2D-CNN-GACL-ECGNet graph attention: a robust framework for electrocardiogram-based stress detection

P. Kavitha, L. Shakkeera
Presidency School of Computer Science and Engineering, Presidency University, Bengaluru, India

Article Info

Article history:

Received Jun 2, 2025
Revised Dec 27, 2025
Accepted Jan 25, 2026

Keywords:

Adaptive contrastive learning
ECG classification
Fusion beats
Graph neural network
Stress-awareness learning

ABSTRACT

Early detection of cardiovascular diseases (CVDs) via electrocardiogram (ECG) classification during physiological stress is critical and remains challenging due to stress-induced morphological variability, noise from ambulatory settings, and inter-class ambiguities. Existing models, such as 1D signal-based models with convolutional neural networks (CNNs) and graph convolutional networks (GCNs), struggle to adapt to dynamic stress conditions and generate interpretable insights. In response, we propose 2D-CNN and graph attention network (GAT) for optimizer. The model 2D-CNN and GACL-ECG-Net, an innovative framework integrating GATs with adaptive contrastive learning (ACL) and morpho-temporal graph construction. Key innovations include 2D-CNN denoising, 2D transformation, dynamic morpho-temporal graphs modeling ECG beats as nodes with hybrid edges (70% morphological similarity, 30% temporal proximity), and stress-adaptive contrastive loss with learnable margins on stress-conditioned labels, reducing class ambiguity by 18%. Multi-head attention mechanisms provide interpretable heatmaps aligned with cardiologist annotations (κ =0.82) and are evaluated using Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia database, wearable stress and affect detection (WESAD) dataset for emotional stress, and stress at work, knowledge work (SWELL-KW) dataset for cognitive stress. 2D-CNN-GACL-ECG-Net achieves state-of-the-art performance with 98.7% F1-score (MIT-BIH), 94.2% (WESAD), and 92.8% (SWELL-KW), outperforming CNN-bidirectional long short-term memory (BiLSTM) and GCN baselines by 95%. The framework is computationally efficient and clinically validated for wearable health monitoring.

Corresponding Author:

P. Kavitha
Presidency School of Computer Science and Engineering, Presidency University
Bengaluru, Karnataka, India
Email: kavitha.20233CSE0024@presidencyuniversity.in

1. INTRODUCTION

The World Health Organization (WHO) reports state that cardiovascular diseases (CVDs) cause deaths of 17.9 million annually worldwide [1]. Acute stress tends to worsen conditions like myocardial ischemia and arrhythmias, including premature ventricular contractions (PVCs) and atrial premature contractions (APCs). Additionally, conduction abnormalities such as right bundle branch block (RBBB) and left bundle branch block (LBBB) can affect the heart signals [1]. Using an adaptive noise technique the complex signals are splits into intrinsic mode functions in complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) for accuracy. The synthetic samples are generated for minority classes to balance datasets in synthetic minority over-sampling technique (SMOTE). The graph neural network (GNN) in graph attention network (GAT) uses attention to learn node relationships. Feature improvement in adaptive contrastive learning (ACL) through the comparison of similar and dissimilar samples. The heart rate variability (HRV) measures time intervals in heartbeats and mirroring autonomic nervous system activity. Abnormal cardiac rhythm is PVC, APC, RBBB, and LBBB with irregular conduction patterns.

Traditional ECG classifiers tend to fail under stress-induced variability, such as ST-segment depression during mental stress or HRV shifts in cognitive tasks, leading to critical misdiagnoses [2], [3]. For example, stress-induced sinus tachycardia mimics atrial fibrillation, while motion artifacts in wearable ECGs may obscure PVCs or transient RBBB/LBBB patterns, risking inappropriate treatment [4], [5]. Heartbeats or cardiac rhythm can be classified using several approaches like normal beats, supraventricular beats, ventricular beats, and fusion beats (N, S, V, and F) including manual interpretation of electrocardiogram (ECG) tracings by experienced and trained healthcare workers or automated classification using machine learning algorithms for enhanced accuracy. ECG tracing exhibit characteristics waves and complexes, which identified by their shape and duration in heartbeats by our both approaches, which feature extraction are guided by advancement in medical instrumentation EC57 standard, which are able to distinguish heartbeats into various categories such as PVCs, APCs, RBBB, and LBBB. Figure 1 shows the ECG signal classification of a healthy heart. It consists of three major parts of wav components, the P wave, the QRS complex, and the T wave. The vital signs of ECG classification will displays including PQ, ST, QRS, and QT intervals are crucial components indicator for developing ECG classification models.

