A Light Weight Deep Learning based Technique for Patient-Specific ECG Beat Classification

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***Abstract*—An electrocardiogram (ECG) is an important medical tool in diagnosing different cardiac disorders. In general, the length of long-term ECG records is 24–48 hours, and it is not easy to analyse these records manually. Therefore, an intelligent computer-based automated tool is required to analyse these records. Deep learning methods have recently improved in identifying arrhythmias in complex ECG readings. Efficient usage of training data, complexity, and performance are the major challenges with deep learning algorithms. A combination of convolutional neural network (CNN) and bi-directional LSTMs (Bi-LSTMs) is proposed in this work for efficient training and classification. Additional training is made possible by bi-directional LSTMs (Bi-LSTMs) since they traverse the input data twice. Bi-LSTMs outperform standard unidirectional LSTMs because of their fixed sequence-to-sequence prediction and increased training capacity. The proposed work is validated on a standard, publicly available physionet arrhythmia database. The time required to detect the beat type by the proposed method is 0.52 (S). Experimental results reveal that the proposed method performs better than the techniques in the literature.**

***Index Terms*—Arrhythmia, Bi-LSTM, Cardiac Disorders, CNN, ECG, LSTM.**

I. Introduction

Electrocardiogram (ECG) is an efficient medical tool in recognising various cardiac disorders. An ECG is a quick and painless way to monitor a patient's heart electrical activity and rhythm. The electrical signals generated by the heart are detected using skin-attached sensors [1]. This test can investigate all signs of cardiac disorders like palpitations, dizziness, and shortness of breath. A series of ECGs are also recorded to monitor a person who has previously been diagnosed with a cardiac problem. In the medical field, three types of ECG data are used to find different heart rhythm problems. A Holter monitor is used to record the ECG signal from the patient for 24–48 hours. These long-term ECG records are termed ambulatory ECG records. The deviation of the ECG beat shape from its regular shape is known as arrhythmia [1]. A professional cardiologist can detect an arrhythmia by examining an ECG signal for heart rate, rhythm, or morphology abnormalities. Analysing long-term ECG records without an automated diagnostic tool is time-consuming. Many studies in the literature have proposed methods for automatically and reliably detecting arrhythmias in ECG signals. The Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) database is treated as benchmark dataset. This database contains 17 different classes. These 17 different types of sub-classes are categorized into 5 super classes named as non-ectopic (N), supraventricular ectopic (S), ventricular ectopic (V), fusion (F), and unknown(Q) beats. The detailed description of these beats are available in [2]. Earlier reported works [3], [4], [2] based on conventional signal processing and machine learning techniques was ineffective in detecting various types of ECG beats. The primary reason for this low effectiveness in classification is in-efficient feature extraction techniques. Majority of the earlier reported techniques are completely dependent on manual feature extraction to detect type of the ECG beat.

To overcome the issues mentioned above, deep learning-based techniques have been introduced recently for automatic feature extraction. If we provide sufficient computing power, deep learning models can easily train on very large datasets and classify various complex features. Chen *et al.* have proposed a serial connection of convolutional neural network (CNN) with memory element to identify different types of arrhythmias [5]. A deep residual network (ResNet) with ECG beat spectrogram technique is implemented in for detecting ECG beats [6]. Furthermore, one-dimensional CNN (1D CNN) [7], recurrent neural neural network (RNN) [8], and LSTM [9] have recently been used in ECG beat detection. Citelstm, proposed an LSTM-based auto-encoder approach to classify ECG beats with a performance accuracy of 99.45%. In [7], the 1D-CNN architecture is employed to categorise ECG beats with the fast Fourier transform (FFT) feature set. There are many ways to figure out the type of ECG beat in the literature, but they all have at least one of the following problems:

- Requirement of large training data.
- Over and under fitting problems with the tuned model.
- The existing models are not able to provide better accuracy for new unseen data.
- Requirement of more number of computations, and trainable parameters.

In order to address these issues, a simple CNN-Bi-linear LSTM (Bi-LSTM) network is proposed in this work. The

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primary contributions of the proposed work are:

- There is no feature extration needed.
- Less number of training beats are utilised to train the model.
- CNN-BiLSTM deep learning model is designed with less number of parameters to make it as light-weight.
- The proposed deep learning architecture is effecient in detecting crucial ECG beat types like S and V.

The remaining portion of this paper is organised as follows: The methodology utilised in ECG beat detection discussed in Section II, The performance of the proposed system is explained in Section III, the conclusion of the proposed approach is covered in Section IV.

