Bulletin of Electrical Engineering and Informatics
Vol. 15, No. 4, August 2026, pp. 3158~3168
ISSN: 2302-9285, DOI: 10.11591/eei.v15i4.10123

HybridArrhyNet: a CNN-BiLSTM framework with attention mechanism for robust arrhythmia classification from ECG signals

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Article Info

Article history:

Received Feb 21, 2025
Revised May 29, 2026
Accepted Jun 19, 2026

Keywords:

Arrhythmia detection
Artificial intelligence
Classification
Deep learning
Electrocardiogram data analytics
Hybrid deep learning attention mechanism

ABSTRACT

Arrhythmia classification is critical for the early diagnosis of cardiac disorders that may lead to sudden cardiac arrest, stroke, or heart failure. However, accurate detection from electrocardiogram (ECG) signals remains challenging due to noise, class imbalance, and the need to identify diagnostically important signal segments. This study presents HybridArrhyNet, a deep learning (DL) framework that integrates convolutional neural networks (CNNs), bidirectional long short-term memory (BiLSTM) networks, and an additive attention mechanism for robust arrhythmia classification. The CNN extracts spatial features from ECG signals, while the BiLSTM captures temporal dependencies in both forward and backward directions. The attention mechanism selectively emphasizes clinically relevant ECG segments, improving classification performance and interpretability. To address class imbalance, random oversampling and weighted cross-entropy loss are employed. The proposed model was evaluated on the MIT-BIH Arrhythmia Database containing over 100,000 annotated beats across five arrhythmia classes (N, S, V, F, and Q). Experimental results demonstrate superior performance, achieving 98.7% accuracy, 98.5% precision, 98.6% recall, and 98.5% F1-score. Ablation studies further confirm the effectiveness of each component, highlighting HybridArrhyNet as a reliable framework for automated arrhythmia detection.

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1. INTRODUCTION

In 2023, almost 19.2 million deaths were caused by cardiovascular diseases (CVDs), nearly 60% of which were due to the most frequent types of these diseases: ischaemic heart disease and strokes, or 60% of all global deaths, were attributable to CVDs. Ischaemic heart disease and strokes were the most common types of CVDs, accounting for almost 60% of all cardiovascular deaths. In the past 30 years, mortality rate has risen from 13.1 million in 1990, highlighting the need to effectively prevent, detect and treat CVDs early. Cardiac arrhythmia (abnormal heart rhythm or heart's electrical system) is one of the most clinically relevant disorders among these, as it may cause stroke, heart failure or sudden cardiac death. In 2021, there were approximately 52.55 million individuals who had atrial fibrillation (AF) in the world and this is projected to rise further by 2050. Furthermore, ventricular arrhythmias also play a significant role in sudden cardiac death, making early and precise detection of arrhythmias important. Electrocardiogram (ECG) is the method used most commonly to monitor the electrical activity of the heart and to diagnose arrhythmias without having to do an invasive procedure. But the manual analysis of ECG recordings is time-consuming, relies on clinical experience and is prone to inter-observation variation, especially in the interpretation of long-term ECG recordings. The limitations have spurred the development of automated computer-aided diagnosis systems which can classify arrhythmia in a fast, accurate, repeatable manner. These systems can help ease the burden of diagnosis on clinicians and enhance the efficiency and accuracy of clinical decision making.

Deep learning (DL) has emerged as a potential and popular method for automated ECG analysis in recent years. In recent years, convolutional neural networks (CNNs) have shown remarkable success for learning discriminative spatial features directly from the ECG waveforms using no handcrafted feature engineering [1]. Similarly, long short term memory (LSTM) networks are capable of learning time-dependent connections in sequential ECG signals which is appropriate for the analysis of rhythm [2]. In recent years, hybrid DL architectures, attention mechanisms, and advanced optimization techniques have emerged as promising avenues for enhancing the accuracy, robustness, and feature representation of arrhythmia detection in ECG signals, as detailed in [3]–[10]. These methods have been able to significantly outperform traditional machine learning methods by directly learning hierarchical representations from raw ECG signals. Yet there are a number of hurdles to overcome. Baseline wander, muscle artefacts, and power-line noise are usually present in the ECG signals and affect the quality of the signal and the classification accuracy. In addition, public ECG datasets are highly class imbalanced, with the "normal" class dominating and the abnormal categories of heartbeat being far less common, leading to poor performance of many models on minority classes. Current methods are also largely limited to either temporal sequence modelling or spatial feature extraction and do not take full advantage of the complementary information that can be gained from ECG signals. This motivates the research to obtain good classification from many different types of arrhythmia, and yet preserve good performance in the presence of noise. Hence, the problem of obtaining robust classification for various types of arrhythmia and yet maintaining good performance in the presence of noise is an open research challenge.

