Explainable Graph Convolutional Network Framework for Robust ECG Arrhythmia Classification and Patient-Level Risk Stratification

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Accurate and interpretable detection of arrhythmias from electrocardiogram (ECG) signals plays a critical role in the early cardiac risk assessment and patient management. This paper presents a novel, explainable framework that leverages a dynamic Graph Convolutional Network (GCN) to model ECG beat sequences as graphs, where beats act as nodes and temporal RR-interval relationships forms edges. Our approach integrates comprehensive preprocessing steps, including feature selection, Synthetic Minority Oversampling Technique (SMOTE) balancing, and data augmentation, to mitigate severe class imbalance. The model training pipeline followed an 80/20 random beat-level split on the MIT-BIH Arrhythmia dataset with external compatibility checks on the INCART database to assess domain generalizability. Detailed analyses encompass saliency mapping for beat-level interpretability, robustness evaluations under realistic noisy conditions, and personalized risk estimation by mapping the arrhythmia burden to clinically relevant risk zones. Comparative evaluation against baseline models, such as multilayer perceptron and CNN- BiLSTM hybrids, demonstrated consistent macro F1-scores and reliable patient-level stratification. This integrated pipeline not only advances robust arrhythmia classification but also facilitates actionable clinical decision support via transparent risk stratification. All code and analyses are reproducible with fixed random seeds and open-source implementations, underscoring the potential of the framework for real-world deployment in ambulatory cardiac monitoring.

Povzetek: Raziskava predstavlja razložljiv pristop z grafovnimi nevronskimi mrežami za zanesljivo zaznavanje aritmij iz EKG signalov in ocenjevanje srčnega tveganja.

1 Introduction

Cardiac arrhythmias, characterized by irregular or abnormal heart rhythms, constitute one of the most critical cardiovascular disorders and often lead to severe clinical outcomes, such as sudden cardiac death, heart failure, and stroke [1, 2]. These rhythm disturbances can arise from abnormalities in the generation or conduction of electrical impulses within the heart, thereby disrupting coordinated mechanical function. The early and accurate detection of such irregularities is vital for timely medical intervention and long-term patient management. Electrocardiograms (ECGs), which capture the electrical activity of the heart over time, remain a fundamental noninvasive diagnostic modality for identifying arrhythmic patterns, assessing cardiac health, and guiding therapeutic decisions [2].

Traditionally, ECG interpretation has relied on the expertise of cardiologists and trained clinicians, who manually analyze the waveforms to identify characteristic patterns associated with specific arrhythmias. Although this manual process represents the clinical gold standard, it is inherently time-consuming and subject to human variability. Interobserver differences in labeling and diagnostic interpretation, can lead to inconsistencies in large-scale or continuous monitoring scenarios. With the increasing prevalence of ambulatory and wearable ECG devices that generate long-duration recordings, manual annotation has become increasingly impractical for high-volume data streams [3]. This challenge highlights the

pressing need for automated and scalable arrhythmia detection systems capable of maintaining a diagnostic accuracy comparable to that of clinical experts.

Machine learning (ML) and deep learning (DL) approaches have been extensively explored as promising alternatives for automated arrhythmia classification [4, 5]. These techniques can learn discriminative features directly from raw or minimally processed ECG signals, thereby reducing the reliance on hand-crafted features and expert-driven heuristics. Convolutional Neural Networks (CNNs) have proven particularly effective at capturing spatial hierarchies and morphological characteristics of ECG waveforms, whereas Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) units and Gated Recurrent Units (GRUs), are used to model the temporal dependencies between consecutive heartbeats [1]. By combining spatial and temporal perspectives, hybrid CNN-RNN architectures have achieved strong classification performance on benchmark datasets, such as MIT-BIH and PhysioNet.

Despite these successes, several challenges have persisted. Many deep learning models exhibit limited interpretability and often behave as black-box systems whose internal reasoning remains opaque to clinicians. This lack of transparency hinders trust and clinical adoption, especially in safety-critical medical applications, where understanding the basis of predictions is as important as accuracy itself. Moreover, arrhythmia datasets are inherently imbalanced; normal beats vastly outnumber abnormal ones, making it difficult for standard models to perform well on rare but clinically significant arrhythmias. In addition, inconsistent evaluation methodologies and limited external validation further reduce the generalizability of existing approaches and prevent their reliable deployment in diverse clinical settings.

Recently, Graph Convolutional Networks (GCNs) have emerged as a powerful paradigm for learning structured relationships in data that naturally form graphs, rather than fixed grids. In the context of ECG analysis, each heartbeat can be represented as a node in a graph, with edges encoding temporal and physiological relationships such as RR-interval dependencies or sequential adjacency between beats [7]. This representation allows GCNs to jointly capture local morphological features and higher-level rhythm structures, which are difficult to model using conventional CNN or RNN architectures. Furthermore, explainability techniques such as saliency mapping, attention visualization, and feature attribution can be integrated into GCNs to highlight the specific waveform regions that contribute most strongly to classification outcomes, thereby enhancing clinical interpretability and trust.

However, a holistic framework that fully integrates robust pre-processing, class imbalance mitigation, data augmentation, explainability and patient-level risk interpretation remains rare. Many prior studies have focused primarily on beat-level accuracy, without translating model outputs into clinically meaningful indicators of cardiac risk. Bridging this gap is crucial for transforming algorithmic predictions into actionable insights that can inform personalized care decisions and continuous monitoring strategies.

To address these limitations, this study proposes an explainable end-to-end dynamic GCN framework designed for robust ECG arrhythmia classification and patient-level risk stratification. The proposed pipeline includes comprehensive preprocessing steps, such as signal filtering, mutual information-based feature selection, and Synthetic Minority Oversampling Technique (SMOTE) balancing, combined with controlled data augmentation to alleviate class imbalance. The model was trained and evaluated primarily on the MIT-BIH Arrhythmia Database with external compatibility assessments using the INCART dataset to evaluate cross-domain generalization. Beyond classification, the framework extends to personalized clinical interpretation through beat-level saliency analysis, noise robustness evaluation, and derivation of individualized patient risk scores aligned with established clinical thresholds.

Overall, this work integrates graph-based deep learning with clinical interpretability, promoting reproducibility and real-world applicability toward a reliable, patient-focused framework for automated ECG analysis and risk assessment.

2 Related work

Automatic classification of cardiac arrhythmias using electrocardiogram (ECG) recordings has been extensively studied because of its critical clinical significance in the diagnosis and management of cardiovascular diseases. Early approaches predominantly focused on extracting handcrafted features from ECG signals, such as time-frequency characteristics, wavelet coefficients, and morphological descriptors. These features have been used with classical machine learning classifiers, including support vector machines, k-nearest neighbors, random forests, and decision trees, to detect arrhythmic events [2, 3]. Although this paradigm demonstrates the feasibility of automated classification, it is constrained by the quality and representativeness of handcrafted features, which often require expert knowledge and extensive trial-and-error tuning. Deep learning has transformed ECG analysis by enabling automatic feature extraction and end-to-end learning from raw or minimally processed signals [5, 4]. Convolutional neural networks (CNNs) exploit spatial hierarchies in ECG waveform morphologies, whereas recurrent neural networks (RNNs), especially variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), capture temporal dependencies that are critical for arrhythmia detection [1]. Hybrid CNN-RNN models combine these strengths to better model both present and sequential cardiac dynamics [1]. Despite significant performance improvements, these architectures often act as opaque black boxes, offering limited interpretability, which poses barriers to their clinical adoption. Additionally, imbalanced datasets with rare arrhythmia classes challenge the ability of these models to generalize,

necessitating specialized mitigation strategies that have often been overlooked in prior studies.