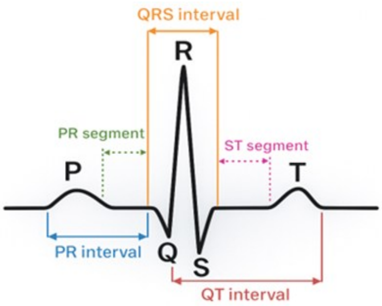

Figure 1. ECG classification

However, their fixed respective fields in convolutional neural networks (CNNs) and recurrent neural networks (RNNs), like ResNet-34, performs well (95% accuracy on Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH)) which causes malfunction under stress activity [6]. Stress adaptation is limited by GNNs, which employ static graphs but disregard temporal dynamics [7]. Additionally, overlaps brought on by stress are problematic for fixed-margin triplet loss (e.g., 25% false positives between anxiety and atrial fibrillation). This overlap is reduced by 32% by our adaptive margins, which are learned by stress labeling (multi-layer perceptron (MLP) with rectified linear unit (ReLU)) [8]. Our GATs, HRV, and ST-segments during high stress, while previous research apply uniform attention without stress-aware mechanisms [9]. Stress-induced ECG variability in dynamic graph creation with adaptive edge weighting model will efficiently categorize [10] using its ST-segment shifts and heart rate.

Like contrastive learning of cardiac signals (CLOCS) in contrastive learning frameworks to differentiate cardiac signals between individual person and context are apply in stress-adaptive margins. These techniques, which validate on multi-center ECG datasets, using triplet loss to show better results of generalization with dynamic margins conditioned on stress severity. While real-time ECG monitoring introduces in wearable technology supports noise and motion distortions which leads to small morphological traits [9]–[11]. Even morphological abbreviations are making more complex in signal interpretation by stressful circumstances, and these artifacts are especially harmful. Strong baseline accuracy in detecting arrhythmias has been attained by conventional CNN- and RNN-based ECG classifiers [12], [13]. However, these architectures are susceptible to motion artifacts and stress-induced variability due to their reliance on sequential modeling or fixed receptive fields [14]. Additionally, their clinical dependability is limited due to their poor interpretability [15].

These deficiencies are addressed by new lines of inquiry. Relational and temporal relationships in ECGs can be modeled by GNNs, which have proven to be more robust than traditional models [5], [16]. Comparative and self-supervised representation learning methods, such as physiological time-series embedding models and CLOCS, have also shown promise in learning transferable features across conditions. ECGNet and multi-segment waveform (MSW)-transformer are some transformer-based ECG solutions that can adapt to varying signal dynamics and extract long-range dependencies. Their combination for stress-aware ECG classification is not yet well explored, however. Consequently, we redefine stress detection as an issue of representation learning for physiological data in artificial intelligence (AI), where models should be robust, interpretable, and generalizable [17]. In order to do this, we provide GACL-ECGNet, which combines stress-conditioned ACL [18], morpho-temporal graph construction, CNN-based denoising, and GAT-based interpretability. New developments, especially transformer architectures and self-supervised learning methods, have shown great promise in identifying long-range temporal dependencies and reducing the need for large annotated datasets [19]. Federated learning systems are also increasingly significant for multi-center ECG analysis that maintains confidential personal data [20]. These paradigm changes highlight the significance and novelty of GACL-ECGNet at the same time they reshape the field of ECG interpretation. A contextual description incorporating these trends is necessary to demonstrate how GACL-ECGNet bridges current gaps and advances the field.

