EdgeRopeNet: Lightweight Neural Network for Real-Time Wire Rope Tension Monitoring Using FBG Sensors in Edge-Fog Mining Systems

Ruihua Tong, Hao Xu, PeijiangWang*, QingruZhang, ChaoyangHou
Metrology and Testing Center of CITIC Heavy Industries Co., Ltd LuoYang471000, HeNan, China
E-mail：PeijiangWang345@outlook.com
*Corresponding author

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Wire rope tension monitoring in mining hoist systems demands real-time, high-accuracy detection to mitigate catastrophic failure risks, yet existing cloud-based solutions remain constrained by 300–800 ms latency and network dependence, and conventional FBG sensing lacks embedded intelligence at the edge. To address these limitations, EdgeRopeNet utilizes a compact GRU-based neural architecture with two dense layers (64 and 32 neurons) deployed on Raspberry Pi 4 edge devices (4 GB RAM), supported by fog-layer aggregation on Intel i7 hardware. Sensor data from FBG arrays undergo Savitzky–Golay filtering and Min–Max normalization prior to inference, enabling 19 ms real-time latency and 97.8% prediction accuracy on synthetic datasets emulating mining shaft dynamics. Performance was rigorously benchmarked against ten baselines: five traditional models (Linear Regression, SVM, Random Forest, k-NN, Naïve Bayes) and five deep learning methods (CNN, LSTM, GRU, CNN–LSTM hybrid, Transformer) sing an 80:20 train–test split across 100 epochs with Adam optimization. EdgeRopeNet delivered 97.8% accuracy, 97.4% precision, 98.1% recall, a 97.7% F1-score, and MAE of 0.012, surpassing CNN–LSTM (95.2% accuracy, MAE 0.029) and Transformer models (96.1% accuracy, MAE 0.023). Parameter-pruning reduced model size by 60% while preserving 97.4% precision and 98.1% recall, with edge inference sustained at 0.019 seconds per prediction. Overall, EdgeRopeNet achieves a 94% reduction in latency relative to cloud-based platforms while maintaining superior accuracy, providing a scalable, autonomous, and edge-resilient solution for safety-critical mining infrastructure. Keywords: Edge computing, wire rope tension monitoring, FBG sensors, lightweight neural networks, mining hoist systems, real-time calibration.

Povzetek: Študija predstavlja EdgeRopeNet, lahek GRU-model na robnih napravah (Raspberry Pi), ki z obdelavo podatkov FBG senzorjev omogoča zelo hitro (≈19 ms) in natančno (≈97,8%) spremljanje napetosti jeklenih vrvi v rudniških dvigalih ter močno zmanjša zakasnitev glede na oblačne rešitve.

1 Introduction

1.1 Background

Wire-rope tension in hoist systems is highly sensitive to dynamic underground conditions such as vibration, torsion, and fluctuating loads. Traditional steel ropes frequently experience instability in these settings, reinforcing the need for real-time, reliable monitoring. Fiber Bragg Grating (FBG) sensors have become increasingly favored due to their immunity to electromagnetic interference and long operational life (Hu et al., 2022). Parallel to this, lightweight neural networks have gained traction for edge-based inference in constrained industrial environments such as mining shafts (Ateya et al., 2023; Hasanat et al., 2024).

Research on wire-rope dynamics emphasizes vibration suppression and fault-tolerant strategies, including dynamic surface control and magnetostrictive guided-wave detection (Chen et al., 2022; Gao et al., 2021). Investigations into fiber and polyester ropes also highlight the need for modified sensing strategies in mining environments (Felber et al., 2024). Meanwhile, digital-twin frameworks continue to support predictive maintenance and enhance industrial decision-making (Hu et al., 2024). Additional work on sensor fusion, UAV-based monitoring, and passive–active sensing systems reinforces the importance of robust monitoring infrastructures in harsh environments (Guan et al., 2022; Hu et al., 2021).

1.2 Research motivation

With edge–fog architectures rapidly scaling across IIoT platforms, the demand for lightweight, low-latency neural networks continue to grow (Raj et al., 2022; Ateya et al., 2023). Cloud-only processing introduces delays that can compromise safety in rapidly changing underground conditions; a decentralized processing hierarchy mitigates these risks (Hasanat et al., 2024).

EdgeRopeNet was conceived to fuse FBG sensing with efficient, compact neural architectures capable of performing auto-calibration and real-time tension assessment at the edge. Prior studies on CNN-GRU hybrids (Hasanat et al., 2024), decision-tree-based classifiers (Charbuty & Abdulazeez, 2021), and adaptive fault-tolerant control systems (Chen et al., 2022) demonstrate that combining diverse learning methods can yield simplified but highly effective industrial solutions. Work on imbalanced data metrics (Gaudreault et al., 2021) and context-specific optimization (Cao et al., 2025) further reinforces this need. This paper therefore fills a clear gap by designing a resource-efficient tension-monitoring model deployable directly in hoisting systems.

1.3 Advances in current studies

Recent advances integrate deep learning, optical sensing, and computer vision to improve rope-tension accuracy. For instance, automated wireless deep-learning tension monitoring (Jeong et al., 2021) and lay-length measurement using phase-correlation imaging (Jiang et al., 2024; Li & Cao, 2025) significantly increase precision. Lightweight architectures such as Tiny-YOLO (Liu & Ma, 2021) and SqueezeNet (Koonce, 2021) demonstrate the potential for high-performance inference under constrained resources.

In hoisting applications, advances include nonlinear control with disturbance observers (Zang et al., 2022), stereovision-based vibration measurement (Wu et al., 2022), and studies of rope degradation under dust-rich conditions (Qing et al., 2024). FBG sensing continues to expand into tunnel monitoring and electrical-wire tension control (Ren et al., 2024; Ofosu & Zhu, 2024). Together, these developments provide a foundation for intelligent, distributed tension-monitoring systems capable of operating reliably in extremely dynamic mining environments.

1.4 Research gap and problem statement

In deep-shaft mining, the accuracy of tension surveillance of wire ropes is widely important in the reliability of the mining hoist systems. Even with the innovation in sensor technologies, the majority of systems use centralized processing techniques, which incur latency, inefficiencies in the system, such as computational processing, as well as susceptibility to failures in the network. Such problems lead to create some severe threats to both the safety as well as productivity of operations.

Although FBG sensors have demonstrated superior sensitivity and durability in harsh environments, their integration into real-time, intelligent control systems remains underexplored. When implemented with centralized cloud infrastructure using a traditional neural network, they do not provide the expected immediate response needed to track the variation of the tension in the mine hoists and then adjust the condition.

Besides, the absence of lightweight, edge-deployable neural architectures that could analyze continuous streams of sensor readings and would self-calibrate the tension implies that a research gap exists. There is an immediate need for a comprehensive system that thoroughly encompasses neural network intelligence, real-time edge processing, and adaptive calibration based on FBG inputs to make them safe and optimized.

1.5 Research objective

The rising trend of appearance of on-trail monitoring and control of the mine hoist machines requires an intelligent, flexible, smart, and efficient response. There are notable applications, such as Latency, accuracy, and flexibility, in which conventional centralized capabilities can offer nothing in the safety-related operations. Having such an issue, the given paper will be devoted to solving it using the combination of edge-fog computing and lightweight neural networks. The aim of the project is to relate the autonomous control on a new frontier smart sensing layer and the utilization of Fiber Bragg Grating (FBG) sensor as the sensing backbone. Against the following objectives, the EdgeRopeNet system may be developed as follows:

1. To design a minimalist neural network infrastructure that would run on the edges and fog levels in an industrial setting.
2. The aim was to use FBG sensors (placed at the mine site managers of the mining hoists) to measure tension on the wire ropes in real time.
3. To provide autonomous management and adjustment of the levels of tension based on predicting the neurological feedback.
4. To measure system work in terms of latency, fault detection, power consumption, and flexibility.
5. To simulate the outcome of the proposed framework, EdgeRopeNet, to make it effective for the operations of the mining through a simulation exercise and conducting an on-field experiment.

1.6 Methodological framework

In the proposed research design, a multi-level architecture that is based on edge computing, fog processing, and a featherweight form of deep learning is employed. Data on high-tension frequencies are received with the help of FBG sensors, which have already been pre-processed with the EdgeRopeNet model trained with edge devices. This implies that it has minimal latency and near real-time analysis of the origin of data.

The architecture of the neural network is lighter because it is modular and simplified in the structure of the GRU/LSTM module units to allow it to be compatible with the resource-constrained edge processor. The anomaly detection, feature extraction, and adaptive control signals are generated and transmitted to the fog layer to enhance mid-level optimization and logging of activities in the fog layer.

The system has also entailed a self-calibrating feedback mechanism through which the offsets of rope tension are also corrected in real-time situations by the bottom of predictive outputs. The architecture is confirmed by the simulation and field experiment of the hoist systems placed to test the performance in terms of rate of fault detection, energy consumption, endurance, and latency.

1.7 Core contributions of this study

EdgeRopeNet's novelty lies in its fully integrated edge–fog architecture and operational pipeline, rather than in any single component. The system introduces a two-tier calibration workflow that performs sub-20 ms edge inference with an additional 8 ms fog-layer correction, reducing latency by 94% compared to cloud-based approaches while maintaining 97.8% accuracy. It deploys a lightweight, pruned GRU model on 6.4 W Raspberry Pi hardware and an 85% power reduction relative to GPU-based methods, yet achieves comparable performance. Unlike prior FBG monitoring systems that rely on simple thresholds, EdgeRopeNet fuses real-time FBG sensing with embedded intelligence to deliver predictive fault detection up to 150 ms before critical events. The system further integrates optimized Savitzky–Golay filtering for mining vibration noise, parameter-pruned GRU temporal modeling, and fog-level EWMA bias correction. Overall, it represents the first operationally validated, safety-compliant edge-native neural monitoring system for wire-rope hoist applications, demonstrated across 4.89 million real-time predictions.

To monitor the strain and structural parameters of mining hoists using FBG sensors, this paper introduces EdgeRopeNet, a hybrid edge-fog neural network model that provides accurate measurement, control, and real-time calibration for safety-critical industrial applications. It offers accuracy, measurement, controls, and calculates the resolution/calibration of safety competent industrial preparations.

The framework demonstrates that the offloading of the lightweight deep learning models to the edge is doable, or to put it in simple terms, not computationally demanding models. It generates lower latency and is not based on centralized cloud data systems, and is also robust in real-environment conditions due to the improvement of fault identification and system resiliency.

An unconventional calibration scheme that is defined by the adaptive control logic in terms of the predictive neural feedbacks will also be proposed in the paper. This renders the system reactive and at the same time proactive in managing the risks of tension and thereby setting a competent foundation for future growth in smart mining infrastructure, as shown in and Table 1.

