

An IoT ECG Monitoring Framework for Arrhythmia Detection Using CNN-BiLSTM

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Abstract

Cardiovascular disease is the leading cause of death worldwide, as many of these deaths are associated with sudden and unexpected heart rhythm disorders. This study presents an IoT-based integrated framework for ECG, based on a hybrid deep learning model that combines CNN and a Bidirectional Long Short-Term Memory (BiLSTM) to classify several types of arrhythmias, with the MIT-BIH Arrhythmia database to verify the performance of the model. Real-time ECG signals were captured with the AD8232 sensor and transmitted via the ESP32 microcontroller into a MATLAB-based processing and classification environment. The classification performance was evaluated under realistic conditions including the imbalance of categories, as the system achieved a total accuracy of 93.22%. In addition, the model was evaluated on the independent ECG5000 database, with a resolution of 90.10%, confirming the ability to generalize the model through different databases. A dedicated application for doctors and integrated with Firebase Cloud Messaging (FCM) has also been developed to send instant notifications when arrhythmia is detected.

Keywords: Electrocardiogram (ECG); Arrhythmia Detection; CNN-BiLSTM Models; IoT-Based Monitoring; MIT-BIH Dataset.

إطار عمل لمراقبة تخطيط القلب الكهربائي معتمد على إنترنت الأشياء

للكشف عن اضطرابات النظم القلبي باستخدام نموذج CNN-BiLSTM

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الخلاصة

تُعد أمراض القلب والأوعية الدموية السبب الرئيس للوفاة على مستوى العالم، إذ يرتبط كثير من هذه الوفيات باضطرابات مفاجئة وغير متوقعة في نظم القلب. يُقدّم هذا البحث إطار عمل متكامل معتمداً على إنترنت الأشياء لتخطيط القلب الكهربائي، يستند إلى نموذج تعلم عميق هجين يجمع بين الشبكات العصبية الالتفافية (CNN) وذاكرة المدى القصير الطويلة ثنائية الاتجاه (BiLSTM) لتصنيف أنواع متعددة من اضطرابات النظم، مع استخدام قاعدة بيانات MIT-BIH للتحقق من أداء النموذج. وقد نُظمت إشارات تخطيط القلب أنياً بواسطة المتحسس AD8232 ونُقلت عبر المتحكم ESP32 إلى بيئة معالجة وتصنيف مبنية على MATLAB. وقُيّم أداء التصنيف في ظروف واقعية تشمل عدم توازن الفئات، إذ حقق النظام دقة إجمالية بلغت 93.22%. وإضافة إلى ذلك، قُيّم النموذج على قاعدة البيانات المستقلة ECG5000 فبلغت الدقة 90.10%، مما يؤكد قدرة النموذج على التعميم عبر قواعد بيانات مختلفة. كما طُوّر تطبيق مخصص للأطباء متكامل مع خدمة Firebase Cloud Messaging (FCM) لإرسال إشعارات فورية عند اكتشاف اضطراب النظم.

1. Introduction

Cardiovascular disease is the leading cause of death globally; The World Health Organization (WHO) estimates that more than 17.9 million deaths annually are attributed to heart disease [1]. In contrast to traditional monitoring, IoT technologies provide a transformative alternative that can integrate low-cost sensors, wireless controllers, cloud communication platforms, and smartphone applications within a single integrated system. These smart technologies have proven their effectiveness in early detection and diagnosis of complex physiological conditions [2]. ECG is the non-invasive gold standard for recording the electrical activity of the heart, as it contains rich clinical information through the waves P, QRS and T, which directly reflects heart arrhythmia [3]. This work presents an integrated system of this type, where the AD8232 sensor captures live ECG signals with three electrodes, while the ESP32 controller sends the digital signal to a Matlab-based processing environment.

The proposed system is based on a hybrid model that combines the Convolutional Neural Network (CNN) and the Bidirectional Long Short-Term Memory (BiLSTM). Despite the great developments in algorithms, most published studies are still limited by Offline, using standard databases, without providing evidence of the system's effectiveness in a real operating environment [6]. This work fills the gap by integrating the CNN–BiLSTM model into the real-time IoT system, checking its performance using the MIT-BIH database, and sending instant alerts to the physician via a dedicated Android application called “Doctor ECG Alert”.

2. Related Work

Gautam [7] proposed a model based on feature extraction followed by classification using a Support Vector Machine (SVM), which was easy to interpret but struggled to represent the complex, high-dimensional temporal structure of ECG signals. In this context, Cheng et al. [8] proposed a hybrid model combining CNNs with a bidirectional long-term and short-term memory network (BiLSTM) for ECG signal classification. Similarly, Hassan et al. [9] used the CNN–BiLSTM model to classify multi-category cardiac disorders, achieving accurate and competitive results using clinical databases.