To overcome these disadvantages, this paper suggests a hybrid DL framework of CNN-based spatial feature extraction, bidirectional long short-term memory (BiLSTM) for temporal dependency modelling and an additive attention mechanism for selectively focusing on the ECG segments that are diagnostic. In addition, the proposed framework uses cross-entropy loss with weights and random oversampling to mitigate the effect of class imbalance. Experimental testing on the MIT-BIH Arrhythmia Database shows that HybridArrhyNet offers superior classification accuracy and robustness, offering potential for automated ECG classification and clinical decision support.

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 presents the proposed method. Section 4 describes the experimental results. Section 5 discusses the findings and section 6 concludes the paper.

2. RELATED WORK

The literature review explores existing DL-based methods for arrhythmia detection, highlighting their strengths and limitations. A DL ECG model was proposed by Ayano *et al.* [1] with high accuracy and easily understandable properties in an attempt to improve diagnostic dependability and accuracy. Din *et al.* [2] provided a CNN-LSTM-Transformer model that they hope will increase the accuracy of ECG-based arrhythmia diagnosis; nevertheless, processing and classification limitations plague it. Qu *et al.* [3] introduced HQ-DCGAN, a method for producing ECG data that increases classification accuracy but has issues with the efficiency and quality of the generated quantum data. Al-Shammary *et al.* [4], the study's Chi-square distance-based classifier, which detects arrhythmias with 98% accuracy, is limited by its reliance on feature selection and optimization. Narotamo *et al.* [5] study results show that 1D ECG networks perform better for classifying CVD than 2D and multimodal approaches, indicating the need for more research on class imbalance and better picture quality.

Bechinia *et al.* [6] addressed class imbalance using ACGAN and achieved reasonable accuracy in ECG arrhythmia diagnosis with a DL model that combines LC-CNN and MobileNet-V2 identification. Upcoming projects will examine sophisticated models, test on various datasets, and do real-time monitoring. Sharma *et al.* [7] presented a hybrid technique for ECG classification that combines SVM-FFBPNN, CS, and DWT, achieving 98.53% accuracy. Additional arrhythmia classes will be included in future development. Zhou and Tan [8] presented the CNN-ELM technique, which achieved an accuracy of 97.50% in ECG categorization. Subsequent research endeavors should focus on enhancing real-time detection and managing signal noise. Sabut *et al.* [9] improved VTA prediction and AED efficiency by creating a 99.2% accurate DNN-based technique for ventricular tachyarrhythmia detection. Future research might simplify the calculations and improve accuracy. Petmezas *et al.* [10] proposed a CNN-LSTM model with a concentrated loss for accurate AF detection, achieving high sensitivity and specificity. Future studies might focus on improving accuracy and addressing computer constraints.

Kaspal *et al.* [11] identify SCD; the paper presents a CNN-RCN model with dropout regularization, improving accuracy to 93.24% and cutting processing time. Time constraints and residual accuracy might be addressed in further studies. A DL model achieving 99.75% accuracy for arrhythmia detection using discrete wavelet transform (DWT), empirical mode decomposition (EMD), and variational mode decomposition (VMD) was proposed by Sahoo *et al.* [12]. More arrhythmia types and a wider variety of data will be tested in future research. Essa and Xie [13] proposed a DL approach that uses multiple models to classify ECG arrhythmias, achieving 95.81% accuracy. Further research will examine larger datasets and a greater variety of arrhythmias. In Fan *et al.* [14], which separates AF from noisy mobile ECG data, the FRM-CNN model achieves an accuracy of 87.22%. Future research will tackle the constraints associated with signal classification. Hammad *et al.* [15] proposed a DL-genetic algorithm model for ECG-based CVD diagnosis that achieves 98% accuracy. The subsequent development will include integrating BiLSTM.