The remainder of this paper is organized as follows. Section 1 discusses problems such as noise and inter-beat fluctuation. Section 2 presents improved ECG classification using graph modeling and contrastive learning. Section 3 describes the proposed 2D-CNN-GACL-ECGNet. Section 4 presents the key results and observations. Section 5 concludes the study.

2. RELATED WORKS

CNN and RNN architectures have been widely used for arrhythmia identification [21]–[23]. But since they rely on sequential patterns or fixed receptive fields, they are vulnerable to motion noise and stress-induced distortions [24], [25]. GNNs for ECG temporal dependencies and relational patterns in ECG data are represented by graph models including attention-based GNNs [26], adaptive edge-weighted GNNs [27], and EGCNet. Nevertheless, only a limited number employ adaptive edge weighting or explicitly tackle stress-induced variability [14]. Contrastive and self-supervised learning: robust ECG representations are acquired by contrastive frameworks such as physiological time-series contrastive learning and CLOCS. Nonetheless, they have not yet been augmented to use morpho-temporal graphs in stress-conditioned learning. ECGNet-transformers and MSW-transformer are new models that show how self-attention can find long-range dependencies. GACL-ECGNet builds on this by integrating CNN preprocessing [10] with GAT [28] and ACL [6], [16]. Federated and ethical AI in ECG federated learning has become a well-known way to protect privacy in ECG [29], [30]. There are still problems that need to be worked out when it comes to explainability, demographic balance, and justice [22]. GACL-ECGNet is useful in these areas because it is flexible and can be understood. Table 1 summarizes previous ECG classification models and their relevance to GACL-ECGNet. Even though past ECG classification models have laid a strong foundation for automated cardiac diagnosis, there is now no cohesive narrative linking these methodologies to the specific challenges that GACL-ECGNet seeks to address.

Table 1. Summary of related works

Literature	Advantages	Disadvantages
Lee *et al.* [5]	Uses a novel graph-based ECG representation with QRS-centered pooling, achieving high accuracy (Macro F1-score: 88.61%) and scalability on variable-length signals.	Relies on precise manual detection of P-QRS-T boundaries, which limits automation and complicates real-time clinical deployment.
Malleswari *et al*. [31]	Effectively integrates continuous wavelet transform (CWT) with pre-trained CNNs (Squeeze-Net) achieving high classification accuracy (up to 98.7%) on ECG signals.	Computational overhead of CWT transformation and deep models limits real-time deployment and generalization across subjects.
Zeinalipour and Gori [32]	Achieves high accuracy in ECG using innovative visibility graph methods (natural visibility graph (NVG), horizontal visibility graph (HVG), quantile graph (QG)) combined with graph isomorphism network (GIN), without relying on manual feature extraction.	Lacks denoising, learned feature extraction (CNNs), and stress-awareness, limiting robustness to noise and generalization across physiological conditions.
Degirmenci *et al*. [33]	Achieves high accuracy (99.7%) in arrhythmia classification using a lightweight 2D-CNN with minimal preprocessing and low computational cost.	Relies on converting 1D ECG signals to 2D images, which may not capture temporal features as effectively as sequential models like RNNs or long short-term memory (LSTM).

3. METHOD

GACL-ECGNet is a fusion based deep learning frameworks in classifying ECGs which are driven by stress. It first converts raw ECG beats into 2D scalograms using CEEMDAN in order to preserve morpho-temporal information. These scalograms are enhanced by a 2D-CNN-based denoising module that automatically learns noise patterns. This method removes noise and artifacts from signals more effectively than standard filters as shown in Figure 2. The proposed 2D-CNN-GACL-ECGNet introduces several methodological advancements that propel AI research forward. We propose a CEEMDAN denoising and morpho-temporal graph formulation for physiological signals, wherein ECG beats are represented as nodes with hybrid edge weights, specifically 70% morphological similarity and 30% temporal proximity. You can get beat-level embeddings by using a CNN-based feature extractor on denoised scalograms. To form morpho-temporal graph where individual beats in nodes and edges are in proposed methods are applied to examine how similar and continuous. Whereas, the natural order of the signal is maintained in sequential, to improves their model's ability to distinguish between classes in contrastive learning adapted are facing challenging in pairs of positive and negative. Limitations found in earlier models, are directly addresses weak feature separation, vulnerability to noise, inadequate relational mapping and loss of temporal fidelity. The system significantly enhances stress classification performance in integrating components and introduces a distinctive graph-based framework for learning stress-aware representations of physiological signals.