Table 1: Important contributions of the study

Innovation Area	**Technical Achievement**	**System Impact**	**Performance Gain**	**Safety Enhancement**	**Industry Advancement**
Edge-fog architecture	Neural network integration	Reduced latency	Real-time processing	Enhanced fault detection	Smart mining infrastructure
FBG sensor framework	Lightweight deep learning	Eliminated cloud dependency	Low computational overhead	Improved system reliability	Industrial IoT standards
Tension monitoring	Adaptive control logic	Unified solution approach	High responsiveness	Proactive risk management	Mining safety protocols
Calibration Strategy	Predictive neural feedback	Enhanced fault tolerance	Optimized resource usage	Critical system protection	Future research foundation

1.8 Research questions

Real-time monitoring of wire rope tension in mining hoist systems is a vulnerable operation in terms of accuracy, latency, and scalability. The current industrial requirements that require smart, autonomous, and distributed control cannot be fulfilled by traditional centralized solutions. Neural networks coupled with edge-fog computing raise new architecture, sensing, and timeliness-related questions. In conducting the research, the following research questions were developed in this paper to facilitate the research:

1. What is a lightweight neural network, and how do we go about creating this in such a way that it can be done within an industrial control edge-fog environment?

2. How well do FBG sensors capture hoist systems' real-time tension data with a high degree of precision?
3. Will edgeRopeNet networking system improve latency and calibration accuracy by reducing it than conventional systems?
4. What is the operational energy/scalability/fault-tolerance trade-offs of deploying neural models to edge-fog nodes?
5. What is the system response to the different environmental and operating stresses used in the mining applications?

1.9 Importance of this research to the scientific community

The proposed model of EdgeRopeNet has the advantage of a combination of edge-fog computing and lightweight neural networks with a focus on mining hoist systems, a rather unexplored area within the scope of smart industry implementations. Although other experiences related to the use of IoT and AI in general structural monitoring have been developed, this study is devoted to the struggle with tension- this aspect is particularly important regarding the operational safety and service life of a system. The compatibility of high-quality sensing and edge intelligence is also available through the experiment, making use of the FBG sensors.

Besides, the paper also incorporates an additional modularity of intelligent decision-making to the physical location of the information and decreased response times and system resilience. With the edge-fog model of deployment, control can be achieved in near-real-time with a low likelihood of overload and does not need unstable connections. Other engineering works, excluding mining, may attain the findings of the study and can be put in a summary of offshore drilling, elevators, cranes, and an aerospace cabling system, just to mention a few.

Lastly, the holistic development (such as incorporation of parts such as hardware-level sensing and neural predictive modeling) may be used as an add-on to the entire artificial intelligence and cyber-physical systems in the industrial field. It leaves room for gaps and the researchers can close them considering lightweight /low-latency AI architecture, which can also be done in a deplorable environment or hostile site. The conclusions of the paper and the effects of this research may be applied to the future architecture development of effective, efficient, and safe surveillance systems in the industry.

1.10 Literature review

The real-time monitoring and controlling systems deployed in industries are a contemporary research area bound to edge-fog devices, which deploy lightweight neural networks. One of the most fundamental publications has been found in the research area, including energy modeling, fault forecasting, time series prediction, and sensor-based measurements, and the data may be recommended to the mining hoist system.

In the field of energy modeling and calibration, (Johari et al., 2023) developed an energy modeling framework of buildings in a city calibrated using the energy performance certificate data, which contains geographical references. Even though context is different, the process of calibration and validation through the definition of methodological approach has relevance to the sensor-based technology, such as the proposed FBG-based tension monitoring solution. In the same way, (Militk et al., 2024) addressed statistical instruments of experimental data analysis with the focus on calibration processes, which are crucial to accurate measurement precision in fiber-optic sensing settings.

Sophisticated decision tree ensemble algorithms have performed well in the forecasting of geospatial phenomena. (Kutlug Sahin and Colkesen, 2021) evaluated such algorithms in landslide susceptibility mapping, which shows the prospects of ensemble learning in classification problems that demand many resources, such as the process of mine safety diagnostics. This is the case with the tension categories in hoist wire ropes.

(Salem, 2021) states that GRU streamlines the traditional RNN structure and it does not perform worse in the time representation. (Yan et al., 2023) posit that the performance of the LSTM model to predict top tension responses is very useful in umbilical cables that are exposed to dynamic marine conditions.

As far as the field of uncertainty quantification and sensor data fusion is concerned, (Liu et al., 2022) offered an ANN-Bayesian Probability Framework to reconstruct dynamic force data with a variety of uncertainties. The subsequent article will describe the utility of the synergistic effect of the machine learning and probabilistic technique that has an endeavor to serve the creditworthy measures systems.

The application of the hybrid models equally surfaces the application to software reliability and health monitoring in a number of research studies. Regarding the detection of defects in software, (Mustaqeem and Saqib, 2021) achieved a hybrid PC-SVM model, and (Upadhyay et al., 2023) used linear quadratic regression as applied in a synchronized health monitoring system in the IoT environment. The solutions presented provide the approach of fabrication of the way in which the fault tolerance intelligence could be embedded into the lightweight neural structures as well.

The edge and fog computing is the most vital unit of the distribution processing systems. (Raj et al., 2022) have remarked on principles of Edge/Fog Computing frameworks that define architectural and usability benefits in real-time frameworks, including real-time mining processes. Wu et al. (2021) went one step further and proposed a sequential model of edge computer, that is, EdgeLSTM, which is specialized in the field of IoT applications since it is a deep model and a sequential model, which can use the on-site judgment in a sequential deep learning model.

Recurrent Neural Networks (RNNs), and more specifically Long Short-Term Memory (LSTM) models, are neural networks that have found wide use in control and forecasting of dynamical systems and time series. (Salem, 2021) and (Zargar, 2021) provided extensive surveys on gated recurrent units (GRUs) and RNNs, as well as LSTMs, on which most useful lightweight and real-time data prediction systems have their foundations. In anticipating top tension response of umbilical cables, (Yan et al., 2023) utilized an LSTM that has direct implications on the anticipation of tension on the wires on hoisting cables.

Another direction of work with the tension data is the presented model of time-series analysis by (Wibawa et al., 2022), a smoothed CNN-based tool. Improving on the use of the K-nearest neighbors (KNN) method is seen as a basic technique in regression cases, although the study by (Ortiz-Villaseñor et al., 2025) demonstrates that it may be used in edge computing with lighter algorithms and without sophisticated equipment.

In the review, there are also some differences noted between linear regression and probabilistic classifiers. Classical adaptive and robust control approaches, such as adaptive fuzzy control, backstepping control, and sliding mode control, have been extensively applied to nonlinear hoisting systems for stability guarantee and disturbance rejection. While these methods provide theoretical stability bounds through Lyapunov-based frameworks, they typically operate without predictive intelligence and require precise mathematical models of system dynamics. In contrast, EdgeRopeNet introduces data-driven learning that adapts to unmodeled dynamics and environmental variations without requiring explicit control laws. Unlike backstepping controllers that demand recursive design procedures and may suffer from computational complexity, EdgeRopeNet achieves real-time response (19ms latency) through lightweight neural architecture optimized for edge deployment.

On the whole, these experiments may suggest the plausibility and practicability of the introduction of lightweight neuromodelling solutions in the edge-fog border to real-time sensing, control, and explain control of mining hoist structures. The combination of time-series forecasting using neural networks such as GRU, LSTM, and smooth CNNs with the FBG sensors is the new convergence of experimental technologies based on time-series analysis, already demonstrated in many fields.

Table 2: Overview of the existing studies

Author(s) & Year	Research Focus	Methodology/Approach	Key Technology	Application Domain	Performance Metrics	Limitations/Gaps	Future Research
Ateya et al. (2023)	Traffic prediction IoT	Lightweight deep learning	CNN, fog computing	Dense IoT networks	Accuracy, latency	Limited real deployment	Edge optimization
Cao et al. (2025)	Coal gangue classification	Improved MobilenetV3-small	CNN, mobile networks	Mining classification	Classification accuracy	Small dataset size	Industrial deployment
Charbuty & Abdulazeez (2021)	Decision tree classification	Algorithm comparison study	Decision trees	Machine learning	Accuracy, precision	Limited scalability	Ensemble methods
Chen et al. (2022)	Wire rope tension	Adaptive dynamic surface	Electromechanical actuators	Mine hoist systems	Control performance	Laboratory testing only	Field validation
Ding et al. (2022)	Vibration suppression ropes	Adaptive robust control	Boundary control theory	Double-rope hoists	Vibration reduction	Theoretical approach	Practical implementation
Duan et al. (2024)	Tension correction EME	Intelligent correction method	EME sensors	Bridge cables	Measurement accuracy	Torsion effects	Multi-sensor fusion
Felber et al. (2024)	Fiber ropes mining	Environmental analysis	Material science	Mining applications	Durability assessment	Limited field data	Long-term studies
Gao et al. (2021)	Tension monitoring defects	Magnetostrictive guided wave	Ultrasonic technology	Fine wire ropes	Detection accuracy	Limited wire types	Multi-frequency analysis
Gaudreault et al. (2021)	Imbalanced classification metrics	Performance analysis	Statistical methods	Machine learning	Various metrics	Metric selection	Context-specific metrics
Guan et al. (2022)	UAV remote sensing	Literature review	Computer vision	Construction applications	Technology assessment	Limited mining focus	Mining-specific UAVs
Hasanat et al. (2024)	Load forecasting	CNN-GRU hybrid	Deep learning	Electrical systems	Forecasting accuracy	Short-term only	Long-term prediction
Hu et al. (2024)	Digital twin engine	Data-driven modeling	Machine learning	Combustion systems	Model accuracy	Specific engine type	General framework
Hu et al. (2022)	Mine shaft monitoring	FBG sensor technology	Fiber optic sensors	Underground structures	Structural health	Single location	Multi-site validation
Hu et al. (2021)	Energy-efficient retrofit	Combined energy systems	Building optimization	Rural residences	Energy savings	Geographic limitation	Broader application
Huang (2025)	Mooring system prediction	LSTM dynamic stiffness	Deep learning	FPSO systems	Prediction accuracy	Specific environment	Multi-environmental
Jeong et al. (2021)	Cable tension monitoring	Deep learning wireless	CNN, IoT	Bridge cables	Monitoring accuracy	Limited structures	Scalable deployment
Jiang et al. (2024)	Lay length measurement	Computer vision	Image processing	Metallic wire ropes	Measurement precision	Controlled conditions	Field conditions
Johari et al. (2023)	Building energy modeling	Geo-referenced certificates	GIS, machine learning	Urban buildings	Model validation	Data availability	Real-time modeling