Ning *et al.* [16] described a hybrid DL model that uses ECG data to detect CHF with 99.93% accuracy. Among the following challenges are improving model robustness and testing shorter ECG data. Pławiak and Acharya [17] proposed a novel three-layer genetic ensemble classifier for ECG data, achieving 99.37% accuracy. Subsequent studies will concentrate on improving algorithms and assessing more signals. Sharma *et al.* [18] presented a rhythm-based ECG analysis technique that uses FB expansion and LSTM to detect arrhythmias with 90.07% accuracy. Testing with larger datasets and different basis functions will be part of future development. Hirsch *et al.* [19] related atrial activity to the RR interval; this work proposes a 97.6% precise real-time method for AF detection. Further studies will expand the feature set and adjust each person's ECG rating. Mahmud *et al.* [20] presented DeepArrNet, a CNN model that uses cutting-edge convolution methods to identify arrhythmias. Upcoming projects will concentrate on improving the application and performance.

Wang *et al.* [21] presented DMSFNet, a CNN that improves arrhythmia identification for multi-scale ECG analysis. Its uses will grow in the future. Yildirim *et al.* [22] proposed a high-accuracy DNN model for arrhythmia detection, but it requires complex hardware; future work will explore multi-task learning. Wang [23] presented an 11-layer CNN-MENN model for very accurate AF detection. Further integration of ENN structures is a future task. Peimankar and Puthusserypady [24] use the DENS-ECG model to achieve high sensitivity and accuracy in real-time heartbeat segmentation. The next endeavor will include a more thorough application and evaluation. Recent state-of-the-art techniques incorporate attention mechanisms to examine diagnostically significant ECG segments directly and have shown improved performance and interpretability. Although attention-based models like HARDC have demonstrated exemplary performance on the MIT-BIH dataset, they continue to struggle with noisy data and the need for more robust classification of Q and F beats, which constitute a minority class compared to N and S heartbeats. Based on these improvements, HybridArrhyNet combines CNN and BiLSTM with a novel attention-based optimization method to enhance spatial-temporal feature learning, address class imbalance, and facilitate focus on key ECG regions. This work fills the void between current techniques and the necessity for a scalable, dependable, and feasible clinical real-time arrhythmia detection method.

3. PROPOSED FRAMEWORK

3.1. System overview

Our preprocessing pipeline proceeds in a carefully sequenced order to maintain signal quality and ensure uniformity across recordings. The raw continuous ECG signal is then subjected to several preprocessing steps, including the application of a bandpass filter (0.5–40 Hz) to eliminate baseline drift and high-frequency noise artefacts. Min-max normalization is also applied to the continuous filtered signal as a single window before segmentation, with fixed-length window sizes that eliminate amplitude bias and amplitude gain between patients and setups (MIT-BIH). Third, heartbeat segmentation is performed on each normalized signal using R-peak detection to extract a fixed-length 128-sample window centered on the detected beat. The ordering here guarantees that normalization applies globally to the whole signal and avoids the inconsistency of beat segments being normalized independently. In the preprocessing step (Figure 1), we first remove noise using bandpass filtering, then normalize the entire continuous signal to zero to one using min-max normalization, and finally segment heartbeats using R-peak detection.

After that, preprocessing involves extracting features, as shown in Figure 1, where the essential features of the ECG signals' time and frequency domains are obtained. Time-domain features are extracted from RR intervals; frequency-domain transformations, such as wavelet analysis, separate arrhythmia patterns. The extracted features then serve as input to the hybrid DL model, which is initialized with a convolutional layer that automatically derives spatial representations of the signals. The BiLSTM units then take the learned feature maps as input and capture temporal dependencies in the ECG waveforms by learning not only from previous sequences but also from forward sequences.