Do et al. [10] presented a set of data augmentation techniques for classifying multi-electrode ECG signals, which proved effective in improving the model's sensitivity to rare categories. Rahman et al. [11] also provided a comprehensive review of ECG data augmentation techniques. Ye et al. [12] studied a CNN–BiLSTM hybrid model for classifying cardiac arrhythmias using the MIT-BIH database and demonstrated the efficiency of bidirectional modeling in improving detection accuracy.

Regarding the integration of Internet of Things (IoT) technologies, Liu et al. [5] developed a cardiac arrhythmia classification system using a multi-branch CNN with an Attention mechanism and BiLSTM, emphasizing the importance of clinically applicable models. Prakash and Atef [6] presented a lightweight cardiac arrhythmia classification model designed to operate on devices with limited resources. However, most of these studies lack a comprehensive system that covers all stages of operation, from signal capture, processing, and classification to cloud-based alert delivery. Therefore, the specific research gaps this work seeks to address is the provision of the following elements within a single, validated, integrated approach: realistic assessment under normal class imbalances in the MIT-BIH database; end-to-end deployment within an IoT system with a measured response time of less than two seconds; and decision interpretability using Grad-CAM.

3. The IoT-based Real-Time Monitoring System

The system consists of the following stages: (i) the capture of the electrocardiogram (ECG) signal using the AD8232 sensor; (ii) converting the signal to a digital format and transmitting it via the ESP32 controller; (iii) pre-treatment and immediate classification of heart rhythm disorders using the CNN-BiLSTM hybrid model within the MATLAB environment; (iv) sending automatic cloud alerts using the Firebase Cloud Messaging (FCM) service to a doctor's dedicated application. However, it should be emphasized that the current implementation is based on the operation of MATLAB on a host PC connected to the ESP32 controller over the USB port, which does not represent a clinically deployable configuration; therefore, the system is provided as a proof-of-concept prototype, not a clinically applicable device.

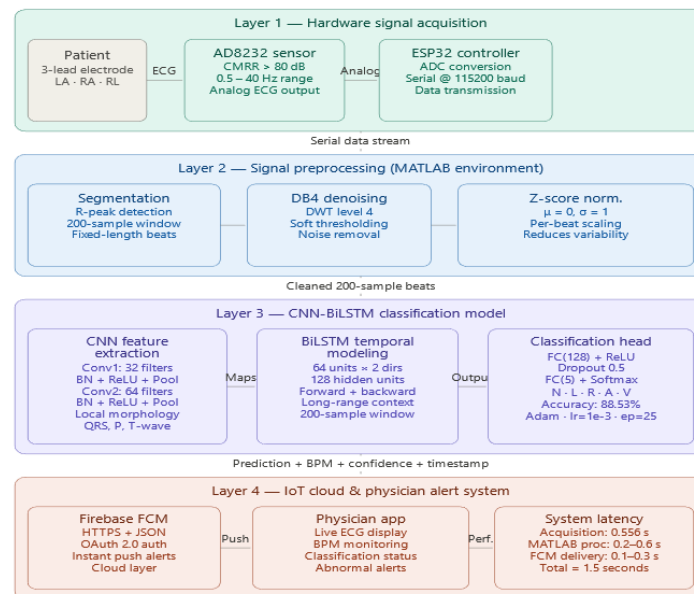


Figure -1 Proposed IoT-based ECG monitoring framework.

3.1 Hardware Components

3.1.1 AD8232 ECG Sensor

AD8232 is an integrated circuit designed specifically for biometric signals, especially single-lead ECG signals, suitable for low-energy portable applications. Three electrodes of Ag/AgCl are connected via a standard (3.5 mm) port, and these electrodes are attached to the patient's body at the following locations: left arm (LA), right arm (RA) and right leg (RL). This module produces an analog ECG signal within a bandwidth of 0.5 to 40 Hz, which is compliant with the sampling requirements used in the MIT-BIH database [17,18].

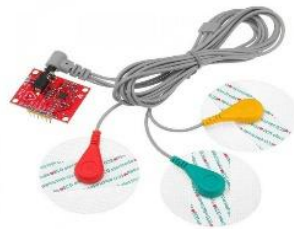


Figure -2 AD8232 ECG acquisition module with three-electrode leads.

3.1.2 The ESP32 Controller

The ESP32 Controller is a dual-core (32-bit) XTENSA LX6 240 MHz microcontroller, and contains a built-in USB serial interface as well as Wi-Fi and Bluetooth support, which makes it very suitable for IoT applications for collecting and transferring data. In the proposed system, the ESP32 acts exclusively as a node to capture and transmit data, as it converts the analog signal from the AD8232 sensor to a digital signal using a 12-bit Successive Approximation ADC, with an exact sampling rate to comply with the 360 Hz standard used in the MIT-BIH database. It is important to emphasize that no signal processing, feature extraction, or classification is performed within the ESP32 itself.