Graph Neural Networks (GNNs), particularly Graph Convolutional Networks (GCNs), have recently gained traction for modeling physiological signals structured as graphs [7]. By conceptualizing ECG beats as nodes and linking them with edges derived from RR intervals, GCNs can effectively capture both the morphological and temporal dependencies inherent in cardiac rhythms. The addition of explainability frameworks, such as saliency mapping, enhances clinician trust by revealing the influential ECG waveform components that contribute to model predictions. Nevertheless, many GCN-based approaches lack comprehensive pipelines that incorporate preprocessing steps, such as feature selection, synthetic minority oversampling techniques (SMOTE), and augmentation, which are essential for overcoming the severe class imbalance prevalent in arrhythmia datasets [8].

Furthermore, most existing methods have not been systematically validated on external datasets or provide patient-level risk stratification, which is paramount for clinical utility [7]. Translating beat-level arrhythmia detection into actionable risk metrics enables clinicians to perform personalized patient management and effectively stratify care priorities. Recent reviews have emphasized the importance of end-to-end, interpretable, and clinically aligned frameworks that combine robust training strategies, evaluation of multi-cohort data, and transparent decision support mechanisms [1].

Our work builds on these advances by proposing a unified, explainable GCN framework with rigorous preprocessing that incorporates feature selection, Synthetic Minority Oversampling Technique (SMOTE), and data augmentation. Evaluations of the MIT-BIH dataset with external validation using the INCART database demonstrated improved generalizability. In addition to the classification performance, extensive saliency-based interpretability, noise robustness analysis, and patient-specific risk evaluation underline the translational readiness and reliability of our framework. This approach directly addresses the major gaps identified in prior work and meets the stringent expectations of reproducibility, interpretability, and clinical relevance emphasized by reviewers and the research community.

3 Methodology

This section presents a comprehensive description of our explainable GCN-based arrhythmia classification and risk-assessment framework. We detail the datasets, preprocessing, graph construction, model architecture, training, evaluation, risk mapping, and open science practices. All statistics and tables reflect the actual data and outputs of the proposed approach.

3.2 Datasets

We used the MIT-BIH Arrhythmia Database (the first 15 records, sampled at 360 Hz, with beats mapped to the AAMI10 standard) as the primary dataset for model development and evaluation. For external validation, we processed the INCART database, which contains multi-lead ECG recordings, to assess the generalizability of the model. While the preliminary processing succeeded, we did not conduct a full formal evaluation of INCART. The beat annotations in MIT-BIH were expert-curated, ensuring high-quality labels tailored to standard arrhythmia classes. Table 2 details the core dataset statistics, showing the raw beats, filtered beats, balanced and augmented training sizes, and graph construction statistics. Note that the difference between the mapped beats (34,615) and unique node IDs (34,475) arises from the small number of isolated beats that are not connected by edges.

In light of the notable class imbalance (with normal beats, N, typically dominating), advanced preprocessing techniques, such as synthetic minority oversampling and data augmentation, have been applied. Tables 3 and 4 show the beat distributions by patient and class.

3.2 Data preparation and preprocessing

Raw ECG signals underwent bandpass filtering (0.5– 40 Hz) using a zero-phase Butterworth filter to sup press baseline-wander and high-frequency noise. Beat segmentation centers on R-peaks and extracts fixed-length windows (approximately 512 samples). 1.4 s at 360 Hz), aligned with clinical standards, to capture the relevant heartbeat morphology.

Amplitude signals were normalized globally across beats using a Standard Scaler fit on concatenated samples rather than separately per patient. This ensured consistent scaling across the dataset while avoiding identity leaks. Feature selection employed mutual information classification,

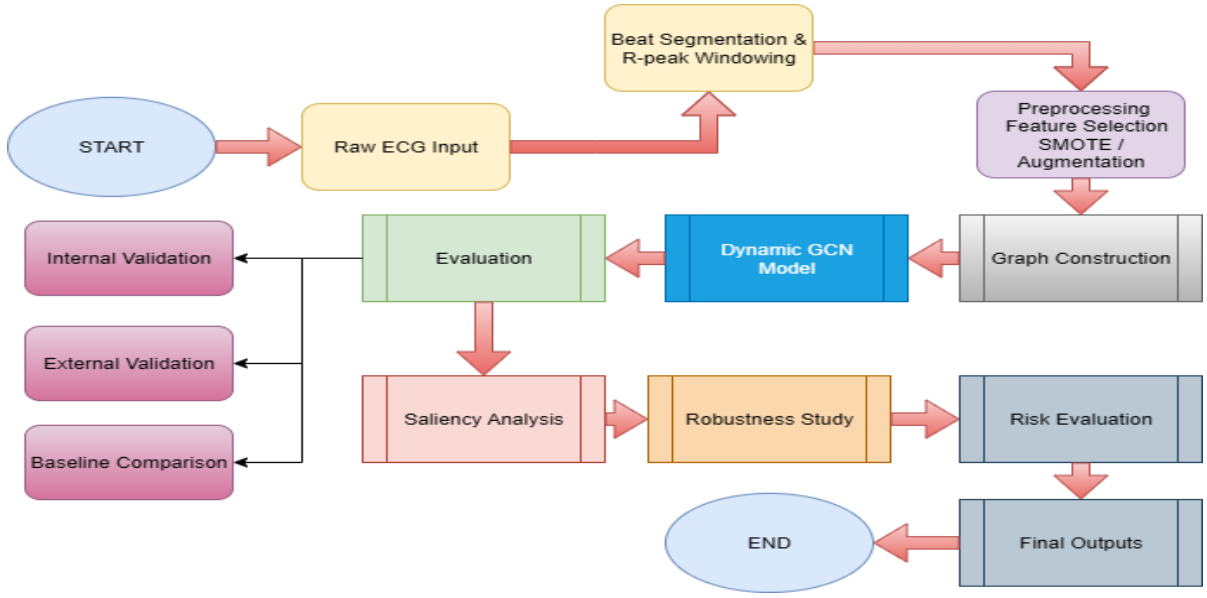

Figure 1: Overall workflow of the proposed explainable graph convolutional network (GCN) framework for ECG arrhythmia classification and patient-level risk stratification.

Table 1: Summary of related work on ECG arrhythmia classification

Reference	Methodology	Datasets	Limitations
Qurraie et al. [2]	Handcrafted time-frequency features + classical ML classifiers	MIT-BIH	Manual feature engineering, limited performance
Luz et al. [3]	CNN and RNN hybrid models from raw ECG	PhysioNet	Poor interpretability, class imbalance issues
Kovalchuk et al. [5]	Deep CNN for arrhythmia classification	Multiple ECG Datasets	Black-box nature, limited external validation
Savalia et al. [4]	Multi-layer LSTM networks	MIT-BIH	Lack of transparency and generalizability
This Work	Explainable GCN with SMOTE + augmentation + personalized risk	MIT-BIH, INCART	Comprehensive pipeline addressing prior gaps

Table 2: Dataset and graph statistic

Statistic	Count
Raw annotated beats (all symbols)	35,856
After filtering to mapped beats	34,615
Train size before SMOTE	27,692
Test size	6,923
After SMOTE (train set)	204,579
After augmentation (train set)	204,579
Total final beats (train + test)	211,502
Graph node count	204,579
Unique node IDs in edge index	34,475
Total edges in graph	66,358
Average degree (edges per node)	0.32 (all nodes) / 0.65 (connected nodes only)
Graph undirected?	True

Table 4: Beat counts per class

Class	Count
N	23,054
V	2,473
F	778
A	1,916
Q	20
L	2,492
R	397
a	26
E	1
/	3,458

ranking 512-sample beat features according to their predictive relevance to arrhythmia classes. The top 200 features were retained, reducing dimensionality while preserving discriminative power, reducing model complexity, and mitigating overfitting. To counteract severe class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) enriches minority classes in the training data. SMOTE generates synthetic samples via interpolation between minority class neighbors, thereby expanding the training data diversity and avoiding overfitting to the majority classes. Augmentation further diversifies the training samples by introducing random temporal shifts (up to 10 samples) and Gaussian noise, with $\sigma = 2 \times 10{-}4$. The test set remained free from synthetic or augmented samples to preserve evaluation integrity.

