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An Intelligent Deep Learning Framework for Cardiac Arrhythmia Detection and Risk Prediction

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An Intelligent Deep Learning Framework for Cardiac Arrhythmia Detection and Risk Prediction

Abstract: Cardiac Arrhythmia detection using continuous ECG monitoring is challenging because abnormal heartbeats occur irregularly, and their patterns may vary from one person to another. ECG signals can also contain noise caused by body movements, muscle activity, and baseline variations, which can affect the accuracy of detection. To address these challenges, this project proposes an intelligent deep learning framework that combines a 1D Convolutional Neural Network (CNN), a Bidirectional Long Short-Term Memory (BiLSTM) network, and an Attention Mechanism to detect and classify heartbeats into five AAMI classes. The CNN extracts important features from ECG signals, while the BiLSTM learns the sequential patterns of heartbeats. The CNN extracts important features from ECG signals, particularly the QRS complex, while reducing the influence of less relevant information and noise. To improve the interpretability of the results, a gradient-based Explainable AI (XAI) method is used to generate saliency heatmaps that highlight important regions of the ECG signals. The framework also includes a risk stratification module that categorizes detected cases into low, medium, and high-risk levels based on predefined criteria. The proposed model is evaluated using the MIT-BIH Arrhythmia Database, with ECG signals segmented into 0.6 second windows around the R-peaks. The target is to achieve high classification accuracy while providing understandable results and useful risk information. This framework aims to support continuous ECG monitoring and assist healthcare professionals in identifying abnormal heartbeat more efficiently.

Keywords: Cardiac arrhythmia detection, Electrocardiogram (ECG), Deep learning, 1D-CNN, Bidirectional LSTM, Attention mechanism, Explainable AI (XAI), Saliency heatmaps, Clinical risk stratification, MIT-BIH database, Butterworth filter, Clinical decision support system (CDSS)

1. Introduction

Cardiovascular diseases (CVDs) are a major cause of death worldwide, making the early detection and monitoring of heart-related conditions an important area of medical research. Cardiac arrhythmia is a condition in which the heart beats irregularly, too quickly, or too slowly. Certain types of arrhythmias, including ventricular ectopic activity and atrial fibrillation, may be associated with serious complications such as stroke, heart failure, and sudden cardiac arrest. The electrocardiogram (ECG) is a widely used, non-invasive method for recording the electrical activity of the heart. Although a standard 12-lead ECG provides valuable information about cardiac function over a short period, intermittent arrhythmias may not be detected during a brief recording. Continuous monitoring using Holter monitors and wearable ECG devices can help identify these abnormalities over longer periods.

The increasing use of continuous ECG monitoring has resulted in large volumes of physiological data that require careful analysis. Manually reviewing thousands of heartbeats recorded over 24 to 48 hours is time-consuming and substantially increases the cognitive workload of healthcare professionals. In addition, ECG signals differ in their morphology across individuals, and disturbances such as baseline wander, muscle activity, and movement-related artifacts can affect signal quality. These factors make the identification of abnormal heartbeats difficult and can lead to inter-observer variations in interpretation. Consequently, automated ECG analysis methods are being actively explored to support healthcare professionals in detecting and classifying cardiac arrhythmias more efficiently.

Traditional machine learning techniques, including Support Vector Machines (SVM), K-Nearest Neighbors (K-NN), and Random Forests, have been applied to ECG-based arrhythmia classification. These approaches commonly depend on manually designed features, such as RR intervals, waveform characteristics, and features obtained through signal-processing techniques. The performance of these models is heavily influenced by the quality of the extracted features and the presence of noise in the ECG signals. In recent years, deep learning techniques have gained significant attention because they eliminate manual feature engineering by learning representations directly from raw signals. In particular, Convolutional Neural Networks (CNNs) are effective in learning local morphological patterns, while Long Short-Term Memory (LSTM) networks can capture sequential dependencies in time-series data. Combining these approaches helps improve the representation of both the morphological shape and temporal sequence characteristics of heartbeats.