Figure -3 ESP32 development board used as the ECG acquisition and serial transmission node.

3.2 Real-time Signal Acquisition and Segmentation

During actual operation, the AD8232 sensor continuously captures the ECG signal at a rate of 360 Hz. The ESP32 controller converts the analog signal to digital using the ADC, then sends the samples to the MATLAB environment via a serial USB connection at a speed of 115200 baud. In MATLAB, a dedicated real-time data capture loop is performed, where the incoming data is read and stored in a circular buffer. When compiling 200 consecutive samples (approximately 0.56 seconds of the signal at 360 Hz — a sufficient time to contain a full heart cycle including P-QRS-T waves in the normal pulse state), these samples are extracted as a segment representing one pulse, then the window is moved by 200 samples to capture the next section. Each section of 200 samples is then passed directly to the same preprocessing steps used during training, which include noise removal using DB4 wavelets at level IV and normalization using Z-Score.



Figure -4 Real-time ECG waveform captured from the AD8232 sensor via the ESP32 microcontroller.

3.3 Cloud Communication Structure

After CNN–BiLSTM classifies each section of the ECG signal, the prediction results, including the class code, the confidence, the BPM, and the ISO timestamp, are compiled in a message in JSON format, and sent to the Firebase Cloud Messaging (FCM) service via the FCM HTTP v1 API over HTTPS. The OAuth 2.0 authentication process is used through the Google Cloud Service Account, where MATLAB gets an access token before each transmission, ensuring that all messages are authorized and encrypted, thus protecting patient data during its transfer.

3.4 Mobile Application

Figure 5 shows the main interface of the application, which enables the physician to follow the patient's condition and receive alerts immediately when any heart rhythm disorder is detected.

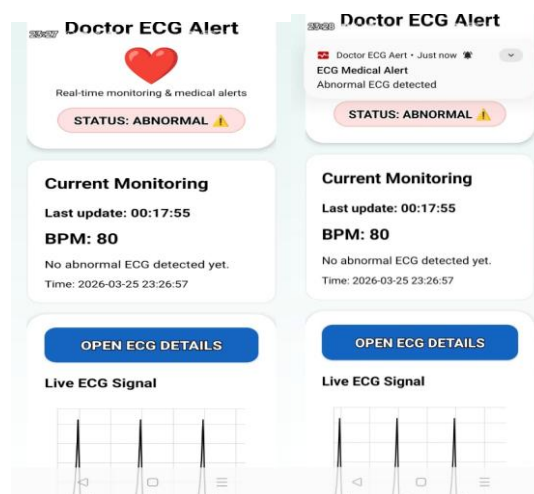


Figure -5 Physician alert mobile application interface.

3.5 System Latency and End-To-End Performance

For signal assembly time, it depends on the number of samples and sampling rate, as the use of a 200-sample window at 360 Hz results in a time of about 0.556 s. Processing and classification time was practically measured within the MATLAB environment using time-metric tools, ranging from 0.2 to 0.6 seconds, depending on the performance of the computer system. While Firebase service time is low, it is only 0.1 to 0.3 seconds. Thus, the total response time of the system ranges from 1 to 2 seconds, confirming the system's ability to operate in real time and making it suitable for practical applications in the field of cardiovascular diseases [19,20].

4. Dataset-Based Analysis Methodology

4.1 Dataset Description

The model is trained and evaluated using the MIT-BIH Arrhythmia [14] database, one of the most widely used databases in cardiac arrhythmias research. The database consists of 48 records of the ECG signal, each recording duration is about 30 minutes, with a sampling rate of 360 Hz and 11-bit resolution within the ± 5 mV range. The heartbeat is extracted by detecting R-peaks and taking a 200-sample window around each R-peak, to ensure that the section contains a complete heart cycle (P-QRS-T). This results in 40,937 heartbeats distributed over five categories according to AAMI: N (normal beat), L (left bundle branch block), R (right bundle branch block), A (atrial premature beat) and V (premature ventricular

contraction). Under severe class imbalance, the N category represents more than 70% of the data, while both A and V represent less than 1% [5].

4.2 Signal Preprocessing

In practical applications, the raw signal is often contaminated with multiple sources of noise, such as baseline drifting, electrode motion artifacts, and power-line interference [4]. A three-stage preprocessing pipeline has been adopted: (1) the use of a 0.5–40 Hz Butterworth-type band-pass filter along with a 50 Hz notch filter to suppress the baseline wander, the noise out of range, and the power-line interference; (2) DB4 wavelet denoising; (3) normalization using Z-Score. The detection of R peaks and the division of the heartbeat were carried out using the Pan-Tompkins algorithm.