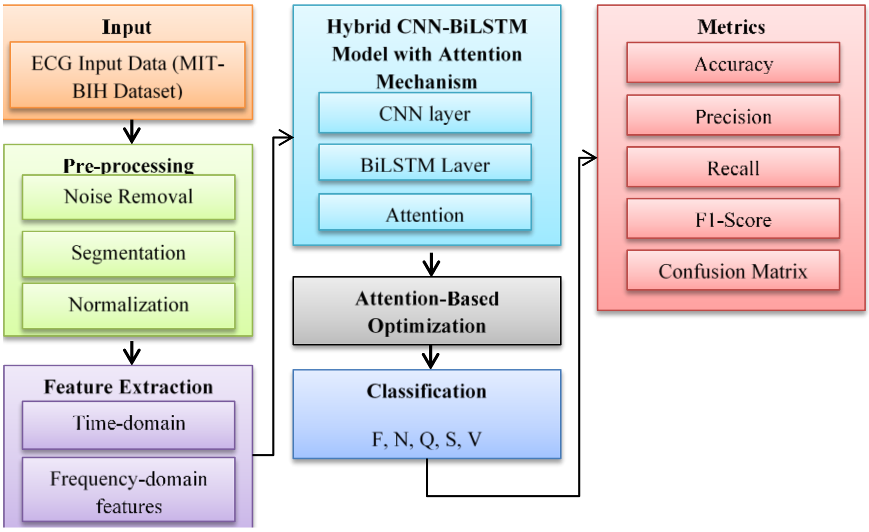

Figure 1. Overview of the proposed hybrid DL framework for arrhythmia detection in ECG signals

3.2. Proposed deep learning model

HybridArrhyNet is a hybrid DL model, comprising a CNN for spatial feature extraction, a BiLSTM for temporally dependent ECG modelling, and an attention mechanism for selective focusing on ECG segments that are diagnostically relevant for arrhythmia classification. Processes ECG signals from the MIT-BIH Arrhythmia Database, processing each ECG signal sequentially and representing distinct features at every step that differentiate arrhythmia types. In this work, we present HybridArrhyNet—a model that combines spatial and sequential learning to achieve higher accuracy and robustness in ECG-based arrhythmia classification.

In Figure 2, for signal quality and consistency, the preprocessing pipeline follows a structured three-step sequence. First, ECG data were filtered with a bandpass filter (0.5–40 Hz) to remove baseline drift and high-frequency noise. Second, min-max normalization was applied to the entire continuous filtered ECG signal using a consistent window length, before any segmentation. This global normalization step is essential to compensate for amplitude bias and signal-gain differences arising from variations in patient physiology, electrode placement, and acquisition hardware across the 48 recordings in the MIT-BIH Arrhythmia Database. Third, heartbeat segmentation was performed on the normalized signal using an R-peak detection algorithm to extract fixed-length 128-sample windows centered on each detected beat. This correct ordering — filter → normalize → segment — ensures uniform feature scaling across all extracted segments and improves the model's ability to generalize across diverse recording conditions. A key contribution of HybridArrhyNet is its attention-based optimisation mechanism, which dynamically assigns importance weights to individual BiLSTM output timesteps, enabling the model to selectively focus on diagnostically critical regions of the ECG signal while suppressing irrelevant or noisy segments. Formally, let $\mathrm{H} = \{\mathrm{h}_1, \mathrm{h}_2, \dots, \mathrm{h}_\mathrm{T}\}$ represent the sequence of BiLSTM hidden states, where $\mathrm{h}_\mathrm{t} \in \mathbb{R}^{2\mathrm{d}}$ is the concatenated forward and backward hidden state at timestep t, and d is the number of hidden units per direction.
The attention score for each timestep is computed using a learnable weight vector* $\mathrm{W}_\mathrm{a} \in \mathbb{R}^{2\mathrm{d}}$ and bias b_a:

$$e_t = tanh\ (W_a h_t + b_a)$$

These raw scores are then normalized using a SoftMax function to produce attention weights α_t that sum to 1 across all timesteps:

$$\alpha_t = \frac{exp\ (e_t)}{\sum_{j=1}^{T} exp\ (e_j)}$$

The final context vector C is computed as the weighted sum of all BiLSTM hidden states:

$C = \sum_{t=1}^{T} \alpha_t \cdot h_t$

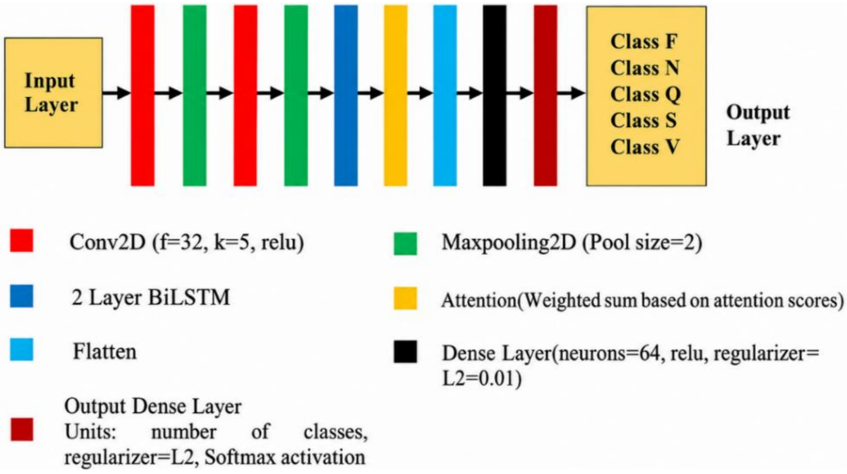

Figure 2. Architectural overview of HybridArrhyNet for arrhythmia detection

The resulting context vector acts as a condensed, attention-weighted feature subset of the entire ECG segment, highlighting timesteps where arrhythmic signatures such as abnormal QRS complexes, irregularities in RR intervals, and T-wave abnormalities are most pronounced. This context vector is then fed into the fully connected classification layers. The model comprises two key features: an attention mechanism that provides two main advantages in this framework. First, an obvious consequence is the enhancement of classification accuracy by guiding learning towards the most informative ECG regions, especially for minority arrhythmia classes such as F and Q beats, which convey subtle morphological differences. Second, it further improves clinical interpretability by offering a heatmap of attention weights across the 12-lead ECG signal, enabling clinicians to pinpoint which segments strongly influenced the model's classification of a patient into various life-threatening arrhythmias. This helps the model focus on regions of the ECG that are particularly informative for diagnosis, thereby minimizing irrelevant variation. The learned representations are passed through fully connected layers with L2 regularization, followed by a SoftMax output layer for arrhythmia classification.

3.3. Proposed algorithm

CNN, BiLSTM, and an attention mechanism are used in HybridArrhyNet, a DL-based hybrid arrhythmia detection technique for ECG signals. Extracting features in spatial and temporal domains while optimizing more significant segments using the attention-based technique. Doing so improves classification performance, minimizes false positives, and is thus applicable to typical clinical and healthcare scenarios. HybridArrhyNet is a well-defined, end-to-end DL model that detects and classifies arrhythmias from ECG signals. The model receives input from the MIT-BIH Arrhythmia Database, which consists of raw ECG signals, and should first undergo preprocessing steps to improve signal quality. The signals are filtered with a bandpass filter to eliminate noise, then segmented into fixed-length windows. Normalization standardizes the samples to ensure uniformity before feature extraction.

Algorithm 1. Hybrid learning and attention-based optimization for arrhythmia detection and classification (HLAO-ADC)
Input:
ECG signals X from MIT-BIH Arrhythmia Database with labels Y.
Output:
Predicted class $\hat{y}$.
Steps:
1. **Preprocessing**
   Apply bandpass filtering, segment ECG signals, and normalize values.
2. **Feature extraction (CNN layer)**
   Extract spatial features using convolution:
   $F_i = \sigma(W_i * X + b_i)$

Apply max-pooling for dimensionality reduction.

3. **Temporal learning (BiLSTM layer)**
   Compute bidirectional hidden states:
   $H_t = \overrightarrow{h_t} \oplus \overleftarrow{h_t}$
4. **Attention mechanism**
   Compute attention scores:
   $\alpha_t = \frac{exp(W_a H_t)}{\sum_{j-1}^{T} exp(W_a H_j)}$

Compute context vector:
$C = \sum_{t-1}^{T} \alpha_t H_t$

5. **Classification**
   Predict arrhythmia class:
   $\hat{y} = softmax(W_o C + b_o)$
6. **Training**
   Optimize cross-entropy loss:
   $L = -\sum_{i-1}^{N} y_i \log(\hat{y}_i)$

Update parameters using Adam optimizer.

7. **Evaluation**
   Compute accuracy, precision, recall, and F1-score.