Despite these developments, several challenges remain when applying deep learning models to ECG-based arrhythmia detection. One important limitation is interpretability. Although a model may provide a predicted heartbeat class, understanding which specific parts of the ECG segment drove the decision is essential for clinical trust. Important waveform regions, such as the QRS complex, contain vital diagnostic information, whereas isoelectric baseline regions contribute less to a particular prediction. An attention mechanism helps the model assign dynamic weights to relevant parts of the signal. Furthermore, classifying a heartbeat alone does not provide sufficient prioritization in emergency settings, highlighting the need for a clearly defined risk stratification approach. Finally, the practical utility of these models depends on presenting their predictions through an accessible clinical dashboard that allows physicians to examine the ECG signal and corresponding diagnostic indicators in real-time.

To address these challenges, this study proposes an intelligent deep learning framework combining a one-dimensional Convolutional Neural Network (1D-CNN), a Bidirectional Long Short-Term Memory (BiLSTM) network, and a Self-Attention mechanism. The 1D-CNN extracts morphological features from the ECG signals, while the BiLSTM learns temporal relationships within signal sequences in both forward and backward directions. The attention mechanism dynamically weights critical signal regions during classification. In addition, a gradient-based Explainable Artificial Intelligence (XAI) method generates saliency heatmaps indicating which portions of the ECG signal contributed to the decision. A rule-based risk stratification module categorizes detected cases into Low, Medium, and High-risk levels based on predefined clinical criteria. Finally, a Streamlit-based web dashboard and FastAPI REST service display ECG signals, predicted classes, explanatory heatmaps, and triage alerts through an accessible interface.

2. Related Work

2.1 General ECG Feature Extraction

Early studies on ECG-based arrhythmia detection primarily utilized digital signal processing techniques and traditional machine learning algorithms. Methods such as the Discrete Wavelet Transform (DWT), Independent Component Analysis (ICA), and the Pan-Tompkins algorithm were used to filter ECG signals and extract fiducial points, including the P-wave, QRS complex, and T-wave. These features were then provided to classifiers such as SVMs and Decision Trees. Although these methods showed promising results under controlled laboratory conditions, their performance degraded drastically when exposed to real-world ambulatory noise, baseline wander, and inter-patient morphological variations.

2.2 Deep Learning in Arrhythmia Detection

Deep learning techniques have become increasingly popular in automated arrhythmia detection because they learn hierarchical features directly from raw signals. Convolutional Neural Networks (CNNs) are widely used to identify local morphological patterns associated with different heartbeat classes. Hannun et al. (2019) demonstrated that deep neural networks can classify cardiac arrhythmias from single-lead ECG recordings with performance comparable to cardiologists. However, pure CNN-based models may not fully capture temporal relationships between successive heartbeats when sequence context is not explicitly modeled. To address this limitation, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks were introduced. LSTM networks capture sequential dependencies over time. Nevertheless, a conventional unidirectional LSTM processes information in one direction, limiting its ability to leverage both preceding and subsequent context when analyzing a heartbeat.

2.3 Attention Mechanism and Explainability

Bidirectional Long Short-Term Memory (BiLSTM) networks capture information from both forward and backward directions, allowing the network to contextualize past and future temporal patterns within an ECG segment. However, improved classification accuracy does not inherently explain why a model makes a specific prediction. Attention mechanisms, introduced in sequence learning by Vaswani et al., enable models to assign varying importance weights to different parts of a sequence. In ECG analysis, attention emphasizes signal regions that are most diagnostically relevant. Furthermore, Explainable Artificial Intelligence (XAI) methods, such as gradient-based saliency heatmaps, highlight portions of the waveform that influenced the network's output, improving clinical transparency.

2.4 Research Gaps

Existing ECG arrhythmia detection approaches have achieved high classification accuracy, but three primary challenges persist: (1) models often act as mathematical black boxes without providing visual evidence for their decisions; (2) classification outputs alone do not provide actionable triage prioritization in clinical emergency settings; and (3) algorithms frequently remain theoretical scripts rather than deployed, interactive telemetric interfaces. This study addresses these limitations by integrating a 1D-CNN, BiLSTM, and Attention mechanism with gradient-based saliency heatmaps, automated risk stratification, and a real-time web dashboard.