4.2.1 Wavelet denoising

The Discrete Wavelet Transform (DWT) is applied using the 4th-ranked Daubechies (DB4) and at a breakdown level of 4. The DB4 was selected due to its morphological similarity with the QRS complex in the ECG signal, so it is effective in maintaining the important components of the cardiac signal during the noise removal process. Figure 6 shows a comparison between the original signal before processing and the signal after noise removal.

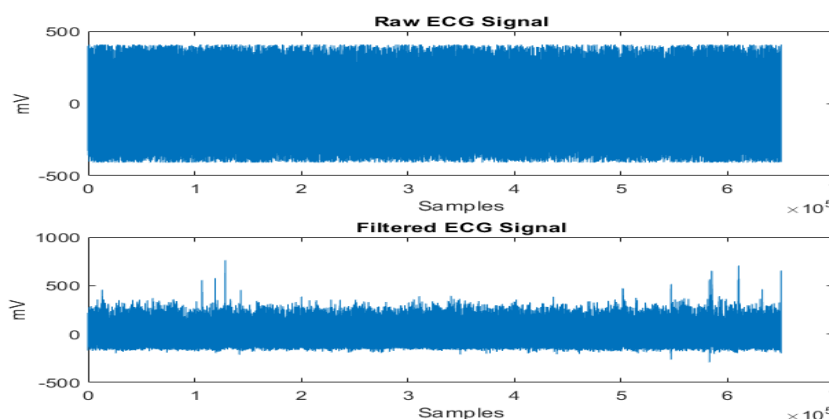


Figure -6 ECG signal preprocessing: raw ECG (top), filtered ECG after DB4 wavelet denoising (bottom).

4.2.2 Z-Score Normalization

Z-Score Normalization was independently applied to each section of the heartbeat, where the signal is converted to mean zero and its standard deviation is equal to one. Normalization contributes to improving the stability of the training process within the deep neural networks.

4.2.3 Fixed-length standardization

All pulse segments are standardized to be a constant length of 200 samples, either by zero-padding or truncation when needed. This step ensures that all data entered into the CNN-BiLSTM model will be of identical dimensions, facilitating the training process and preventing errors from different signal lengths, while the basic time structure of each pulse was maintained without affecting the important properties of the signal.

4.3 Data Splitting

The data set was divided using 80/20, with 80% assigned to training and 20% for testing. Beat-wise splitting is adopted, and each heartbeat is treated as an independent unit. As the division is at the level of the pulse, heartbeats from the same patient may appear in each of the training and testing groups. This is a known source of data leakage in ECG

research, which means that the reported accuracy values should be interpreted as an upper-bound estimate, and may not fully reflect the model's ability to generalize to new patients.

4.4 Class Imbalance Handling

To address this problem, a dual strategy has been adopted. A range of conversions that simulate realistic changes in ECG signals have been used, including: adding Gaussian noise ($\sigma = 0.01$) to simulate the measurement noise; time shifting within ± 5 samples to represent the normal timing variations; amplitude scaling within the 0.95–1.05 range to simulate the differences between patients; and slight time stretching/compression by re-sampling within the 0.98–1.02 range. All data augmentation conversions were applied to training data only, after the data was divided into the training and test groups, and none of them were applied to the held-out test set.

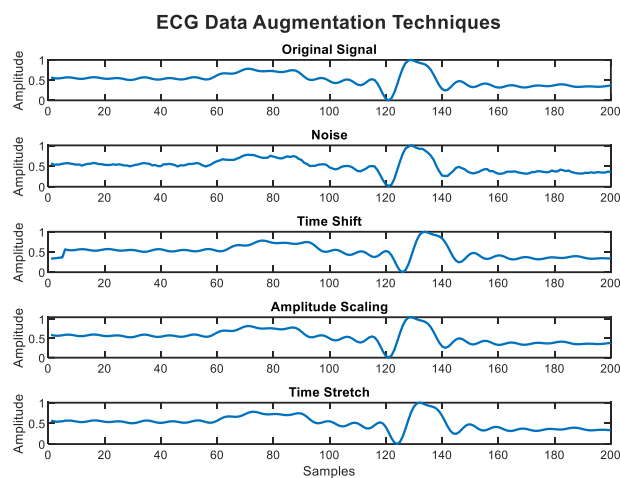


Figure -7 Illustration of ECG data augmentation techniques.

4.4.1 Class weighting

The weights of each category were calculated depending on the inverse class frequency within the data set, and then these weights were entered into the cross-entropy loss function during the training process. When data augmentation is combined with the category weights, a clear performance improvement has been observed: recall value for rare categories increased by 12% to 18%, and accuracy by 8% to 10% compared to models that have not used these technologies.