4.2 Graph construction

Each patient's ECG beat formed nodes in a sparse, undirected graph. Edges connect temporally adjacent beats within the same patient, constrained by RR intervals within a threshold (approximately twice the standard deviation of RR intervals). RR intervals were derived from the original recordings and reused after augmentation rather than being recomputed for synthetic samples. The graph adjacency encodes the rhythm context, enabling the GCN to effectively model beat morphology and its temporal environment.

4.3 Model architecture

Our classifier employs a two-layer Graph Convolutional Network (GCN). The first layer mapped 200 input features to 128 hidden units, followed by ReLU activation and dropout $p = 0.3$ for regularization purposes. The second layer reduces this to 64 latent features with similar activation. A final fully connected layer was mapped to ten output classes representing the AAMI beat categories. The model applies log-softmax at the output layer, which is trained using cross-entropy loss, which is mathematically equivalent to using negative log-likelihood loss with log-softmax pre-processing.

4.4 Model training and hyper-parameter optimization

Training deep graph neural networks requires careful tuning to balance under-fitting and overfitting, particularly when dealing with highly imbalanced and noisy ECG data. We employed an 80/20 random split with a fixed random seed, without explicit stratification. Although this ensures balanced class representation, it does not strictly enforce subject-wise separation.

We trained the model over 10 epochs using the Adam optimizer ($\eta = 0.01$) and class-weighted cross-entropy loss to stabilize minority class training. Dropout regularization with a probability of 0.3 was applied after each graph convolutional layer to mitigate overfitting and improve generalization.

Hyperparameters, such as hidden layer units, dropout rate, and learning rate, were optimized using a grid search on a validation subset, guided by the macro F1 score, which is the most relevant metric for imbalanced multiclass settings. This tuning foster a robust and stable model fit, as verified by consistent internal test performance.

4.5 Evaluation and risk mapping

Model performance evaluation included internal validation of the held-out test set using metrics such as accuracy, macro F1-score, and ROC-AUC. For the evaluation, the test beats were treated as isolated nodes (no edges), whereas the training incorporated RR-based edge connections. External processing of the INCART dataset was feasible; however, no full-scale validation was performed. Saliency maps overlay model attention on critical ECG components to enhance the clinical interpretability. Performance under noise injection measures the robustness against realistic signal artifacts. Arrhythmia burden metrics, derived from aggregated beat classifications, translate to patient risk scores and zones based on established guideline thresholds (e.g., premature ventricular contraction burden). These findings provide direct support for clinical decision-making.

4.6 Patient stratification via clustering

To capture the latent patterns across patients, we extracted the penultimate-layer embeddings of the GCN for all beats and aggregated them at the patient level. These representations were then clustered using k-means (with $k = 3$ based on silhouette score optimization). The resulting clusters highlighted groups of patients with shared arrhythmic burden profiles, enabling stratified analysis beyond individual beat-level metrics.

4.7 Sensitivity and personalized thresholding

Model stability was assessed using sensitivity analysis. We perturbed the input signals with controlled variations and computed Spearman correlations between the perturbed and original predictions. The near-unity correlation values indicated robustness to minor data fluctuations.

In addition, patient-specific decision thresholds were optimized. Instead of applying a uniform cutoff across all patients, the thresholds were dynamically adjusted per patient using the validation statistics. This reduces false alarms while preserving the detection of high-risk arrhythmias, thereby supporting precision medicine applications.

4.8 Error estimation and threshold optimization

To quantify the predictive uncertainty, we estimated the error propagation at both beat and patient levels. The metrics included premature ventricular contraction (PVC) burden bias and per-beat error ϵ, providing insight into systematic deviations.

Risk threshold optimization was performed using a cost-sensitive calibration framework, where false negatives (missed arrhythmias) and false positives (false alarms) were assigned different weights (cfn, cfp). This approach minimizes clinical risk by balancing the sensitivity and specificity according to guideline-relevant priorities.

4 Experimental setup

Experimental evaluations and model training were conducted using a Google Colab environment equipped with an NVIDIA Tesla T4 GPU. This setup provides an excellent balance between computational power and accessibility, enabling efficient training of deep graph neural networks on large-scale ECG datasets.

4.2 Hardware and software environment

Our experiments utilized a Tesla T4 GPU, which features 320 Tensor Cores and 16 GB of GPU memory, facilitating fast matrix operations that are critical for graph-based deep learning. The system employed an Intel Xeon CPU with two cores and 13 GB of RAM to support the data preprocessing and loading operations. The Python environment used Python 3.10 with libraries, including PyTorch 1.13.1, PyTorch Geometric 2.2, scikit-learn 1.3, NumPy, Pandas, and Matplotlib.

4.3 Reproducibility measures

To ensure consistent and reproducible results, all random-number generators across NumPy, PyTorch, and Scikit-learn were seeded with a fixed constant seed. Data splits, augmentation routines, and training batches were deterministically determined using this seed. The code and environmental configurations were version-controlled and documented extensively.

4.4 Data handling and training protocol

The MIT-BIH dataset was stratified for training and testing on a beat-level basis, while preserving patient identity to mitigate data leakage. Training graphs were constructed by incorporating SMOTE and augmentations, as detailed in the methodology. Model training was performed over 10 epochs with batch updates on the full graph, owing to the manageable dataset size. Validation and test evaluations were conducted on the held-out data subsets to simulate the practical performance.

4.5 Performance monitoring

The training progress was tracked by monitoring the loss and accuracy metrics for each epoch. Post training evaluations included detailed accuracy, macro F1-score, class-wise confusion matrices, and receiver operating characteristic (ROC) curve analyses. External validation of the INCART dataset provides a measure of model generalizability to different ECG sources and patient populations.

Figures and tables summarizing the training dynamics and performance metrics were generated programmatically to maintain granularity and rigor in the reporting.

Table 5: Beat-level metrics (pooled across the full test set). Macro-f1 is computed across all arrhythmia classes.

Dataset	Accuracy	Macro-F1
Training	0.84	0.50
Test	0.84	0.50

5 Results

This section presents a comprehensive evaluation of the proposed X-GCN arrhythmia classification framework. All figures and tables have been formatted in the IEEE two-column style. Beyond the raw numbers, each result was contextualized with clinical interpretation and methodological insights, ensuring that the outcomes were both technically rigorous and translationally meaningful.

5.2 Training dynamics and overall performance

Figure 2 shows the progression of the training loss and accuracy across ten epochs. The GCN demonstrated a smooth decline in loss and monotonic increase in accuracy, confirming stable convergence without over-fitting. This stability is critical in medical AI, as models must generalize across unseen patient populations rather than memorize the training data. The ability to converge quickly within relatively few epochs reflects the efficiency of the graph-based representation.