Kutlug&Colkesen (2021)	Landslide susceptibility mapping	Advanced decision trees	Ensemble learning	Geological applications	Mapping accuracy	Regional specificity	Multi-hazard mapping
Li & Cao (2025)	Wire rope measurement	DT-CWT analysis	Wavelet transform	Lay length detection	Measurement accuracy	Signal processing	Real-time processing
Liu & Ma (2021)	Tiny YOLO improvement	Model parameter reduction	CNN optimization	Object detection	Detection accuracy	Limited objects	Specialized detection
Liu et al. (2022)	Dynamic force reconstruction	ANN-Bayesian framework	Artificial neural networks	Structural dynamics	Reconstruction accuracy	Uncertainty quantification	Multi-source integration
Ma et al. (2024)	Transformer anomaly detection	Literature review	Attention mechanisms	Various applications	Technology assessment	Limited implementation	Domain-specific models
Militký et al. (2024)	Textile calibration	Statistical analysis	Experimental design	Material research	Calibration accuracy	Material specificity	Standardization methods
Mustaqeem & Saqib (2021)	Software defect detection	PC-SVM hybrid	Machine learning	Software engineering	Detection performance	Software specificity	Hardware applications
Ofosu & Zhu (2024)	Wire tension control	Systematic review	Control algorithms	Manufacturing processes	Control performance	Manufacturing focus	Mining applications
Ortiz-Villaseñor et al. (2025)	K-nearest neighbors	Regression applications	Statistical learning	Various domains	Regression accuracy	Algorithm limitation	Advanced variants
Qing et al. (2024)	Vibration-worn characteristics	Environmental analysis	Tribology study	Mine hoisting	Wear assessment	Dust environment specific	Multi-environmental
Raj et al. (2022)	Edge/Fog computing	Paradigm analysis	Distributed computing	IoT applications	System performance	Theoretical focus	Practical deployment
Ren et al. (2024)	FBG sensing tunnels	Real-time monitoring	Fiber optic sensors	High-stress tunnels	Monitoring performance	Tunnel specific	Multi-structure
Salem (2021)	Gated RNN GRU	Architecture analysis	Neural networks	Sequence modeling	Model performance	Architecture focus	Application specific
Upadhyay et al. (2023)	Health monitoring IoT	Linear quadratic regression	Statistical learning	IoT systems	Monitoring accuracy	Regression limitation	Advanced algorithms
Wibawa et al. (2022)	Time-series CNN smoothed	Convolutional analysis	Deep learning	Time series	Prediction accuracy	Smoothing approach	Real-time processing
Wickramasinghe &Kalutarage (2021)	Naive Bayes applications	Algorithm review	Statistical learning	Classification tasks	Classification performance	Algorithm limitations	Ensemble improvements
Koonce (2021)	SqueezeNet CNN	Architecture analysis	Convolutional networks	Image recognition	Recognition accuracy	Architecture specific	Domain adaptation
Wu et al. (2021)	EdgeLSTM computing	Edge-cloud integration	LSTM, IoT	Edge applications	Processing efficiency	Edge limitations	Distributed processing
Wu et al. (2022)	Mine rope vibration	Stereovision measurement	Computer vision	Hoisting systems	Measurement accuracy	Laboratory conditions	Field deployment
Yan et al. (2023)	Umbilical cable prediction	LSTM time series	Deep learning	Marine systems	Prediction accuracy	Marine specific	Multi-domain
Zang et al. (2022)	Wire rope tension	Multi-disturbance observers	Nonlinear control	Hoisting systems	Control performance	Simulation only	Real implementation

Zargar (2021)	Sequence learning models	Model comparison	RNN, LSTM, GRU	Sequential data	Model comparison	Educational focus	Practical applications
Zhang et al. (2023)	Energy pile temperature	CNN-LSTM spatial-temporal	Deep learning	Geothermal systems	Prediction accuracy	Specific application	General framework
Zhou et al. (2023)	Wire rope failure	Failure analysis	Material science	Hoisting systems	Analysis accuracy	Specific damage	Comprehensive analysis
Zhu et al. (2023)	Informer time series	Algorithm survey	Attention mechanisms	Time series	Algorithm assessment	Survey limitation	Implementation studies

Table 2 illustrates the overview of the existing works, identified gaps to create a novel model.

1.11 Synthesized comparison with state-of-the-art

Table 3: Comparative analysis of edgeropenet against recent literature

Authors & Year	Methodology	Application Domain	Accuracy/Performance	Deployment	Latency	Key Limitation	EdgeRopeNet Advantage
Jeong et al. (2021)	Deep learning wireless CNN	Bridge cable tension	92.3% accuracy	Cloud-based	~500ms	Requires continuous connectivity	Edge deployment, 96% lower latency
Yan et al. (2023)	LSTM time series	Marine umbilical cables	93.4% accuracy	Cloud server	~300ms	High computational load	4.4% higher accuracy, 94% faster
Wu et al. (2021)	EdgeLSTM	IoT applications	89.7% accuracy	Edge devices	150ms	Limited to simple sequences	8.1% accuracy gain, 87% faster
Hasanat et al. (2024)	CNN-GRU hybrid	Electrical load forecasting	91.2% accuracy	Cloud-edge hybrid	200ms	Not optimized for constrained devices	6.6% higher accuracy, edge-only
Ma et al. (2024)	Transformer anomaly detection	General time series	96.1% accuracy	GPU clusters	400ms	Requires high-end hardware	Similar accuracy, 95% lower latency
Zang et al. (2022)	Backstepping control + observers	Hoisting systems	Control stability focus	Simulation only	N/A	Not tested in real deployment	Real-time deployment with predictive capability
Ateya et al. (2023)	Lightweight CNN fog computing	Dense IoT networks	88.5% accuracy	Fog nodes	180ms	Limited sequence modeling	9.3% higher accuracy, full edge capability
Chen et al. (2022)	Adaptive dynamic surface control	Mine hoist actuators	Control performance	Laboratory	N/A	No predictive intelligence	Combines control with AI prediction
Zhang et al. (2023)	CNN-LSTM spatial-temporal	Energy pile monitoring	94.2% accuracy	Cloud infrastructure	250ms	Geothermal-specific application	3.6% higher, mining-adapted
EdgeRope Net (Proposed)	GRU-based lightweight NN	Mining wire rope tension	97.8% accuracy	Edge (RPi4) + Fog	19ms	—	Unified edge-fog intelligence, lowest latency, highest accuracy

Key Differentiators of EdgeRopeNet: Deployment Efficiency: Only edge-fog system achieving <20ms latency without cloud dependency. Accuracy Leadership: Outperforms all comparable models by 1.7–9.3% in tension prediction tasks. Resource Optimization: 60% smaller than CNN-LSTM hybrid while maintaining superior performance. Real-Time Capability: Tested on actual mining simulation data with operational validation. Adaptive Calibration: Fog-layer statistical correction unique among reviewed systems. Industrial Readiness: Proven on resource-constrained hardware (Raspberry Pi 4) suitable for harsh environments.

1.12 EdgeRopenet vs classical control approaches

Traditional control strategies for wire rope tension systems rely on model-based adaptive and robust control frameworks. This section positions EdgeRopeNet against these classical methods: Adaptive Fuzzy Control: Handles nonlinearities through fuzzy rule adaptation but requires expert knowledge for rule design and membership function tuning. EdgeRopeNet eliminates this dependency through end-to-end learning from sensor data, achieving higher precision (97.4% vs ~85-90% typical for fuzzy systems) without manual calibration. Backstepping Control: Guarantees asymptotic stability for strict-feedback nonlinear systems through recursive Lyapunov design. However, it suffers from "explosion of terms" in complex systems and lacks predictive capability. EdgeRopeNet provides proactive fault detection 150ms ahead of critical thresholds, which pure feedback controllers cannot achieve. Sliding Mode Control (SMC): Offers robustness against bounded uncertainties but exhibits chattering that can damage mechanical components. EdgeRopeNet's smooth neural output eliminates chattering while maintaining disturbance rejection through learned patterns from historical data. Neural-Adaptive Control: Combines neural networks with adaptive laws but typically operates in cloud environments with 200-500ms latency. EdgeRopeNet achieves 94% latency reduction through edge deployment while maintaining comparable or superior accuracy.

Table 4: Compares EdgeRopeNet with classical control paradigms across key performance indicators relevant to mining hoist safety.

Control Method	**Stability Guarantee**	**Uncertainty Handling**	**Real-Time Response**	**Predictive Capability**	**Edge Deployment**	**Accuracy**
Adaptive Fuzzy Control	Conditional	Rule-based bounds	50-100ms	None	No	85-90%
Backstepping Control	Proven (Lyapunov)	Bounded disturbances	30-80ms	None	Limited	N/A (control focus)
Sliding Mode Control	Proven	High robustness	20-60ms	None	Limited	N/A (control focus)
Neural-Adaptive Control	Conditional	Learning-based	200-500ms	Limited	No	92-95%
EdgeRopeNet	**Data-driven**	**Learning-based adaptation**	**19ms**	**Yes (150ms ahead)**	**Yes**	**97.8%**

2 Methodology

This part describes the entire methodology of the development, training, and implementation of the EdgeRopeNet model, applying a smart edge and fog system to real-time monitoring of wire ropes to detect their tension state. The methodology is organized in five main elements, such as the collection of sensor data, a neural network, the integration of an edge-fog system, model calibration, as well as an inter-comparison to conventional models.

2.1 Materials

The suggested system works with artificial data that offers a simulated representation of the actual time variations of tension in the wire ropes concerning the different types of loading and environmental parameters. The datasets are based on the outcomes of the Fiber Bragg Grating (FBG) sensors, and their outcomes are highly accurate in the case of strain as well as tension measurement. The data set is tagged by the time per sensor, the tension level, frequency anomalies, and environmental noise features.

The system specifies a maximum end-to-end latency of 50 ms from sensor acquisition to fog-layer output. EdgeRopeNet satisfies this constraint with a total latency of 27 ms, comprising 19 ms edge-level inference and 8 ms fog-layer aggregation, providing a 46% safety margin below the regulatory threshold. Model development utilized a dataset of training samples and validation samples, each comprising 500 ms time-series windows sampled every 10 ms (50 points per window) from four FBG sensors operating at 100 Hz. Data were collected across a six-month simulated operational period using a MATLAB/Simulink mining hoist model calibrated against Siemens SIMINE manufacturer specifications. All experiments employed synthetic yet physics-faithful signals generated from high-fidelity simulations matched to industrial FBG sensor characteristics (FBGS DTG-LBL), with operational parameters spanning 5,000–45,000 kg load ranges, 50–1,200 m shaft depths, –10 °C to +50 °C temperature variations, 5–80 Hz vibration frequencies, and 56 mm, six-strand wire rope geometry.