5. Proposed CNN–BiLSTM Model

5.1 Suggested CNN–BiLSTM Architecture

As shown in Figure 8, the model starts with a serial input layer that receives single-dimensional ECG signals with a constant length of 200 samples.

LAYER INFORMATION					
	Name	Type	Activations	Learnable Sizes	State Sizes
1	input Sequence input with 1 dimensions	Sequence Input	$1(C) \times 1(B) \times 200(T)$	-	-
2	conv1 32 5x1 convolutions with stride 1 and pa...	1-D Convolution	$32(C) \times 1(B) \times 200(T)$	Weights $5 \times 1 \times 32$ Bias 1×32	-
3	bn1 Batch normalization with 32 channels	Batch Normalization	$32(C) \times 1(B) \times 200(T)$	Offset 32×1 Scale 32×1	TrainedMean 32×1 TrainedVari... 32×1
4	relu1 ReLU	ReLU	$32(C) \times 1(B) \times 200(T)$	-	-
5	pool1 Max pooling with pool size 2, stride 2, an...	1-D Max Pooling	$32(C) \times 1(B) \times 100(T)$	-	-
6	conv2 64 3x3 convolutions with stride 1 and p...	1-D Convolution	$64(C) \times 1(B) \times 100(T)$	Weigh... $3 \times 3 \times 64$ Bias 1×64	-
7	bn2 Batch normalization with 64 channels	Batch Normalization	$64(C) \times 1(B) \times 100(T)$	Offset 64×1 Scale 64×1	TrainedMean 64×1 TrainedVari... 64×1
8	relu2 ReLU	ReLU	$64(C) \times 1(B) \times 100(T)$	-	-
9	pool2 Max pooling with pool size 2, stride 2, an...	1-D Max Pooling	$64(C) \times 1(B) \times 50(T)$	-	-
10	bi_lstm BiLSTM with 64 hidden units	BiLSTM	$128(C) \times 1(B)$	InputWeigh... 512×128 RecurrentW... 512×128 Bias 512×1	HiddenSta... 128×1 CellState 128×1
11	fc1 128 fully connected layer	Fully Connected	$128(C) \times 1(B)$	Weights 128×128 Bias 128×1	-
12	relu3 ReLU	ReLU	$128(C) \times 1(B)$	-	-
13	drop1 50% dropout	Dropout	$128(C) \times 1(B)$	-	-
14	fc_out 5 fully connected layer	Fully Connected	$5(C) \times 1(B)$	Weights 5×128 Bias 5×1	-
15	softmax softmax	Softmax	$5(C) \times 1(B)$	-	-
16	output Class weighted crossentropy with '1' a...	Classification Output	$5(C) \times 1(B)$	-	-

Figure -8 Proposed CNN–BiLSTM model architecture showing the sequential layer configuration.

5.2 Temporal Modeling using BiLSTM

The feature maps from the convolutional network (CNN) are passed into the BiLSTM layer, which is prepared using 64 units in each direction, the end output being a hidden 128-unit vector. Unlike a one-way LSTM model that handles the sequence in only one time direction, the BiLSTM layer handles the signal in two directions: the forward direction (from start to end) and the backward direction (from the end to the start), and then the hidden states are integrated from both directions, allowing the model to take advantage of the full-time context of the signal [8,9].

5.3 Training Configuration

The model was trained using the Adam (Adaptive Moment Estimation) optimizer, according to the following settings: an initial learning rate of 5×10^{-4} , and a mini-batch size of 128, a segmented learning rate table, and a maximum number of 100 training epochs, with 10% of training data allocated as a verification set, and data shuffling applied in each training epoch. Figure 9 shows accuracy and loss curves, which show a stable convergence during training and no overfitting.

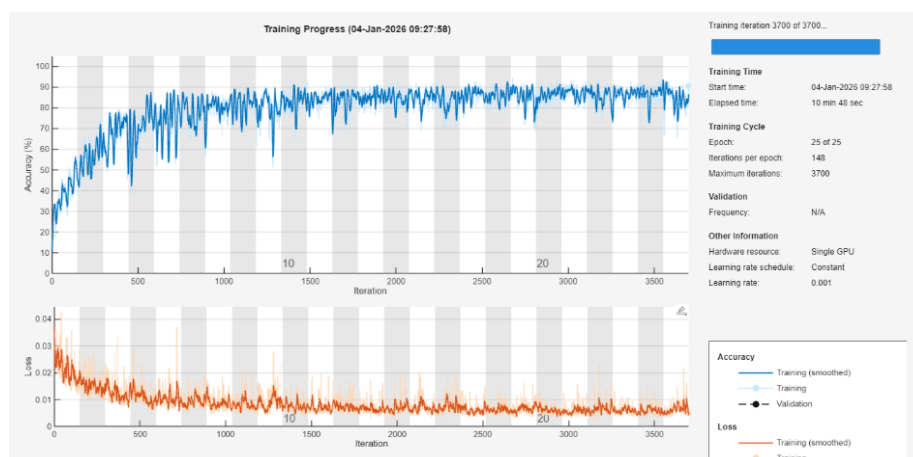


Figure -9 Training accuracy/loss curves demonstrating stable convergence.