The HLAO-ADC algorithm operates through seven sequential steps as follows:

a. Step 1, the raw ECG signal undergoes bandpass filtering (0.5–40 Hz) for noise removal, followed by min-max normalization applied to the full continuous signal, and then segmentation into fixed-length 128-sample windows using R-peak detection.
b. Step 2, spatial features are extracted via the CNN convolution operation $F_i = \sigma(W_i * X + b_i)$, where X is the input ECG segment, W_i and b_i are the learnable filter weights and bias of the i-th convolutional filter, σ denotes the rectified linear unit (ReLU) activation function, and F_i is the resulting feature map, followed by max-pooling for dimensionality reduction.
c. Step 3, the BiLSTM computes bidirectional hidden states $H_t = \overrightarrow{h_t} \oplus \overleftarrow{h_t}$, where $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ are the forward and backward hidden states respectively, $\oplus$ denotes concatenation, and $d = 64$ hidden units per direction, allowing the model to capture both past and future temporal context at each timestep.
d. Step 4, the attention mechanism first computes energy scores $e_t = \tanh(W_a h_t + b_a)$, where W_a and b_a are learnable attention weights and bias, then normalizes them into attention weights $\alpha_t = \frac{\exp(e_t)}{\sum_{j=1}^{T}\exp(e_j)}$, where T is the total number of timesteps and $\sum_{t=1}^{T} \alpha_t = 1$, and finally computes the context vector $C = \sum_{t=1}^{T} \alpha_t \cdot H_t$, which is an attention-weighted representation emphasizing diagnostically critical ECG regions such as abnormal QRS complexes and irregular RR intervals.
e. Step 5, the context vector C is passed through fully connected layers with L2 regularization ($\lambda = 0.01$) and classified using $\hat{y} = softmax(W_o C + b_o)$, where W_o and b_o are the output layer weights and bias, and $\hat{y}$ represents the predicted probability distribution over the five arrhythmia classes (N, S, V, F, and Q).
f. Step 6, the model is trained by minimizing the weighted cross-entropy loss $L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$, where N is the total number of training samples, y_i is the true class label, and $\hat{y}_i$ is the predicted probability, with parameters updated using the Adam optimizer (learning rate=0.001, batch size=32, 50 epochs, early stopping based on validation loss).
g. Step 7, model performance is evaluated using accuracy, precision, recall, and F1-score computed across all five arrhythmia classes.

3.4. Dataset details

MIT-BIH Arrhythmia Database—one of the well-known benchmark datasets for ECG-based arrhythmia detection models. MIT and the Beth Israel Hospital Arrhythmia Laboratory maintain the first data set, which includes 47 patients' 48 half-hour ambulatory ECG recordings. With a sampling frequency of 360 Hz and a resolution of 11 bits over a range of ±10 mV, recordings were made for samples that mainly consisted of inpatients and outpatients at the Beth Israel Deaconess Medical Center. The recording includes two-lead ECG signals, and the dataset provides more than 100000 annotated heartbeats classified into various arrhythmia types per American Heart Association (AHA) standards. This particular dataset comprises primarily unknown beats (Q), ventricular ectopic beats (V), supraventricular ectopic beats (S), fusion beats (F), and regular beats (N). Its equitable spread of common and rare arrhythmias makes it a critical resource for DL models for automatic ECG classification and clinical decision support systems. This database has been made available by PhysioNet and is easily accessible for research and clinical studies.

4. EXPERIMENTAL RESULTS

We conducted the experiments using the MIT-BIH Arrhythmia Database [25], a widely used benchmark dataset for ECG-based arrhythmia classification. The dataset contains segments of ECG recordings in different arrhythmic patterns (e.g., regular beats, premature beats, and other types), providing various heart conditions for evaluating the models. ECG signals accessible in the open domain were preprocessed through a well-defined pipeline to maintain signal quality and consistency. The raw continuous signals were filtered with a bandpass filter (0.5–40 Hz) to remove noise and artefacts. The filtered signal was then min-max normalized before segmenting into individual data points to amplitude-scale all 48 recordings in the dataset to the same scale, ensuring that inter-record variation is accounted for. We used normalized signals, then cut them into 128-sample windows centered on detected R peaks for feature extraction and model input.

4.1. Data analysis through exploration

The data analysis through exploration of the ECG signals of the MIT-BIH Arrhythmia Database is presented in this section. Exploratory data analysis (EDA) in a model is essential because we need to understand the characteristics and distribution of data before moving to model training.

The bar plot in Figure 3 shows the sample size after applying the oversampling method to increase representation of underrepresented groups. Each line on the x-axis indicates the number of samples, while each line on the y-axis denotes the classes (N, V, S, Q, and F). The bars indicate the number of samples in a class after oversampling, while the colors denote the class. From the chart, it can be seen that the proportion of minority classes is much higher than that of the majority class (N); this is due to the oversampling effect, which helps the machine learning models process this dataset more efficiently.