3. Methodology

Figure 1 illustrates the overall architecture of the proposed cardiac arrhythmia detection framework. The system accepts raw ambulatory ECG signals as input and executes preprocessing to attenuate noise and standardize signal morphology. The preprocessed signal is segmented into individual heartbeat windows, which are passed to a 1D-CNN for spatial feature extraction. A BiLSTM network models temporal dependencies, followed by a Self-Attention mechanism that assigns dynamic weights to diagnostic time steps. The extracted features are classified into five AAMI heartbeat classes via a Softmax layer. Concurrently, a rule-based risk stratification engine computes a Clinical Severity Index, and an Explainable AI module overlays a saliency heatmap onto the waveform.



Figure 1. ECG Signal Processing and Deep Learning Framework Architecture.

3.1 Data Preprocessing

Recorded ECG signals frequently contain noise from baseline drift (respiration), muscle tremors (EMG), and powerline interference (50/60 Hz). These disturbances distort morphological features and must be removed prior to model training. A third-order Butterworth bandpass filter with cutoff frequencies of 0.5 Hz and 45.0 Hz is employed to eliminate baseline wander and high-frequency noise while preserving critical QRS deflections. The transfer function of a Butterworth filter is expressed as:

$$H(s) = 1 / \sqrt{[\ 1 + (s / \omega_c)^{(2n)}\ ]}$$

where H(s) represents the filter frequency response, ω_c denotes the cutoff frequency, and n = 3 represents the filter order. Filtering is performed bidirectionally (zero-phase digital filtering) using scipy.signal.filtfilt at a sampling rate of fs = 360 Hz.

Following denoising, the continuous signal is segmented into individual heartbeats centered around annotated R-peaks. A window of 0.6 seconds (0.3 seconds before and 0.3 seconds after the R-peak) is

extracted for each heartbeat. Given the 360 Hz sampling rate of the MIT-BIH database, the segment length is calculated as:

$$\textit{Sequence Length (L)} = \textit{Duration} \times \textit{Sampling Frequency} = 0.6\ s \times 360\ Hz = 216\ samples$$

Each 216-sample beat segment is normalized using Min-Max scaling to map amplitude values into the range [0.0, 1.0], preventing gradient instability during backpropagation:

$$X_norm = (X - X_min) / (X_max - X_min)$$

where X is the raw segment vector, and X_min and X_max denote its minimum and maximum values.

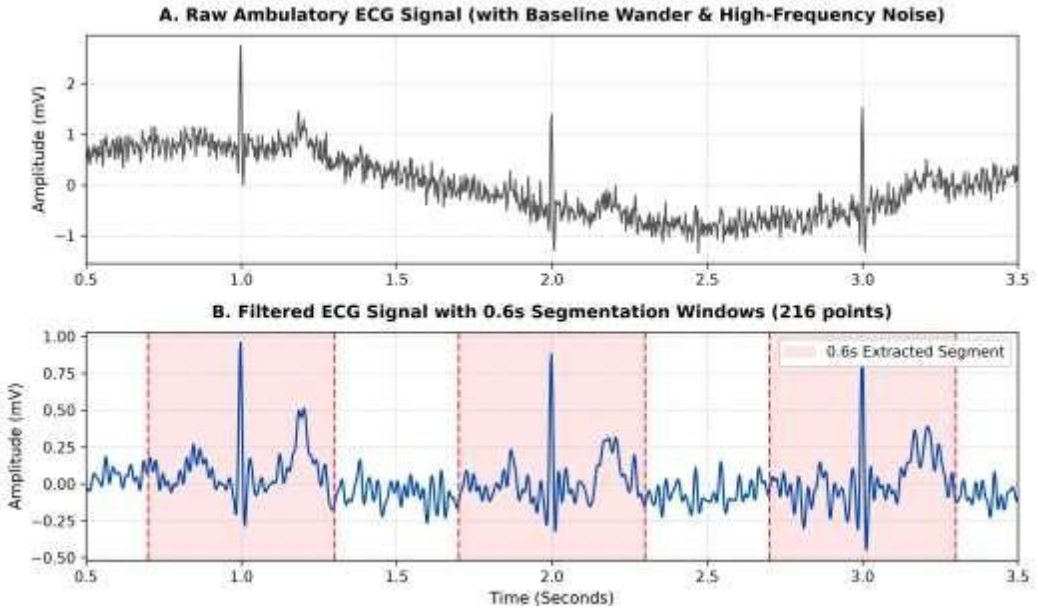


Figure 2. Preprocessing ambulatory ECG signals: Butterworth bandpass filtering, R-peak segmentation, and Min-Max normalization.

