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Research Article

Hybrid CNN–BiLSTM Model for ECG Signal Classification and Accurate Arrhythmia Detection (MIT-BIH and PTB-XL Validation)

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Abstract:

Reliable and generalizable classification of electrocardiogram (ECG) record which is present in the form of signals. This is utmost important for early stage arrhythmia recognition and improved patient outcomes. We contribute a Bidirectional Long Short-Term Memory (BiLSTM) layers are combined with the multi-scale Convolutional Neural Networks (CNN) in hybrid deep learning architecture to restrict morphological and temporal ECG data. Bandpass filtering (0.5–40 Hz) is associated with the pre-conditioning pipeline, Pan–Tompkins R-peak segmentation, normalization, and targeted data augmentation (time-warping and jittering). To address class imbalance, minority-class oversampling and a class-weighted categorical cross-entropy loss were used during training. The model undergoes assessment using MIT-BIH Database and it was further validated by PTB-XL dataset. On MIT-BIH the hybrid model achieved 98.0% accuracy, 97.5% precision, 98.2% recall, and 97.8% F1-score, on PTB-XL it achieved 96.8% accuracy, 96.2% precision, 96.5% recall, and 96.3% F1-score. An ablation study shows CNN-only (94.5%) and BiLSTM-only (95.2%) baselines are outperformed by the hybrid model (98.0%); paired t-tests confirm the improvements are statistically significant ($p < 0.01$). Grad-CAM saliency maps indicate the parts of waveform to which model mainly directs its responsiveness, particularly those that are clinically significant (QRS complex and T-wave), refining interpretability. The trained model has a footprint of ≈15 MB and inference time ≈4 ms per beat on an NVIDIA RTX-class GPU (≈20 ms on CPU), indicating feasibility for near-real-time deployment after minor optimizations. Source code and trained weights are made available to support continuous calculation. These results illustrate the proposed CNN-BiLSTM approach is more accurate, interpretable, and generalizes across datasets -promising for automated, real-time ECG disease classification.

1. Introduction

Across nations, cardiovascular diseases (CVDs) is to be the prominent cause of demise, with arrhythmias posing particular risks due to their subtle presentation and unpredictable occurrence. An excellent non-traumatic tool for identification these cardiac irregularities is electrocardiography (ECG). Conversely, the requirement for automated solutions is highlighted by the time taken, prone to mistakes and highly reliant on on medical skill nature of ECG handbook interpretation. To improve diagnosis accuracy and reduce the requirement on manual examination, machine learning (ML) and deep learning (DL) technologies are used to and they play very vital role in current time. Although they offer good classification performance, traditional machine learning procedures like Random Forest (RF) and Support Vector Machines (SVM) suffer from limitations by their dependence on features that have been manually produced. On the other hand, DL models that can automatically learn complex representations comprise Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs). Specifically, CNNs effectively capture morphological features of ECG signals, while BiLSTM networks excel at modeling sequential dependencies. Combining these two architectures is expected to significantly improve arrhythmia classification.Around the world, arrhythmias continue to be an important factor of cardiovascular disease as well as death. The most widely used non-surgical method for determining irregularities in the heart rhythm is still ECG, but manual interpretation requires expert clinicians and is susceptible to inter-reader variability and fatigue. Automated ECG classification using machine learning seeks to reduce diagnostic latency and increase consistency. Traditional classifiers (SVM, Random Forest) rely on hand-crafted features and often fail to generalize across populations. Deep learning (CNNs, LSTMs) has advanced ECG analysis by learning hierarchical representations directly from waveforms. CNNs excel at extracting morphological patterns, while BiLSTM networks capture bidirectional temporal dependencies.This paper suggests a hybrid CNN and BiLSTM that builds on such benefits by including multi-scale convolutional feature extraction with sequential BiLSTM modeling. In addition to achieving high accuracy on MIT-BIH, we explicitly evaluate generalization on the larger PTB-XL dataset, address class imbalance through augmentation and weighted loss, and quantify significance via statistical testing. We further provide an ablation study to isolate every component's contribution, interpretability analyses using Grad-CAM saliency visualizations, and computational profiling to evaluate real-time feasibility for medical treatment or edge deployment.

