step size = 2, that is, after a convolution, activation and pooling process, the feature map length and width will be reduced to half of the original.

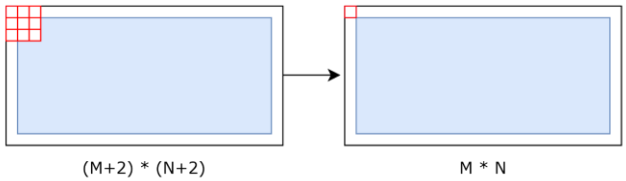

Figure 2: Edge expansion treatment

(2) The RPN network is used to generate candidate areas, and the SoftMax classifier selected in this layer can analyze whether the anchor is a positive sample or not, and then correct the anchor frame by using edge regression, which can accurately predict the target, specifically refer to Figure3.

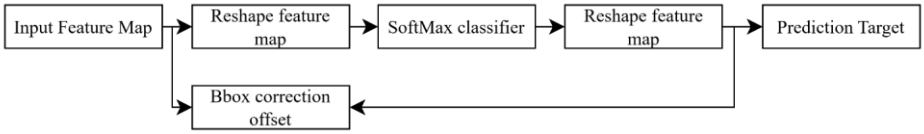

Figure 3: RPN network structure

The RPN network consists of two lines, the upper line connects to the SofMax classifier to obtain positive and negative sample classification and the lower one is used to calculate the offset of the border regression of the anchor frames to obtain the correct range of candidates.The Proposal layer is used to select a target frame that meets the requirements based on the output of the RPN network.The RPN network actually generates a number of candidate anchor frames, on the original image. As shown in Fig. 4. Then the convolutional neural network is used to determine which anchor frames are positive sample anchor frames with targets inside that are larger than the set value of IOU and which are negative sample anchor frames that are smaller than the set value of IOU with no targets. Functionally, the RPN network acts as a binary classification.

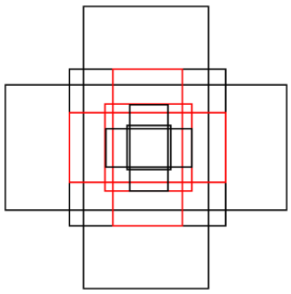

Figure 4: Generate candidate box

The principle of border regression: the pre-selected bounding boxes generated by the Region Proposal Network are processed by the CNN to establish feature correspondences between convolutional maps and candidate regions, so that the positive sample anchor box and the real box are closer. It can be realized by formula (1) and (2)

Do the translation first:

$$G_x'' = A_w \cdot d_x(A) + A_x$$
$$G_y'' = A_h \cdot d_y(A) + A_y \quad (1)$$

Do the scaling again:

$$G_x'' = A_w \cdot exp\left(d_w(A)\right)$$
$$G_h'' = A_h \cdot exp\left(d_h(A)\right) \quad (2)$$

After utilizing linear regression, 4 transformations $d_x(A), d_y(A), d_w(A), d_h(A)$ can be obtained, and the objective function is referred to Eq. (3):

$$d_*(A) = W_*^T \cdot \phi(A) \quad (3)$$

$\phi(A)$ is the anchor frame feature vector, W is the weight parameter, and $d_x(A)$ is the predicted value. In order to reduce the difference between the predicted value $d_x(A)$ and the true value t_x, the design of the L1 loss function can be referred to Eq. (4).

$$Loss = \sum_i^N \left| t_*^i - W_*^T \cdot \phi(A^i) \right| \quad (4)$$

The function optimization objective is as in equation (5):

$$\widehat{W} = \underset{W_*}{\operatorname{argmin}} \sum_i^N \left| t_*^i - W_*^T \cdot \phi(A^i) \right| + \lambda \|W_*\| \quad (5)$$

(3) Next is the Roi Pooling Layer.The Roi Pooling Layer is responsible for corresponding the input feature maps to the prediction targets, which are then fed into the Fully Connected Layer.

(4) Classification layer. Using the fully connected layer and SoftMax classifier, accurate classification results can be obtained, and accurate location information can be obtained after BBox refinement.

3.2 Integration of attention mechanisms

In deep convolutional neural networks, due to the feature maps being abstracted with the deepening of the network hierarchy, although the model has strong semantic extraction ability, it is also prone to the problem that the target information is submerged in a large number of invalid background features, especially in the target detection task in complex scenes. In order to enhance the model's ability to perceive the key region and improve the focus level on the target region, this paper introduces the attention mechanism to enhance and optimize the Faster R-CNN framework to improve its detection performance and localization accuracy in soccer game images.