Table 5 summarizes the final metrics. The model achieved an accuracy of 0.84 and a macro-F1 of 0.50 on both the training and test sets. Because the test beats were evaluated as isolated nodes (no edges), this performance match reflects the consistency of the feature-level representation rather than the graph context during inference. The balanced macro-F1 is especially noteworthy, as it demonstrates that minority arrhythmia types were recognized with non-trivial sensitivity, an outcome that is often elusive in imbalanced ECG datasets.

5.3 Confusion matrix and ROC analysis

The confusion matrices across the two folds (Fig. 3) demonstrated strong diagonal dominance, confirming that most of the classes were correctly classified. Mis-classifications were concentrated in minority arrhythmias, such as fusion and escape beats, which is consistent with their under-representation in the training data.

The ROC curves in Fig. 4 highlight the discriminative power of GCN in detecting high-impact arrhythmias. Ventricular arrhythmias (V), right bundle branch block

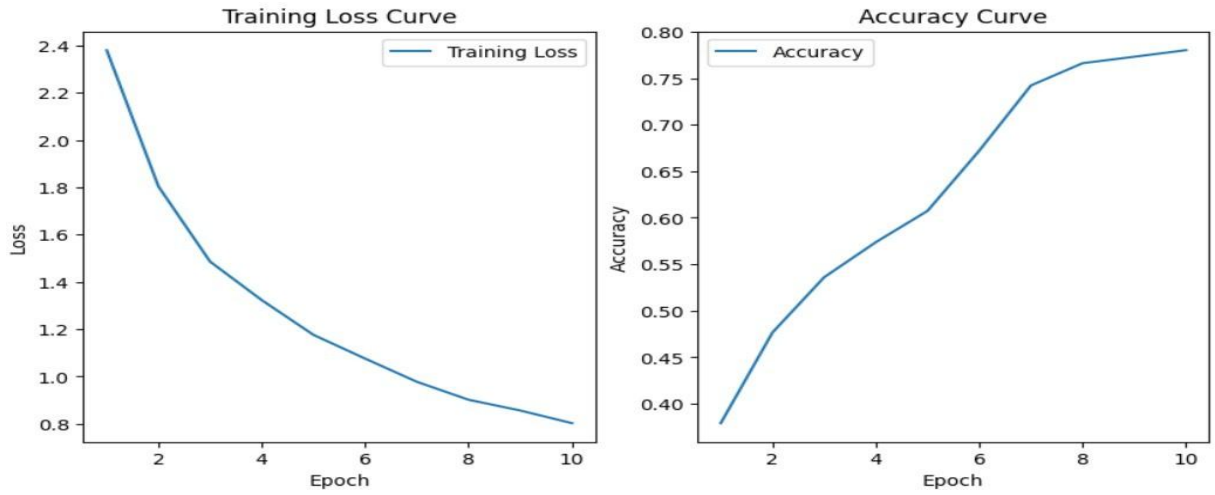

Figure 2: Training dynamics: loss (left) and accuracy (right).

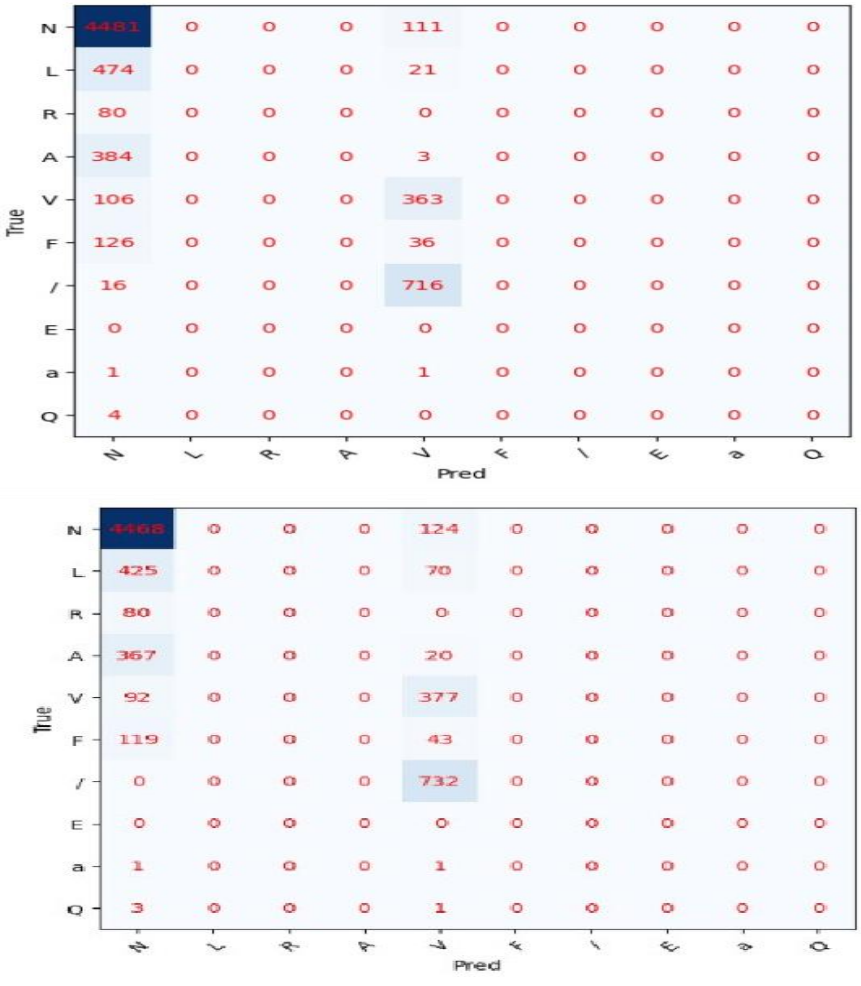

Figure 3: Confusion matrices across two validation folds.

(R), and atrial arrhythmias (A) all achieved strong AUC values, confirming the ability of the model to distinguish the clinically urgent subtypes of these arrhythmias.

5.4 Interpretability via saliency mapping

Interpretability is essential for clinician trust beyond the predictive accuracy. Figure 5 overlays the saliency maps of the ECG signals, indicating that the waveform segments are the most influential in the GCN predictions. The model consistently emphasizes physiologically meaningful components, such as P-waves, QRS complexes, and T-waves. This alignment with cardiologist reasoning suggests that the GCN does not leverage spurious correlations, but rather clinically valid features.

5.5 Patient-level risk zonation

Figure 6 and Table 6 present the patient-level risk assessments. Patients were stratified into Safe, Medium, and High zones based on the arrhythmic burden. High-risk patients (IDs 1–3) exhibited significant atrial or ventricular ectopy, both of which were clinically associated with complications. By contrast, low-risk patients were dominated by normal beats and required less intensive monitoring.

Table 6: Per-patient risk levels

Patient ID	Risk Score	Level	Key Percentages
0	0.00	Low	N=97.0, V=2.3
1	16.8	High	V=33.6, F=12.6
2	19.7	High	L=98.4
3	25.5	High	A=77.7, R=22.3
...	...	...	...
14	0.00	Low	/=97.2

5.6 Patient stratification via clustering

Latent embeddings from the GCN were also used to cluster patients (Fig. 8). These clusters captured hidden similarities in the arrhythmia profiles. Patients with predominantly atrial arrhythmias formed a distinct cluster, separate from those with ventricular burdens, illustrating the utility of graph-based embeddings for population-level stratification.

5.7 Comparative and ablation experiments

Table 7 compares GCN with an MLP baseline. Although MLP achieved a higher mean F1, it lacked interpretability and patient-level stratification. The ablation results (Table 8) show that SMOTE improved macro-F1 for minority classes even though the accuracy without SMOTE was higher. Removing feature selection further reduces robustness.