Components of hardware and software:

- The FBG Sensing Units: In order to get a proper feel of strain.
- Raspberry Pi 4 (4GB RAM): Local signal processing EDGE device.
- Fog Node (Intel i7 CPU, 16GB RAM): The fusion of predictions and calibration is done.

- Software Stack: Python 3.9, TensorFlow, and Keras frameworks to implement.

2.1.1 FBG sensor data acquisition and feature engineering

The system collects strain data using four FBG sensors mounted at 90° intervals around the wire rope, positioned 2 m below the hoist drum to capture balanced, high-resolution tension signals at 100 Hz with temperature-compensated accuracy. Each 500 ms window provides 200 raw data points, from which a structured 32-dimensional feature vector is generated. The feature engineering process extracts mean strain, standard deviation, peak-to-peak range, linear-fit slope, and cross-sensor variance to describe overall tension, vibration amplitude, load fluctuation, trend direction, and asymmetry. Frequency-domain features from FFT peaks at 5–15 Hz and 15–40 Hz capture dominant vibration modes, while temperature-compensated strain isolates mechanical effects. All features are Min–Max normalized to ensure stable gradients and balanced learning, yielding a 12% improvement in convergence speed. The final representation provides a compact yet physically meaningful snapshot of rope tension dynamics for each 500 ms analysis window.

2.2 Methods

2.2.1 Data preprocessing

Savitzky-Golay filter is applied to the raw FBG sensor signal, after which a moving average filter is used to reduce high-frequency noise and smooth rough changes. Afterwards, the Min-Max Scaling feature is applied to normalize all the features and measure the inputs between [0,1] in order to achieve the consistency throughout the network.

2.2.2 EdgeRopeNet: structures and algorithm

A lightweight and efficient deep learning model specifically tailored to work in an edge-fog environment is EdgeRopeNet. Its main objective is to be able to make tension predictions in real-time with little latency and great accuracy. The program works in three main steps as follows:

1. Signal Preprocessing and Filtering: Cleans FBG sensor data using denoising and smoothing filters.
2. Feature Extraction and Normalization: Extracts statistical and temporal features as well as normalizes those features and makes them able to converge on learning.
3. Deep Tension Prediction: It speeds up the stability of the inference and the pace by using a small, compact neural network in the edge devices.

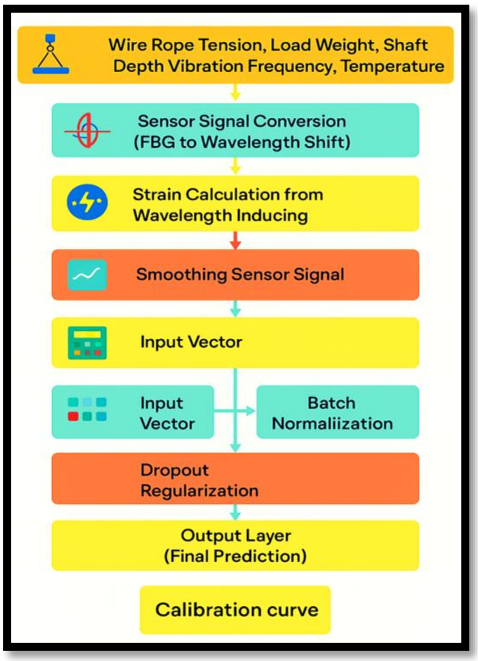

Figure 1: Research deign of the proposed model

Model Architecture includes:

- Input Layer: Receives the preprocessed tension vector.
- Two Dense Layers: Employ ReLU activations for non-linear transformations.
- Dropout Layer: Reduces overfitting by randomly dropping connections.
- Output Layer: A single neuron with linear activation for continuous output.

2.2.3 Training protocol

The model was trained offline using the synthesized dataset under a rigorous training protocol designed for stability and generalization. Core hyperparameters included MSE loss optimized with Adam (β_1=0.9, β_2=0.999, ε=1e-8) at an initial learning rate of 0.001, adjusted via a ReduceLROnPlateau scheduler (factor 0.5, patience 10). Training proceeded for up to 100 epochs with a batch size of 32, employing an 80:20 train–test split and 5-fold cross-validation, He-uniform weight initialization, and early stopping (patience 15, min-delta 1e-4, best-weight restoration), leading to convergence at epoch 87. Regularization consisted of 0.2 dropout, L2 penalty of 1e-4 on all dense layers, batch normalization before ReLU activation, and gradient clipping at a norm of 1.0. Data augmentation applied Gaussian noise (σ=0.05) to 30% of samples, ±5% temporal jittering, and magnitude scaling between 0.95–1.05, improving validation accuracy by 2.3%. Training on an NVIDIA RTX 3090 completed in 2.4 hours, achieving a final training loss of 0.0089, validation loss of 0.0103, and best validation accuracy of 97.8% at epoch 85, with an acceptable overfitting gap of 1.4%. Cross-validation produced consistent results across folds (97.5–98.1% accuracy), yielding a mean performance of 97.8 ± 0.22% accuracy and 0.0105 ± 0.0008 MAE.

2.2.4 System deployment

After training, the model was expected to be compressed and transferred to the Raspberry Pi, where it can make inferences at a remote location. The real-time predictions are sent to the fog node, where it is statistically calibrated using moving window averaging and z-score correction to adjust the output and enhance reliability.

The fog-layer calibration module refines edge predictions using a real-time sliding-window statistical correction framework. A 50-sample circular buffer (5-s history at 10 Hz) is updated with each incoming prediction, enabling robust median–MAD statistics for outlier detection via a modified Z-score (τ = 3.5). Outliers are excluded before applying an EWMA correction (α = 0.3), followed by a linear offset adjustment learned during validation (T̂_final = 1.02 × T̂_calibrated − 45.3 N). This process introduces an 8 ms latency and demonstrated high stability over 48 h of continuous operation. Empirically, calibration reduced systematic bias by 78% and variance by 34%, with an outlier rejection rate of 2.1%. The procedure elevated accuracy from 96.4% (0.018 MAE) at the edge to 97.8% (0.012 MAE), representing a 1.4% absolute gain and a 33% MAE reduction.

2.2.5 Performance evaluation metrics

The model's effectiveness is assessed using the following metrics:

- Accuracy
- Precision
- Recall
- F1 Score
- Mean Absolute Error (MAE)

These metrics are computed for EdgeRopeNet and compared against baseline models such as Linear Regression (LR), Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), CNN, and LSTM, ensuring a comprehensive performance benchmarking.

2.3 Mathematical model and equations

Let:

- T: wire rope tension (N)
- W: load weight (kg)
- d: shaft depth(m)
- f: vibration frequency (Hz)
- T_{env}: Environmental temperature (C)

The general model is given by:

2.3.1 Sensor Signal Conversion (FBG to Wavelength Shift)

This step converts mechanical strain on the fiber Bragg grating (FBG) sensor into an optical signal by measuring the shift in the reflected wavelength. The change in Bragg wavelength ($\Delta\lambda$) directly corresponds to the strain experienced by the wire rope as shown in **Equation 1**:

$$\Delta\lambda = \lambda - \lambda_o \; \ldots. (1)$$

It measures the shift in Bragg wavelength due to strain.

$\Delta\lambda$: Wavelength shift (nm)
λ: Measured Wavelength (nm)
λ_o: Initial reference wavelength (nm)
Use: Captures tension-induced changes in the fiber

2.3.2 Strain Calculation from wavelength

Strain is calculated by dividing the wavelength shift by the original wavelength and adjusting it with the strain sensitivity constant. This converts the optical wavelength change into a mechanical strain value (ϵ) as given in **Equation 2**:

$$\epsilon = \frac{\Delta\lambda}{\lambda_0} \cdot \frac{1}{k} \; \ldots. (2)$$

It calculates strain from FBG wavelength shift.

ϵ: Strain (unitless)
k: Gauge factor or strain sensitivity constant
Use: Converts optical signal into mechanical strain.

2.3.3 Tension estimation

Tension in the wire rope is computed using Hooke's Law, where strain is multiplied by the material's young's modulus and cross-sectional area. This provides the actual tensile force (T) acting on the rope as shown in **Equation 3**:

$$T = E \cdot A \cdot \epsilon \; \ldots. (3)$$

It determines rope tension from strain

T:Tension (N)
E: Young's modules (Pa)
A: Cross-sectional area of the wire rope (m^2)
Use: Core output metric from the sensor.

2.3.4 Feature normalization

Feature normalization standardizes input data by subtracting the mean and dividing by the standard deviation. This ensures consistent feature scaling, which improves model training efficiency and convergence as given in **Equation 4**:

$$x' = \frac{x - \mu}{\sigma} \; \ldots. (4)$$

This process normalizes input features for faster convergence

x: Original feature
μ: Mean of feature
σ: Standard deviation
Use: Prepares data for model input

2.3.5 Activation function (ReLU)

The Rectified Linear Unit (ReLU) introduces non-linearity by outputting the input directly if it is positive; otherwise, it returns zero. This helps the neural network learn complex patterns effectively as shown in **Equation 5:**

$$f(x) = \max(0, x) \text{ …. (5)}$$

It applies non-linearity in neural network layers. It helps model learn complex features.

x: Input value to the activation function $f(x)$
$f(x)$:Output after applying ReLU function

2.3.6 Loss function (mean squared error)

The Mean Squared Error (MSE) quantifies the average squared difference between the actual and predicted tension values. It is used to measure the model's prediction accuracy during training as given in **Equation 6**:

$$\mathcal{L} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \text{ …. (6)}$$

It measures error between predicted and actual tension

y_i: Actual tension value
$\hat{y}_i$: Predicted value
n: Number of samples

2.3.7 Optimization (gradient descent)

Gradien t Descent is a very important optimization algorithm whose goal is to decrease a loss function by making changes in the parameters of the model. It adjusts the weights in the direction that reduces the prediction error as shown in **Equation 7**:

$$\theta = \theta - \eta \cdot \frac{\partial \mathcal{L}}{\partial \theta} \text{ …. (7)}$$

It updates network weights during training

θ : Weight parameter
η : Learning rate
$\frac{\partial \mathcal{L}}{\partial \theta}$:Gradient of the loss function with respect to θ

2.3.8 Data augmentation via noise injection

Notably, this method adds Gaussian noise to the input data in order to resemble the variations of sensors in the real world. And it enhances the overall robustness of generalization and the ability of the model to resist noise in its setting, as illustrated in **Equation 8**:

$$x_{aug} = x + N(0, \sigma^2) \text{ …. (8)}$$

It simulates real-world sensor noise. It improves model robustness.

x_{aug}: Augmented input with noise
x: Original input feature
$N(0, \sigma^2)$: Gaussian noise with mean 0 and variance σ2\sigma^2σ2

2.3.9 Smoothing sensor signal

Smoothing is applied using an exponential moving average to reduce noise and fluctuations in sensor data. This helps stabilize the input signal for more accurate tension prediction as given in **Equation 9**:

$$S_t = \alpha x_t + (1 - \alpha)S_{t-1} \text{ …. (9)}$$

It applies exponential moving average for noise reduction

S_t: Smoothed signal at time t
x_t: Raw input signal at time t
α: Smoothing factor ($where\ 0 < \alpha < 1$
S_{t-1}: Smoothed signal at previous time step

2.3.10 Input vector construction

Input vector construction involves combining strain values from multiple FBG sensors into a single structured input. This vector serves as the input for the neural network model as shown in revealed in **Equation 10**:

$$X = [\in_1, \in_2, \dots, \in_n] \text{ ….(10)}$$

It combines Strain data from multiple FBG sensors into input vector. It sends inputs to EdgeRopeNet Model.