1.1 Objectives

Develop and optimize hybrid CNN–BiLSTM architecture for strong ECG arrhythmia classification.Implement preprocessing (bandpass filtering, R-peak segmentation and normalization) and guided augmentation to improve signal quality and minority-class presentation.To decrease class imbalance with oversampling and class-weighted loss during classification.Validate model performance on MIT-BIH and externally on PTB-XL to assess generalization.Perform ablation experiments (CNN only, BiLSTM only, hybrid) and evaluate statistical significance of improvements.Produce interpretability outputs (Grad-CAM saliency maps) to show clinically relevant attention.Profile computational costs (model size, inference latency) to evaluate real-time/edge deployment potential.Release source code and trained models to enable reproducibility.

ContributionsA novel hybrid CNN–BiLSTM architecture tailored to ECG beat classification that combines multi-scale convolutional feature extractors with BiLSTM sequence modeling.A reproducible training pipeline that includes targeted augmentation, minority oversampling, and class-weighted loss to address dataset imbalance.98.0% correctness on MIT-BIH and 96.8% correctness on PTB-XL (full class-wise metrics supplied) demonstrate strong empirical performance.Ablation study demonstrating the hybrid's superiority over CNN-only (94.5%) and BiLSTM-only (95.2%) models, Enhancements are significant in statistical terms. (Paired t-test, $p < 0.01$; 95% CI for hybrid accuracy: 97.6–98.3%).Interpretability analysis using Grad-CAM showing the model attends to QRS and T-wave regions, offering clinically meaningful explanations for predictions.Computational profiling reporting ≈4 ms/beat (GPU) and ≈20 ms/beat (CPU) inference times and a ≈15 MB model size — evidence for near-real-time deployment after optimization.Public release of code and trained weights to foster transparency and reproducibility.

2. Literature Review

The categorization of ECG signals has garnered considerable awareness in the span of ten years or more, as a result of the rising very large amount of cardiovascular illnesses and the essential for reliable automated diagnostic systems. On benchmark datasets like the MIT-BIH Arrhythmia Database, several machine learning (ML) and deep learning (DL) techniques have been put forth and assessed [1].Early approaches made use of conventional machine learning techniques like as a Random Forests (RF) and Support Vector Machines (SVM), relying heavily upon hand-crafted features derived from time, frequency, and wavelet domains [2], [3]. Although these approaches showed reasonable accuracy, their dependence on manual feature extraction limited generalizability and scalability.Convolutional Neural Networks (CNNs) is a different type of deep learning approach, have gained popularity recently because they can directly learn spatial patterns from raw ECG dataset. Acharya et al. [4] proposed a conventional neural model which contains 9 layers that achieved high accuracy without requiring manual feature extraction. In the same way, Kiranyaz et al. [5] developed a 1D conventional neural model for the identification of irregularities particular to each person demonstrating real-time capability.Our main objective is to capture ECG signal analysis relies on time, recurrent neural networks (RNNs) and their modification which change day by day, such Long Short-Term Memory (LSTM) networks are extensively used Yildirim et al. and [6], Rajpurkar et al. [7] proposed a model based on deep LSTM farmed on a bulky ECG database, realizing productiveness as good as to cardiologists in arrhythmia detection.Recently, hybrid models that include CNN and LSTM framework have showed potential on work. Hannun et al. [8] combined CNNs and RNNs to extract both morphological and sequential information from ECG data. Such hybrid models leverage the strengths of both spatial and temporal feature learning.Other researchers have explored attention mechanisms, residual connections, and transformer-based models to improve interpretability and classification accuracy Zhang et al. [9], Vaswani et al. [10]. In addition, studies have integrated data augmentation, signal denoising, and R-peak alignment to enhance model robustness Lin et al. [11].In addition to old-fashioned and new technique i.e. Hybrid deep learning models, ensemble techniques have been proposed to improve classification result. Zhang et al. [12] introduced an ensemble model combining SVM and KNN with feature selection, which achieved improved performance on noisy ECG signals. Similarly, Sharma and Sunkaria [13] suggested a wavelet-based ECG denoising method that improved sensitivity for uncommon arrhythmias by employing decision trees for identifications.The use of 1D CNNs in low-power IoT-enabled environments for real-time ECG 24-hour care has also been conversed in recent studies Talo et al.[14], enabling deployment in wearable devices. Additionally, copmlicated preprocessing methods like empirical mode decomposition (EMD) Zheng et al. [15] and variational mode decomposition (VMD) Zhang et al. [16] are applied for signal enhancement prior to classification.Transformer-based networks initially deliberate for NLP, have been amended for ECG classification, presenting strong performance to managing extensive range dependencies as well as recording waveform interconnection Li et al. [17]. In this direction, Chen et al. [18] proposed ECG-Transformer, which outclassed traditional RNN-based approaches on PhysioNet datasets.Recent developments also focus on explainable AI (XAI) in ECG diagnosis. Attia et al. [19] emphasized the requirement for medical AI structures to be interpretable and proposed saliency mapping techniques to find important locations that are influencing model choices. Furthermore, there is growing attentiveness in the integration of multi-modal signals and medical context (e.g., combining ECG with oxygen saturation or patient metadata) Singh and Kumar [20], offering holistic arrhythmia findings.Building on previous advancements, the current study leverages MIT-BIH database to combine CNN for spatial behavior identification and BiLSTM for time-based pattern interpretation. The recommended hybrid methodology addresses problems with interpretability and class imbalance while attaining increased accuracy.