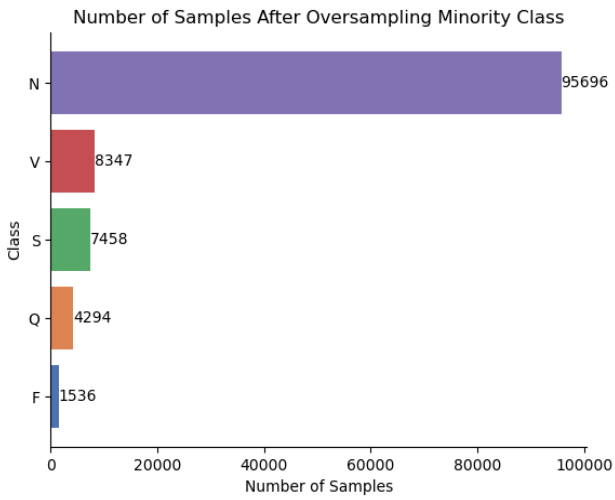

Figure 3. Number of samples after oversampling minority class

The two bar charts in Figure 4 compare the number of samples per class before and after oversampling. We have the number of samples on the x-axis and the various classifications on the y-axis. (N, V, S, Q, and F) The left chart shows the original sample distribution (class N has many more samples than any other class). The chart on the right compares this result; with oversampling applied, the minority classes are boosted to achieve a ratio similar to that of the majority class. No explanation is provided for the oversampling that is being done. Still, it is likely being used to tackle the class imbalance problem, which can benefit the performance of ML algorithms trained on this dataset.

4.2. Performance comparison

In this section, we provide a performance comparison between HybridArrhyNet and multiple baseline models, including CNN, LSTM, CNN-LSTM, and attention-based LSTM. The comparison evaluates the models' performance using key metrics such as accuracy, precision, recall, and F1-score. These results further support the effectiveness of HybridArrhyNet, as it outperforms existing methods in arrhythmia detection while also revealing the advantages of a hybrid approach over classical methods.

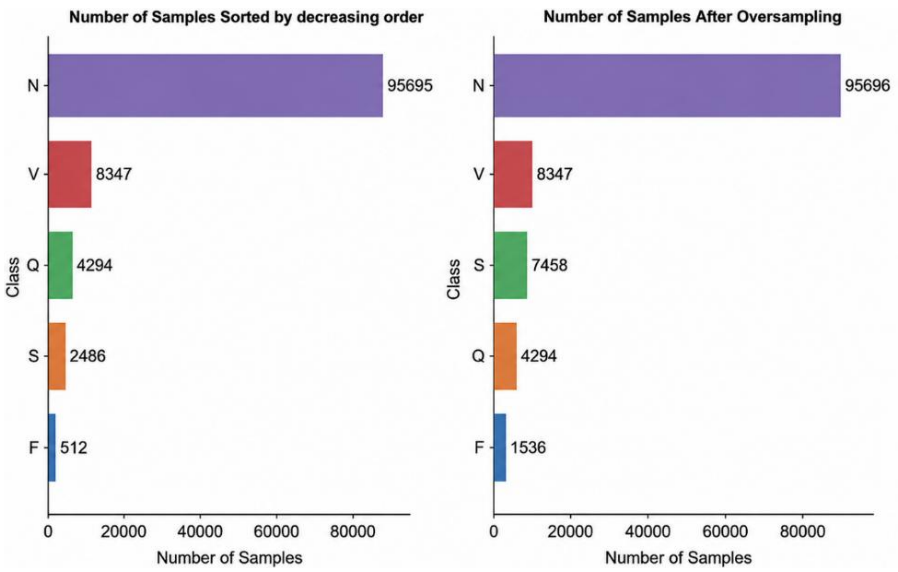

Figure 4. Number of samples sorted by decreasing order and number of samples after oversampling

In particular, the attention mechanism improves the model's ability to suppress false positives and negatives, which is crucial in clinical practice because mislabeling can have detrimental effects. Therefore, highlighting the sections of the first 6-lead ECG signals that are most relevant helps ensure that HybridArrhyNet maintains its performance across all available arrhythmia types, robustness to noise, and data variability. Overall, HybridArrhyNet is a more accurate and reliable model for real-world arrhythmia detection due to its improved feature learning from the hybrid architecture.