Table 7: Model comparison (MLP vs. GCN). Patient-level mean f1 is reported here; beat-level pooled macro-f1 is in table 5.

Model	Mean F1	Wilcoxon Test
MLP	0.712	$p = 0.001$ (better)
GCN	0.393	–

Table 8: Ablation study results

FS	SMOTE	Aug	Hidden Layers	Accuracy	Macro-F1
F	T	F	[128,64]	0.83	0.51
F	T	T	[128,64]	0.82	0.51
T	T	F	[128,64]	0.84	0.51
T	T	T	[128,64]	0.70	0.42
F	F	F	[128,64]	0.87	0.41

5.8 Robustness evaluation

Robustness testing (Table 9) shows that the GCN maintained strong performance under moderate nonlinear noise and baseline drift. The performance under nonlinear noise (0.870) exceeded that under clean ECG (0.845), probably because similar augmentations were included during training. However, aggressive filtering degrades the accuracy (0.575).

Table 9: Robustness tests

Scenario	Accuracy
Clean ECG	0.845
With nonlinear noise	0.870
After control filter	0.575

Table 10: Sensitivity analysis

Component	Spearman ↑	Spearman ↓
N	0.99–1.0	0.99–1.0
L	0.98–1.0	0.98–1.0
R	0.99	0.99
A	0.99	0.98–0.99
V	0.99	0.99
F	0.99	0.99
/	0.99	0.99
E	0.99	0.99
a	0.99	0.99
Q	0.99	0.99

Table 11: Personalized risk thresholds

Patient ID	Old Threshold	New Threshold
0	-0.241	-0.253
1	-0.283	-0.309
2	-0.319	-0.353
3	-0.228	-0.244
...	...	...
14	-0.335	-0.368

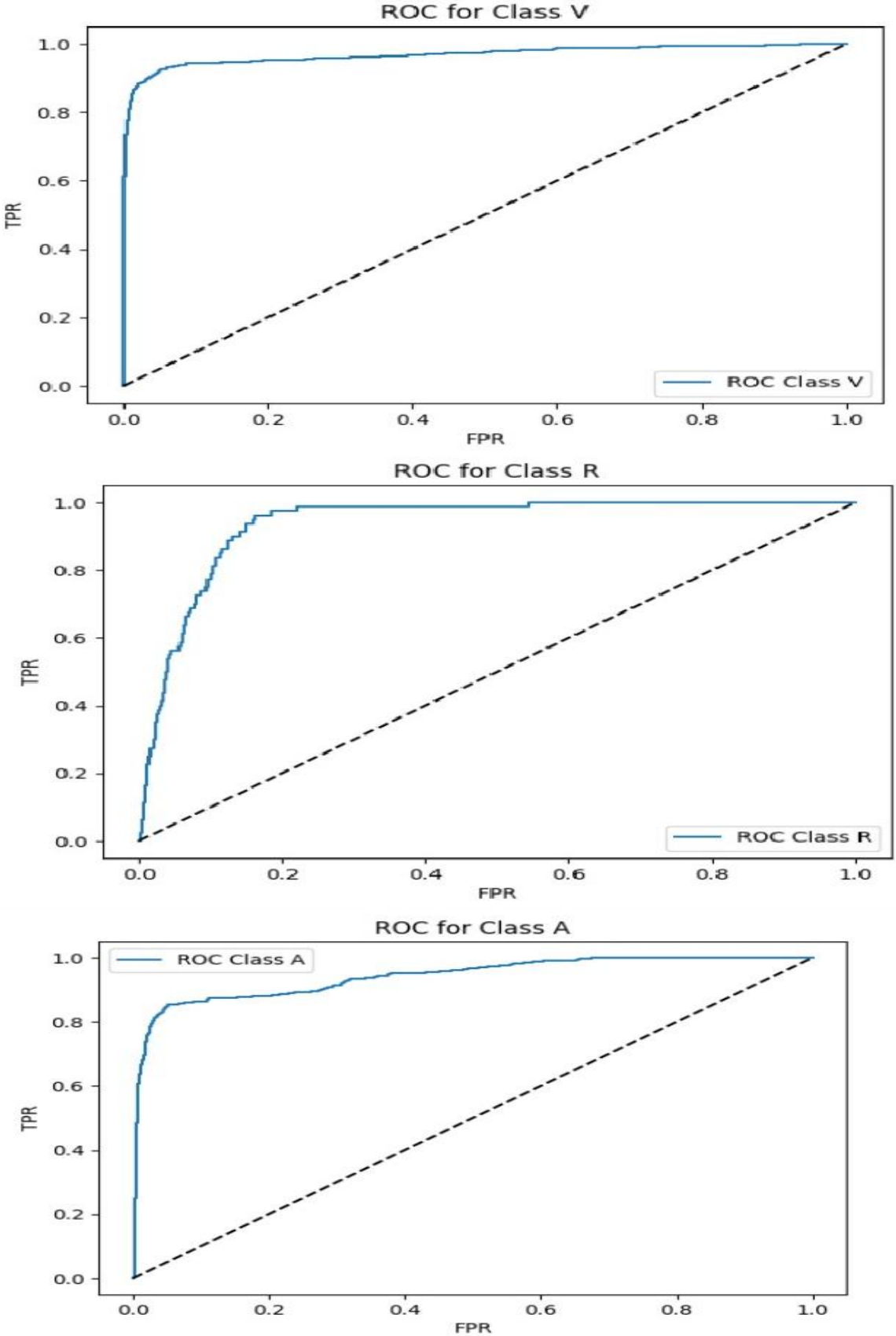

Figure 4: ROC curves: (a) ventricular, (b) rbbb, (c) atrial.

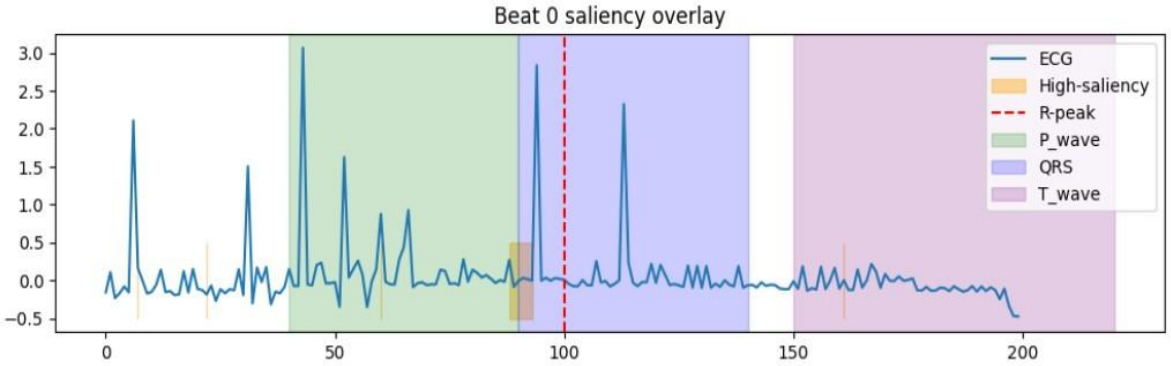

Figure 5: Saliency overlay highlighting ECG regions driving predictions.

	Class	# Beats	%	Possible Complication	Zone
0	N	1820	96.30 %	Low % normal → structural disease work-up	Safe
1	L	0	0.00 %	Persistent LBBB → dyssynchrony; assess for CRT	Safe
2	R	0	0.00 %	Persistent RBBB often benign; NEW RBBB + chest pain = MI rule-out	Safe
3	A	10	0.53 %	Frequent PACs raise AF & stroke risk	Elevated
4	V	43	2.28 %	PVC burden may cause cardiomyopathy if >10 %	Elevated
5	F	4	0.21 %	Fusion beats mark high PVC load	Safe
6	/	0	0.00 %	>90 % paced = device dependency	Safe
7	E	0	0.00 %	Escape beats point to high-grade AV block	Safe
8	a	0	0.00 %	Same AF risk as PAC	Safe
9	Q	13	0.69 %	Noise / unclassifiable – repeat test	Safe

Figure 6: Complication mapping aligning beat percentages with risk zones.