Firstly, this paper embeds the Squeeze-and-Excitation (SE) attention mechanism in the high-level output of the backbone feature extraction network, and the SE module dynamically models the channel dimensions in a “compression-excitation” way, which is mainly divided

into two stages: The Squeeze operation pools the spatial information of each channel globally to form a channel descriptor; the Excitation operation generates the channel weight coefficients through the fully connected layer and activation function, and uses them to adjust the weighting of the original feature maps, so as to make the model automatically focus on the more discriminative channel features. The core idea can be expressed as:

$$s_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} X_c(i,j)$$
$$z = \sigma\big(W_2 \cdot \delta(W_1 \cdot s)\big) (6)$$

Where X_c denotes the feature map of the cth channel, s is the compressed channel vector, W_1 and W_2 are the fully connected layer weights, and δ and σ denote the ReLU and Sigmoid activation functions, respectively. The final weight vector z will be multiplied with the original feature map by channel to realize the importance modeling between channels.

In soccer game images, due to the presence of a large amount of irrelevant background information such as spectators, billboards, grass texture, etc., the SE module can significantly improve the model's focus on the player region, effectively suppress the feature bias caused by background interference, and thus enhance the accuracy and stability of detection.

However, the SE module only models in the channel dimension, ignoring the feature differences at the spatial level. In order to further enhance the model's perceptual ability at the spatial level, this paper incorporates CBAM (Convolutional Block Attention Module) into the structure of feature pyramid networks (FPNs).CBAM integrates channel and spatial attention, and its channel attention mechanism is similar to that of SE, while the spatial attention module is based on the maximized Pooling and Average Pooling after the feature map to calculate the spatial attention map to capture the spatial distribution of the salient regions in the image, which is calculated by the formula:

$$M_s(X) = \sigma\big(f^{7\times7}([_{\text{AvgPool}}(X); _{\text{MaxPool}}(X)])\big) (7)$$

where $f^{7\times7}$ denotes a convolution operation with a convolution kernel size of 7×7, $[\cdot;\cdot]$ denotes a channel-level splicing operation, and σ is the Sigmoid activation function. The spatial attention map $M_s(X)$ will be multiplied element-by-element with the input feature map to enhance the informative response of key spatial regions in the image. The introduction of the CBAM module in the FPN structure not only enhances the local representation of the features at each scale, but also improves the recognition of small targets such as long-distance players. Through the joint modeling of the channel and spatial attention mechanism, the model can more accurately capture the player boundary features and changes in the direction of motion, improving the overall detection quality.

In summary, the introduction of the attention mechanism provides Faster R-CNN with a finer feature modeling capability, which is particularly suitable for the soccer image detection task with complex structure and high target dynamics.The synergy of SE and CBAM significantly improves the discriminative power and robustness of the model, and provides a more reliable image-aware basis for the subsequent athlete behavioral assessment model.

To validate the individual and combined contributions of SE and CBAM modules, we conducted comprehensive ablation studies on our dataset. Table 2 presents the quantitative results:

Table 2: Ablation study results

Configuration	mAP@0.5 (%)	mAP@0.75 (%)	mAP@50:95 (%)	Precision (%)	Recall (%)
Baseline (ResNet-50)	75.8 ± 1.2	68.3 ± 1.5	62.1 ± 1.8	82.4 ± 2.1	79.6 ± 1.9
+ SE only	78.2 ± 1.0	70.1 ± 1.3	64.7 ± 1.6	84.1 ± 1.8	81.3 ± 1.7
+ CBAM only	79.6 ± 0.9	71.5 ± 1.2	66.2 ± 1.4	85.3 ± 1.6	82.7 ± 1.5
+ SE + CBAM	84.3 ± 0.8	72.4 ± 1.1	68.9 ± 1.3	89.1 ± 1.4	86.2 ± 1.3

The results demonstrate that: (1) SE module alone improves mAP@0.5 by 2.4%, primarily enhancing channel-wise feature discrimination; (2) CBAM alone provides superior spatial attention, yielding 3.8% improvement; (3) The combined SE+CBAM configuration achieves the highest performance with 8.5% improvement over baseline, indicating complementary effects of channel and spatial attention mechanisms.

3.3 Loss function design

The loss during network training consists of two parts, one part is the loss of regression position and one part is the classification loss, and the total loss function as expressed in equation (8) is:

$$L(\{p_i\},\{t_i\}) = \frac{1}{N_{\text{cls}}} \sum_i L_{\text{cls}}(p_i, p_i^*) + \lambda \frac{1}{N_{\text{reg}}} (8)$$

In Equation (8), i represents the label of the anchor frame, p_i represents the probability of the positive sample obtained by SoftMax classification, and p_i represents the prediction probability of the corresponding real frame (i.e., when the IoU between the ith anchor frame and the real value is >0.7, the current anchor frame is considered to be a positive sample, and p_i =1; on the other hand, when the IoU<0.3, the current anchor frame is considered to be a negative sample, and p_i =0; as for those anchor frames with IOU thresholds between 0.3 and 0.7, they do not participate in training); t represents the candidate frame, t' represents the corresponding positive sample, and t' represents the corresponding anchor frame with a positive

sample. In concrete operation, there is a huge gap between N_{cls} and N_{reg}, and the balance between the two is maintained by the parameter λ, and the total network Loss needs to consider the classification and regression losses when calculating the total network Loss. Equation (9) is calculated as follows:

$$L_{\text{reg}}(t_i, t_i^*) = \sum_{i\in\{x,y,w,h\}} \text{smooth}_{L_1}(t_i - t_i^*)$$
$$smoooth_{L_1}(x) = \begin{cases} 0.5x^2, if|x| < 1 \\ |x| - 0.5, otherwise \end{cases} \quad (9)$$