5. DISCUSSION

The accurate detection of arrhythmia from ECG signals plays a crucial role in early diagnosis and treatment of CVDs. The experimental results show that HybridArrhyNet is capable of effectively resolving major problems in automated ECG classification such as noisy signals, class imbalance and avoiding problems of capturing spatial and temporal characteristics. The proposed framework obtained a high classification accuracy of 98.7%, and high precision, recall, and F1-score results, which demonstrate the robustness of the proposed framework for arrhythmia detection. The synergies of the model parts are responsible for the enhanced performance. The CNN successfully extracts the spatial features of the ECG waveforms, and the BiLSTM extracts temporal features between the successive beats. Moreover, the attention mechanism is used to highlight the ECG segments that are diagnostic for the classification and suppress the segments that are not, thus improving the classification. This approach allows the model to learn more discriminative representation than individual DL architectures. The results also indicate better minority class recognition, especially Q and F beats, which are often impacted by class imbalance. Oversampling along with weighted cross-entropy loss led to a decrease in misclassification as well as an improvement in the performance of each class. The confusion matrix verifies that the proposed framework is balanced in all different categories of arrhythmias. Overall, HybridArrhyNet acts as a better baseline model than standard baseline models and emphasizes the benefits of incorporating spatial feature extraction, temporal modelling, and attention mechanisms to ensure accurate automated ECG interpretation and clinical decision support.

5.1. Limitations

While we obtain promising findings from this study, there are several limitations and other possible solutions to be considered to inform future work. First, the model was validated only on the MIT-BIH Arrhythmia Database, which does not fully capture the diversity of ECGs inheriting different clinical demographics, patient populations, and recording conditions; this limitation is addressable by validating HybridArrhyNet on multiple external datasets to rigorously analyze cross-population generalizability, such as the PhysioNet Challenge dataset, China Physiological Signal Challenge dataset, and European ST-T Database. Second, although this is a relatively large dataset, it is itself limited in the number of arrhythmia patterns, thereby limiting the model's generalizability to unseen or rare arrhythmia patterns. This could be tackled in the future by data augmentation with clinically realistic samples, e.g., via generative adversarial network (GAN)-based synthetic ECG generation. Third, the authors tried to deal with serious class imbalance by random oversampling and weighted cross-entropy loss between types, but this is too simplistic way to simulate the real clinical distribution of each type of arrhythmia, so that they may try more advanced types of oversampling techniques like synthetic minority over-sampling technique (SMOTE) or conditional GANs to create the minority class samples.

6. CONCLUSION

We propose a new hybrid DL-based approach for arrhythmia classification from ECG signals, termed HybridArrhyNet, consisting of a CNN to extract spatial features, a BiLSTM to model temporal dynamics, and an attention mechanism for selective feature weighting. An integrated model was developed that aims to solve the main problems of the ECG signal study: i) noise, ii) class imbalance, iii) class overlap, and iv) classification of rare types of arrhythmia (F and Q beats). In experiments on the MIT-BIH Arrhythmia Database, HybridArrhyNet achieved the highest performance over baseline models (CNN, LSTM, CNN-LSTM, and attention-based LSTM) with 98.7% accuracy, 98.5% precision, 98.6% recall, and 98.5% F1-score. The subsequent ablation results confirm that each architectural component contributes nontrivially and that the combination of CNN, BiLSTM, and attention layers is essential for stable performance.

From a clinical standpoint, fewer false-positive and false-negative predictions can help with more confident decision-making and the timely identification of high-risk patients. Interpretability is improved through the attention mechanism, which draws clinicians' attention to diagnostically important ECG sections and enhances trust in the model. It also holds promise for connecting to wearables and edge platforms for prolonged, real-time cardiac monitoring. However, the model was validated only on one dataset, so it may not generalize to heterogeneous populations. There are plans to validate the model across multiple external ECG datasets, extend it to different lead signals as they become available, and find ways to compress the model for deployment on small devices with limited computational resources. Further increases in transparency through integration with explainable AI methods like Grad-CAM and SHAP are also in the pipeline. In summary, HybridArrhyNet establishes a scalable, interpretable, and high-quality baseline for complicated ECG-based cardiac diagnosis systems.

FUNDING INFORMATION

No financial support was received by the authors in this research.

AUTHOR CONTRIBUTIONS STATEMENT

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

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

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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