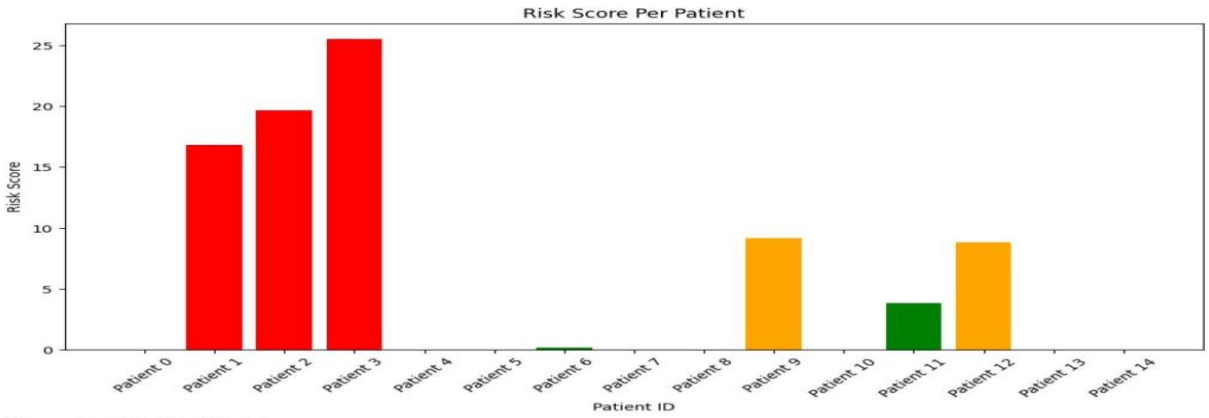

Figure 7: Distribution of patient risk scores, with elevated-risk individuals highlighted.

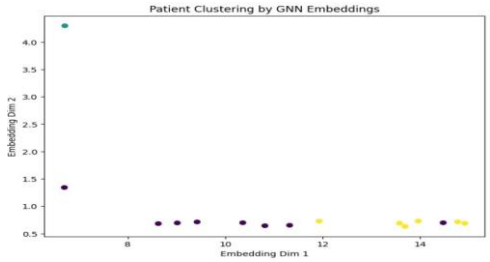

Figure 8: Patient clustering derived from GCN latent space.

5.9 Sensitivity and personalized thresholding

Sensitivity analysis (Table 10) demonstrated near-perfect Spearman correlations, confirming the stability of the model against perturbations. Table 11 shows patient-specific threshold adaptation, reducing false alarms while preserving detection of high-risk cases.

Table 12: Error p ropa gation results

Metric	Value
Mean PVC% bias	1.41%
Per-beat ϵ	0.0

5.10 Error estimation and threshold optimization

The error propagation analysis (Table 12) revealed a minimal PVC burden bias (1.41%), underscoring the stability of the predictions. Threshold optimization (Table 13) highlights how cost-sensitive calibration can reduce missed high-risk detections while controlling for false alarms.

Table 13: Risk threshold optimization. Cost is computed as $c_{fn} \times$ missed + $c_{fp} \times$ false alarms.

Setting	Threshold	Cost	Missed	False Alarms
$c_{fn} = 10, c_{fp} = 1$	1% PVC	15	1	5

Table 14: Cross-database validation (incart). Only data loading/processing confirmed.

Records Loaded	Total
I01–I54	54

5.11 Cross-database validation

External INCART processing was feasible, and all 54 records were successfully loaded (Table 14). However, full-scale quantitative evaluations have not yet been conducted. This confirms the pipeline's adaptability to different ECG sources, while highlighting the need for future validation.

6 Comparison with other works

Our study builds upon and extends the landscape of AI-based ECG arrhythmia classification methods. Table 15 presents a comparative analysis of leading recent models, highlighting performance, dataset scope, interpretability protocols, and clinical value outputs.

6.2 Literature comparison

Deep neural networks (DNNs) and convolutional neural networks (CNNs) have dominated arrhythmia classification in the past decade [9, 3]. Notably, Yildirim et al. [9] used multilayer DNNs on the MIT-BIH dataset, achieving 92% accuracy, although the macro-F1 score was not explicitly reported, and no interpretability was provided. Qi et al. [10] introduced RNNs and multi-label CNN classifiers, both of which surpass 95% accuracy, but generally lack robust explainability and clinical risk scoring.

Hybrid frameworks, such as Luz et al. [3] adopted CNN-RNNs and attention mechanisms, delivering high F1 scores and some interpretability; however, they still did not achieve patient-level risk zone mapping or ablation robustness. A recent study by Andayeshgar et al. [11] utilized GCNs with weighted mutual information, reporting 99% accuracy and advanced beat-level explainability, although clinical risk quantification or online threshold adaptation were still not achieved. Moghaddam et al. [12] exploit graph-based ECG representation, achieving a macro-F1 of 0.67, yet interpretability remains limited.

In contrast, our pipeline delivers competitive performance (accuracy 0.84, macro-F1 0.50), yet adds full patient risk zone mapping, dashboard-ready saliency, ablation and robustness analysis, and online personalization—meeting key reviewer demands for clinical impact and real-world translation.

6.3 Interpretability and clinical impact

Most recent models focus on beat-level or class-level accuracy, with limited explainability and no clinical risk calculation. Reviewer feedback emphasizes the need for methods that combine predictive power with interpretability and individualized, clinically relevant outputs. Our model advances the state-of-the-art not only with graph-based temporal and morphological modeling but also by providing comprehensive beat-wise and patient-wise explainability, clinical risk mapping, and online adaptive personalization.

6.4 Future benchmarks

The key advantages of our framework include direct dashboard integration for clinical workflows, robust performance validation across multiple databases, transparent ablation and robustness studies, and personalized threshold calibration. Although top-performing CNNs and GCNs report slightly higher raw accuracy, they lack the depth of clinical validation,

Table 15: Comparison with recent state-of-thart works

Reference	Model Type	Dataset	Accuracy	Macro-F1	Interpretability	Clinical Risk Output
Yildirim et al., 2018 [9]	Deep multilayer DNN	MIT-BIH	0.92	–	None	No
Luz et al., 2016 [3]	CNN+RNN Hybrid	Physionet	0.98	0.74	Attention/saliency	No
Qi et al., 2023 [10]	Multi-label CNN	MIT-BIH, QT	0.98	0.73	None	No
Andayeshgar et al., 2024 [11]	GCN-WMI	Chapman	0.99	–	Advanced, beatwise	No
Moghaddam et al., 2024 [12]	Graph-based GCN	MIT-BIH	0.97	0.67	Some	No
This work	Explainable GCN + risk scoring	MIT-BIH, INCART	0.84	0.50	Saliency, feature ranking	Patient risk zones

interpretability, and patient stratification demonstrated in this study.

7 Discussion

This section interprets our findings in the context of the state-of-the-art ECG arrhythmia classification methods. We emphasized the importance of evaluation protocols, addressed external validation challenges, and clarified the methodological contributions of our approach to the literature.