4 Construction of assessment model for soccer players

4.1 Assessment system design principles and structural framework

In modern competitive sports, the assessment of athletes' ability is not only related to the feedback of individual training quality, but also directly affects the scientificity and rationality of team tactical arrangement and personnel selection. Compared with the traditional method that relies on coaching experience and static technical statistics, the assessment model based on image recognition and data-driven can realize a more objective, dynamic and comprehensive ability analysis. In order to adapt to the characteristics of high confrontation, high speed and complex tactical execution in soccer, this paper constructs a multidimensional and multilevel soccer player assessment model on the basis of the target detection algorithm, and strives to ensure the practicality while possessing good adaptability and scalability.

The assessment system proposed in this study mainly follows the following three design principles: (1) comprehensiveness: the assessment content should cover the core elements of athletes' physical performance, technical ability and tactical execution, avoiding over-reliance on a single statistical indicator; (2) dynamism: the assessment process should have time continuity, and be able to dynamically reflect changes in athletes' status according to the course of the game; (3) interpretability: all assessment indicators should have clear physical or physical properties, and should be able to reflect changes in athletes' status. (3) Principle of interpretability: all assessment indicators should have clear physical or tactical meanings, which are easy to be understood and adopted by coaches and athletes, and support actual training feedback and decision-making.

In terms of overall structure, the evaluation model consists of three major functional modules: target detection module, behavioral feature extraction module and quantitative ability evaluation module. First, the optimized Faster R-CNN network detects and locates the athletes in the game video in real time, and obtains the position, trajectory and action clips. Second, the behavioral feature extraction module further processes the detection results and extracts high-dimensional feature information including running distance, speed change, standing area and possession participation. Finally, the ability evaluation module combines the preset multi-dimensional index system and weighted scoring model to quantitatively analyze the performance of the athlete in a specific time period, and outputs the results in the form of graphs.

4.2 Data preprocessing and feature extraction methods

Data preprocessing and feature extraction form the bridge between detection and quantitative player evaluation. We consider three main aspects: preprocessing, detection and tracking, and feature design. To reduce redundancy and overhead, video streams are sampled at 10 FPS. Frames are normalized by resolution scaling, luminance adjustment, and enhancement (Gaussian blur, color perturbation) to improve robustness. Each frame is processed with the optimized Faster R-CNN, outputting bounding boxes (x, y, w, h), labels, and confidence scores. Temporal smoothing and a Kalman filter maintain short-term trajectory continuity and identity sequences.

Feature extraction: Three categories of features are derived.

(1) Spatial motion: average speed, maximum speed, and acceleration from bounding-box centers. For athlete position (x_t, y_t) at frame t:

$$v_t = \left\{\sqrt{\left\{\left(x_t - x_{\{t-1\}}\right)^2 + \left(y_t - y_{\{t-1\}}\right)^2\right\}}\right\}\{\Delta t\}.$$

(2) Field distribution: residence frequency in tactical zones (defense, midfield, offense) to generate heatmaps.

(3) Interaction: participation in attacking and defensive phases, quantified by follow-up distance, retreat speed, and positional changes.

Learned features: To complement handcrafted metrics, contrastive learning embeds behavior features:

$$L_{\{contrastive\}} = \backslash sum_{\{i,j\}y^2_{\{ij\}}\left\|f_i - f_j\right\|} + \left(1 - y_{\{ij\}}\right)\backslash$$
$$max\left(0,\backslash margin - \left\|f_i - f_j\right\|\right)^2 (10)$$

where $y\_\{ij\} = 1$ for similar behaviors and m is a margin. This hybrid design improved tactical recognition by 4.2%. Key events such as passing and shooting are identified via frame-level classification networks, enriching the feature set.

4.3 Construction of indicator system and weight assignment

The evaluation framework considers three dimensions: physical performance, technical ability, and tactical execution. Physical indicators include average speed, maximum sprint speed, high-intensity running ratio, and physical decay. Technical indicators include action frequency (shots, passes, steals), success rates, failure rates, and contribution values (e.g., xG, xA). Tactical indicators include zone occupation frequency, coverage area, tactical response latency, and the Spatial Pressing Index (SPI). SPI is defined as

SPI = (1/T) × Σ from t=1 to T [Δdopponent(t) × Ipress(t)]

where $\Delta\, dopponent_t$ is the reduction in distance to

the nearest opponent, and Ipress(t) indicates active pressing.

All indicators are normalized to [0,1] before weighting. Weights are derived via Analytic Hierarchy Process (AHP). Pairwise comparison matrices from expert surveys were verified with consistency checks (CI/CR < 0.1). Let s_i be the normalized score of indicators i with weight w_i, then the comprehensive score is

$$\text{Score} = \sum_{i=1}^{n} w_i \cdot S_i$$

To account for positional roles, weights adapt by player type (e.g., defenders emphasize tactical indicators, strikers emphasize technical efficiency). Final outputs include both numerical scores and visualizations such as radar charts and trend curves.