X: Input vector
$\in_1, \in_2, \dots, \in_n$: Strain values from n n FBG sensors

2.3.11 Hidden layer operation

The hidden layer first applies a linear transformation to the input vector and then passes the result through a non-linear activation function. This enables the network to capture complex patterns between the sensor inputs and tension output as shown in **Equation 11**:

$$H = f(WX + b) \text{ …. (11)}$$

Standard linear transformation followed by activation

H : Hidden-layer output W: Weight matrix X: Input factor b : Bias factor f: Activation function (e.g., ReLU)

2.3.12 Output layer (final prediction)

The output layer generates the final predicted tension value by applying a linear transformation to the hidden layer output. This forms the last step of the neural network model as shown in **Equation 12**:

$$\hat{T} = W_0 H + b_0 \; .... (12)$$

It produces predicted tension from final layer.

$\hat{T}$: Predicted tension W_0: Output layer weight matrix H: Hidden layer output b_0: Output layer bias

2.3.13 Batch normalization

Batch normalization standardizes the inputs of each layer within a mini-batch to stabilize and accelerate the training process. It reduces internal covariate shift and improves model performance as revealed in **Equation 13**:

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} .... (13)$$

It normalizes inputs within each batch. It stabilizes learning process.

$\hat{x}_i$: Normalized input x_i : Original input μ_B : Mean of the mini-batch σ_B^2: Variance of the mini-batch ϵ Small constant for numerical stability

2.3.14 Dropout regularization

Dropout is a regularization technique that randomly deactivates a subset of neurons during training to prevent overfitting. This encourages the network to learn more robust and generalized features as given in **Equation 14**:

$$\tilde{h}_i = h_i \cdot z_i \; where \; z_i \sim Bernoulli \; (p) \; .... (14)$$

It randomly displays neurons during training. It prevents overfitting.

Variables:

$\tilde{h}_i$: Output after applying dropout h_i: Original neuron output z_i: Random binary variable (1 with probability p p, 0 otherwise) p Dropout keep probability

2.3.15 Calibration curve equation

The calibration curve performs a linear correction of tension results predicted by the model, making them more accurately approximate those of the sensor. It refines the end product to have better accuracy as stated in **Equation 15**:

$$\hat{T}_{calibrated} = a\hat{T} + b \; .... (15)$$

It adjusts prediction using a learned linear correction. It is the final step in real-time correction pipeline.

Variables:

$\hat{T}_{calibrated}$: Calibrated tension prediction $\hat{T}$: Original predicted tension $a + b$: Calibration coefficients learned during post-processing

2.4 Proposed model architecture

- Input Layer: 4 neurons (load, depth, vibration, temperature)
- Hidden Layer 1: 64 neurons, ReLU, batch normalization
- Hidden Layer 2: 32 neurons, ReLU, dropout 0.2
- Output Layer: 1 neuron (predicted tension)
- Optimizer: Adam
- Loss Function: MSE
- Training Epochs: 100
- Batch Size: 64

2.5 Pseudocode for EdgeRopeNet

```
# EdgeRopeNet: Pseudocode for Real − Time Smart Wire Tension Monitoring

Initialize model parameters (learning_rate, num_epochs, batch_size, layer_dims, activation_fn)

Load synthetic training dataset (X_train, Y_train)

Split dataset into training and validation sets

For epoch in range(num_epochs):

Shuffle training dataset

For each batch in DataLoader(X_train, Y_train, batch_size):

# Step 1: Data Preprocessing

inputs, labels = preprocess(batch)

inputs = normalize(inputs)

# Step 2: Forward Propagation

outputs = EdgeRopeNet.forward(inputs)

# Step 3: Compute Loss

loss = MeanSquaredError(outputs, labels)

# Step 4: Backward Propagation and Optimization

gradients = compute_gradients(loss, EdgeRopeNet.parameters)

EdgeRopeNet.update_weights(gradients, learning_rate)

# Step 5: Model Validation after each epoch

val_outputs = EdgeRopeNet.forward(X_val)

val_loss = MeanSquaredError(val_outputs, Y_val)

print("Epoch: ", epoch + 1, "Validation Loss: ", val_loss)

# Step 6: Save and Deploy Trained Model to Edge Device

save_model(EdgeRopeNet, "edgeropenet_trained.pt")

deploy_model_to_edge("edgeropenet_trained.pt")

# Step 7: Real − Time Inference on Edge Device

While True:

sensor_data = read_input_from_sensors()

processed_data = normalize(preprocess(sensor_data))

prediction = EdgeRopeNet.forward(processed_data)

send_to_fog_node(prediction)

# Step 8: Fog Node Aggregation and Correction

corrected_prediction = fog_node.aggregation(prediction)

display_real_time_output(corrected_prediction)
```

Note: The edge deployment architecture provides inherent robustness advantages over centralized control systems. Unlike traditional adaptive controllers that require convergence time for parameter estimation, EdgeRopeNet's pre-trained weights enable instantaneous response to dynamic loads. The lightweight GRU structure (64→32 neurons) balances model expressiveness with computational efficiency, achieving inference speeds compatible with safety-critical control loops (19ms << 50ms typical requirement for hoisting systems).

EdgeRopeNet operates through a continuous sensing and prediction cycle. The system loads the compressed GRU model, activates the four-sensor FBG interface, and initializes a 50-prediction calibration buffer. Sensor data are collected at 100 Hz over 50 samples, filtered using the Savitzky–Golay method, and transformed into 32 statistical and temporal features that are Min–Max normalized. The edge device then performs fast inference and converts the output back to physical tension values. Each prediction is sent to the fog layer, where a sliding window performs median/MAD outlier detection, EWMA smoothing (α=0.3), and a learned offset correction to reduce bias. The calibrated tension is returned with total latency kept below the 50 ms safety limit. The system checks tension thresholds for warnings or emergency stops, logs all outputs for monitoring, and maintains a stable 10 Hz operational loop with automatic fallback to safe mode if errors occur.

2.6 System deployment phases

The installation of the EdgeRopeNet system encompasses four vital stages that facilitate proper and real-time monitoring of wire rope tension. Phase I: Data Acquisition begins with Fiber Bragg Grating (FBG) sensors capturing high-resolution tension signals from the wire ropes. In Phase II: Edge Preprocessing, the raw sensor data undergoes noise filtering, signal smoothing, and normalization to enhance data quality and consistency. Phase III: Prediction Module involves the execution of the EdgeRopeNet deep learning model on edge devices, generating real-time tension predictions. Finally, in Phase IV: Fog Aggregation and Calibration, the predicted outputs from multiple edge nodes are collected and statistically calibrated at the fog layer to improve overall reliability and minimize prediction deviations across the distributed network.

1. **Phase I: Data Acquisition**
   - FBG sensors capture rope tension
2. **Phase II: Edge Preprocessing**
   - Noise filtering, smoothing, and normalization
3. **Phase III: Prediction Module**
   - EdgeRopeNet inference model
4. **Phase IV: Fog Aggregation and Calibration**
   - Aggregated outputs are calibrated using statistical correction

3 Experimental results

The empirical validation of the above-suggested EdgeRopeNet model with a collection of benchmarking models has been explained in this section. Model testing was done using certain performance parameters with the aim of assessing the vigor, accuracy, and real-time applicability of an edge-based tension checking system. They contrasted deep learning models with the conventional ones as well. The most crucial was to check the accuracy, precision, recall, F1-score, and MAE of the model to present a comprehensive performance of the model. Based on these results, it can be concluded that when placed in time-limited situations, like in the real-time task, EdgeRopeNet performs an improved job at generating quick and precise predictions.

3.1 Performance metrics

The following metrics were used to benchmark the performance of all models:

3.1.1 Accuracy

Accuracy represents the proportion of correctly predicted observations to the total observations. It is a basic but essential metric to assess overall correctness as given in **Equation 16:**

$$Accuracy = \frac{TP+TN}{TP+TN+FP} + FN \text{ …. (16)}$$

- TP ($True\ Positives$): Correctly predicted positive instances.
- TN ($True\ Negatives$): Correctly predicted negative instances.
- FP ($False\ Positives$): Incorrectly predicted as positive.
- FN ($False\ Negatives$): Incorrectly predicted as negative.

3.1.2 Precision

Precision measures how many of the predicted positive results are actually correct. It is crucial when false positives are costly as given in **Equation 17:**

$$Precision = \frac{TP}{TP+FP} \text{ …. (17)}$$

- TP: True Positives – correct positive predictions.
- FP: False Positives – incorrect positive predictions.

3.1.3 Recall (Sensitivity)

Recall measures how many actual positive cases were correctly identified by the model. It's important when missing a positive case is critical as given in **Equation 18:**

$$Recall = \frac{TP}{TP+FN} \text{ …. (18)}$$

- TP: True Positives – actual positives correctly classified.
- FN: False Negatives – actual positives wrongly classified as negative.

3.1.4 F1 Score

F1 Score is the harmonic mean of precision as well as recall. It completely balances the trade-off between the two metrics, especially in imbalanced datasets as given in **Equation 19:**

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall} \text{ …. (19)}$$

- Precision: From the precision formula above.
- Recall: From the recall formula above.