II. Proposed Methodology

The genealised block diagram for ECG beat detection in this work is represented in Fig. 1. In proposed methodology section, the major steps for ECG beat classification:(i) pre-processing of the ECG signals, (ii) data separation for training and testing of the proposed deep learning model, and (iii) ECG beat classification using CNN-BiLSTM architecture are discussed. Effectiveness of the deep learning architecture is verified using the MIT-BIH dataset [10]. This database comprises 48 ECG recordings that are collected from 47 individuals. Every recording contains two lead data sets, MLII and V5. The sampling frequency of the each ECG record is 360 Hz. The database contains roughly 1,09,000 heartbeats, each tagged with one of sixteen possible annotations. Four records (102, 104, 107, and 217) do not have appropriate quality out of 48 ECG records. Because of this, certain files are not considered when calculating the proposed strategy's effectiveness.

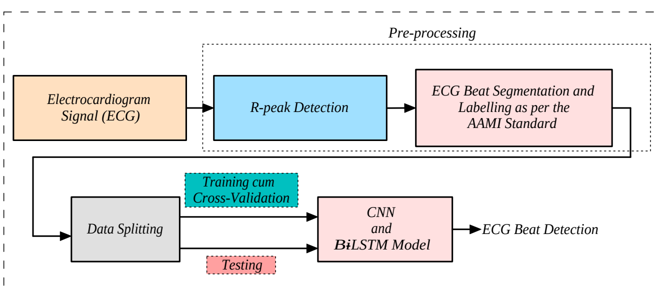


Fig. 1. Proposed methodology for ECG beat detection.

A. Pre-processing of the ECG signals

Filtering, R-peak detection, and beat segmentation is combindely known as pre-processing. The dataset can be directly applied to the deep learning models. Still, to get further accurate results, the ECG signal was denoised with the help of a discrete wavelet transformation (DWT). The basic equation for wavelet transformation, where a is the scaling and b is the transformation factors, is given as [10]:

$$\psi_{a,\tau}(t) = a^{-\frac{1}{2}} \psi\left(\frac{t-b}{a}\right), \quad a > 0, \tau \in R \tag{1}$$

$$W_f(a,\tau) = a^{-\frac{1}{2}} \int_{-\infty}^{+\infty} f(t) \psi\left(\frac{t-b}{a}\right) dt \tag{2}$$

Here $\psi_{a,\tau}(t)$ is the wavelet function. It is also called the mother function. $W_f(a,\tau)$ gives the wavelet coefficients.

There are seven major families of wavelets, symlet-4 (Sym4) has been used to denoise the input signal. The ECG signal is deconstructed as multi-scale components to denoise the input signal. The high-frequency wavelet coefficients that are noisy are then removed. The noise free signal is formed by recombining remaining wavelet coefficients. Pan-tompkins algorithm [8], is used to identify R-peak location. Segmented beats are labelled as per AAMI standard.

B. Data separation for training and testing of the proposed deep learning model

Testing, validation, and training are separated from the entire database. 15% of the data for training and the remaining 85% unknown data is used for testing of the proposed network. The procedure involves dividing a dataset into two subsets: (i) training and validation and (ii) testing. Hyper parameters of the proposed deep learning architectur is tuned with the help of training and validation dataset. After proper training, the model is tested with the testing set. This attempt aims to determine the deep learning model's performance on new data that was not used in the model‘s training.

C. ECG beat classification using CNN-BiLSTM architecture

This work uses the combination of CNN-BiLSTM to detect the different types of ECG beats. The benefits of CNN and Bi-LSTM are combined in this work to get better performance. Initially, a one-dimensional convolutional layer extracts features from the input signal, which are then processed by the Bi-LSTM layers. The Bi-LSTM consists of two LSTMs, which take input from both forward and backward directions, effectively allowing it to learn from past and future data. This combination works better compared to the regular LSTM. The two-layer Bi-LSTM model is utilised inside the framework of this architecture. Both the first and second layers are made up of Bi-LSTM, with the first layer having 90 units and the second layer having 180 units. A fully connected layer which consist flattening, dropout, and dense layer just like in the traditional CNN model followed by preceeding layers. The proposed architecture for ECG beat classifcation is shown in Fig. 2. A conv1D layer employing rectified linear unit (ReLU) activation and a kernel size of 13 or 16 filters is employed. An average pooling of 3 and 2 strides follows this layer. There are 15 and 32 filters in the second conv1D layer. The second Conv1D employs the same average pooling layer as the first one. Furthermore, a flattening layer converts the output from the Bi-LSTM into a 1D vector. The Adam optimiser is used in this work to replace random gradients and cross-entropy for the loss function as below.

$$\text{Loss} = -\sum_{b \in B} \sum_{c=1}^{C} \hat{p}_c(b) \cdot \log\left(p_c(b)\right) \tag{3}$$

