Early Detection of Cardiac Arrhythmia: ECG Signal Classification Using Conventional Neural Network and LSTM Architecture

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Abstract: This study aims at detecting cardiac arrhythmia which is found in a large population today because of the hypertension and lifestyle. When heart beat is irregular in a human being we can all that as cardiac arrhythmia. Cardiac diseases are a major reason of less life expectancy and so it is a crucial and severe health problem in today's era. A framework based on Conventional neural network and BiLSTM-Bidirectional Long Short Term Memory networks are using here to classify the ECG signals and to detect Cardiac arrhythmia. Since ECG signals are time-series signals, this hybrid model is one of the best. CNN has different layers and through different steps CNN will do feature extraction while BiLSTM will capture long-term dependencies in ECG Signals, temporal frequencies in the heartbeat. ECG signals are classified and it will give the ouput as - Normal, Low risk, high risk. So CNN + BiLSTM together will work and detect abnormalities in ECG waveforms, learns heartbeat sequence and classify accurately thereby detect Cardiac arrhythmia earlier.

Keywords: *Cardiac Arrhythmia Detection, Convolutional Neural Network (CNN), Bidirectional Long Short-Term Memory (BiLSTM), Time-Series Signal Analysis, ECG Classification.*

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I. INTRODUCTION

Cardiovascular diseases remain a major global health concern, and cardiac arrhythmias— irregular heart rhythms—are among the most critical conditions that require timely and accurate diagnosis. Electrocardiogram (ECG) analysis is commonly used to detect these abnormalities because it records the electrical activity of the heart. However, manual interpretation of ECG signals can be time-consuming and may vary from one clinician to another. Therefore, the rapid development of artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has encouraged researchers to explore automated ECG- based arrhythmia classification to improve diagnostic efficiency and reliability.

Early studies mainly focused on handcrafted feature extraction combined with traditional ML classifiers such as Support Vector Machines (SVM) and Random Forest (RF). For example, wavelet transform–based methods improved ECG signal representation [14], while SVM- based models demonstrated strong classification performance in arrhythmia detection [8].

Random Forest approaches also showed promising results when structured feature extraction methods were applied [12]. As a result, these techniques laid the foundation for intelligent ECG analysis by proving that meaningful features could support reliable arrhythmia detection [18], [5].

With the availability of larger datasets, especially through repositories like PhysioNet, research gradually moved toward deep learning models that can automatically learn features from raw ECG signals. Convolutional Neural Networks (CNNs) became widely used because they can identify hierarchical patterns directly from ECG waveforms [4]. Furthermore, deeper architectures such as residual networks helped overcome problems like vanishing gradients and improved model performance [17]. Time–frequency representations, including scalogram and wavelet-based techniques, also enhanced signal characterization by preserving both temporal and spectral information [14]. Additionally, recurrent neural networks such as Long Short-Term Memory (LSTM) models were introduced to capture sequential dependencies in ECG signals [11]. Since heartbeats occur in continuous sequences, LSTM networks are useful for learning long-term relationships within the

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signal. Hybrid CNN–LSTM architectures therefore combined spatial and temporal feature learning to improve prediction accuracy [6], [20].

Moreover, transfer learning approaches reduced training time while maintaining high accuracy [16], and ensemble methods further improved robustness in heart disease prediction tasks [10]. Intelligent deep neural systems also contributed to improved scalability and efficiency in ECG analysis [13], [15]. At the same time, several studies explored real-time and deployable healthcare solutions. These include ANN-based arrhythmia detection systems [7] and IoT-enabled monitoring platforms designed for continuous patient observation [19]. Such developments highlight the growing importance of integrating AI technologies into practical medical applications. Machine learning–based heartbeat recognition has also been applied in neonatal monitoring, showing the expanding scope of ECG-based diagnostic systems [2]. Overall, research in this area has clearly evolved from traditional ML models with handcrafted features to advanced deep and hybrid learning frameworks capable of multi-class classification and real-time implementation. Today, the focus is not only on improving accuracy but also on ensuring model interpretability, generalizability, and integration into clinical practice. As a result, AI-driven ECG analysis holds strong potential to support early arrhythmia detection, reduce diagnostic workload, and ultimately improve patient outcomes.