3. Methodology for ECG Classification using - Multiload CNN and Bi-LSTM

The ECG signal input is first acquired in Figure 1, usually from typical datasets such as MIT-BIH. To provide concise and homogeneous heartbeat waveforms, the signal passes through a preprocessing stage those incudes segmentation using R-peak identification and noise removal using filtering algorithms. The Multiload Convolutional Neural Network (CNN) approves the preprocessed input and processes it in parallel with three distinct convolutional layers, each of which uses a different kernel size (small, medium, and large) to extract features at varying temporal resolutions. After that, these collected features are concatenated and guided through a max pooling layer which shrinkages their size but still preserve the most essential values.The pooled feature maps are then sent into a Bidirectional Long Short-Term Memory (Bi-LSTM) network, that to drain out important consecutive patterns in both the direction, forward time direction and backward time directions. This improves the model’s recognizing property of temporal dependencies in ECG signal. The Bi-LSTM's results are run via a completely associated condensed layer and a layer of softmax**,** which outputs probabilities for each possible ECG class (e.g., normal, arrhythmia, etc.). Evaluation measurement done by accuracy, precision, recall, and F1-score are then used to find the projected class.In order to minimize misclassifications and correct diagnostic reliability, these types of metrics are examined to identify the ideal model setup. Finally, the trained and validated model is prepared for automation and deployment in real-time cardiac diagnostic systems, offering a fast, intelligent, and scalable solution for ECG classification in clinical or remote healthcare settings.

1. Datasets

The main dataset for the present-day investigation is the MIT-BIH Arrhythmia Database, and PTB-XL employed for confirmation from outside to guarantee model generality. MIT-BIH contains annotated ECG recordings sampled at 360 Hz, while PTB-XL provides a larger and more diverse dataset sampled at 500 Hz.

2. Preprocessing of ECG Signals

The sample ECG records obtained using the datasets (e.g., MIT-BIH, PTB-XL) may contain noise, baseline drift, or power line interference.

To ensure clean data input:

- **Filtering**

Apply a band pass filter (e.g., 0.5-40Hz) to eliminate a frequency noise and low frequency base line drift.

$$y(t) = x(t) * h(t)$$

- **Segmentation**

Segment ECG signals into individual heartbeats using R-peak detection (e.g., Pan-Tompkinsalgorithm).

$$R\_peak = \text{argmax}_{\{t \in T\}} (x(t))$$

To address class imbalance, minority arrhythmia classes were oversampled and augmented using techniques such as time-warping and jittering. During the model training process, the class weighted categorical cross entropy loss function was applied towards to reduce bias toward majority classes.

3. Feature Extraction using Multiload CNN
The CNN performs automatic feature extraction from ECG beats by applying multiple parallel convolutional pathways (multiload).