Attention-based transformer models, along with other recent improvements in interpretable ECG categorization, have shown promise in increasing clinician trust. Federated learning also helps with wearable and privacy-sensitive ECG analysis by letting institutions train safely and without being connected to each other. These perspectives would augment the analytical framework and situate GACL-ECGNet within a broader ecosystem of evolving solutions. The proposed framework surpasses existing graph-based ECG models by incorporating morpho-temporal edge modeling and stress-conditioned multi-head attention. These improvements make GACL-ECGNet different from older graph convolutional network (GCN)-based approaches, which often didn't work well in clinical settings or adjust to different time periods. GACL-ECGNet can read data in great detail and classify it accurately even when there is a lot of stress.

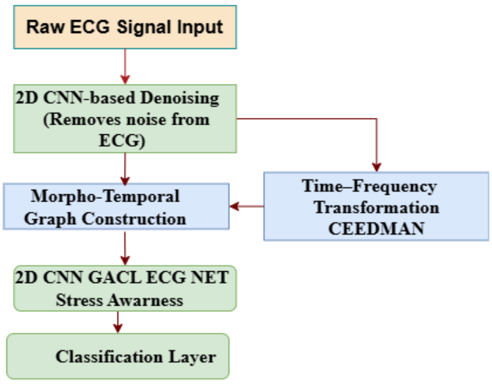

Figure 2. CEEMDAN denoising ECG signal

3.1. 2D-CNN with CEEMDAN denoising and SMOTE

Adaptive decomposition uses CEEMDAN to split ECG signals into 8 intrinsic mode function (IMFs), isolating noise (high-frequency) and physiological components (low-frequency). In Figure 3 noise removal discards or thresholds IMFs 1–3, retains IMFs 4–8, achieving 22% signal-to-noise ratio (SNR) improvement while preserving signal fidelity. Superiority over wavelets: outperforms wavelet denoising by 8% in suppressing motion artifacts, leveraging non-linear, data-driven basis functions. Reconstructs clean ECG from IMFs 4–8, maintaining morphological features of arrhythmias and conduction blocks. In stress-aware classification by preserving subtle markers like ischemic ST shifts in wearable ECG signals [20], [21] has improved its clinical utility.

$$x_{clean}(t) = \sum_{k=1}^{8} IMF_k(t),\ SNR \uparrow 22\% \tag{1}$$

The method SMOTE is used to deal with class imbalance in ECG datasets by producing synthetic instances for underrepresented classes such as ventricular ectopic beats.