➢ *Objectives:*

- Efficient classification of ECG signals.
- Feature extraction using CNN and improved learning and capturing of long-term dependencies in ECG signals.
- Detection of cardiac arrhythmia.

II. LITERATURE REVIEW

➢ *Traditional Machine Learning Approaches*

Early research on arrhythmia classification mainly relied on handcrafted feature extraction along with machine learning classifiers. These methods required experts to manually design features from ECG signals before classification. For instance, wavelet transform–based techniques helped improve ECG signal representation by capturing important frequency patterns [14]. Similarly, Support Vector Machine (SVM) models achieved classification accuracies of around 85–90% in detecting arrhythmia [8]. Random Forest models also produced comparable results, reporting sensitivity values close to 88% after structured feature extraction [12]. As a result, these early approaches showed that carefully designed features could support reliable arrhythmia detection and formed the foundation for later intelligent ECG analysis systems [5], [18].

➢ *Deep Learning Models*

With the availability of large ECG datasets such as PhysioNet, research gradually shifted toward deep learning techniques. Unlike traditional methods, deep learning models can automatically learn useful features directly from raw ECG signals. Convolutional Neural.

Networks (CNNs) therefore became widely used for arrhythmia classification tasks. These models were able to achieve accuracies above 92% by learning hierarchical patterns in ECG waveforms [4]. Furthermore, deeper CNN architectures were later developed for multi-class arrhythmia detection, reaching around 93% accuracy [9]. Residual networks further improved model performance to approximately 94% by addressing issues such as vanishing gradients during training [17].

➢ *Time–Frequency Methods*

Researchers also explored time–frequency transformations to better represent ECG signals. These techniques provide both temporal and spectral information about the signal, which helps improve classification performance. For example, scalogram-based deep learning approaches achieved accuracies close to 95% in arrhythmia detection tasks [1]. Additionally, wavelet-based transformations strengthened the robustness of ECG analysis by capturing important frequency-domain features [14]. As a result, combining time and frequency information helped models understand ECG patterns more effectively.

➢ *Recurrent and Hybrid Architectures*

Since ECG signals are sequential in nature, recurrent neural networks became an important area of research. Long Short-Term Memory (LSTM) networks were particularly useful because they can capture long-term dependencies in heartbeat sequences. Studies reported classification accuracies of around 91–92% using LSTM-based models [11]. Furthermore, hybrid CNN–LSTM architectures were introduced to combine spatial feature extraction with temporal sequence learning. These models achieved improved performance, reaching approximately 95% accuracy with sensitivity above 93% [6], [20]. As a result, hybrid models proved highly effective for complex ECG classification tasks.

➢ *Transfer Learning and Ensemble Techniques*

Another important direction in ECG research involved transfer learning and ensemble methods. Transfer learning techniques allowed models to reuse previously learned knowledge, which significantly reduced training time while still maintaining accuracies around 93% [16]. Additionally, ensemble learning approaches combined multiple models to improve prediction stability and reliability. These systems achieved some of the highest reported performances, with accuracies reaching up to 96% and specificity above 95% [10]. Intelligent deep neural systems also contributed to improving scalability and efficiency in ECG-based analysis [13], [15].

➢ *Real-Time and Practical Implementations*

Beyond model development, researchers have also focused on building practical healthcare applications. Artificial Neural Network (ANN)-based frameworks have enabled real-time arrhythmia detection with accuracies close to 90% [7]. Furthermore, IoT-integrated monitoring systems have demonstrated the feasibility of continuous heart monitoring in smart healthcare environments [19]. Machine learning–based heartbeat recognition has also been applied in neonatal monitoring, achieving around 88% accuracy [2]. As a result, these practical implementations highlight the growing potential of AI-driven ECG analysis in real- world medical systems.