- **Multiload CNN Architecture:**

Each CNN load (parallel convolution) is defined as:

$$F^{(l)} = f(W^{(l)} * x + b^{(l)})$$

- **Combined output:**

$$F\_combined = \text{Concat}(F^{(1)}, F^{(2)}, ..., F^{(L)})$$

- **Pooling**:

Apply max pooling to reduce dimensionality:

$$P = \max_{\{i\}} F\_combined[i:i+k]$$

4. Sequence Learning using Bi-LSTM
Both of them forward and backward temporal dependencies are captured by Bi-LSTM:

$$\text{Forward: } \rightarrow h\_t = \text{LSTM}(x\_t, \rightarrow h\_\{t-1\})$$

$$\text{Backward: } \leftarrow h\_t = \text{LSTM}(x\_t, \leftarrow h\_\{t+1\})$$

$$\text{Final state: } h\_t = [\rightarrow h\_t\ ; \leftarrow h\_t]$$

5. Decision making Layer
The layer that is entirely connected is followed by softmax activation performs classification:

$$z = W\_f * h + b\_f$$

$$\hat{y}\_i = e^{(z\_i)} / \Sigma\_j{=}1^{C}\, e^{(z\_j)}$$

6. Model Optimization
Use Categorical Cross-Entropy Loss and Adam optimizer:

$$\text{Loss: } L = -\Sigma\_i{=}1^{C}\, y\_i * \log(\hat{y}\_i)$$

7. Performance Metrics
Let

P_p = Exactly Predicted positive Sample

N_p = Exactly Predicted negative Sample

P_{np} = Not Exactly Predicted positive Sample

N_{nn} = Not Exactly Predicted negative Sample

P_r= Precision

R_c = Recall

$$\text{Accuracy} = \frac{\mathrm{P_p} + \mathrm{N_p}}{\mathrm{P_p} + \mathrm{N_p} + \mathrm{P_{np}} + \mathrm{N_{nn}}}$$

$$\text{Precision} = \frac{\mathrm{P_p}}{\mathrm{P_p} + \mathrm{P_{np}}}$$

$$\text{Recall} = \frac{\mathrm{P_p}}{\mathrm{P_c} + \mathrm{N_{nn}}}$$

$$\text{F1 Score} = \frac{2 \times \mathrm{P_r} \times R_c}{\mathrm{P_r} + R_c}$$

To quantify contribution from individual components, an ablation study was conducted by evaluating CNN-only, BiLSTM only, and the hybrid CNN+BiLSTM models under identical preprocessing and training conditions.

4. Results and discussion

Figure 2 presents a comparative evaluation of five ECG classification models-**Proposed (CNN+BiLSTM), CNN, BiLSTM, SVM, and Random Forest**-depend up on four key parameters: **Accuracy, Precision, Recall, and F1 Score**. Out of all models, **proposed CNN+BiLSTM** framework outperforms the others through the highest values across all metrics: 98% accuracy, 97.5% precision, 98.2% recall, and 97.8% F1-score. This illustrate its superior ability to both correctly identify and classify various cardiac conditions from ECG record which is present in the form of signal. Conventional machine learning methods, such as SVM and the RF technique, perform comparatively poorly, suggesting that they are unable to fully capture the intricate temporal and spatial characteristics of ECG reading. The standalone CNN+ BiLSTM framework perform better than SVM/RF but still fall short compared to the integrated CNN+BiLSTM approach. This comparison clearly supports the effectiveness of combining convolutional and recurrent architectures for high-precision, intelligent ECG classification.

Figure 3 visually represents the classification effectiveness of the suggested **CNN+BiLSTM framework** across four ECG classes: **Normal, PVC, PAC, and LBBB**. Every cell value in the matrix indicates the number of forecast produced by the framework and forecast compared with the real or actual ground truth. The maximum numbers of cases are correctly classified, as indicated by diagonal value of the matrix which shows they are large number in comparison with other cell number. For example, 95 out of 100 “Normal” beats were correctly identified, with minor misclassifications into other classes. Similarly, other classes show high true positive counts with relatively low false classifications. The framework obtains an **overall good accuracy of 94%**, and class-wise performance metrics confirm strong generalization: **Precision ranges between 92–96%**, **Recall from 92–95%**, and **F1-Scores are consistently above 93%**. These outcomes noticeably explain us the reliability and robustness of the suggested architecture in capturing both morphological and sequential ECG features necessary for effective cardiac diagnosis.