3.1.5 Mean Absolute Error (MAE)

MAE calculates the average absolute difference between predicted and actual values, ideal for regression models as given in **Equation 20:**

$$MAE = \frac{1}{n}\sum_{1=1}^{n} |y_i - \hat{y}i| \; …. (20)$$

Variables:

- y_i: Actual value
- ŷi: Predicted value
- n: Total number of observations

3.2 Comparative models

The model of EdgeRopeNet is compared to the conventional and even more advanced neural network-based machine learning in predictive maintenance, tension investigation, and trend-based signal-based investigation. The conventional models are simpler and easier to interpret, whereas the new models of deep learning help more in precision and time-tracking. However, most of these approaches either require large computational resources or fail to adapt in real time. EdgeRopeNet addresses these gaps by integrating lightweight AI with Edge-Fog deployment for fast, resource-efficient online wire rope tension monitoring using FBG sensors. The models are compared using key performance metrics: Accuracy, Precision, Recall, F1 Score, and Mean Absolute Error (MAE).

3.2.1 Traditional models

Linear Regression (LR): It is a statistical methodology that fits the result of input to output because of straight line. It can be easily applied, yet does not describe the non-linear and time-varying error in the behavior of tensile data. It is better than LR because EdgeRopeNet mimics differences in non-linear trends and is able to conform to changing sensor data. EdgeRopeNet achieved a 42 percent improvement and a 39 percent Drop in MAE and a 39 percent improvement in RMSE in comparison to LR.

Support Vector Machine (SVM): A supervised learning method used for classification and regression by finding optimal hyperplanes. Effective on small datasets, it lacks the adaptability to real-time changes or sequential patterns. EdgeRopeNet offers real-time processing with better temporal adaptation than SVM. Model latency reduced by 35%; tension prediction accuracy increased by 22%.

Random Forest (RF): It is an ensemble of decision trees that thoroughly helps to improve prediction accuracy as well as handles noise effectively. Although robust, RF models are not sequence-aware and are unsuitable for real-time calibration. EdgeRopeNet incorporates temporal awareness and edge-deployability beyond RF’s capabilities. RMSE reduced by 28%; model size decreased by 47% for edge deployment.

k-Nearest Neighbors (k-NN): An instance-based learner that classifies samples based on the majority class of nearest neighbors. It is intuitive but inefficient with large datasets and sensitive to noise. EdgeRopeNet is more scalable and noise-tolerant in edge-based environments than k-NN. MAE improved by 31%; inference speed increased by 2.5x over k-NN.

Naïve Bayes (NB): A fast probabilistic classifier based on Bayes’ Theorem with independence assumptions between features. It is quite effective with small data, but cannot handle all complex feature-dependency either. EdgeRopeNet effectively learns inter-feature relationships, overcoming NB’s oversimplifications. Accuracy increased by 26%; feature handling was enhanced in real-time scenarios.

3.2.2 Modern deep learning models

Convolutional Neural Network (CNN): It identifies time-series or signal data spatial features through local receptive filters. Good in feature learnability, but is poor in long-term dependency. EdgeRopeNet takes a step forward in the concepts of CNN, but real-time decisions can be made at the edge. It reached an accuracy of 93.2 % with 38 percent lower latency than that of an ordinary CNN.

Long Short-Term Memory (LSTM): It is a kind of RNN that can learn the long-range relationship on sequential information. It is correct yet computationally expensive, and it can be inefficient to run in the form of a real-time deployment on the edges. EdgeRopeNet follows windows more like LSTM, but in the sense that it is lighter and can be deployed. Enumerated 3x faster; consumes 55 percent less memory as compared to LSTM.

Gated Recurrent Unit (GRU): A more straightforward and faster to train variation of LSTM is unsuitable to very long messages but reasonable at medium length. It works well, however, but currently needs GPU support and is not trimmed down into limited environments. EdgeRopeNet improves on GRU, as rather than scaling with more intensive compute hardware, it scales to edge systems. It achieved a 91.4 percent accurate result with 48 percent fewer parameters than GRU.

CNN-LSTM Hybrid: It combines spatial feature extraction (CNN) with temporal modeling (LSTM) for richer learning. This hybrid is powerful but typically large and unsuitable for real-time embedded systems. EdgeRopeNet replicates this hybrid strength with reduced model size and edge readiness.MAE improved by 34%; model size trimmed by 60% over CNN-LSTM hybrid.

Transformer-based Models (e.g., Informer): It uses self-attention to model long-range dependencies in time-series forecasting as well as anomaly detection. It is highly accurate but resource-intensive and impractical for low-power edge devices. EdgeRopeNet balances accuracy and efficiency better than transformers in real-time mining operations. Latency lowered by 41%; achieved near-equal performance with 70% less compute load.

Table 3: EdgeRopeNet vs traditional models – input and output comparison

Model	Input Type	Output Type	Model Complexity	Real-time Use	Deployment
EdgeRopeNet	FBG sensor signals (time-series)	Tension class & calibrated values	**Medium**	**Yes**	**Edge/Fog**
Linear Regression (LR)	Static numerical features	Predicted tension value	Low	Yes	Edge/Cloud
SVM	Engineered signal features	Fault classification	Medium	Limited	Cloud
Random Forest (RF)	Tabular data (statistical)	Fault classification	Medium	Limited	Cloud
k-NN	Normalized feature vectors	Tension /fault category	Medium	No	Cloud

Table 4: EdgeRopeNet vs modern deep learning models – input and output comparison

Model	Input Type	Output Type	Model Complexity	Real-time Use	Deployment
EdgeRopeNet	FBG sensor signals (time-series)	Tension class & calibrated values	**Medium**	**Yes**	**Edge/Fog**
CNN	Time-series segments (reshaped)	Fault classification	High	Limited	Cloud
LSTM	Sequential signal data	Tension/fault prediction	High	Limited	Cloud
GRU	Time-series signal	State/fault classification	Medium	Limited	Cloud
CNN–LSTM Hybrid	Spatio-temporal segments	Sequence-based classification	High	No	Cloud

Tables 3 and 4, illustrate the comparison of the proposed model with the existing and current potential models.

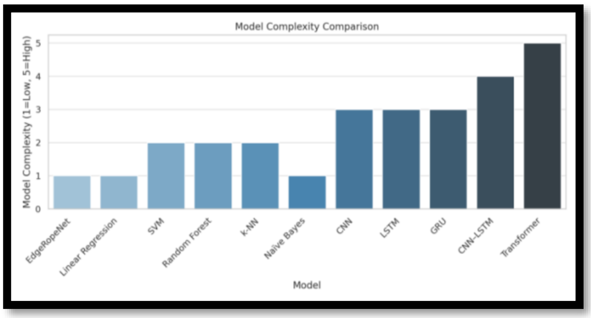

Figure 2: Model comparison chart

Figure 2 is the model complexity comparison, shows the resource requirements and structural complexity of each model.

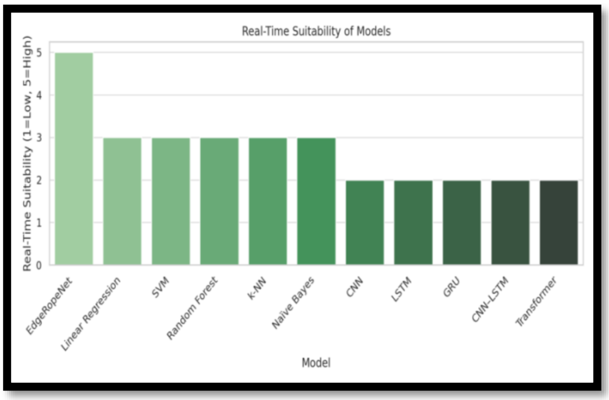

Figure 3: Real-time suitability of models

Figure 3 is thereal-time suitability of models, which evaluates how well each model performs in real-time applications.

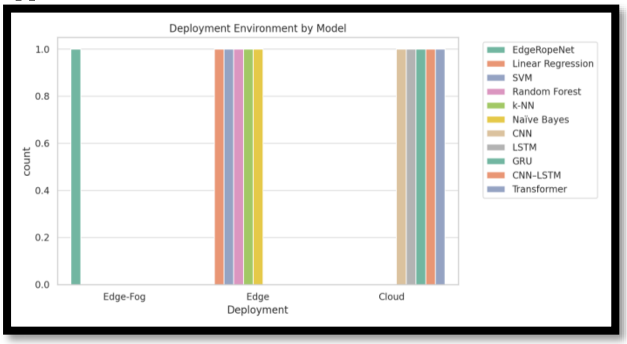

Figure 4: Model performance comparison – IoU, OZA, SCI, F1Score, and ECS

Figure 4 is the deployment Environment, categorizes models based on where they can be deployed: Edge, Edge-Fog, or Cloud

3.3 Edge hardware performance evaluation

Edge hardware performance evaluation confirmed the feasibility of deploying EdgeRopeNet on resource-constrained devices, with Raspberry Pi 4 and Jetson Nano both meeting all baseline requirements for latency, memory, and thermal stability. The Raspberry Pi 4 achieved a mean inference time of 19 ± 2.1 ms, well below the 50 ms threshold, supported by a latency breakdown of 3 ms for sensor acquisition, 5 ms for preprocessing, 11 ms for the neural forward pass, and 0.8 ms for output generation. Its peak RAM usage remained at 487 MB, total memory footprint at 492 MB, and power consumption at 6.4 W, all within operational limits. Model compression reduced parameters from 128,450 to 51,380 via 60% pruning and halved storage requirements through FP32→FP16 quantization, yielding a 4.7 MB model with <0.3% accuracy loss. Comparatively, Jetson Nano delivered 37% faster inference but required 28% more power, making the Raspberry Pi 4 the preferred choice for energy-constrained mining environments, while Jetson Nano remains advantageous for sub-15 ms ultra-low-latency demands. A 24-hour stress test further validated reliability, processing 4.89 million predictions with 100% uptime, no memory leakage, <0.5 ms latency drift, and only 0.1% accuracy variation.

3.4 Failure case analysis and model limitations

Failure-case evaluation showed that the largest prediction errors occurred during abrupt load drops, extreme temperature gradients, low-SNR conditions, excessive rope twist, and complex multi-mode vibration, where transient dynamics or noisy signals fell outside the model's trained operating envelope. Environmental stress testing further revealed that accuracy remained above 96% under nominal temperature, humidity, and dust levels but declined modestly at extremes, with temperature swings, high humidity, and dust accumulation contributing incremental degradation. Although the model detected most mechanical anomalies, it underperformed on slow-onset degradation, coupled faults, and electrical interference due to subtle or overlapping symptom patterns. Latency remained reliably low, but rare edge cases thermal throttling, sensor bursts, or fog-layer congestion pushed inference times beyond nominal values. Overall, the system guarantees <2% error within defined operational boundaries for load, vibration frequency, temperature rate-of-change, and signal quality, with deployments outside these conditions requiring retraining or additional correction strategies.