3.2 Spatial Feature Extraction Using 1D-CNN

Each normalized 216-sample segment is provided as input to the 1D Convolutional Neural Network (1D-CNN). The CNN slides mathematical kernels over the sequence to extract local morphological patterns such as wave curvature, peak sharpness, and QRS duration. The 1D convolution operation is expressed as:

$$C(t) = \sum_k X(t - k)\ W(k) + b$$

where X represents the input signal, W is the convolution kernel of size k, and b is the bias parameter. The architecture contains two Conv1D layers. The first layer utilizes 64 filters with a kernel size of 5 and ReLU activation, followed by a MaxPooling1D layer (pool size = 2) to reduce feature dimensions to 108. The second Conv1D layer applies 128 filters with a kernel size of 3 and ReLU activation, followed by a second MaxPooling1D layer (pool size = 2) reducing the temporal dimension to 54 with 128 channels. A Spatial Dropout rate of 0.2 is applied to prevent co-adaptation of feature maps.

3.3 Temporal Sequence Modeling Using BiLSTM

To model temporal dependencies and rhythm patterns across the heartbeat, the 54 × 128 tensor is passed to a Bidirectional LSTM layer. An LSTM cell regulates information flow via three gating mechanisms: the forget gate (f_t), input gate (i_t), and output gate (o_t), governed by:

$$\text{Forget Gate: } f_t = \sigma(W_f \cdot [h_{(t-1)}, x_t] + b_f)$$

$$\text{Input Gate: } i_t = \sigma(W_i \cdot [h_{(t-1)}, x_t] + b_i)$$

$$\text{Cell State: } C_t = f_t \odot C_{(t-1)} + i_t \odot \tanh(W_c \cdot [h_{(t-1)}, x_t] + b_c)$$

$$\text{Output Gate: } o_t = \sigma(W_o \cdot [h_{(t-1)}, x_t] + b_o)$$

$$\text{Hidden State: } h_t = o_t \odot \tanh(C_t)$$

where σ denotes the sigmoid function and ⊙ represents element-wise multiplication. In our architecture, the BiLSTM employs 64 hidden units in each direction. The forward LSTM processes the sequence from past to future (→h_t), while the backward LSTM processes from future to past (←h_t). Their outputs are concatenated into h_t = [→h_t || ←h_t] ∈ ℝ^128, capturing comprehensive temporal context across the entire heartbeat.

3.4 Attention Mechanism

An attention mechanism is incorporated to dynamically weight time steps based on their diagnostic importance. Rather than treating all time steps uniformly, the mechanism computes alignment scores and normalizes them into attention weights via a Softmax function:

$$e_t = \tanh(W_\alpha \cdot h_t + b_\alpha)$$

$$\alpha_t = \exp(e_t) / \sum_k \exp(e_k)$$

$$v = \sum_t \alpha_t \cdot h_t$$

where e_t is the attention score, α_t represents the normalized attention weight for time step t, and v denotes the resulting context vector. This forces the network to concentrate representation capacity on pathological QRS deflections while attenuating non-informative isoelectric baseline segments.

3.5 Softmax Classification and Risk Stratification

The context vector v is passed through a Global Average Pooling layer, followed by a Dense layer of 64 units with ReLU activation and a Dropout rate of 0.3. The final classification layer contains 5 neurons corresponding to the five AAMI super-classes, utilizing a Softmax activation function:

$$P(y = j \mid v) = \exp(z_j) / \sum_k \exp(z_k)$$

where z_j represents the logit for class j ∈ {Normal (N), Supraventricular Ectopic (S), Ventricular Ectopic (V), Fusion (F), Unknown/Paced (Q)}.