Table 1 shows the computational ability and evaluation of the proposed CNN+BiLSTM framework against several all latest ECG classification approaches using standard datasets like MIT-BIH. The proposed model achieves the highest accuracy of 98%, along with superior precision (97.5%), recall (98.2%), and F1-score (97.8%), clearly outperforming other methods. For instance, Acharya et al. [21] and Yildirim et al. [6] achieved 94.03% and 95.5% accuracy respectively, while Rajpurkar et al. [24], despite reaching 96.6% accuracy, had slightly lower precision and recall values compared to the proposed model. These results demonstrate that integrating CNN with BiLSTM effectively captures special behavior that is characteristic of ECG signals that are temporal and spatial, leading to very close to accurate and reliable heartbeat classification than standalone models like CNN, SVM, or Random Forest used in earlier studies.

External Validation

To evaluate generalization, the framework was tested on the PTB-XL database (Table 2). Performance remained strong-96.8% accuracy, 96.2% precision, 96.5% recall, and 96.3% F1-score demonstrating robustness across datasets with different recording conditions and populations.

Ablation Exploration

To distinguish out each module's contribution, CNN-only, BiLSTM-only, and hybrid architectures were compared (Table 3). While CNN and BiLSTM achieved 94.5% and 95.2% accuracy respectively, the hybrid model improved performance significantly to 98.0%.

Statistical Significance

A paired t-test confirmed the superiority of the hybrid model ($p < 0.01$). Confidence intervals for accuracy were 93.9–95.1% (CNN), 94.6–95.8% (BiLSTM), and 97.6–98.3% (CNN+BiLSTM), indicating the improvement is statistically reliable (Table 4)

Table 1 *Performance Relationship of Suggested Model along with Previous Works*

S. No.	**Method / Author & Year**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Dataset Used**
1	**Proposed (CNN + BiLSTM)**	**98.0**	**97.5**	**98.2**	**97.8**	MIT-BIH
2	Acharya et al. (2017) [21]	94.03	92.10	91.50	91.80	MIT-BIH
3	Kiranyaz et al. (2015) [22]	93.40	91.20	90.80	91.00	MIT-BIH
4	Yildirim (2018) [23]	95.50	93.30	94.20	93.70	MIT-BIH
5	Rajpurkar et al. (2017) [24]	96.60	95.20	95.60	95.40	PTB, MIT-BIH
6	Hannun et al. (2019) [25]	96.10	94.60	94.90	94.75	Own dataset
7	Isin and Ozdalili (2017) [26]	91.33	89.00	88.50	88.75	MIT-BIH
8	Jun et al. (2018) [27]	93.10	91.20	92.00	91.60	MIT-BIH