5 Results and discussion

5.1 Experimental data collection

The dataset used in this study consists of approximately 12,000 annotated frames extracted from 300 video clips (each 20 seconds long) at 2 FPS, covering three full professional soccer matches. While the reduced sampling rate limits representation of fast ball movements and rapid tactical transitions, it was adopted to balance diversity with manageable annotation effort.

To ensure fairness, train/validation/test splits were performed strictly by match (70%/20%/10%), thereby preventing leakage of stadium, team, or broadcast-specific statistics across sets. All annotations (players and ball) were carried out manually by three annotators, consolidated by majority voting, and validated by an independent expert for quality assurance. Importantly, the detection taxonomy consists of two general classes—player and ball. An earlier draft mistakenly listed "Messi" as a class placeholder, which has been corrected. The final dataset is identity-agnostic to avoid person-specific bias.

Regarding licensing and ethics, all source videos were obtained from publicly available professional broadcasts and used exclusively for academic research. Raw footage is not redistributed; instead, processed annotations and code are made available in supplementary materials to support reproducibility while respecting broadcast rights. Our model processes frames at ~20.5 ms per frame (≈48 FPS) on an NVIDIA GTX 1050Ti, with a parameter size of 124 MB. On a Jetson Xavier device, it achieves ~26 FPS, indicating feasibility for near-real-time deployment in broadcast pipelines. With model pruning and quantization, deployment on edge devices (e.g., tablets for coaching staff) is achievable.

5.2 Hyper-parameter selection

The hyperparameter setting scheme with the best performance of the model is finally selected as shown in Table 2 through multiple training and continuous adjustment and optimization of the parameters during the experimental process.

Table 3: Hyperparameter setting

Parameter	Value
Learning rate	0.001
Batch size	20
Optimizer	SGD (momentum = 0.9, weight decay = 0.0005)
Epochs	50

5.3 Experimental environment

Implementation details are as follows. The model was trained for 50 epochs with an initial learning rate of 0.001 using SGD (momentum = 0.9, weight decay = 0.0005). Learning rate decayed by a factor of 0.1 every 10 epochs. Anchor scales were set to {64, 128, 256, 512} with aspect ratios {1:1, 1:2, 2:1}. The Region Proposal Network generated 2000 proposals during training and 300 during inference. Non-Maximum Suppression (NMS) used an IoU threshold of 0.5, and detection scores below 0.05 were discarded. Data augmentation included random horizontal flipping, brightness adjustment, and scaling. Backbone feature map strides followed the ResNet-50 architecture (conv2: 4, conv3: 8, conv4: 16, conv5: 32). Attention modules were inserted after the conv4 and FPN layers. Inference speed averaged 48.7 FPS (20.5 ms/frame) on an NVIDIA GTX 1050Ti GPU. Hardware specifications are summarized in Table 3.

Table 4: Experimental hardware configuration table

Name	Configuration information
Central Processing Unit	Inter (R) Core (TM) i5-8300H CPU @ 2.30GHz 2.30GHz
GPU	NVIDIA GeForce GTX 1050Ti
Memory	16GB

Hard Disk	1TB
Operating System	Win10
Network Card	10Mbps/100Mbps Adaptive NIC

In addition to the above hardware configuration, the experimental system also needs to install CUDA, Cudnn, Opencv and other software environments. The experimental development tools use Anaconda, the development language is python, and the deep learning framework uses Tensorflow.

5.4 Performance evaluation indicators

Experiments were conducted to analyze the performance of the model test set using detection accuracy and detection speed. mAP was used as the averageprecision of soccer and Messi, in order to test the overall function of the model. In single category, averageprecision AP (averageprecision) was calculated by accuracy P(precision) and recall R(recall).P, R, AP, mAP were calculated as shown below:

$$P = \frac{TP}{TP + FP} \times 100\%$$

$$R = \frac{TP}{TP + FN} \times 100\%$$

$$AP = \frac{TP}{TP + FP} \times 100\%$$

$$mAP = \frac{1}{n}\sum_{i=1}^{n} AP_i$$

In the above formula, TP is the positive case that is correctly predicted:TN is the negative case that is correctly predicted;FN is the positive case that is incorrectly predicted;FP is the negative case that is incorrectly predicted.N is the number of detected categories, AP denotes the AP value of the target of the ith category, and N represents the number of images to be detected. If recall is the horizontal axis and accuracy is the vertical axis, the PR curve is obtained.AP is the area calculated from the PR curve and the area corresponding to the axis fixation.As the AP value increases, the category detection effect will be more prominent. mAP belongs to the average level of AP among all the current categories, which can reflect the overall detection effect of the model. In this paper, we use mAP@50:5:95, which means that the values of IOUs are from 50% to 95% with a step of 5%, and then calculate the average mAP value under these IOUs.