6. Experimental Results and Analysis

Experimental results showed a gradual and continuous improvement in the performance of the classification across the proposed framework stages, as follows: (1) baseline: before any preprocessing or data imbalance processing, accuracy was about 67.52%, confirming that training using raw data is not enough for clinical use; (2) after preprocessing: after applying wavelet denoising and normalization with Z-Score, the accuracy increased to about 75.3%; (3) after data augmentation: accuracy rose to about 82.1%, which contributed to improving the balance of categories and enhancing the model's ability to generalize; (4) the proposed final model: after combining preprocessing, data augmentation and class weighting, the accuracy was 93.22%. As shown in Figure 10, a clear gradual improvement can be seen in all performance indicators across the proposed system stages.

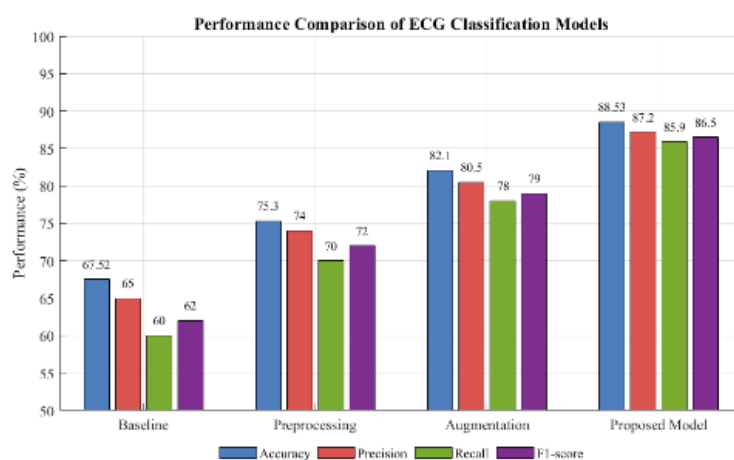


Figure -10 Performance comparison of the ECG classification model across different stages.

Classes N, L and R showed good and consistent performance across all evaluation indicators, with high values of Precision, Recall and F1-Score. In contrast, Class A (PAC) has improved compared to the results of basic models in ablation baselines, but it has remained difficult to classify, as F1-Score = 0.286, indicating that some patterns are still difficult to detect.

Table 1- Per-class classification performance of the proposed CNN-BiLSTM model on the MIT-BIH Arrhythmia Database.

classes	Precision	Recall	Spec	F1
N	0.9534	0.88506	0.85907	0.91796
L	0.75382	0.96312	0.96008	0.84571
R	0.6075	0.83696	0.94658	0.704
A	0.15294	0.050193	0.99092	0.286
V	0.125	0.200	0.98839	0.154

* Class V (PVC) contains only 31 samples (about 0.08% of the total data set). PVC results should therefore be interpreted as suitable for screening-level only.

6.1 Analysis of waveforms of the heart arrhythmia disorders

Figure 11 shows mean waveforms representing the heartbeat for each of the five categories. Clear morphological differences can be observed between the N, L and R classes, which respectively represent the normal beat, left bundle branch block (LBBB), and right bundle branch block (RBBB). In contrast, A and V — atrial premature contraction (PAC) and

premature ventricular contraction (PVC) — show minor and less pronounced morphological differences, making their distinction more difficult, particularly in the unbalanced training distribution of categories.

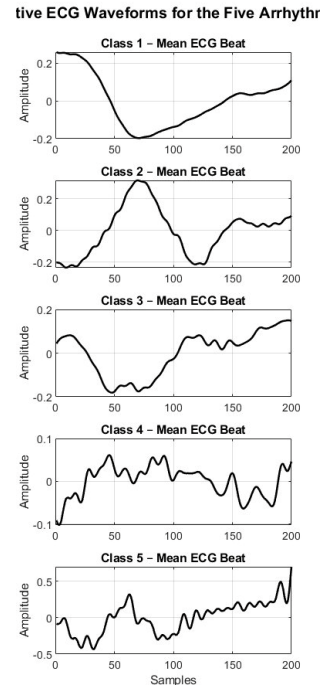


Figure -11 Mean ECG beat waveforms per arrhythmia class illustrating inter-class morphological variation.