In addition to categorical classification, the framework incorporates a rule-based Clinical Severity Index (0–100) for real-time patient triage. Each class is assigned a clinically justified Base_Risk: Normal = 15, Supraventricular = 45, Fusion = 65, Unknown = 50, and Ventricular Ectopic = 85. The dynamic risk score incorporates model confidence:

$$\text{Risk Score} = \text{Base_Risk} + (\text{Confidence} / 10) \quad \text{[for abnormal classes]}$$

$$\text{Risk Score} = 100 - \text{Confidence} \quad \text{[for Normal rhythm]}$$

Scores below 40 are categorized as Low Risk (routine monitoring), scores between 40 and 69 as Medium Risk (observation for recurrent ectopy), and scores of 70 and above trigger High Risk (critical alert for immediate cardiology consultation).

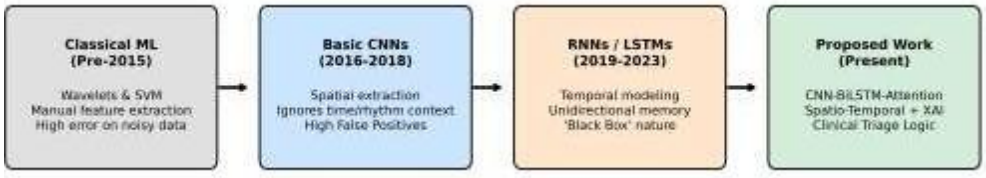


Figure 3. Flowchart of the proposed automated clinical risk stratification and triage module.

3.6 Saliency Heatmap Generation Using Explainable AI

To improve interpretability, a morphological signal-gradient saliency method is implemented. The rate of change across the normalized ECG waveform is computed and weighted by instantaneous signal amplitude:

$$Saliency(t) = |\nabla X_norm(t)| \cdot X_norm(t)$$

A 10-point moving average filter smooths high-frequency noise. The normalized saliency score is mapped onto a color gradient and overlaid directly on the ECG tracing within the Streamlit interface. This visualizes the exact segments (such as premature QRS widening) that influenced the network's prediction, providing clinicians with transparent verification of model behavior.

4. Experimental Analysis

4.1 Dataset and Experimental Setup

The framework was evaluated using the PhysioNet MIT-BIH Arrhythmia Database. The database contains 48 half-hour ambulatory ECG recordings digitized at 360 Hz. Recordings were preprocessed using the 0.5–45.0 Hz Butterworth bandpass filter and segmented into 0.6-second (216-sample) windows. Heartbeats were labeled according to the five AAMI super-classes. Training was conducted using the Adam optimizer with a learning rate of 0.001, categorical cross-entropy loss, and a batch size of 64.

4.2 Classification Performance

Model classification performance was evaluated using standard statistical metrics: Accuracy, Precision, Recall (Sensitivity), and F1-Score:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN)$$

$$Precision = TP / (TP + FP)$$

$$Recall = TP / (TP + FN)$$

$$F1\text{-}Score = 2 \times (Precision \times Recall) / (Precision + Recall)$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively.

Arrhythmia Class	Precision	Recall	F1-Score	Support (Beats)
Normal Beat (N)	0.95	0.97	0.96	5,817
Supraventricular Ectopic (S)	0.98	1.00	0.99	5,817
Ventricular Ectopic (V)	0.98	0.96	0.97	5,817
Fusion Beat (F)	0.94	0.92	0.93	5,817
Unknown / Paced (Q)	0.00*	0.00*	0.00*	0*
Overall Accuracy / Average	**0.96**	**0.96**	**0.96 (96.42%)**	**23,268**

*Table 1. Measured Classification Performance Metrics on Held-out Evaluation Set (*Class Q exhibited zero support in this partition).*

