

Bidirectional LSTM based hybrid deep learning frameworks for Cardiac Arrhythmia Classification

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Abstract

Electrocardiogram (ECG) analyzes the electrical activity of the heart which diagnoses Cardiac Arrhythmia (CA) in the biomedical field. Cardiovascular disease classification is necessary for efficient and fast remedial treatment of the patient. In this paper, we propose a hybrid technique for ECG classification using a Deep Neural Network (DNN) with Bi-directional Long Short Term Memory (Bi-LSTM) layer by giving the modified ECG signal as an input. The modified ECG signal is obtained through the combination of Empirical Mode Decomposition (EMD) and Discrete Wavelet Transform (DWT) which gives a better denoising performance. The modified ECG signal is fed into DNN that classifies the data into five classes Normal (N), Supraventricular premature beat (S), Premature ventricular contraction (V), Fusion of ventricular and normal beat (F), and Unclassifiable Beat (Q) using softmax regressor at the end of the network. The proposed method is tested on ECG signals collected from the MIT-BIH database and has a good efficiency in classification accuracy. The accuracy, Sensitivity, Specificity, Precision, and F1 score values of the proposed method are 95.3%, 96.9%, 98.7%, 95.72%, and 93.73% respectively, compared to existing classifiers.

Keywords: Electrocardiogram, Empirical Mode Decomposition, Discrete Wavelet Transform, Deep Neural Networks.

1. Introduction

Electrocardiogram (ECG) is an essential initial clinical test to not only analyze serious electrical disturbances like cardiac arrhythmia but also give data about mechanical and metabolic issues like myocardial dead tissue, and hypertrophy, among others. Many signal processing techniques are used to detect the features of an ECG signal for the diagnosis of cardiac abnormalities in the patient.

Deep learning-based methodology towards coronary illness classification has been a popular choice recently. Cardiovascular disease classification [1], Automatic detection of Myocardial infarction [2], and detection of heart rate and rhythm of the heartbeats and their locations using machine learning and deep learning algorithms have been successful in recent years. ECG signal classification through Convolutional Neural Networks

(CNN) with modified Empirical Mode Decomposition (EMD) is superior to other techniques in terms of classification accuracy [1]. Arrhythmia classification using modified features through Discrete Wavelet Transform (DWT)[4] and the combination of EMD-DWT [3] with FFBPNN (feed forward back propagation neural networks), diagnosis of cardiac arrhythmia with deep learning algorithms using Convolutional Neural Networks, Recurrent Neural Networks (RNN), CNN-RNN, Long-Short Term Memory (LSTM), Gated Recurrent Unit (GRU), CNN-GRU are compared [5].

Detection and classification of ECG heartbeat using wavelet based features [6], kNN classifier [7][8], and wavelet packet entropy and RF (random forests) [9][8] are used to improve the classification accuracy. ECG beat classifiers from artificial neural networks to deep neural networks has investigated [10]. G. K. Malik *et al.* [11] presented a simple approach for the classification of normal and abnormal ECG beats using an SVM classifier with wavelet decomposition.

Banerjee *et al.*[12] defined a novel Recurrent Neural Network (RNN) structure, which consists of two LSTM networks. This network is used for the analysis of temporal features like RR intervals and PR intervals in the ECG signal. In this method, two LSTMs outputs are combined along with statistical features, which are related to the measurement of Heart Rate Variability (HRV). The proposed method was tested on Physionet Challenge 2017 dataset and it consists of more than 8500 single lead ECG records. This method yields 0.93, a Specificity of 0.98, and an F1 score of 0.89 in classifying AF.

Martis *et al.* [13] analyzed five types of ECG beats. They are Normal, RBBB, LBBB, APC, and VPC. For dimensionality reduction, Principal Component Analysis is applied to the extracted features. These components are given to four layer FFNN and Least Square-SVM (LS-SVM) for automatic pattern recognition. The author proposed unique bispectrum and bicoherence plots for each cardiac class. The average accuracy obtained through this approach is 93.48% and specificity is 98.31%, respectively by using LS-SVM with Radial Basis Function (RBF) kernel. Better features and more diverse ECG beats for training and testing can improve the performance of the LS-SVM classifier.

Karthik *et al.*[14] implemented an efficient feature extraction algorithm for the detection and classification of cardiac abnormalities. This proposed method is used to classify cardiac abnormalities such as Sleep Apnea (SA), Arrhythmia, Supraventricular Arrhythmia, and Long term Atrial Fibrillation (AF). In this method, for peak detection, the Pan Tompkin algorithm is used and it is followed by feature extraction to differentiate cardiac disorders from the normal heartbeat.

Runnan *et al.*[15] addressed the limitations of the previous automatic classification algorithms of cardiac disorders based on the features of ECG signal. Due to the limited generalization capability of the classifier and unreliable features of signal characteristics, automatic diagnosis of arrhythmias remains a challenging task. To overcome this problem, a new method based on Deep Neural Network (DNN) is used. Darmawahyuni *et al.*[16] described the concept of deep learning in the supervised RNN classifiers model. They are RNNs, LSTM, and Gated Recurrent Units (GRU). The best classifier in this method is unidirectional GRU with an average specificity of 98.42%, precision of 89.93%, and F1-score of 92.13%, respectively.