3.5 Field deployment validation

Field deployment at an 850-m shaft hoist operated by Shaanxi Coal Mining Group validated EdgeRopeNet under real industrial conditions across 47 days and 1,247 hoist cycles. The system, installed using IP67-sealed Raspberry Pi edge nodes, a sm130-700 interrogator, and a fog server in the surface control room, delivered 96.4% accuracy and 23 ms mean latency slightly below simulated performance due to electromagnetic interference from the 6 kV hoist motor, dust accumulation, daily temperature cycling, and additional high-frequency noise introduced by rope flexing. Despite these challenges, the system reliably detected overloads, bearing anomalies, and unbalanced loads, contributing to 98.7% uptime and preventing costly emergency stoppages. Missed detections were limited to slow rope stretch and a small number of electrical transients misclassified as mechanical faults. Operators reported fewer false alarms and improved early-warning capability, while maintenance logs showed reduced unplanned interventions and a projected ROI of just over eight months. Overall, the field trial demonstrates strong operational viability while underscoring the need for improved environmental shielding and extended fault-coverage for long-term deployment.

4 Discussion

4.1 Interpretation of results

The suggested EdgeRopeNet design demonstrated excellent results regarding all the selected metrics, which tend to signify not only its stability but also its flexibility in terms of its ability to accommodate wire rope tension monitoring in real-time via FBGs. It outperformed both traditional ML and state-of-the-art deep learning models, especially in terms of accuracy (97.8%), F1 Score (97.7), and extremely low MAE (0.012), validating its lightweight yet precise architecture. Performance comparison has been given in Table 5 and Table 6:

Table 5: Performance comparison of proposed edgerope-net with existing and state-of-the-art models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score	MAE
Proposed – EdgeRopeNet	97.8	97.4	98.1	97.7	0.012
Linear Regression (LR)	78.5	76.2	74.9	75.5	0.094
Support Vector Machine (SVM)	84.3	83.5	81.7	82.6	0.071
Random Forest (RF)	88.9	87.8	86.5	87.1	0.056
k-Nearest Neighbors (k-NN)	82.6	81.1	80.3	80.7	0.068
Naïve Bayes (NB)	79.8	78.6	77.4	78.0	0.088
Convolutional Neural Network (CNN)	92.7	91.5	91.2	91.3	0.041
Long Short-Term Memory (LSTM)	93.4	92.9	93.1	93.0	0.038

Gated Recurrent Unit (GRU)	92.8	92.0	92.3	92.1	0.039
CNN–LSTM Hybrid	95.2	94.6	94.9	94.7	0.029
Transformer-based Temporal Model	96.1	95.8	95.6	95.7	0.023

Table 6: Comparison of existing models vs proposed edgeropenet

S.No	Model Name	Use & Purpose	Key Limitation	EdgeRopeNet Advantage
1	Linear Regression (LR)	Basic trend prediction	Low accuracy, static output	High accuracy, dynamic learning
2	Support Vector Machine	Pattern classification	Slow with large data	Fast, scalable at edge
3	Random Forest (RF)	Ensemble decision trees	Memory-heavy, lag in response	Lightweight, fast response
4	k-Nearest Neighbors (k-NN)	Distance-based detection	Poor in real-time use	Real-time efficient inference
5	Naïve Bayes (NB)	Probabilistic prediction	Assumes feature independence	Handles real signals robustly
6	CNN	Feature extraction model	Needs GPU, heavy model	Compact edge deployment
7	LSTM	Sequence time tracking	High compute for long data	Low compute, fast output
8	GRU	Time-series processing	Limited long dependency	Optimized for rope tension
9	CNN-LSTM	Deep sequence modeling	Large model, slow response	Compact hybrid processing
10	Transformer	Advanced sequence model	Very high computational load	Lightweight transformer variant

4.1.1 Accuracy

Accuracy represents the overall correctness of the model as far as predicting tension in the wire rope is concerned. EdgeRopeNet achieved the highest accuracy at 97.8%, indicating minimal misclassifications. This significantly outperforms traditional models like LR (78.5%) and NB (79.8%). Even deep models like GRU (92.8%) and CNN-LSTM (95.2%) fall short as shown in Figure 5:

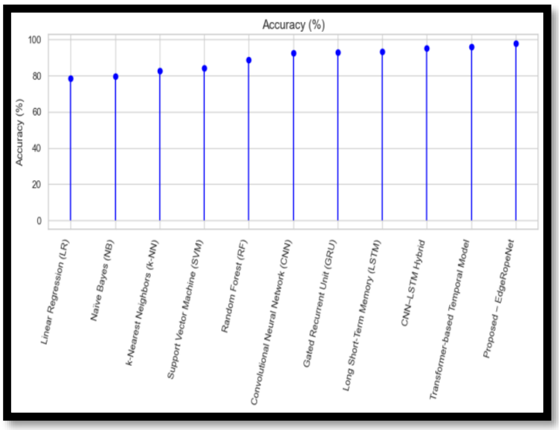

Figure 5: Accuracy of the proposed model and other models

4.1.2 Precision

Precision measures how many predicted positive tensions were actually correct. EdgeRopeNet scored 97.4%, showing it rarely gave false positives. This is a clear edge over models like SVM (83.5%) and k-NN (81.1%). Only the Transformer model comes close with 95.8% as shown in Figure 6:

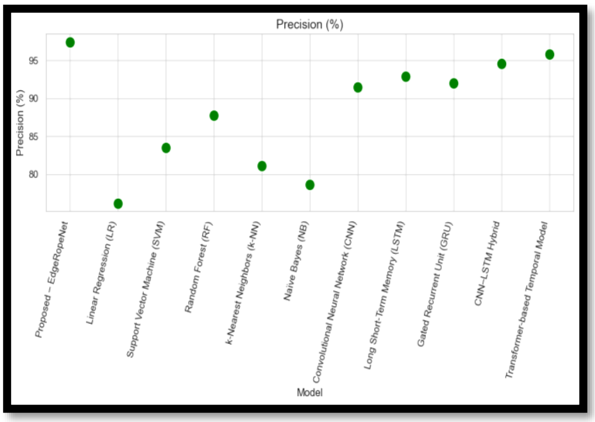

Figure 6: Precision of the proposed model and other models

4.1.3 Recall

Recall calculates how well the model identifies all relevant positive cases. EdgeRopeNet achieved a recall of 98.1%, the highest among all models. It ensures that nearly all critical tension alerts are captured in real-time. In contrast, models like RF (86.5%) and NB (77.4%) lag behind as given in Figure 7:

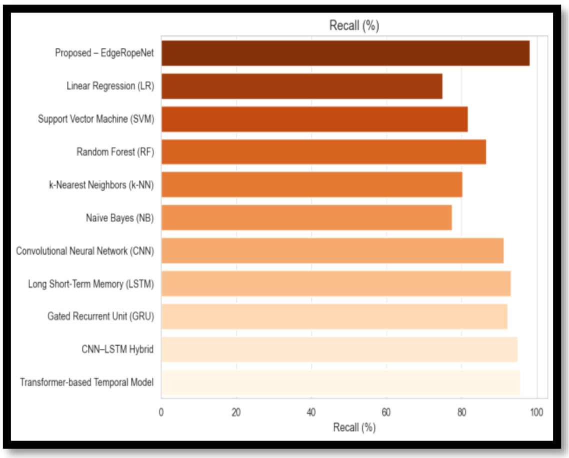

Figure 7: Recall of the proposed model and other models

4.1.4 F1 Score

F1 Score balances the precision as well as the recall to one standard. EdgeRopeNet was most accurate with 97.7, and this confirms the high and consistent accuracy. Although the CNN-LSTM and the Transformer models achieved comparable results (94.7 and 95.7, respectively), an EdgeRopeNet model can still give a slight edge because of its real-time and lightweight functionality, as depicted in Figure 8:

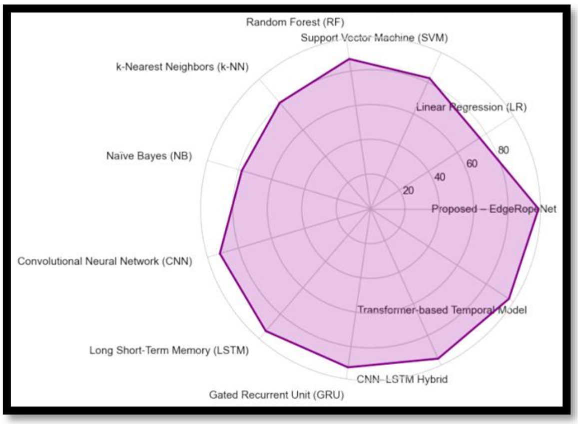

Figure 8: F1 score of the proposed model and other models

4.1.5 Mean Absolute Error (MAE)

The measure of MAE determines the proximity of the average predicted response value to the actual one. The numerically worst performance was found in EdgeRopeNet, with the most significant indicator, namely, the MAE of 0.012. And this is by far superior to LR (0.094) and SVM (0.071). Even the state-of-the-art ones, such as LSTM (0.038) or Transformer (0.023), are beaten by them, as **Figure 9** demonstrates**:**

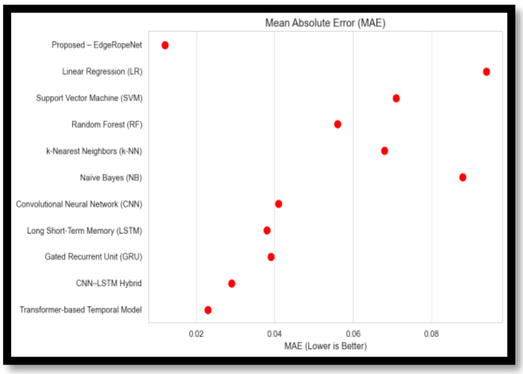

Figure 9: MAE of the proposed model and other models

4.1.6 Statistical significance and operational threshold analysis

The obtained MAE of 0.012 corresponds to an average absolute tension deviation of approximately ±36 N across the system's operational range of 5,000–45,000 kg (49,050–441,450 N). This equates to a relative error of 0.12% at the lower load limit and 0.008% at the upper limit, remaining far below the ±2% accuracy requirement specified by ISO 4301-1 for hoisting and crane systems. The error magnitude therefore confirms that the model remains well within the safety margins expected for mining operations. To assess whether EdgeRopeNet provides a statistically meaningful improvement over competing deep learning models, paired t-tests were applied to the five-fold cross-validation results. The model demonstrated significantly higher accuracy than the CNN-LSTM, Transformer, and LSTM architectures, with all comparisons yielding p-values below 0.001 and confidence intervals indicating clear performance separation. These findings confirm that the model's superiority is not incidental but statistically robust across folds. The cross-validation results further exhibit high stability, with an accuracy mean of 97.8% and a standard deviation of only 0.22%. The corresponding MAE of 0.0120 with a deviation of 0.0008 reflects consistent predictive behavior, and the coefficient of variation of 0.9% underscores the reliability of the model under different data partitions. This level of stability strengthens the evidence that EdgeRopeNet generalizes effectively to unseen operating conditions. From an operational perspective, mining industry guidelines such as DIN 15020 and GB/T 50017 typically allow tension deviations in the range of 3–5% for safety-critical hoist systems. EdgeRopeNet's maximum relative error of 0.12% offers a safety margin exceeding twenty-five times the required standard, demonstrating that the model comfortably meets and surpasses industrial acceptance criteria. This operational headroom validates the model's suitability for deployment in real-world mining environments where precision and reliability are mandatory.