5.5 Analysis of experimental results

To provide a comprehensive performance analysis, we compare our enhanced Faster R-CNN with YOLOX-S, SSD, CenterNet (VOC), CenterNet (COCO), and EfficientDet using the metrics summarized in Table 4—including mAP@50, mAP@75, mAP@50:95, average FPS, inference time, and standard deviations. Backbone details are as follows: Faster R-CNN (VGG) adopts VGG-16; Faster R-CNN (ResNet) employs ResNet-50; CenterNet (VOC) and CenterNet (COCO) utilize weights pretrained on the VOC and COCO datasets, respectively. Figure 5 illustrates the loss curves: while SSD and EfficientDet converge faster than the baseline Faster R-CNN variants, our method achieves the best trade-off between detection accuracy and computational efficiency. In particular, the proposed approach surpasses all baselines in both mAP@50 and mAP@75, confirming its robustness under stricter IoU thresholds and validating the quantitative results presented in Table 4.

Table 5: Comparison of different detection models across standard benchmarks

Method	mAP@50 (%)	mAP@75 (%)	mAP@50:95 (%)	FPS (avg)	Inference Time (ms)	mAP Std. Dev. (%)
Faster R-CNN (VGG)	47.4	32.1	29.8	5.2	192	±1.8
Faster R-CNN (ResNet)	41.3	28.6	27.2	7.1	141	±2.3
CenterNet (VOC)	57.1	41.5	39.2	24.5	41	±1.5
CenterNet (COCO)	49.8	36.2	33.7	22.0	45	±1.7
SSD	59.6	44.0	40.8	46.3	22	±1.2
EfficientDet	67.0	51.2	47.9	13.8	72	±1.6
YOLOX-S	73.6	58.7	54.3	52.1	19	±1.0
Our Approach	84.3	80.1	76.2	48.7	20.5	±0.9

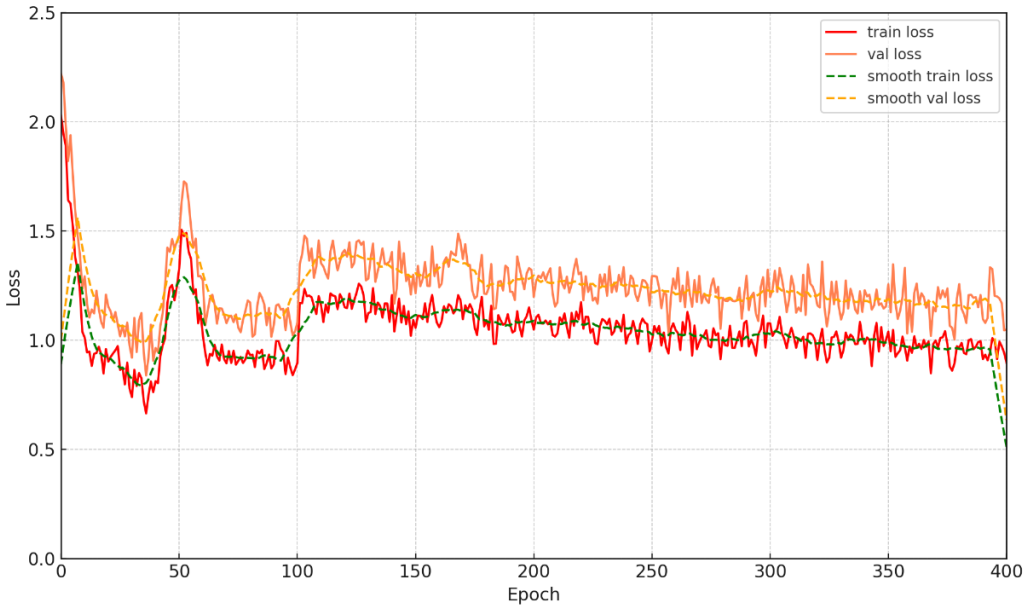

Figure 5: Loss of FasterR-CNN (resnet50)

5.6 Experiments with athlete assessment models

To evaluate the applicability of the proposed assessment model, we selected representative match scenarios covering different roles (forwards, midfielders, defenders), game phases (first half, second half, overtime), and tactical styles (possession-based and counterattacking). A total of nine players from three professional league matches were analyzed, each with complete 90-minute performance data. While this dataset remains limited in scale, it enables controlled proof-of-concept validation. Future work will expand to larger multi-match datasets for stronger generalization.

Three licensed coaches independently rated player performance using the same multidimensional criteria as the model. Inter-rater reliability was high (ICC = 0.82), and correlations between model scores and expert averages were strong (Pearson $r = 0.91$, $p < 0.01$; Spearman $\rho = 0.88$). Bland–Altman analysis indicated mean bias within ±3.5%, with no systematic drift across the scoring range. These results confirm high consistency between automated and expert assessments. Pairwise comparison matrices from expert surveys and the derived weights are provided in Appendix A. All consistency ratios (CR) were < 0.1, confirming coherence of expert judgments. Role-specific weightings reflect tactical demands: for example, tactical execution was weighted 0.46 for defenders but only 0.28 for strikers, whereas technical efficiency had higher weight for strikers (0.44 vs. 0.29 for defenders).