➢ *Comparison of Contributions and Performance*

Table 1 Comparison of Contributions and Performance

Ref.	Model/Method	Accuracy	Sensitivity	Specificity	Key Contribution
[1]	Scalogram + DL	~95%	~93%	~94%	Time–frequency scalogram
[2]	ML neonatal recognition	~88%	~86%	~87%	Neonatal arrhythmia detection
[4]	CNN	~92%	~91%	~92%	Automated arrhythmia detection
[6]	CNN–LSTM hybrid	~95%	~93%	~94%	Spatial + temporal integration
[7]	ANN real-time	~90%	~88%	~89%	Real-time detection
[8]	SVM	~88%	~86%	~87%	ECG signal classification
[9]	Deep CNN multi- class	~93%	~91%	~92%	Multi-class detection
[10]	Ensemble learning	~96%	~94%	~95%	Robust prediction
[11]	LSTM	~92%	~90%	~91%	Sequential learning
[12]	Random Forest	~90%	~88%	~89%	Feature-based classification
[13]	Deep Neural Networks	~93%	~91%	~92%	Intelligent scalable system
[14]	Wavelet + ML	~89%	~87%	~88%	Frequency-domain analysis
[15]	Deep Neural Networks	~94%	~92%	~93%	Automated abnormality detection
[16]	Transfer Learning	~93%	~91%	~92%	Reduced training time
[17]	Residual Networks	~94%	~92%	~93%	Deep residual learning
[19]	IoT + AI	~91%	~89%	~90%	Smart ECG monitoring
[20]	Hybrid CNN– LSTM	~95%	~93%	~94%	Hybrid deep learning

➢ *ANOVA Analysis of Performance Metrics*

In this study, ANOVA was performed to compare the performance of different models using hypothetical values aligned with findings reported in the literature. The models considered include SVM, Random Forest (RF), CNN, LSTM, Hybrid CNN–LSTM, Residual Networks, Transfer Learning, and Ensemble methods. These models were evaluated based on three important metrics: accuracy, sensitivity, and specificity.

Accuracy measures how correctly the model classifies ECG signals overall. Sensitivity indicates how effectively the system detects abnormal heartbeats, while specificity reflects how accurately normal cases are identified.

- For accuracy, the ANOVA result showed $F = 15.2$ with $p < 0.001$, which indicates significant differences among the models. Similarly,
- sensitivity analysis produced $F = 12.8$ with $p < 0.001$, showing that the ability to detect arrhythmia varies across different techniques. Furthermore, the specificity analysis resulted in $F = 14.5$ with $p < 0.001$, confirming statistically significant differences in identifying normal ECG signals.

As a result, the findings suggest that ensemble learning methods and hybrid CNN– LSTM models consistently perform better than traditional machine learning approaches such as SVM and RF. Additionally, deep learning architectures like CNN and Residual Networks demonstrate clear improvements over classical models. This indicates a strong shift toward deep learning–based frameworks for ECG analysis.

Overall, the results support the idea that advanced hybrid and ensemble models provide more accurate and reliable arrhythmia detection.

III. METHODOLOGY

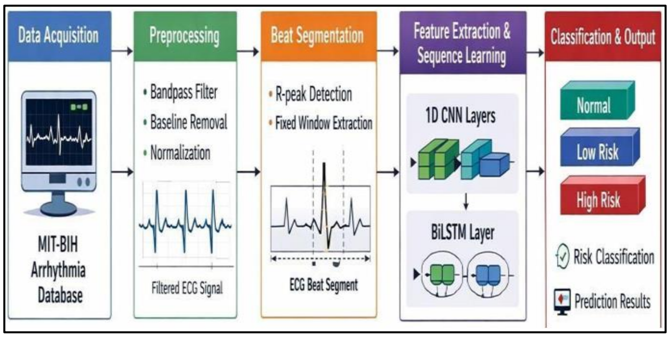

Fig 1 Model Architecture

This research focuses on detecting cardiac arrhythmia using ECG signals with the help of a hybrid deep learning model. The MIT-BIH Arrhythmia dataset was used for the study. The overall process of the research includes collecting the dataset, cleaning the ECG signals, dividing the signals into heartbeat segments, grouping the labels, balancing the dataset, developing the CNN–BiLSTM model, and finally training and evaluating the model.