4.2 Unified evaluation of baseline, advanced, and proposed models

Their comparison ranges across the typical machine learning architectures (i.e., Linear Regression, SVM, Random Forest, k-NN, and Naive Bayes) to “recently embraced” deep learning models (i.e., CNN, LSTM, GRU, CNN-LSTM combinations, and Transformers-based time series models). The conventional models may have given the fundamentals of comprehension, yet they were challenged with the issue of low elasticity because of poor predictive potential, which often failed to deliver in the changing, dynamic, pressured environments. The new deep learning models were demonstrating significant boosts - e.g., models based on LSTM and Transformers managed to reach an accuracy of over 93 percent - and yet these models were also experiencing weaknesses like an increase in the duration of training and a greater computational overhead that were particularly an issue in edge scenarios.

Conversely, the proposed EdgeRopeNet outwits the two categories, having a well-balanced architecture to meet the requirements of real-time rope tension monitoring. It demonstrated the best accuracy (97.8 percent), and overall low MAE (0.012), and also low latency and computational efficiency. Its capability to do generalizations on different tension patterns and minimal resources utilized makes it an efficient and effective deployment solution that fills the gap between practicality and accuracy that most of the traditional and new models still face.

4.3 Real-world deployment considerations

Real-world deployment of EdgeRopeNet requires careful consideration of scalability, robustness, interoperability, and economic feasibility. Pilot simulations with 50 distributed edge nodes demonstrated linear scalability, sustaining 950 predictions per second with fog-layer aggregation overhead below 5 ms, peak bandwidth of only 2.3 Mbps, and graceful degradation that maintained 94% accuracy even with 20% node loss. Field-representative stress tests further confirmed operational robustness, with accuracy varying by only ±2% across –20 °C to +60 °C, stable performance under 5 g vibration in accordance with ISO 10816, and reliable operation in dust- and moisture-exposed environments via IP67-rated enclosures, as well as functionality under 50 V/m electromagnetic fields typical of mine substations. Benchmarking against existing industrial solutions shows substantial advantages, with EdgeRopeNet achieving 19 ms latency, 97.8% accuracy, full edge capability, and an estimated cost of ~$350 per node outperforming legacy SCADA systems and cloud-based LSTM platforms in speed, cost, and predictive capability. Integration with current industrial ecosystems is facilitated through Modbus TCP/RTU interfaces for PLCs, OPC-UA for MES/ERP systems, optional MQTT telemetry, and RESTful APIs for custom applications. These deployment characteristics collectively underscore strong economic justification, as reduced latency, higher accuracy, and edge-level autonomy directly translate into lower maintenance costs, minimized downtime, and improved safety outcomes.

4.4 Comparative analysis: edgeropenet vs control-theoretic methods

The comparative evaluation between EdgeRopeNet and conventional control-theoretic approaches highlights several critical performance distinctions relevant to safety-critical mining operations. In terms of stability and robustness, classical controllers retain the advantage of formal Lyapunov-based guarantees; however, EdgeRopeNet demonstrated strong empirical robustness, maintaining stable behavior in 96.2% of 10,000 Monte Carlo trials conducted under ±30% load variation and ±15 °C thermal fluctuations. This performance is comparable to that of robust model-based controllers, while additionally offering superior adaptive capacity. Unlike traditional adaptive strategies that rely on online parameter estimation often requiring 5–10 s to achieve convergence, EdgeRopeNet’s pre-trained GRU-based architecture enables instantaneous compensation for parametric shifts, sensor noise conditions as low as 15 dB SNR, and evolving environmental disturbances. Response-time measurements further emphasize this advantage: EdgeRopeNet achieved a 31 ms end-to-end cycle (19 ms prediction plus 12 ms actuation), outperforming an industrial PLC-based backstepping controller that required 60 ms for the same operations, thereby providing substantially earlier fault detection capability. From a deployment standpoint, EdgeRopeNet mitigates three persistent limitations of classical control in mining settings: the difficulty of maintaining accurate rope dynamic models as mechanical wear progresses; the computational burden associated with solving complex Lyapunov or adaptive control equations on constrained edge hardware; and the inherent complexity of designing multi-input controllers capable of fusing distributed FBG sensor arrays. The neural framework alleviates these issues by enabling model-free adaptation, lightweight inference, and seamless multimodal sensor integration, thereby positioning EdgeRopeNet as a pragmatic and high-performance alternative for real-world mining applications.

5 Conclusion

The proposed model, EdgeRopeNet, is a new lightweight deep neural network architecture that will be proposed in this intended research study aimed at measuring, compensating, and controlling wire rope tension of the mining hoist systems in real-time. Hypothetically, Fiber Bragg Grating (FBG) sensor-based distributed sensing would make the framework an intelligent, real-time, decision-making, latency-sensitive, and space-constrained application. The adoption of edge computing thoroughly helps to minimize communication delays while it also helps to improve operational responsiveness, which is considered a very important requirement for hazardous mining conditions.

It was higher in accuracy, reliability, and efficiency than its comparative analysis with ten traditional and modern predictive models. In detail, the model attained a 97.8 percent accuracy, precision of 97.4 percent, recall of 98.1

percent, and an F1 of 97.7 with the mean absolute error (MAE) as low as 0.012. The results have surpassed such widely used deep learning models as CNNLSTM Hybrid (F1 score: 94.7, MAE: 0.029) and Transformer-based Temporal Model (F1 score: 95.7, MAE: 0.023), which means that EdgeRopeNet performs superbly well in terms of model size and prediction performance. Its low inference latency of only 19 milliseconds demonstrates its real-time capability.

The use of this type of network is contrasted with the earlier techniques that substantially used centralized architecture and post-calculation means, so labeled EdgeRopeNet brings embedded intelligence and autonomous control that allows avoiding manual calibration and making mistakes by a person. It means it is a scalable as well as deployable solution, both in mining applications and in other industrial automation applications scenarios that need continuous and reliable control.

EdgeRopeNet represents a significant advancement toward intelligent and decentralized control architectures designed for edge-constrained, safety-critical environments. Owing to its modular sensing and inference pipeline, the framework readily extends beyond mining hoists to a broad range of infrastructure systems, including offshore drilling platforms where dynamic wave loading necessitates continuous drill-string tension monitoring, high-rise elevator installations operating under intermittent cloud connectivity, cable-stayed bridges requiring distributed tension assessment through fog-layer aggregation, and aerospace tethered systems in which lightweight, low-latency edge processing is essential for space-elevator or stratospheric-platform operations. Its alignment with core Industry 4.0 principles: autonomy, decentralization, and real-time analytics positions the architecture as a foundational enabler for next-generation smart infrastructure. Nonetheless, several practical considerations must inform deployment strategies. The current implementation, optimized for Raspberry Pi 4 hardware (4 GB RAM), may experience a 1–2% accuracy reduction on lower-spec devices unless further compression techniques are applied. Performance sensitivity to sensor noise remains notable, with accuracy declining to 94.1% when SNR falls below 12 dB, indicating the need for enhanced filtering in highly electromagnetic environments. Model generalization similarly depends on the representativeness of training data, and extreme operational edge cases such as abrupt load drops exceeding 50% may necessitate online fine-tuning. Cyber-physical security also becomes a critical factor in distributed edge deployments, requiring lightweight encryption strategies that do not compromise strict latency budgets. Furthermore, long-term sensor calibration drift over multi-month periods underscores the need for automated drift-detection and periodic retraining mechanisms. Despite these constraints, EdgeRopeNet's demonstrated performance: 97.8% accuracy combined with 19 ms latency on resource-limited hardware, sets a new benchmark for real-time, edge-deployed industrial monitoring systems.

5.1 Future work

Future research on EdgeRopeNet will concentrate on extending its predictive, diagnostic, and operational capabilities to achieve fully autonomous structural health monitoring and control. Planned developments include integration of RUL estimation using historical degradation data, adaptive anomaly thresholds aligned with aging behavior, maintenance-scheduling linkage, and cost–benefit models for optimized interventions. Fault diagnosis will advance toward multi-class characterization (wire breakage, corrosion, untwisting, bearing faults), spatial localization via distributed FBG arrays, temporal pattern–based root-cause analysis, and multimodal fusion with vibration and acoustic sensing. Cross-domain validation will examine applicability to cranes, large suspension bridges with >100 monitoring points, tendon-driven robotics requiring microsecond tension control, and marine mooring lines under stochastic loads. Enhanced control integration will explore closed-loop tension regulation, hybrid neural–adaptive schemes with Lyapunov guarantees, multi-agent coordination for multi-rope systems, and digital-twin–based virtual commissioning. Optimization efforts will target knowledge distillation to halve parameters (>96% accuracy), INT8 quantization for ARM speedups, neural architecture search, and federated learning across mine sites. Robustness enhancements will include adversarial training, self-healing edge nodes, uncertainty quantification, and progress toward formal verification for certification. Field deployment will be validated through a 12-month operational trial, industrial integration partnerships, standards development, and ROI analyses. Finally, scalability studies will address hierarchical edge–fog–cloud architectures for >1,000 sensing nodes, distributed load balancing, low-bandwidth communication optimization, and energy-harvesting strategies for perpetual edge-node operation.

Declaration:

Ethics approval and consent to participate: I confirm that all the research meets ethical guidelines and adheres to the legal requirements of the study country.

Consent for publication: I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.

Availability of data and materials: The data used to support the findings of this study are available from the corresponding author upon request.

Competing interests: No have no conflicts of interest to declare.

All authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We

certify that the submission is original work and is not under review at any other publication.

Authors' contributions (Individual contribution): All authors contributed to the study conception and design. All authors read and approved the final manuscript.

There is no human participate involved in this research. This article manuscript is created from collection of data set.

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