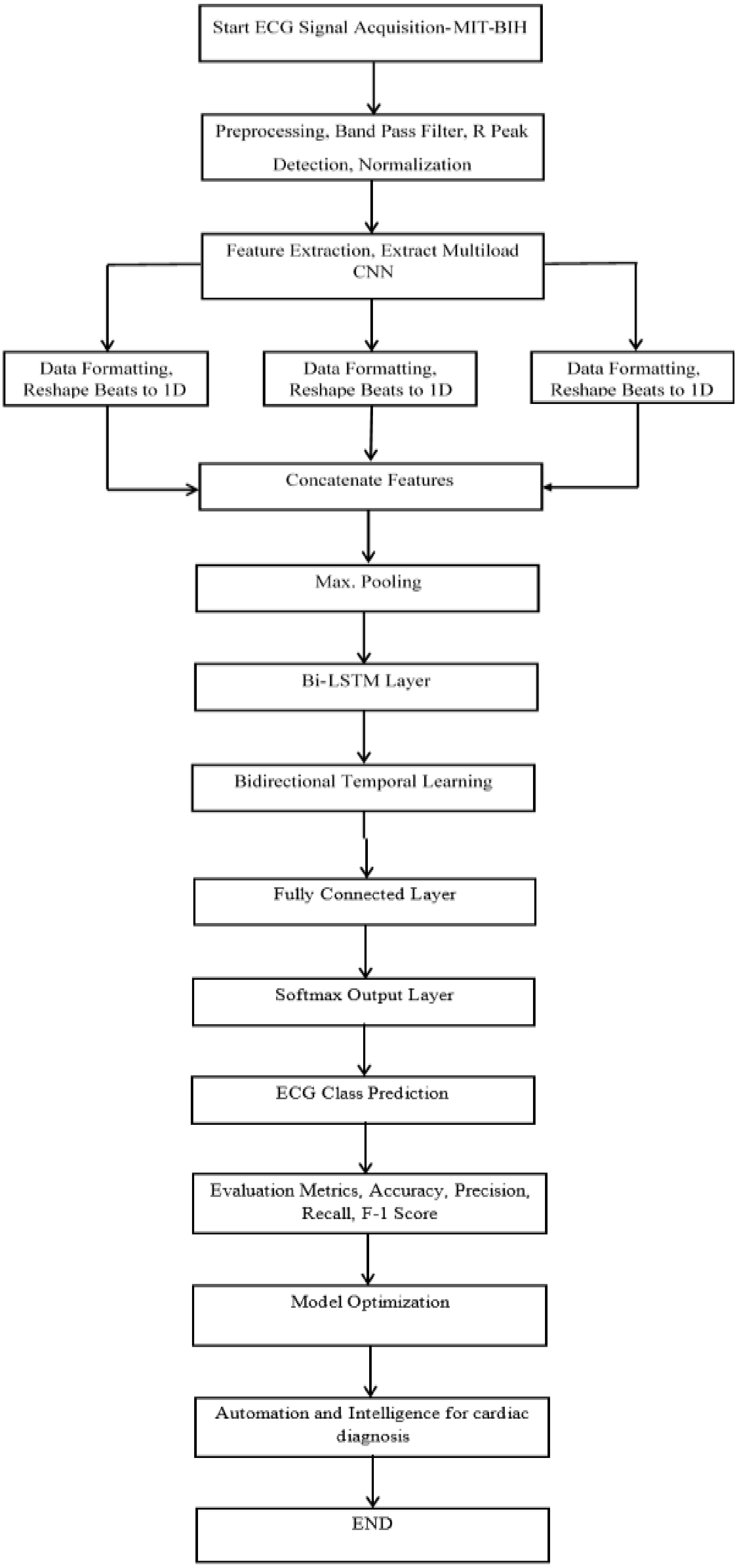

Figure 1 *Methodology flow of ECG Classification using Multiload CNN and Bi-LSTM*