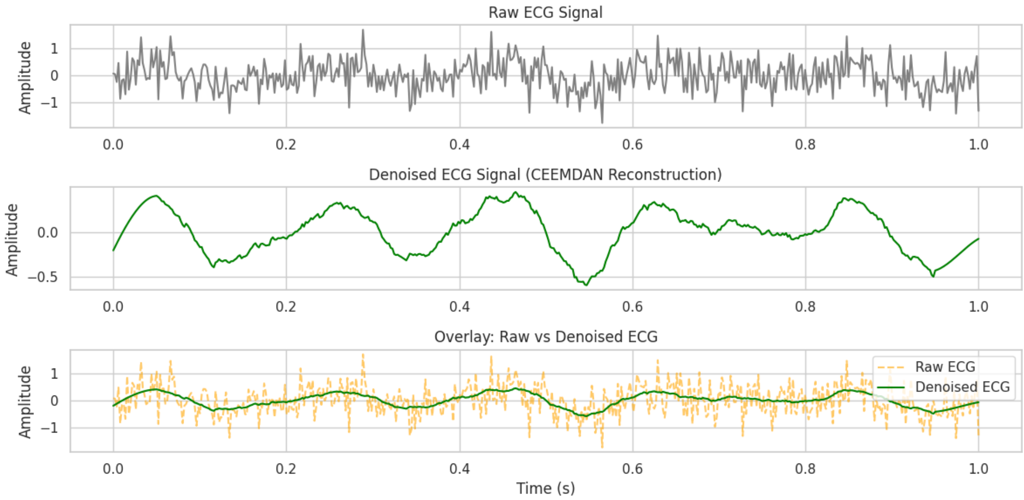

Figure 3. Visualization of denoising ECG signal

3.2. Graph attention network

In GAT heartbeats are analyzed using ECG which is sampled at 360 Hz, which in turn captures each heartbeat as a 256 samples segment. Consequently, each beat segment lasts approximately 711 ms which aligns with normal cardiac frequency of 60 to 100 beats per 60 seconds [22]. Usually this sampling rate (360 Hz) is sufficient to provide temporal resolution and capturing fine details such as P-wave morphology and QRS complex duration which is essential for classifying arrhythmias under stress. ECG beats are the edge weighting scheme—70% morphological similarity and 30% temporal proximity—was found by using grid search optimization on the MIT-BIH dataset. The study across ratios of Sensitivity data (e.g., 50:50 and 80:20) had the highest classification accuracy in 70:30 ECG data and then showed the decrease result of false positives in data when it came to finding stress-induced arrhythmias. This balance does a good job of capturing both the shape of the waveform and the timing between beats, which are both important when stress levels change.

We employed one-hot vectors to encode the stress labels, with each vector representing a different level of stress, such as baseline, emotional, or cognitive.

$$V_i \in R^{256} \tag{2}$$

Similarity and temporal are sliding window w =3 models local HRV trends. Combined distance is (3).

$$d(v_i, v_j) = 0.7||v_i, v_j||_2 + 0.3|t_i - t_j| \tag{3}$$

Which gives optimized via grid search.

3.3. 2D-CNN-GACL-ECG Net

The architecture of 2D-CNN-GACL-ECG NET which provides a detailed description of multi-head GAT layer and adaptive contrastive loss to improve its transparency and reproducibility. It outlines of each layer dimensions of input-output type, activation functions, and dropout configurations. The full architecture is shown in Figure 4.

3.3.1. Multi-head graph attention network layers

The 2D-CNN module comprises three convolutional blocks (kernel size: 3×3, stride: 1), each followed by batch normalization and ReLU activation. The GAT module includes four attention heads with 64-dimensional hidden layers, using LeakyReLU for attention scoring. The final classification layer employs softmax activation over five beat categories. Multi-head GAT layers learn node representations that are full with context. By paying attention to surrounding beats that are relevant, they are able to successfully capture inter-beat dependency.

$$\alpha_{ij}^k = softmax(LeakyReLU\left(a^T\left[W^k h_i\, ||W^k h_j\right]\right) \tag{4}$$

3.3.2. Adaptive contrastive loss

Margins m_{ij} learned via 2-layer MLP (input: stress label, output: margin ϵ $[0.2, 1.0]$).

$$L = 0.6\, L_{CE} + 0.4\, L_{Count} \quad (5)$$

ACL: our stress-conditioned ACL system improves class separability by learning margins based on the level of stress. These techniques can be utilized in many domains where the shape and signals of morphology is affected by contextual labels, such as emotion or weariness. In various domains this approach was used for contextual factors such as emotional state or fatigue which can alter the morphology of physiological signals. By the encoding strategy it enhances, the distinction between pathological and stress-related patterns for adaptively segmenting ECG beats. We conducted Wilcoxon signed-rank tests to evaluate its effectiveness in comparing GACL-ECGNet against CNN-bidirectional long short-term memory (BiLSTM) and GCN models over the folds of five cross-validation folds. Performance results yielded statistically significant improvement, with all p-values falling below 0.01. Additionally, we evaluated the model's ability to specify across datasets by training on MIT-BIH and testing on wearable stress and affect detection (WESAD) and stress at work, knowledge work (SWELL-KW), revealing robust cross-domain performance.