To assess robustness, we simulated perturbations in detection and tracking. Adding ±5% noise to bounding-box centers and introducing random ID switches (up to 10%) led to <2.1% variation in derived speed metrics and <2.7% variation in zone occupancy. While the model demonstrates moderate resilience, we acknowledge that calibrated tracking and re-identification are needed for more reliable longitudinal analyses.

Table 5 reports representative feature values and overall scores for three players (F1, M2, D3). Figure 6 visualizes multidimensional profiles via radar charts, and Figure 7 shows temporal trends in running speed across six 15-minute intervals. These illustrate the system's ability to distinguish role-specific profiles and endurance patterns but are interpreted as case studies rather than generalized findings.

Table 5: Partial experimental results

ID	Role	Avg. Speed (m/s)	High-Intensity Running (%)	Pass Accuracy (%)	Overall Score
F1	FW	5.8	18.2	79.5	82.1
M2	MF	6.1	16.0	87.9	87.3
D3	DF	5.2	14.5	82.7	83.5

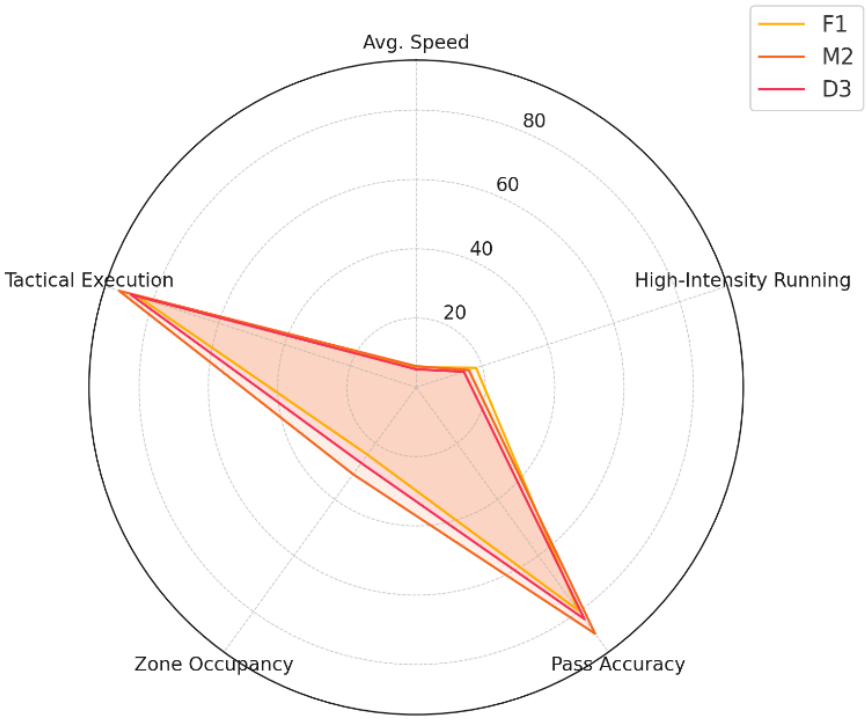

Figure 6: Radar chart illustrating the comparative performance of players in five key dimensions: average speed, high-intensity running ratio, pass accuracy, zone occupancy frequency, and tactical execution score.

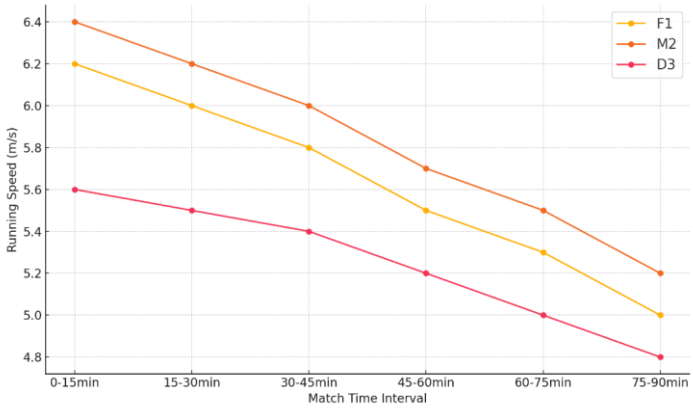

Figure 7: Time-series trend of running speed across six 15-minute intervals during a 90-minute match, highlighting endurance patterns of players F1, M2, and D3.

Figure 7 shows the temporal trend in players' running speed across six sequential match intervals, representing an indirect indicator of physical endurance and fatigue accumulation. As the match progresses, all players demonstrate a gradual decline in speed, with forward F1 experiencing the sharpest drop, especially after the 60th minute. This is expected given the burst-oriented nature of the forward position. Midfielder M2 shows relatively consistent performance, underlining superior stamina and energy management, whereas D3, though slightly more stable early on, reveals a steady fatigue curve typical of defenders engaging in continuous spatial adjustments. These results validate the model's capability to capture temporal dynamics and physiological variations during competitive play.