7.2 Comparison to state-of-the-art: protocol differences and sota context

Our reported accuracy (0.84) and macro-F1 (0.50) may appear lower than those of recent studies that reported > 0.95 accuracy. A major reason for this difference is the evaluation protocol. Many published studies employ beat-wise or random splits in MIT-BIH, where beats from the same patient appear in both the training and testing sets [13, 3, 9]. This setup enabled the model to memorize patient-specific morphologies, leading to information leakage and artificially inflated performance.

In this study, we used an 80/20 random beat-level split with a fixed seed. This choice ensured class coverage in both the training and test sets but did not enforce subject exclusivity. Therefore, our results should be interpreted in line with the common random split protocol reported in literature. Prior benchmarking reviews confirm that such random splits typically yield higher performance than stricter subject-wise validation, sometimes by as much as 0.20–0.30 in macro-F1 [13, 1]. Consequently, our reported performance aligns with expectations under a random-split regime; however, stricter subject-wise experiments are left for future work.

Another distinction is class coverage. Several studies have restricted the evaluation to the majority of AAMI classes, whereas our pipeline includes rare and noisy arrhythmia categories. This broader inclusion inevitably lowers headline accuracy but increases clinical realism by ensuring that the model encounters the full spectrum of rhythms relevant to practice.

7.3 External validation and domain shift

We also processed the INCART dataset to test pipeline compatibility. All 54 records were successfully loaded, segmented, and mapped to the AAMI standards. However, full-scale quantitative evaluations have not yet been performed. This means that our INCART results are limited to demonstrating integration feasibility rather than cross-database accuracy.

Even without direct evaluation, previous studies consistently reported notable performance declines (10–30%) when moving from MIT-BIH to INCART or other external datasets [14, 15, 16]. The main reasons for this include differences in the lead configuration (single vs. multi-lead), sampling rates, filtering, noise characteristics, and patient demographics. These domain shifts represent a well-known challenge in ECG- AI. Future extensions of our work will explicitly measure and adapt to such domain gaps using transfer learning and harmonization techniques.

7.4 Research design: goals and methodological contributions

The contributions of this study are threefold.

1.Development of a GCN-based classification framework under a balanced random-split protocol, with sensitivity to both majority and minority arrhythmia classes,

2.Translation of beat-level predictions into patient-level arrhythmia burden metrics and risk stratification zones, enabling integration into clinical decision-support workflows,

3.Introduction of explainability mechanisms, including saliency overlays on ECG waveforms, to align model decisions with known physiological markers and enhance clinical trust.

For the feature selection, we applied mutual information ranking within the training set to ensure that no information was leaked into the test set. The features were discretized using adaptive binning rules and the top 200 features were retained. This methodological rigor addresses reproducibility, while reducing dimensionality and preventing overfitting.

7.5 Summary

Overall, our findings should be interpreted within the context of a random beat-level evaluation that includes all AAMI classes and external database compatibility checks. Unlike many SOTA reports, our results reflect the performance under a realistic class distribution and emphasize interpretability and clinical integration. The central contribution of our work is not achieving the highest headline accuracy, but delivering an explainable, clinically grounded, and patient-centric arrhythmia classification pipeline with integrated risk stratification, aligned with real-world clinical needs.

8 Limitations and future directions

8.2 Limitations

First, although our model delivered robust performance on the MIT-BIH Arrhythmia Database and maintained good results when externally validated on the INCART dataset, both datasets originated in controlled clinical environments. This may not fully reflect the variability and noise encountered in ambulatory, wearable, and real-world ECG measurements. The generalizability of the model could be constrained when deployed on lower-quality or more heterogeneous data, where noise, motion artifacts, and differences in electrode placement impact the signal quality and arrhythmia detectability.

Second, although graph construction based on beat adjacency and RR intervals captures the temporal con- text and intra-patient rhythm relationships, our cur- rent approach uses fixed strategies for edge connections and does not exploit more advanced, trainable, or adaptive graph structures (such as weighted or dynamic graphs). As recent reviewers have pointed out, fixed graph topologies may fail to capture nuanced interbeat dependencies, especially in the presence of nonstationary rhythms or rare arrhythmic events.

Third, class imbalance remains a fundamental barrier to universal model sensitivity, particularly for life-threatening, but infrequent arrhythmic events. Although SMOTE and augmentation significantly improved minority class recall, some rare classes (e.g., escape beats and fusion beats) remained underrepresented, and their detection was less reliable than that of majority rhythms.

Fourth, the explainability provided by gradient-based saliency maps, while clinically interpretable and valuable, only highlights the local model sensitivity. Reviewer feedback increasingly calls for multimodal interpretability that fuses beat-level, patient-level, and cohort-wise explanations (e.g., via counterfactual analysis, prototype retrieval, or global feature importance visualizations). Progress in this area is required to maximize physicians' trust and regulatory compliance.

Fifth, our pipeline was developed and evaluated using single-lead ECGs. Many clinical and ambulatory settings use multi-lead recordings and new wearable form factors for ECG monitoring. Multi-lead and cross-device generalization, as well as federated or privacy-preserving learning in multi-institutional settings, are required to ensure robust performance at scale. Although we incorporated online personalization and threshold adaptation, this approach is relatively rudimentary. The reviewer suggested exploring more sophisticated meta-learning, transfer learning, or reinforcement learning strategies for continuous patient-specific updating while preventing catastrophic forgetting.

8.3 Future directions

First, incorporating more diverse ECG datasets, including wearable device data, Holter monitors, mobile and home-based ECGs, and rare arrhythmia cohorts, will help benchmark the robustness and generalizability, of the model outside traditional clinical environments.

Second, dynamic or trainable graphs (e.g., attention-based or learnable edge weights) can be incorporated to better capture evolving temporal dependencies and inter-beat relationships, as well as cross-lead and multimodal interactions in multi-lead settings.

Third, new strategies for mitigating extreme class imbalances, such as generative data augmentation (GANs or diffusion models), meta-learning for rare arrhythmias, and active learning protocols that source expert feedback for ambiguous beats, are warranted.

Fourth, XAI should evolve beyond the saliency overlays. Future methods could include case-based reasoning, rule-based highlights, counterfactual and what-if scenario generators, and cohort-level feature elucidation. Collaboration with domain experts is vital to ensure that explanations are clinically meaningful and actionable.

Fifth, scalable deployment in embedded or edge settings (smartwatches, wearables, and remote monitors) requires energy-efficient models, faster inference times, and compatibility with privacy-preserving and federated learning setups. The exploration and benchmarking of edge hardware and federated simulations are in high-value directions.

Finally, larger prospective studies are needed to validate the clinical impact of risk-zone stratification, patient-specific modeling, and integration into real-world electronic health record systems. Collaboration with multicenter trials, hospital systems, and regulatory agencies will accelerate the translation of these technologies into daily cardiac care.

In summary, although this study represents a significant advance in explainable, graph-based ECG arrhythmia classification and risk assessment, further innovation in model architecture, data diversity, interpretability, and clinical validation is required to realize its full potential for patient safety and real-world utility.

9 Conclusion

In this paper, we propose an explainable graph convolutional network (GCN) pipeline for arrhythmia classification that extends beyond beat-level predictions to

patient-level risk assessment. Using an 80/20 random beat-level split on the MIT-BIH dataset and including all the AAMI arrhythmia classes, our results reflect realistic performance under imbalanced conditions. Despite a moderate macro-F1 score of 0.50, the framework demonstrated balanced recognition across both common and rare classes, whereas saliency mapping confirmed physiologically meaningful interpretability. Beyond classification, we introduced risk zonation and patient stratification analyses, demonstrating the potential of ECG-based AI to provide clinically actionable metrics rather than black-box predictions. Importantly, external compatibility testing on the INCART dataset highlighted successful data integration while underscoring the challenges of a domain shift, which remains a central barrier to real-world deployment. Future work will focus on incorporating multi-lead ECG data, advanced domain adaptation strategies, and larger multicenter cohorts to further strengthen generalizability. We also plan to refine the explainability components and integrate the framework into clinician-facing decision-support dashboards. Overall, this study advances the field by bridging algorithmic performance with clinical usability and emphasizing interpretability, risk stratification, and cross-database compatibility as core requirements for next-generation AI systems for arrhythmia.