6.2 Comparative Analysis with Prior Work

Table 2 puts the proposed model in the context of comparison with a number of recent studies based on the MIT-BIH database. Although some of these studies have reported higher accuracy, such as Ma et al. [15] with 99.4% and Pandey et al. [13] with 98.25% accuracy, these results are often attributed to the use of artificially balanced datasets, simplified evaluation protocols, or the lack of effective treatment of the problem of data imbalance.

Table 2- Comparative analysis of arrhythmia classification performance on the MIT-BIH database.

Study	Dataset	Model	Imbalance	Accuracy	Clinical Notes & IoT / Deployment
Pandey et al. (2024) [13]	MIT-BIH	CNN–BiLSTM	Partial	98.25%	Simplified data; no IoT
Ma et al. (2022) [15]	MIT-BIH	CNN	No	99.4%	Balanced subset; inflated;no IoT
Proposed	MIT-BIH	CNN–BiLSTM	Aug + Weighting	93.22%	Full IoT: AD8232+ESP32+Firebase+Mobile Alert
Proposed (Balanced subset)	MIT-BIH	CNN–BiLSTM	Undersampling + Aug (training only)	99.00%	4-class balanced subset (PVC excluded); isolates imbalance effect; Full IoT [21, 22, 23]

6.3 Model Interpretability using Grad-CAM

To assess the model's interpretation and ensure that the CNN–BiLSTM structure learns clinically meaningful cardiac properties, rather than learning data set patterns,

Gradient-Weighted Class Activation Mapping (Grad-CAM) [16] was applied on ECG impulses from the test set.

Figure 12 shows a single-dimensional Grad-CAM heatmap, along with the class-score profile, for a section of the ECG signal in the test set correctly classified as Class 1 (normal). The heatmap shows a clearly defined activation pattern, where the highest degree of importance was given, with a value of approximately 1.0 represented by dark red, to a narrow area between the samples 125–155, which precisely corresponds to the QRS complex and the R-peak region in the ECG signal.

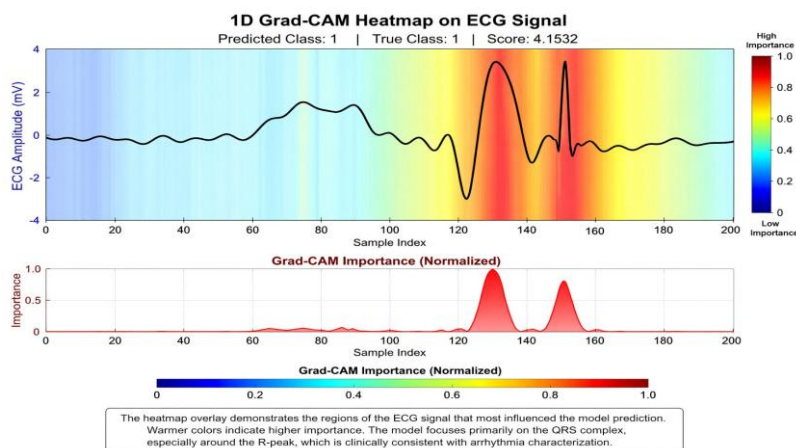


Figure -12 1D Grad-CAM heatmap for a correctly predicted Normal beat (Class 1, score 4.1532).

Figure 13 analyzes the same ECG section under two classification hypotheses: Class 1 (normal) and a competitive alternative category (Class 2), revealing a clear qualitative difference in activation patterns. For the predicted category (Class 1 the top panel), the heatmap shows a high and local concentration of activation around the QRS complex within the 120–137 sample range, with almost complete disregard for the baseline areas, which appear in dark blue. In contrast, the alternative class (Class 2 the bottom panel) shows a wide and non-local distribution of activation on a large time range of approximately 80–150, along with additional intermittent activation bands at the two ends of the signal, without matching known cardiac features such as the P wave, QRS complex or T wave. These findings confirm that the model relies on meaningful physiological properties and complies with published literature [3],[9].

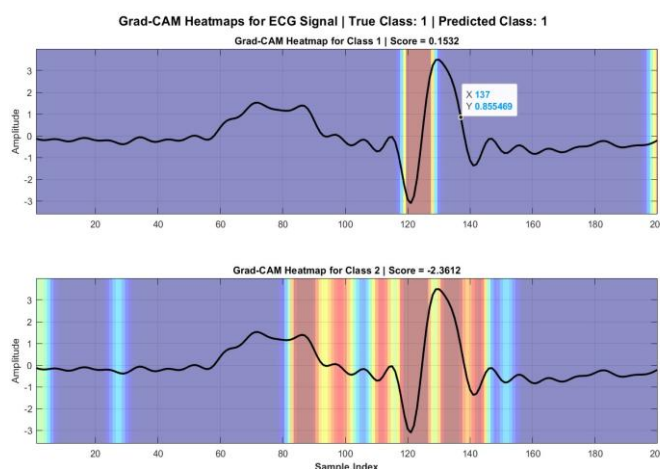


Figure -13 Comparative Grad-CAM heatmaps for the same ECG segment.