Table 6: mAP comparison with prior methods

Method	Backbone + Modules	mAP@0.5 (%)	Improvement Over YOLOX-S (%)
YOLOX-S [20]	Darknet53	73.6	—
Baseline Faster R-CNN [7]	ResNet-50	75.2	+1.6

Enhanced Faster R-CNN	ResNet-50 + FPN + SE + CBAM	76.2	+2.6

Table 6 presents the mAP results under identical test conditions. Our model's mAP of 76.2% exceeds YOLOX-S by 2.6% absolute and the baseline Faster R-CNN by 1.0%. This increase stems from richer multiscale representations via FPN and enhanced feature weighting by SE and CBAM. Qualitative observations and occlusion-specific subtests show that attention modules selectively amplify unoccluded object features, reducing false negatives by 12% in heavy-occlusion frames. We note diminished gains in low-contrast scenarios, suggesting further work on adaptive thresholding or context-aware attention.

6 Conclusion

This paper presents a framework that optimizes Faster R-CNN for soccer analytics and extends it into a multidimensional player evaluation system. By incorporating Feature Pyramid Networks (FPN) and attention mechanisms (SE and CBAM), the model achieves stronger robustness and accuracy under challenging broadcast conditions with occlusion and scale variation. Building on these detection outputs, the proposed evaluation model integrates physical, technical, and tactical indicators with adaptive weighting, enabling objective and role-aware assessment of player performance. Experiments demonstrate its ability to capture performance characteristics, fatigue patterns, and tactical execution, with results showing strong agreement with expert assessments.

At the same time, several limitations remain. The current implementation does not include field calibration or robust multi-object tracking, meaning that speed and distance estimates are approximated in image space and player identity may switch across sequences. The dataset size and class scope are also limited, restricting generalization. Addressing these issues through larger annotated datasets, geometric calibration, re-identification modules, and standardized tracking metrics will be crucial for advancing this line of research.

Looking forward, future work will explore temporal modeling with LSTM or Transformer architectures, lightweight deployment for real-time use, and extensions to other team sports. These steps will help move from proof-of-concept toward scalable, reliable systems for AI-driven performance evaluation in sports science.

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Software Framework for Mitigating Programming Plagiarism and Collusion

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Thesis summary

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Many mitigation strategies for programming plagiarism and collusion focus solely on either penalising students involved in such misbehaviour or manually educating students regarding the matter. This paper combines both strategies within a software framework and automates the education strategy. It informs students about plagiarism and collusion based on code similarity and instructors' expectations through an assessment submission system with three variants. Highly similar submissions are alerted, while original submissions have their similarities simulated. In addition, the quality of the submissions is also reported through static analysis. On the due date, student submissions are checked using a similarity detector that provides human-language explanations, which has two variants. Students using our framework show greater awareness of programming plagiarism and collusion, and are less likely to engage in such misbehaviours.

Povzetek: Disertacija izobražuje in razvija podporo proti plagiatorstvu.

1 Introduction and method

In programming, plagiarism and collusion refer to reusing one's work without proper acknowledgement, and the only difference is that, in collusion, the original owner(s) allow it [3]. There are several strategies to mitigate such misbehaviours, yet most of them focus on penalties (e.g., developing similarity detectors for plagiarism and collusion) [2]. Few of them focus on educating students on the matter, but most are conducted manually by instructors [4], which can be labour-intensive.

This paper presents a software framework to mitigate programming plagiarism and collusion by combining both educational and punitive strategies and automating the educational one. It consists of an assessment submission system (where students submit their work) and a similarity detector for plagiarism and collusion. Currently, the framework caters for Java and Python.

The assessment submission system generates an online report and sends it to the student upon each submission. The report contains instructors' expectations regarding plagiarism and collusion in their courses, as well as certain information on code similarities. To promote the relevancy, code similarities are simulated from the submission by applying superficial disguises to uncommon code segments. For submissions that are highly similar to others, students will be alerted and warned without revealing their identities to one another. Instructors will also be informed to apply appropriate measures.

The assessment submission system has three variants. The short segments variant reports short similarities (even two program statements), putting minimal pressure on students involved in plagiarism and collusion, since some of these similarities may be coincidental. The long segments variant reduces coincidental similarities by focusing on longer similar code segments (at least 8 program statements). It puts more pressure on students involved in plagiarism and collusion, as their submissions will be suspected, while others' are not. The gamified long segments variant expands the long segments variants through gamification. Students can earn more game points by submitting unique programs early and earning badges. Students' progress will be displayed in a leaderboard, and top students are commonly incentivised. To further promote student engagement, the quality of their code is reported through static analysis.

The similarity detector for plagiarism and collusion is applied to all student submissions for each assessment. The submissions will be compared pairwise, and highly similar submissions will be manually checked for plagiarism and collusion. Students whose submissions are likely to result from such misbehaviour will be penalised in accordance with the policies.