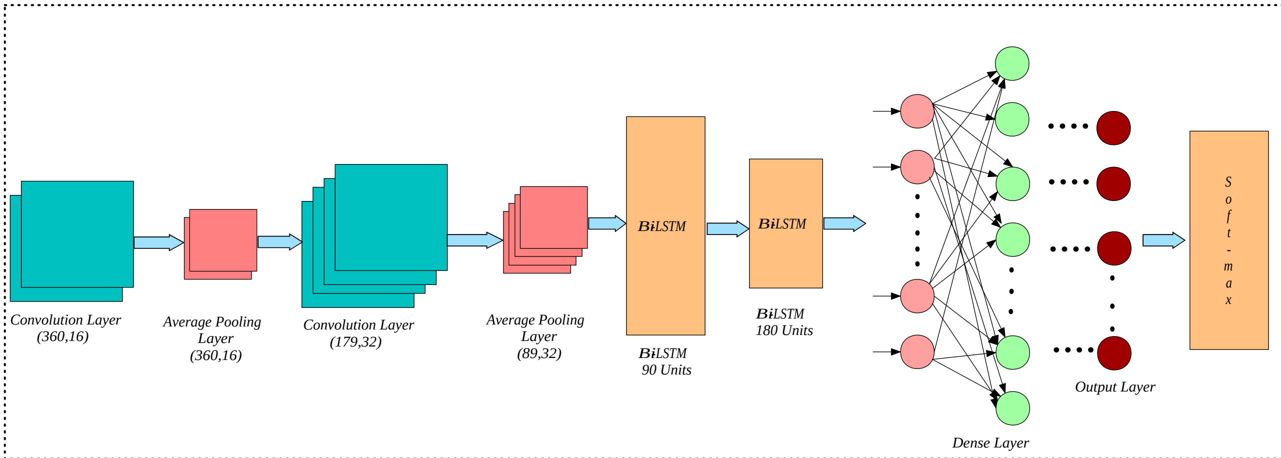


Fig. 2. Block diagram of proposed deep learrning architecture.

where $p_c(b)$ is the probability that beat b is from class c and $\hat{p}_c(b)$ either 1 or 0 based on the softmax output which says whether class c is the correct class or not respectively.

III. Experimental results

A complete experimental investigation for the identification of beats been described in this section. In this work, the classification was made possible using a hybrid architecture that suitably extracts the features of different beats. The experiment results were conducted on a well-known, publicly accessible ECG five-class dataset (obtained from 47 patients). The proposed CNN-BiLSTM model has also been compared to two widely used deep learning (DL) models (CNN and Bi-LSTM) to demonstrate the model's performance and robustness. The deatiled hyperparameters of the proposed model is shown in Table I.

TABLE I
Hyper-parameters of the proposed model after tuning

Parameter	**Value**
Learning Rate	0.001
Batch Size	32
Input Shape	360×1
Output Size	5
Dropout	0.5
Kernel regulariser L2	0.0001
Bias regulariser L2	0.0001
Epochs	50

Database details used to train and validate the proposed model is shown in Table II. In this work, a common training dataset of 75 beats of each type N, S, and V, 13 beats of type F, and 7 beats of type Q. These beats were picked at random from the first 20 recordings (from 100 to 124). In addition to these 245 beats, first five minutues data from the recods (200-234) are added. Training cum validation and testing data each contain 8672 and 49,564 ECG beats.

TABLE II
Details of the number of ECG beats utilised for training and testing

Name of the ECG beat	Total beats	Training beats	Testing beats
N	46074	3883	42191
S	3871	1642	2229
V	6816	2345	4471
F	1413	760	653
Q	62	42	20

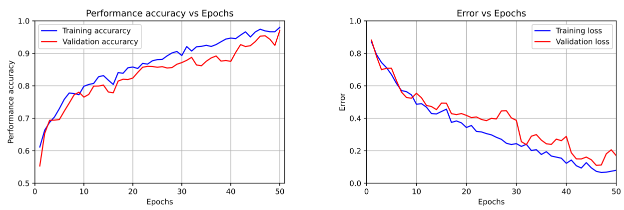
A. Performance metrics

The elements that have been successfully categorised can be found on the diagonal of the matrix. The performance of proposed deep learning model is assesed based on the following parameters: accuracy (*Acc*), sensitivity (*Sen*), specificity (*Spe*), positive-predictivity (*Ppr*), and *F*-Score (*F*) [11].

B. The performance of the proposed method

The performance of the proposed ECG beat classification system is evaluated using different metrics. Fig. 3, represents the training cum validation performance and loss curve. Validation curve is smoothly followed the training curve, that means that the network is perfectly trained without over-fitting. The network is reached steady state for 50epochs.