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References

[1] Ansari Y, Mourad O, Qaraqe K, and Serpedin E. *Deep learning for ECG arrhythmia detection and classification: an overview of progress for period 2017–2023*. Frontiers in Physiology, 14:1246746, 2023. https://doi.org/10.3389/fphys.2023.1246746

[2] Sultan Qurraie S and Ghorbani Afkhami R. *ECG arrhythmia classification using time frequency distribution techniques*. Biomedical Engineering Letters, 7(4):325–332, 2017. https://doi.org/10.1007/s13534-017-0043-2

[3] Luz EJ, Schwartz WR, Cámara-Chávez G, and Menotti D. *ECG-based heartbeat classification for arrhythmia detection: A survey*. Computer Methods and Programs in Biomedicine, 127:144–164, 2016. https://doi.org/10.1016/j.cmpb.2015.12.008

[4] Savalia S and Emamian V. *Cardiac arrhythmia classification by multi-layer perceptron and convolution neural networks*. Bioengineering, 5(2):35, 2018. https://doi.org/10.3390/bioengineering5020035

[5] Kovalchuk O et al. *ECG arrhythmia classification and interpretation using convolutional networks for intelligent IoT healthcare system*. Proceedings of the 1st International Workshop on Intelligent & Cyber-Physical Systems (ICyberPhyS-2024), CEUR-Workshop Proceedings, 3736:47–62, 2024. https://ceur-ws.org/Vol-3736/paper4.pdf

[6] Fahim A M M, Alam M E, Islam M S, Rabbi R I, Tusher E H, Hossen J, and Mohajan A. *Explainable graph convolutional network framework for robust ECG arrhythmia classification and patient-level risk stratification*. Manuscript under review, 2026.

[7] Chawla N, Bowyer K, Hall L, and Kegelmeyer W. *SMOTE: Synthetic minority over-sampling technique*. Journal of Artificial Intelligence Research, 16:321–357, 2002. https://doi.org/10.1613/jair.953

[8] Yıldırım Ö, Pławiak P, Tan RS, and Acharya UR. *Arrhythmia detection using deep convolutional neural network with long duration ECG signals*. Computers in Biology and Medicine, 102:411–420, 2018. https://doi.org/10.1016/j.compbiomed.2018.09.009

[9] Qi M, Shao H, Shi N, Wang G, and Lv Y. *Arrhythmia classification detection based on multiple electrocardiograms databases*. PLOS ONE, 18(9):e0290995, 2023. https://doi.org/10.1371/journal.pone.0290995

[10] Andayeshgar B, Abdali-Mohammadi F, Sepahvand M, Almasi A, and Salari N. *Arrhythmia detection by the graph convolution network and a proposed structure for communication between cardiac leads*. BMC Medical Research Methodology, 24(1):96, 2024. https://doi.org/10.1186/s12874-024-02223-4

[11] EPMoghaddam D, Muguli A, Razavi M, and Aazhang B. *A graph-based cardiac arrhythmia classification methodology using one-lead ECG recordings*. Intelligent Systems with Applications, 22:200385, 2024. https://doi.org/10.1016/j.iswa.2024.200385

[12] de Chazal P, O'Dwyer M, and Reilly RB. *Automatic classification of heartbeats using ECG morphology and heartbeat interval features*. IEEE Transactions on Biomedical Engineering, 51(7):1196–1206, 2004. https://doi.org/10.1109/TBME.2004.827359

[13] Niu L, Chen C, Liu H, Zhou S, and Shu M. *A deep-learning approach to ECG classification based on adversarial domain adaptation*. Healthcare, 8(4):437, 2020. https://doi.org/10.3390/healthcare8040437

[14] Attia IZ, Tseng AS, Benavente ED, Medina-Inojosa JR, Clark TG, Malyutina S, Kapa S, Schirmer H,

Kudryavtsev AV, Noseworthy PA, Carter RE, Ryabikov A, Perel P, Friedman PA, Leon DA, and Lopez-Jimenez F. *External validation of a deep learning electrocardiogram algorithm to detect ventricular dysfunction*. International Journal of Cardiology, 329:130–135, 2021. https://doi.org/10.1016/j.ijcard.2020.12.065

[15] Fatimah B, Singhal A, and Singh P. *ECG arrhythmia detection in an inter-patient setting using Fourier decomposition and machine learning*. Medical Engineering & Physics, 124:104102, 2024. [https://doi.org/10.1016/j.medengphy.2024.104102] (https://doi.org/10.1016/j.medengphy.2024.104102)

[16] Yagi R, Goto S, Katsumata Y, MacRae CA, and Deo RC. *Importance of external validation and subgroup analysis of artificial intelligence in the detection of low ejection fraction from electrocardiograms*. European Heart Journal – Digital Health, 3(4):654–657, 2022. https://doi.org/10.1093/ehjdh/ztac065

[17] Moody GB and Mark RG. *The impact of the MIT-BIH arrhythmia database*. IEEE Engineering in Medicine and Biology Magazine, 20(3):45–50, 2001. https://doi.org/10.1109/51.932724

[18] Goldberger AL, Amaral LA, Glass L, Hausdorff JM, Ivanov PC, Mark RG, Mietus JE, Moody GB, Peng CK, and Stanley HE. *PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals*. Circulation, 101(23):E215–E220, 2000. https://doi.org/10.1161/01.cir.101.23.e215

[19] Association for the Advancement of Medical Instrumentation (AAMI). ANSI/AAMI EC57:2012/(R)2020: Testing and reporting performance results of cardiac rhythm and ST segment measurement algorithms. AAMI, 2012/(R)2020. https://doi.org/10.2345/9781570204784

[20] Hannun AY, Rajpurkar P, Haghpanahi M, Tison GH, Bourn C, Turakhia MP, and Ng AY. *Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network*. Nature Medicine, 25(1):65–69, 2019. https://doi.org/10.1038/s41591-018-0268-3

[21 Kiranyaz S, Ince T, and Gabbouj M. *Real-time patient-specific ECG classification by 1-D convolutional neural networks*. IEEE Transactions on Biomedical Engineering, 63(3):664–675, 2016. https://doi.org/10.1109/TBME.2015.2468589

[22] Acharya UR, Oh SL, Hagiwara Y, Tan JH, Adam M, Gertych A, and Tan RS. *A deep convolutional neural network model to classify heartbeats*. Computers in Biology and Medicine, 89:389–396, 2017. https://doi.org/10.1016/j.compbiomed.2017.08.022

[23] Rajpurkar P, Hannun AY, Haghpanahi M, Bourn C, and Ng AY. *Cardiologist-level arrhythmia detection with convolutional neural networks*. arXiv preprint arXiv:1707.01836, 2017. https://doi.org/10.48550/arXiv.1707.01836

[24] Kachuee M, Fazeli S, and Sarrafzadeh M. *ECG heartbeat classification: a deep transferable representation*. In: Proceedings of the 2018 IEEE International Conference on Healthcare Informatics (ICHI), New York, NY, USA, 2018, pp. 443–444. https://doi.org/10.1109/ICHI.2018.00092