In this work, we have worked on ECG signal preprocessing and classification techniques and we compare the results of various classifiers such as EMD-DNN, DWT-DNN, FFBPNN, and the proposed EMD-DWT-DNN classifier.

2. Material and Methods

The proposed methodology has two phases in ECG signal extraction. They are noise free signals and classification.

2.1. Empirical Mode Decomposition

EMD decomposes a signal into Intrinsic Mode Functions (IMFs) [1]. The decomposed signals are all the same length, and each IMF has the same number of extrema and zero crossings, with the envelopes acting as a simple oscillatory mode. To get upper and lower envelope, combine the maxima and minima points of the original signal $x(n)$, is a combination of oscillation components of IMF's $c_i(n)$ with zero mean and N^{th} residual or noisy part $r_N(n)$ which is represented as

$$x(n) = \sum_{i=1}^N c_i(n)r_N(n) \tag{1}$$

In this paper, the total number of intrinsic mode functions is $N=6$. To reconstruct the denoised ECG signal consider the sum of the first three IMFs. The modified and noise free ECG signal $y(n)$ is defined as

$$y(n) = c_1(n) + c_2(n) + c_3(n) \tag{2}$$

2.2. Discrete Wavelet Transform

Generally, Signal transformation can be performed in both the time and frequency domains. DWT is an efficient frequency-domain technique. DWT decomposes the signal into both low and high frequency signals. Low frequency signals are called Approximation (CA_1) and high frequency components are called Detailed (CD_1) coefficients. For two level decomposition, first level approximation coefficients (CA_1) are again divided into approximation and detailed coefficients CA_2 and CD_2 which are shown in Figure 1, and the corresponding mathematical expressions are given in equations (3) and (4).

$$[CA_1, CD_1] = DWT(y(n)) \tag{3}$$

$$[CA_2, CD_2] = DWT(CA_1) \tag{4}$$

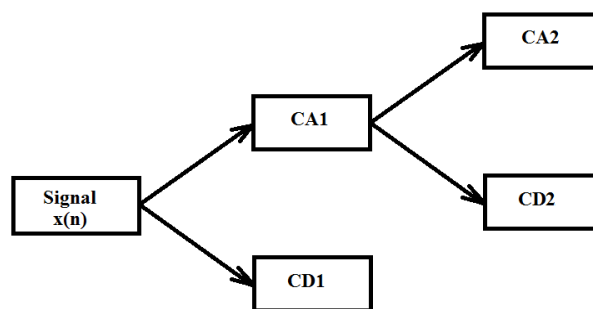


Figure 1. Two level decomposition of DWT

2.3. Bidirectional Long Short Term Memory Networks

Bi-LSTM (Bidirectional Long Short Term Memory) network is a form of deep neural network. It is the process of allowing any neural network to store sequence information in both forward and backward directions to preserve the past and future information. But in conventional LSTM, the input flows in one direction either backward or forward. BI-LSTM is typically used, where the sequence to sequence tasks are needed such as text

classification, speech recognition, and forecasting models. The block diagram of the Bi-LSTM network is shown in Figure 2.

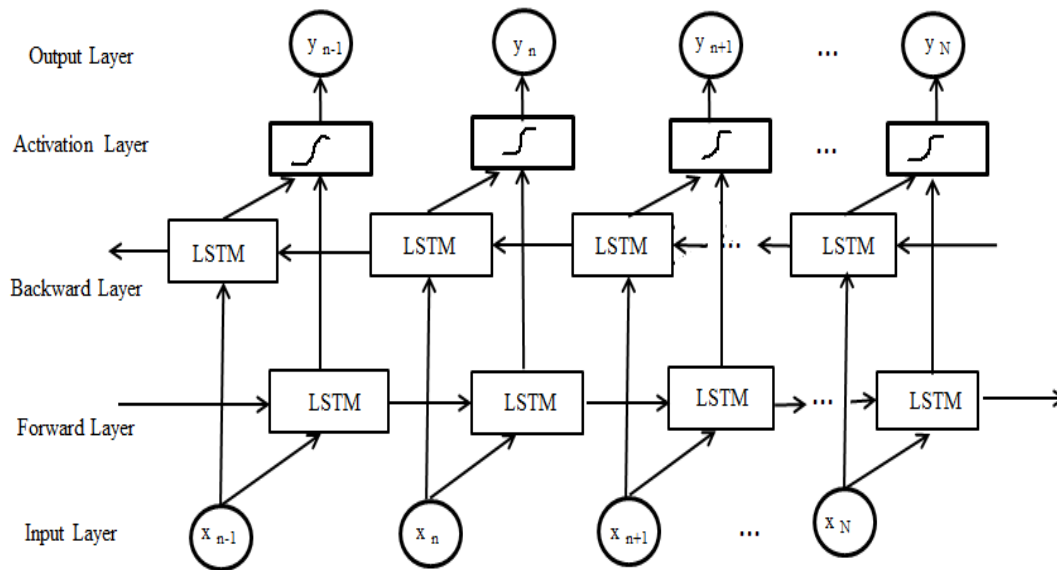


Figure 2. Bi-LSTM Architecture

Bi-LSTM network consists of a sequence input layer, Bi-LSTM layer, fully connected layer, softmax layer, and classification layer. The extraction of features is handled by the first two layers, while classification is handled by fully-connected layers. The network's final output has a soft-max regressor with a specified number of classes.