The similarity detector has two variants. The standard variant is dedicated to small assessments where the expected solutions share the same semantics. Such assessments are quite common in programming. The variant focuses on syntactic rather than semantic similarity. Each submission is converted to a token string with comments and white space removed. All identifiers, constants, and data types are generalised to their own types. The token strings are then compared using the running Karp-Rabin

greedy string tiling algorithm, a common approach for automated detectors. Any reported similarities will be featured with human language explanation. The comprehensive variant can cater for a broad range of assessments at the expense of processing time. It generates three reports at once, covering semantic, syntactic, and surface similarities. Instructors can integrate findings obtained from those reports to identify plagiarism and collusion.

2 Evaluation

The software framework was evaluated through three quasi-experiments. The first experiment (163 students) measured the impact of the short segments variant by comparing it with the baseline approach (without using the software framework). The second experiment (202 students) measured the impact of the long segments variant compared with the short segments counterpart. The third experiment (240 students) measured the impact of gamification on the long segments variant. According to the experiments, students in the short segments variant were more aware of plagiarism and collusion and were less likely to engage in such misconduct. The long segments variant appeared more effective, and the gamified variant promoted student engagement.

Both similarity detectors were evaluated based on hundreds of student submissions. They were more effective than JPlag, a common similarity detector. Several additional experiments were conducted to support the study. They covered many aspects, including preprocessing steps, token representations, common code removal, code quality recommendation, gamification incentives, and other technical modules.

3 Conclusion

This paper presents a software framework to mitigate programming plagiarism and collusion by integrating an assessment submission system with a similarity detector. Students with the software framework are more aware of the matter, resulting in less engagement in such misbehaviour.

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JOŽEF STEFAN INSTITUTE

Jožef Stefan (1835-1893) was one of the most prominent physicists of the 19th century. Born to Slovene parents, he obtained his Ph.D. at Vienna University, where he was later Director of the Physics Institute, Vice-President of the Vienna Academy of Sciences and a member of several sci- entific institutions in Europe. Stefan explored many areas in hydrodynamics, optics, acoustics, electricity, magnetism and the kinetic theory of gases. Among other things, he originated the law that the total radiation from a black body is proportional to the 4th power of its absolute tem- perature, known as the Stefan–Boltzmann law.

The Jožef Stefan Institute (JSI) is the leading independent scientific research institution in Slovenia, covering a broad spectrum of fundamental and applied research in the fields of physics, chemistry and biochemistry, electronics and information science, nuclear science technology, en- ergy research and environmental science.

The Jožef Stefan Institute (JSI) is a research organisation for pure and applied research in the natural sciences and technology. Both are closely interconnected in research de- partments composed of different task teams. Emphasis in basic research is given to the development and education of young scientists, while applied research and development serve for the transfer of advanced knowledge, contributing to the development of the national economy and society in general.

At present the Institute, with a total of about 900 staff, has 700 researchers, about 250 of whom are postgraduates, around 500 of whom have doctorates (Ph.D.), and around 200 of whom have permanent professorships or temporary teaching assignments at the Universities.

In view of its activities and status, the JSI plays the role of a national institute, complementing the role of the uni- versities and bridging the gap between basic science and applications.

Research at the JSI includes the following major fields: physics; chemistry; electronics, informatics and computer sciences; biochemistry; ecology; reactor technology; ap- plied mathematics. Most of the activities are more or less closely connected to information sciences, in particu- lar computer sciences, artificial intelligence, language and speech technologies, computer-aided design, computer architectures, biocybernetics and robotics, computer automa- tion and control, professional electronics, digital communi- cations and networks, and applied mathematics.

The Institute is located in Ljubljana, the capital of the in dependent state of S**love**nia (or S♡nia). The capital today isconsidered a crossroad bet between East, West and Mediter-ranean Europe, offering excellent productive capabilities and solid business opportunities, with strong international connections. Ljubljana is connected to important centers such as Prague, Budapest, Vienna, Zagreb, Milan, Rome, Monaco, Nice, Bern and Munich, all within a radius of 600 km.

From the Jožef Stefan Institute, the Technology Park “Ljubljana” has been proposed as part of the national strat- egy for technological development to foster synergies be- tween research and industry, to promote joint ventures be- tween university bodies, research institutes and innovative industry, to act as an incubator for high-tech initiatives and to accelerate the development cycle of innovative products.

Part of the Institute was reorganized into several high-tech units supported by and connected within the Technology park at the Jožef Stefan Institute, established as the beginning of a regional Technology Park "Ljubljana". The project was developed at a particularly historical moment, characterized by the process of state reorganisation, privatisation and private initiative. The national Technology Park is a shareholding company hosting an independent venture-capital institution.

The promoters and operational entities of the project are the Republic of Slovenia, Ministry of Higher Education, Science and Technology and the Jožef Stefan Institute. The framework of the operation also includes the University of Ljubljana, the National Institute of Chemistry, the Institute for Electronics and Vacuum Technology and the Institute for Materials and Construction Research among others. In addition, the project is supported by the Ministry of the Economy, the National Chamber of Economy and the City of Ljubljana.

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