The detailed performance matrix of the CNN-BiLSTM is shown in Table III. Table III demonstrates the performance of each class. Table III indicates that the proposed model outperforms other ECG beat, detection models. The proposed model has an accuracy of 99.78% when it is being trained, 99.56% when it is being validated, and 99.21% when it is being tested. The proposed CNN-BiLSTM model has a sensitivity of 99.32% for training and 98.12% for validation, *F*-score of 0.98 for training and 0.97 for validation.



(a) (b)

Fig. 3. A curves of (a) Training & validation accuracy, (b) Training & validation loss.

TABLE III
PERFORMANCE OF THE PROPOSED METHOD

		Performance matrix				
Proposed Method	Class	Acc (%)	Sen (%)	Spe (%)	Ppr (%)	**F-Score**
	N	99.27	99.98	98.89	99.16	**1.00**
	S	99.17	95.00	97.11	95.15	**0.97**
CNN-BiLSTM	V	99.19	99.00	98.33	99.00	**0.99**
	F	99.16	90.00	97.13	89.23	**0.96**
	Q	99.26	65.20	74.55	62.84	**0.19**

The obtained confusion matrix of the proposed deep learning archutecture is shown in Fig.4 with the test dataset. From the Fig.4, it is observed that very few beats are misclassified as N-73, S-107, V-75, F-48, and Q-1 respectively by the proposed method. It is observed that the proposed method detected S and V beats decently, which are very important in cardiac clinical diagnosis. The number of trainable and non-trainable parameters of the proposed method is 10,215 and 1,015 respectively. The same hyper-parameters are used to implement CNN and Bi-LSTM independently. The trainable and non-trainable parameters in implementation of those architectures are approximately same as the combination of CNN-BiLSTM. The proposed system show best performance with the less trainable parameters, Hence the method is called as light weight hybrid deep learning algorithm.

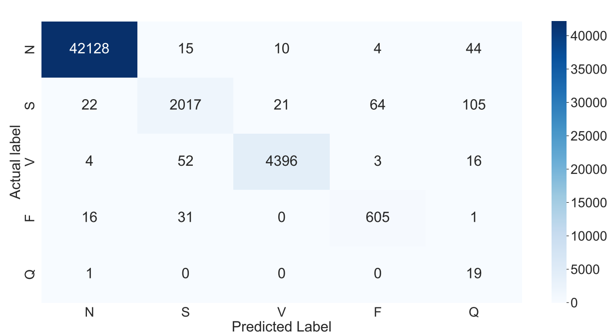


Fig. 4. The confusion matrix of the CNN-BiLSTM model.

C. Performance of the proposed method with recent ECG beat classification techniques

In this section, the performance of the proposed method is compared with the recent techniques on ECG beat classification. From Table IV, it is observed that the proposed beat detection method shows better performance accuracy compare to the earlier techniques. The proposed method also works better than other methods with small training datasets that have been reported in the past.

TABLE IV
COMPARISION OF THE PROPOSED METHOD WITH RECENT LITERATURE

Literature	**Number of classes**	**Architecture**	**Input Features**	**Performance accuracy (in %)**
Plawiak *et al.*, 2018 [1]	5	CNN-SVM	Filtering, Normalisation & L2 Regularization	96.00
Shaddeli *et al.*, 2021 [12]	5	CNN-LSTM	Patient Specific Features	98.10
Dang *et al.*, 2019 [13]	5	DCNN	Pre-processing by Re-scaling	91.33
Wang *et al.*, 2021 [11]	17	CNN-BiLSTM	RR Duration	96.77
Oh *et al.*, 2018 [2]	5	2D CNN	Robust Noised Filtering	99.02
Nabanita *et al.*, 2022 [14]	5	Deep Neural Network	Empirical mode decomposition	99.05
CNN	5	CNN	Raw ECG signal	98.91
Bi-LSTM	5	Bi-LSTM	Raw ECG signal	98.21
Proposed Method	5	CNN-BiLSTM	Raw ECG signal	99.21

IV. CONCLUSION

A new technique based on CNN-BiLSTM is developed for patient-specific ECG beat detection in this work. Bi-LSTM is used to solve the gradient degradation problem and make networks less complicated. Bi-LSTM offers various parameters, including learning rates, input, and output biases. As a result, there is no requirement for precise modifications. The Bi-LSTM automatically recognizes dependencies in sequence data through its gate mechanism and memory units. However, learning local features in sequence data is challenging due to the limitations of the learning mechanism. CNN compensates for this issue by extracting locally relevant characteristics from the input using convolution kernels. Consequently, a coupled network can substantially enhance the predictive capabilities of models. This work identified and removed the problems with traditional manual feature extraction-based models. Temporal and spatial features are accurately extracted from the dataset and then concatenated with CNN and Bi-LSTM models to create our final proposed model. This model was trained and tested on the MIT-BIH dataset, and the results show better performance with 99.21% accuracy.

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