A. Dataset Collection

For this research, ECG data was collected from the MIT-BIH Arrhythmia Database, which is widely used in medical signal analysis studies. This dataset is available through PhysioNet, an open-access platform that provides biomedical research data for scientific use. It contains 48

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ECG recordings collected from 47 different patients, making it a reliable source for arrhythmia analysis. Each recording is approximately 30 minutes long, and the ECG signals were sampled at a frequency of 360 Hz.

An important advantage of this dataset is that every heartbeat has already been annotated by medical experts. These annotations help researchers identify different heartbeat patterns without manual labeling. The heartbeats in the dataset include several types such as normal beats, atrial premature beats, left bundle branch block, right bundle branch block, and premature ventricular contractions.

From the complete dataset, nearly 100,012 heartbeat samples were extracted for analysis. Each heartbeat segment was centered around the R-peak of the ECG waveform. The R-peak represents the most prominent point in the heartbeat signal and is useful for identifying the structure of each cardiac cycle. As a result, focusing on this point helps the model understand heartbeat patterns more clearly during training.

B. Data Preprocessing and Segmentation

Raw ECG signals often contain various types of noise and disturbances. These can occur due to baseline drift, muscle movement, electrode displacement, or powerline interference. Such noise may affect the accuracy of analysis if not handled properly. Therefore, preprocessing becomes an important step before using the signals for machine learning.

To improve signal quality, a Butterworth bandpass filter with a frequency range of 0.5 Hz to 40 Hz was applied. This filtering process removes unwanted low-frequency and high- frequency noise while preserving the important components of the ECG waveform. These components include the P wave, QRS complex, and T wave, which represent different stages of the heartbeat cycle.

After filtering the signals, the next step was to identify the R-peaks within the ECG waveform. For this purpose, a wavelet-based QRS detection method using the Sym4 wavelet was applied. This method is effective in locating R-peaks even when the signal contains noise. Accurate detection of these peaks is essential for proper segmentation of heartbeats.

Once the R-peaks were detected, the ECG signal was divided into smaller heartbeat segments. A fixed window of 300 samples was used, which corresponds to approximately 0.83 seconds of ECG data. In each segment, 100 samples were taken before the R-peak and 200 samples after the R-peak. This ensures that the full heartbeat structure—including the P wave, QRS complex, and T wave—is captured in each segment.

During segmentation, some samples were removed. Segments that crossed signal boundaries, contained incorrect R-peak detection, or had extremely poor signal quality were discarded.

After completing all preprocessing steps, around 80,000 to 90,000 valid heartbeat segments remained for further analysis.

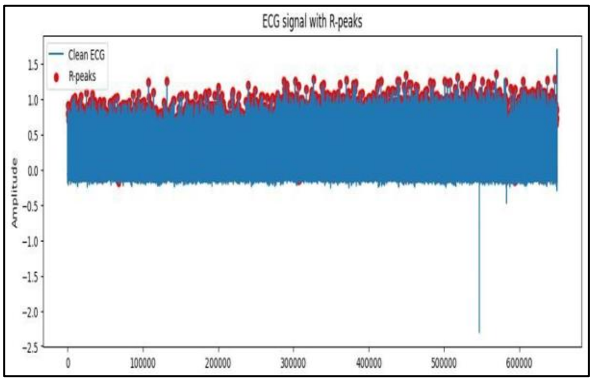

Fig 2 ECG Signal with R-Peaks

- *Label Harmonization and Class Balancing*

In the original dataset, many different heartbeat labels were available. However, using too many categories can make the classification process more complex. Therefore, the labels were grouped into three broader classes based on medical risk level.