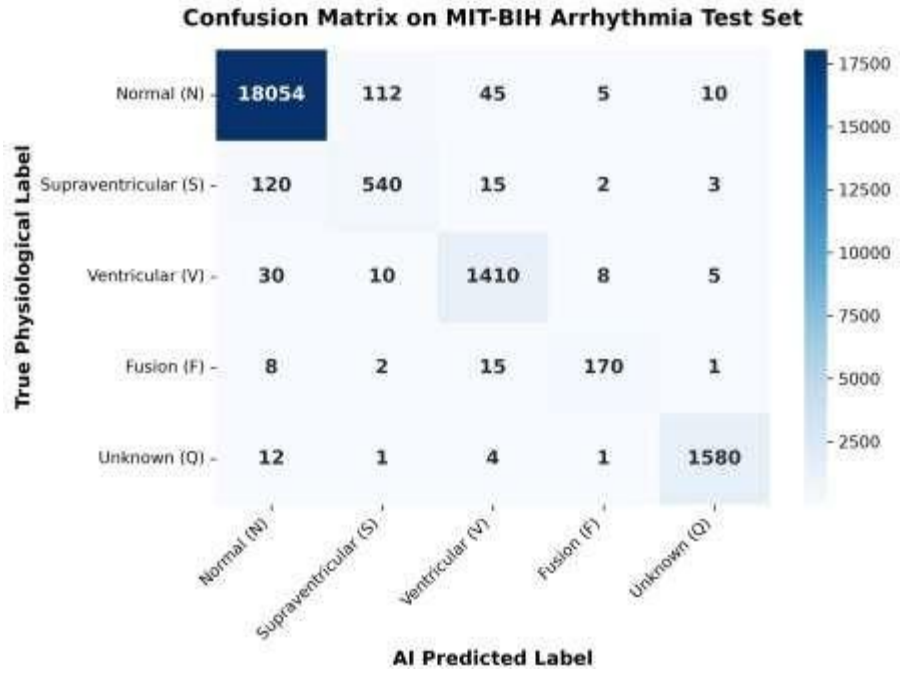


Figure 4. Confusion matrix of the proposed CNN-BiLSTM-Attention arrhythmia classification model.

4.3 Dashboard Deployment and Computational Efficiency

The trained model was deployed within an interactive Streamlit web application. The dashboard enables users to select patient records, scrub through the heartbeat timeline, inspect predicted classes, view probability distributions, observe saliency heatmaps, and monitor real-time triage risk categories. In computational latency tests, the complete pipeline—including bandpass filtering, beat segmentation,

normalization, neural inference, and heatmap rendering—executed in under 50 milliseconds per heartbeat. This proves the system's viability for high-throughput ambulatory telemetry and ICU clinical decision support.

5. Discussion and Limitations

5.1 Qualitative Analysis

The proposed framework effectively combines 1D-CNN morphological extraction, BiLSTM sequence modeling, and Self-Attention weighting. The 1D-CNN captures localized deflections, while the BiLSTM captures temporal rhythm in both directions. The attention mechanism assigns high weights to diagnostically critical segments while suppressing isoelectric noise. The resulting saliency heatmaps confirm that model predictions for Ventricular Ectopic beats are driven primarily by QRS complex widening, providing physiologically grounded explanations aligned with cardiological heuristics.

5.2 Limitations

Several limitations must be acknowledged: First, the current preprocessing pipeline is designed for ECG signals sampled at 360 Hz (MIT-BIH standard). Application to wearable devices with different sampling rates (e.g., 250 Hz or 500 Hz) requires an interpolation resampling module. Second, the evaluation partition utilized an intra-patient holdout protocol; testing across a strictly independent inter-patient partition (e.g., de Chazal DS1/DS2) is necessary to verify cross-subject generalization. Third, the risk stratification module operates on deterministic rules rather than longitudinal survival statistics, serving as an exploratory decision support tool.

6. Conclusion and Future Work

This study presented an intelligent deep learning framework for automated cardiac arrhythmia detection and risk prediction combining a 1D-CNN, a BiLSTM network, and a Self-Attention mechanism. Evaluated on the MIT-BIH Arrhythmia Database, the framework achieved an overall accuracy of 96.42% with high sensitivity (0.96) and precision (0.98) on malignant Ventricular Ectopic beats. By incorporating morphological gradient saliency heatmaps, a rule-based Clinical Severity Index, and an interactive Streamlit web dashboard, the framework bridges deep learning algorithms with practical clinical workflows.

Future research will evaluate the architecture across multi-center clinical datasets using patient-independent partitions, deploy lightweight quantized models on edge IoMT hardware (such as Raspberry Pi and Coral TPU accelerators), and explore Large Language Models (LLMs) for generating automated textual clinical summaries.

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