6.4 Multi-Dataset Experimental Evaluation

Although the base model had an accuracy of 93.22% on the full data set, the confusion matrix showed a clear weakness in the discovery of rare classes, particularly the PVC class, which contains only 31 samples of the original 40,937 samples, approximately 0.08%. To ascertain whether this vulnerability was caused by an imbalance of data or the model itself, a balanced subset of four categories of the MIT-BIH database was created. Using the same CNN-BiLSTM structure and the same training settings used in the basic model, the model achieved a total accuracy of 99.00% on the balanced subgroup. This confirms that the performance limit in the full data set is mainly affected by the imbalance of categories, not by the architectural constraints of the model [21,22,23].

6.4.1 Cross-Dataset Generalization (ECG5000)

The ability to generalize through different databases (ECG5000) was assessed to ensure that the properties of the model are transferable beyond the MIT-BIH database. 5,000 univariate signals are divided into five categories, with a severe natural imbalance between the categories. With the same class balancing strategy, the same data augmentation pipeline, and the same architectural structure, the model achieved a total accuracy of 90.10%, with strong performance in the prevailing categories, as F1-Score reached 0.978 for Class 1 and 0.902 for Class 2, while the performance was weaker, as expected, in the rare categories, as F1-Score reached 0.433, 0.383 and 0.125 for classes 3–5 respectively. Specificity has also exceeded the value of 0.96 for all five categories, indicating a severe decrease in the false-positive rate.

7. Discussion

The noise removal process by using DB4 wavelets has greatly contributed to reducing the impact of baseline drifting, electrode movement, and high-frequency EMG noise. This finding is consistent with what Hassan et al. [9] and Sattar et al. [3] indicated, as they emphasized that noise is one of the most important factors that limit the performance of deep learning models in the classification of ECG signals.

However, two main constraints must be recognized directly. First, the model only weakly detects PVC, with F1-Score = 0.154 and Recall = 0.200, and the PAC class is still difficult to detect. Since PVC is a clinically important disorder, the system should be considered an initial screening and detection aid that alerts to the existence of abnormal beats to be verified by a specialist, and not an independent diagnostic tool for these subtypes. Second, the beat-wise train/test split enables the same patient to appear in each of the training and test groups, so the reported results are an upper-bound estimate. Therefore, a patient-level division protocol is required before any clinical claim can be made.

8. Conclusion

This study presents the design and implementation of an integrated Internet of Things (IoT)-based real-time cardiac monitoring system to address the clinical need for continuous, remote monitoring of cardiac arrhythmias. The system is based on a CNN-BiLSTM hybrid learning model, validated using the MIT-BIH Arrhythmia database, and provides near-real-time classification with a total response time of 1.0–1.5 seconds from signal capture to alert arrival. The model achieved 93.22% accuracy under realistic conditions that reflect the natural imbalance between categories in the MIT-BIH database. However, performance in rarer categories remained limited, particularly the detection of the PVC category, with an F1 score of 0.154. To confirm that this shortcoming stems from data scarcity rather than model capability, the model was also evaluated on a balanced subset of four classes, achieving 99.00% accuracy, and on the independent ECG5000 database, achieving 90.10% accuracy.

9. Future Work

Future work will focus on the following: (1) implementing a strict patient-wise split for training and testing to prevent data leakage and ensure generalizability to users the model has not previously encountered; (2) utilizing generative adversarial networks (GANs) to generate realistic waveforms of underrepresented classes, particularly the PVC class; (3) porting the model implementation from a connected MATLAB computer to edge processing units or microcontrollers, for example using TensorFlow Lite, to achieve fully mobile and decentralized deployment; (4) integrating multi-lead ECG inputs instead of relying on a single-channel AD8232 configuration to improve diagnostic accuracy in complex cardiac arrhythmias; (5) developing hierarchical/multi-stage classification models, along with prospective clinical validation.

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Compliance with Ethical Standards

The current ECG records contained in this research were recorded by the authors themselves, using superficial electrodes, for the sole purpose of clarifying the mechanism of signal acquisition, transmission and transmission of alerts. No data was collected for the patients, and no clinical study was conducted involving human participants. All the quantitative classification results contained in this article are derived from the two generally available databases of MIT-BIH Arrhythmia Database and ECG5000 Dataset.

Conflict of Interest

Conflict of Interest: The authors declare that they have no conflicts of interest.

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