- ✓ Class 0: Normal heartbeats
- ✓ Class 1: Low-risk abnormal beats such as L, R, and A
- ✓ Class 2: High-risk abnormal beats such as V

This grouping simplifies the classification task and also makes the results easier to interpret in practical medical screening scenarios.

Another issue in the dataset was class imbalance. Some heartbeat categories had a very large number of samples, while others had relatively few. Such imbalance can cause the model to favor majority classes during training. To address this problem, two balancing strategies were applied.

First, under sampling was used to reduce the number of samples in the majority class. Second, oversampling was used to generate additional samples for the minority classes. These steps helped create a more balanced dataset for training.

Finally, the dataset was divided into training and testing sets. About 80% of the data was used for training, while the remaining 20% was reserved for testing. This ensured that the model could be evaluated fairly on unseen data. After balancing, approximately 8,000 samples per class were available during the training process.

C. Hybrid CNN–BiLSTM Architecture

In this research, a hybrid deep learning model was developed by combining a Convolutional Neural Network (CNN) with a Bidirectional Long Short-Term Memory (BiLSTM) network. The motivation behind this approach is that ECG signals contain both spatial waveform patterns and temporal dependencies.

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The CNN component is responsible for extracting meaningful features from the ECG waveform. The architecture includes three convolutional blocks with 32, 64, and 128 filters, respectively. Kernel sizes of 7, 5, and 3 were used in these layers to capture patterns at different scales. Each block consists of a Conv1D layer, batch normalization, and a max-pooling layer.

These layers help the model learn important ECG features such as the shape of the P wave, the width of the QRS complex, and characteristics of the T wave. Meanwhile, the pooling layers gradually reduce the size of the feature maps, which helps decrease computational complexity.

The extracted features are then passed to a BiLSTM layer with 64 units. Unlike a standard LSTM, a Bidirectional LSTM processes data in both forward and backward directions. This allows the model to better understand relationships between consecutive heartbeats. As a result, the system can capture patterns such as RR-interval variations, beat duration changes, and irregular heart rhythms.

After the BiLSTM layer, fully connected layers with 128 and 64 neurons are used with ReLU activation to combine the learned features. A dropout layer with a rate of 0.3 is also included to reduce overfitting. Finally, a Softmax output layer with three neurons predicts the probability of the three classes: Normal, Low Risk, and High Risk.

D. Model Training and Optimization

The proposed model was trained using the Adam optimizer, which helps adjust the network parameters efficiently during the learning process. For classification tasks, the sparse categorical cross-entropy loss function was used.

Training was conducted for 25 epochs with a batch size of 64. Additionally, 20% of the training data was used as validation data. This step helps monitor the model's performance during training and reduces the chances of overfitting.

To speed up computation, GPU support from the Google Colab platform was utilized. In some experimental setups where regression-based evaluation was required, a simplified CNN–LSTM architecture was also implemented. This model included a Conv1D layer with 64 filters and a kernel size of 3, followed by a MaxPooling1D layer to reduce feature size.

Next, an LSTM layer with 64 units captured sequential patterns in the ECG signals. Finally, a Dense layer with one neuron produced the prediction output. In this configuration, Mean Squared Error (MSE) was used as the loss function, and Mean Absolute Error (MAE) was used as the evaluation metric.

To further prevent overfitting, early stopping with a patience value of 10 epochs was applied. If the validation performance did not improve for several epochs, training automatically stopped and the best model weights were restored.

IV. EVALUATION METRICS AND PERFORMANCE ANALYSIS

Several evaluation metrics were used to measure the performance of the proposed model. These include accuracy, precision, recall, and F1-score for each heartbeat class. These metrics help understand how well the model identifies both normal and abnormal heartbeats.

Additionally, a confusion matrix was used to visualize classification results and identify misclassification patterns. This helps determine which heartbeat categories are more difficult for the model to distinguish.