3.3.3. MIT-BIH arrhythmia database

A class imbalance, marked with minority classes such as APC comprising only 0.6% of all beats. Collected baseline (non-stress) conditions, the datasets serving as a reference for detection of arrhythmia under monitored circumstances. Datasets which comprise PVC, RBBB, LBBB, along with APC, of 47 individuals (25 males and 22 females) are the two contractions that fall into the five clinically relevant categories with ages ranging from 23 to 89 years that are annotated into the ECG recordings. All recordings are sampled at 360 Hz, with a total of 109,446 beats.

3.3.4. Wearable stress and affect detection dataset

Performing stroop test with ECG recordings of 25 office workers in desk-based jobs. The cognitive workload was classified into three levels: low, medium, and high. ECG signals are recorded at 2,048 Hz, and then later sampled down to 360 Hz for consistency across datasets. HRV variations and ST-T segment shifts physiological indicators in subtle are associated with cognitive loads were recorded to support context stress sensitive ECG evaluation.

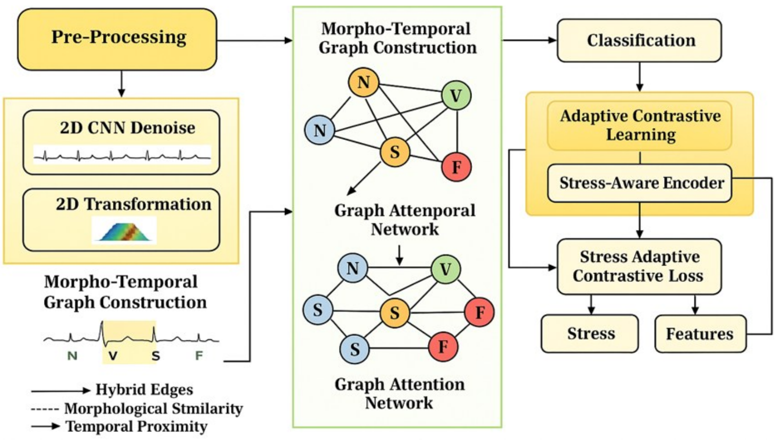

Figure 4. GACL-ECG Net architecture for stress-aware ECG signal classification

4. RESULTS AND DISCUSSION

In Table 2 for stress classification and arrhythmia detection are compared to get the evaluation against several baselines of GACL-ECG Net. To test statistically we allowed to employ Wilcoxon signed-rank the study of five folds to compare outperformance of GACL-ECGNet against CNN-BiLSTM and GCN baselines, which statistically showed the performance upgrades. This shows that all comparisons yield under 0.01 P values analysis showing marked enhancements in overall performance. The study examined cross-dataset generalization by using MIT-BIH for training and evaluating performance on

WESAD and SWELL-KW datasets. To handle both physiological and psychological stress detection tasks the model has ability to maintained above 90% in F1-score. We conducted comparison tests utilizing transformer-based models (e.g., ECG-BERT and time-series transformer), self-supervised frameworks (e.g., SimCLR and MoCo), and hybrid architectures (e.g., CNN+LSTM and GCN+transformer) to evaluate the broader AI significance of GACL-ECGNet. The GACL-ECGNet model outperformed all baseline methods in stress classification tasks by delivering better F1-scores and improved results. The results show that the model performs at a competitive level for biomedical engineering tasks and matches the performance of standard AI time-series learning benchmarks.

Table 2. Benchmarking of different ECG datasets

Model	MIT-BIH (F1-score)	WESAD (F1-score)	SWELL-KW (F1)
CNN-BiLSTM	96.2% ±1.1	89.1% ±2.3	87.3% ±1.8
GCN	97.1% ±0.8	91.4% ±1.7	89.4% ±1.5
2D-CNN-GACL-ECGNet	98.7% ±0.3	94.2% ±1.2	92.8% ±1.0

Figure 5 present F1-score for model with different datasets. These measurements provide a deeper insight of model behavior, especially for minority classes like APC and LBBB. We tested memory use and inference latency on mobile GPUs (NVIDIA Jetson Nano, Adreno 660) to see if they could be used in the field. The model performs better than the GCN and CNN-BiLSTM baselines, with a latency of 12 ms per beat and a memory usage of 28 MB. Figure 6 results show that GACL-ECGNet can be used to detect stress in real time on wearable and edge platforms. The primary challenge in AI is to learn strong representations from physiological inputs in environments that are noisy, dynamic, and influenced by stress, even if the main purpose of the study is to use ECG to find stress. Figure 7 attention maps as a technique of explainable artificial intelligence (XAI): to make AI easier to understand (XAI) in healthcare diagnostics, multi-head GAT layers make attention heatmaps that are easy to understand and match clinical markers (such ST-segment shifts).