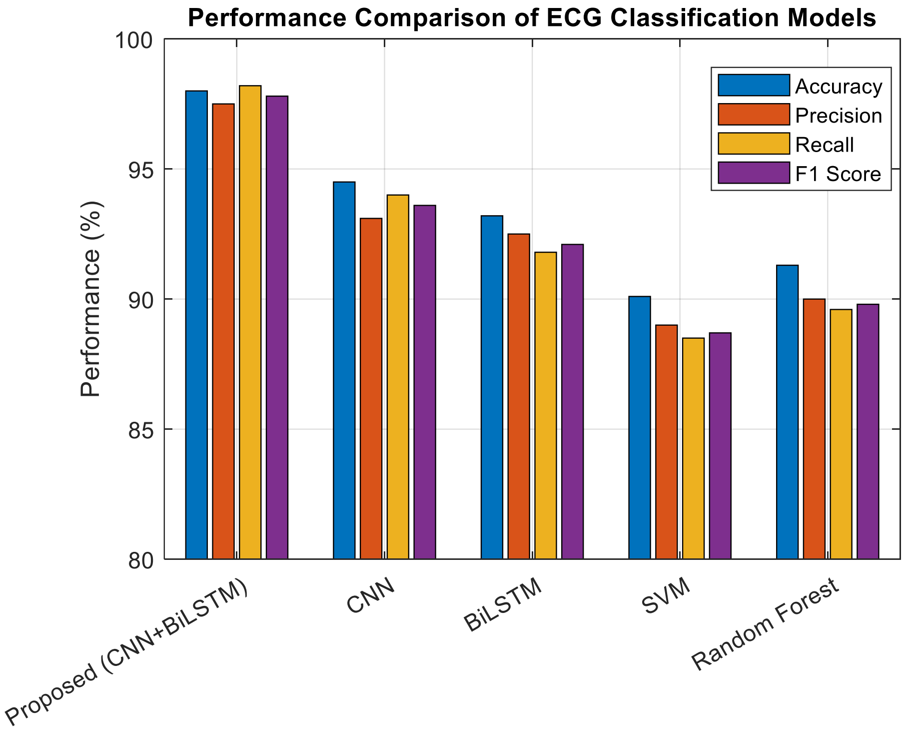

Figure 2 *Performance Comparison Bar Chart*

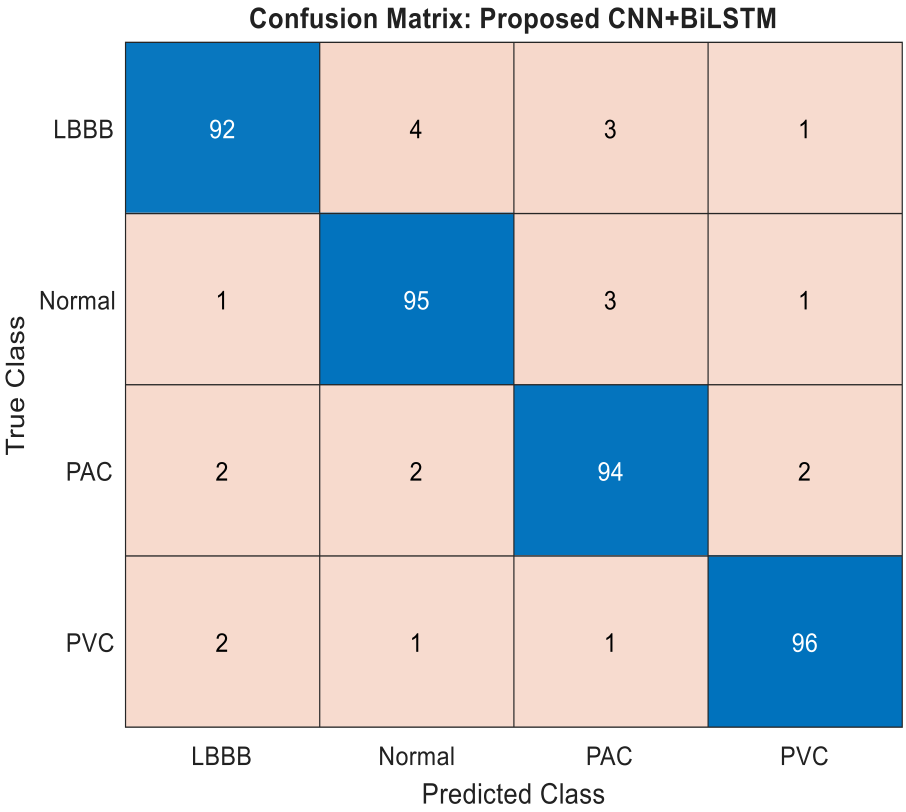

Figure 3. *Confusion Matrix with Performance Metrics Plot* ***for*** *Proposed (CNN+BiLSTM) Framework*