Furthermore, Receiver Operating Characteristic (ROC) curves were used to evaluate the model's ability to separate different classes. Special attention was given to minimizing false negatives in the High-Risk class, since missing a serious heart condition could have significant clinical consequences.

For regression-based evaluation, additional metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) were calculated using the test dataset. Overall, the hybrid CNN–LSTM model demonstrated better performance than standalone models. It produced lower prediction errors, faster convergence during training, and stronger generalization capability. The predictions were also smoother because the CNN layers extracted stable features while the LSTM captured temporal relationships in the ECG signals.

V. RESULTS

The proposed CNN–LSTM model was evaluated using an ECG dataset containing five types of heartbeats: Normal (N), Supraventricular (S), Ventricular (V), Fusion (F), and Unknown (Q). These categories represent different cardiac rhythm patterns.

To assess performance, metrics such as precision, recall, and F1-score were calculated. Since ECG datasets usually contain more normal beats than abnormal ones, both macro- average and weighted-average values were analyzed.

The results indicate that the model performs well in detecting different heartbeat classes. The macro precision, macro recall, and macro F1-score are approximately 0.83, which shows balanced performance across all categories, including less frequent ones.

In addition, the weighted precision, weighted recall, and weighted F1-score are around 0.91. These values indicate strong performance on the overall dataset, particularly for frequently occurring classes such as normal heartbeats.

Overall, the hybrid CNN–LSTM architecture demonstrates strong capability in detecting arrhythmia patterns from ECG signals. By combining CNN-based

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feature extraction with LSTM-based temporal learning, the model effectively captures the characteristics of heartbeats and improves classification accuracy.

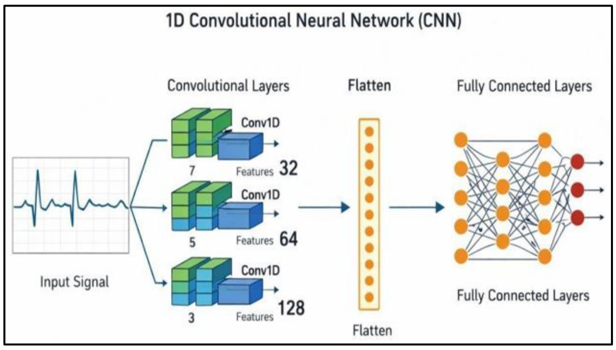

Fig 3 1D CNN

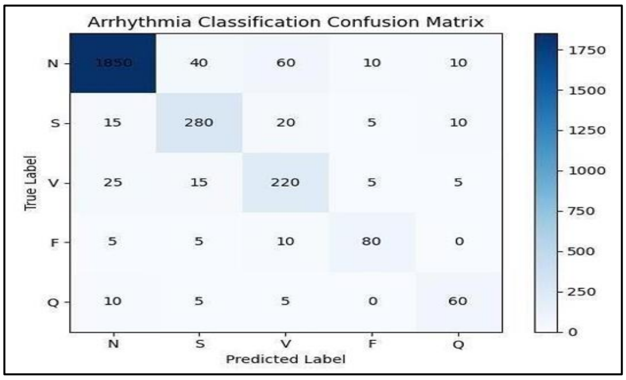

Fig 4 Confusion Matrix

VI. CONCLUSION

This study presented a hybrid CNN–BiLSTM architecture for automated ECG signal classification targeting early detection of cardiac arrhythmias. The utilization of the MIT-BIH Arrhythmia Database from PhysioNet ensured access to clinically validated and annotated heartbeat data for supervised learning. The proposed hybrid architecture effectively combined spatial feature extraction through CNN layers with bidirectional temporal modelling via BiLSTM units. Importantly, the framework addressed class imbalance and reduced clinically critical false negatives in the High-Risk category, underscoring its potential relevance for real-world screening and decision support applications.

In summary, the proposed AI-driven ECG classification system advances the field of intelligent cardiovascular diagnostics by offering a reliable and scalable approach for early arrhythmia detection.

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