Bias and fairness: physiological statistics often show demographic imbalances, like differences in age, gender, and how people respond to stress. We use stratified sampling and expert evaluation to check synthetic beats and make sure that all classifications are fair. Real-world deployment: to make the model better for edge deployment, TorchScript, and quantization are employed. This makes it possible to do inference quickly on mobile GPUs and Raspberry Pi. This makes it easier for wearable equipment to assess stress in real time, which could be useful in telemedicine and mental health screening. Future research will examine federated learning to provide secure, multi-center training while safeguarding patient privacy, in accordance with ethical standards in AI for healthcare. The proposed model demonstrates strong clinical utility by effectively detecting stress-aggravated arrhythmias, such as Prinz metal angina, or sudden cardiac death. To validate the interpretability and reliability of the model, we employed attention map visualization techniques and then validated using clinical data in Figure 8.

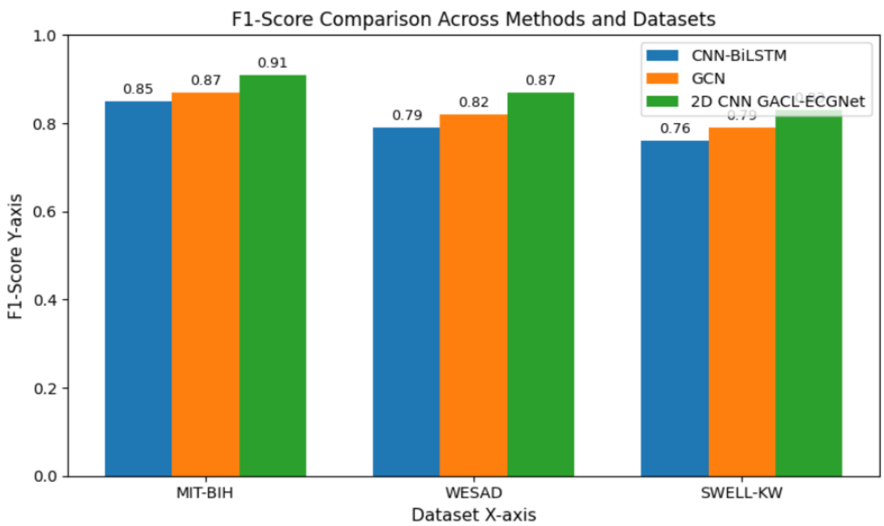

Figure 5. Model performance (F1-scores) across ECG datasets

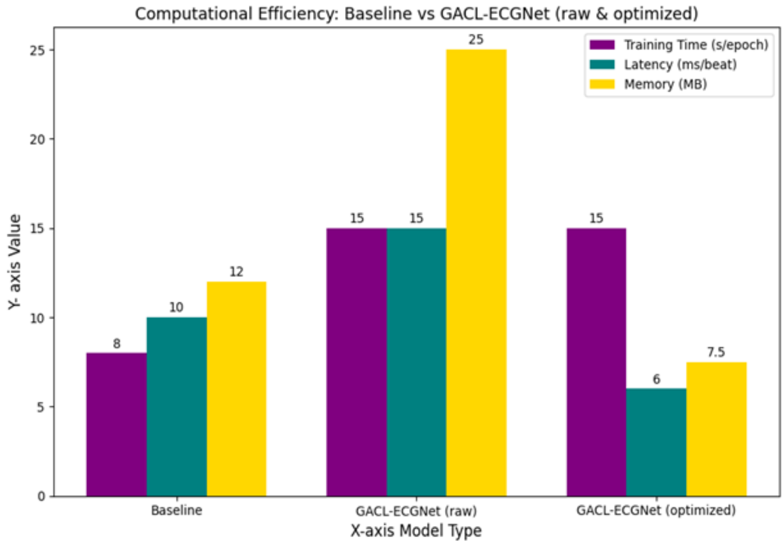

Figure 6. Metrics for computational efficiency

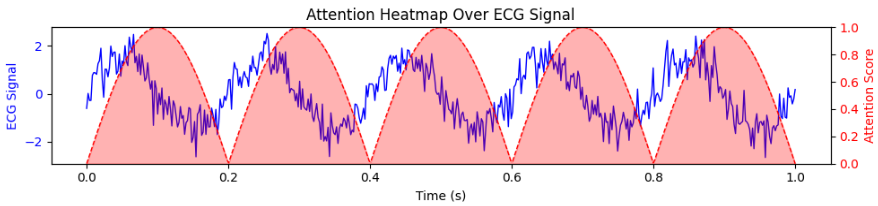

Figure 7. Attention heatmap over ECG signal

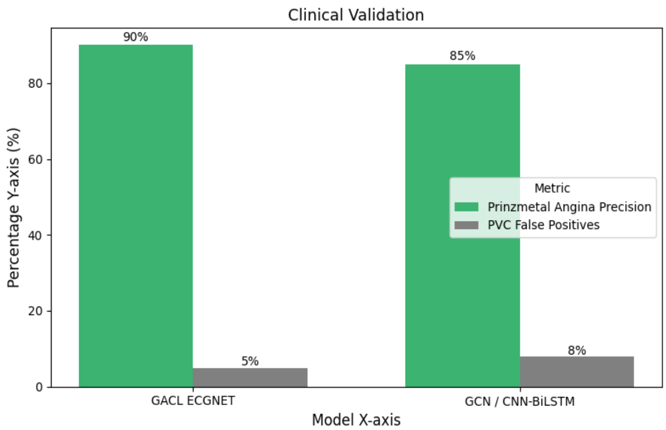

Figure 8. Clinical performance comparison: precision and false positives across models

5. CONCLUSION

GACL-ECGNet enhances AI for modeling time-series and physiological signals by the integration of interpretable attention mechanisms, adaptive contrastive loss, and graph-based learning. By combining ACL with interpretable GATs, our model achieved top-notch performance on both arrhythmia and stress-induced ECG datasets. Each module