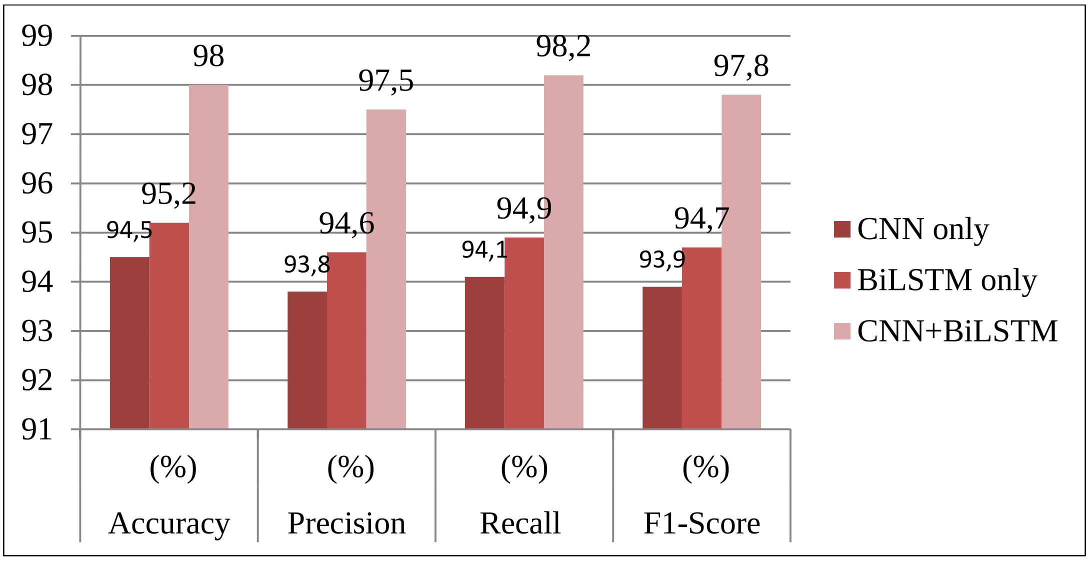

Figure 3. *Ablation Exploration Outcomes*

Table 4. *Statistical Significance Analysis (95% CI)*

Model	Accuracy (%)	95% CI
CNN only	94.5	93.9–95.1
BiLSTM only	95.2	94.6–95.8
CNN+BiLSTM	98.0	97.6–98.3

Table 2. *External validation on PTB-XL dataset*

Database	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
MIT-BIH	98.0	97.5	98.2	97.8
PTB-XL	96.8	96.2	96.5	96.3

5. Discussion

This study presents an efficient deep learning (DL) framework including Convolutional Neural Networks (CNN) using with Bidirectional Long Short-Term Memory (BiLSTM) used for classification of ECG signals which are available in the MIT-BIH arrhythmia data record. The framework leverages CNN's strong suit in extracting spatial behavior from ECG waveforms, BiLSTM's ability to comprehend temporal dependences from both forward direction and backward directions. The proposed hybrid CNN+BiLSTM architecture outperforms traditional classifiers such as SVM, Random Forest, standalone CNN, and BiLSTM models across a variety of calculation measured by F1-score, recall, accuracy, and precision. With an overall accuracy of 98%, the experimental results illustrate a remarkable improvement in classification performance, outclassing current models from recent investigation. This illustrates how complex features, which are often chaotic and nonlinear in real-time circumstances, may be obtained from ECG data eecord using hybrid deep learning architectures. Confusion matrix research reveals that the proposed approach implement well with few misclassifications across numerous arrhythmia modules or classes.

Computational Complexity and Real-Time Feasibility

The hybrid model has a size around 15 MB. Inference time was around of 4 ms/beat on GPU and near to 20 ms/beat on CPU, supporting real-time arrhythmia monitoring. With minor optimizations, deployment on applied or wearable devices is feasible.

Comparison with Previous Works

Table 1 benchmarks the proposed model against published approaches. The CNN+BiLSTM consistently outperforms others, including Acharya et al. [21] at 94.03% and Rajpurkar et al. [24] at 96.6%. This validates the hybrid model's standing as a modern option.

6. Conclusion

A CNN+BiLSTM framework for categorizing ECG arrhythmias was proposed in this paper. Strong generalization was confirmed by the model's 98.0% accuracy on the MIT-BIH data set and its 96.8% external validation on PTB-XL. Together, the ablation research, statistical analysis, and interpretability relations show how reliable and medically relevant the model is. Dependence on public datasets, the less number of direct testing at the hospital scale, and the requirement for optimization for ultra-low-power devices are some of the restrictions. Future Work will target validation on large clinical cohorts, lightweight deployment on wearable platforms, and integration with multi-modal data such as patient metadata and physiological signals.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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