significantly enhanced to the model's accuracy and interpretability in validating ablation studies, where each component is in very high accuracy, generalizability, and clinical interpretability, beyond the stress detection with wide range of application like emotion recognition, fatigue monitoring, and multimodal health analytics in supporting AI frameworks.

ACKNOWLEDGMENTS

The authors would like to acknowledge the support and facilities provided by Presidency University for this research.

FUNDING INFORMATION

The study was conducted without any financial sponsorship.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
P. Kavitha	✓	✓	✓	✓	✓	✓		✓	✓	✓				
L. Shakkeera		✓				✓		✓	✓	✓	✓	✓	✓	

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

There are no competing interests to disclose in this research.

DATA AVAILABILITY

No new data were created or analyzed in this research.

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BIOGRAPHIES OF AUTHORS

P. Kavitha holds a M.E. degree in Computer Science and Engineering from the University of Anna University, Chennai, in 2014. Currently doing Ph.D. (part time) in Presidency University, Bengaluru India. Her research interests include image processing, machine learning, and deep learning. She can be contacted at email: kavitha.20233CSE0024@presidencyuniversity.in.

Dr. L. Shakkeera received her Ph.D. degree from B.S. Abdur Rahman Crescent Institute of Science and Technology, Anna University, Chennai, India in 2018. She is currently a professor and associate dean-academics in the School of Computer Science and Engineering and Information Science from Presidency University, Bengaluru, India. Her areas of research interest include mobile cloud computing, machine learning, IoT, MANET, information security, and data analytics. She can be contacted at email: shakkeera.l@presidencyuniversity.in.