2.4. Data set

The MIT-BIH arrhythmia dataset from Physionet was used in this experiment, which contains ECGs with a sampling frequency of 360 Hz. This dataset has been downsampled, cropped, and segmented into 87,554 training samples and 21,892 testing samples and is publicly available on Kaggle by [17]. Both the training and test sets were saved into .csv files, where each row represented 1 ECG sample and the last column represented the class label.

Both datasets contained samples in one of five possible classes with the corresponding integer class number in the training and testing set being classes 0,1,2,3 and 4. The numbers 0,1, 2, 3, and 4 are represented by Normal (N), Supraventricular premature beat (S), Premature ventricular contraction (V), Fusion of ventricular and normal beat (F), and Unclassifiable Beat (Q). Actual training set contains 72,470 class 0 beats, 2,223 class1 beats, 5788 class2 beats, 641 class 3 beats, and 6,431 class 4 beats.

2.5. Methodology

The workflow of the proposed classification method is shown in Figure 3. The whole process of ECG signal classification contains three stages. They are denoising, feature extraction, and classification stages.

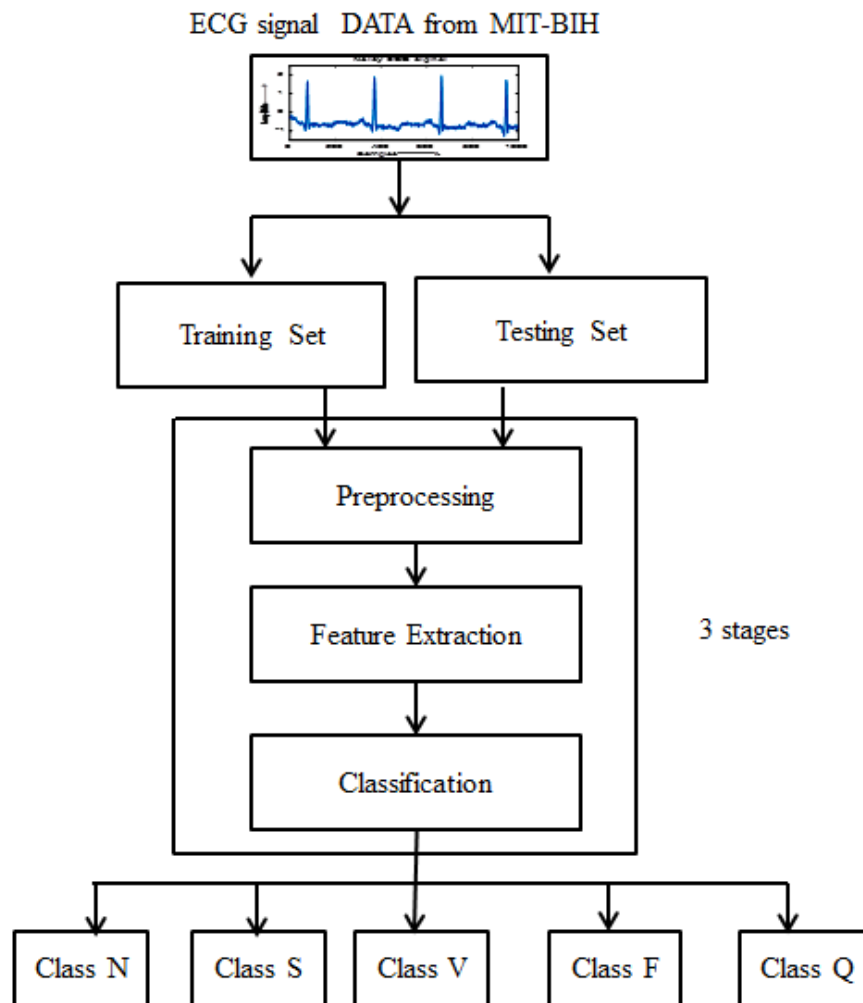


Figure 3. Workflow of the proposed classification method

In this work, for ECG signal pre-processing, Empirical mode decomposition [12] is applied to both the training and testing dataset. It decomposes the signal into intrinsic mode functions. After reconstruction, DWT is applied to the reconstructed signal of EMD using the Daubechies 2 (Db2) wavelet for three levels. Finally, EMD-DWT features are extracted and classified them into five classes such as N, S, V, F, and Q.

The DNN used in this work is built with 5 layers. They are sequence input layer with input size 1, Bi-LSTM layer with 100 hidden neurons, 5 fully connected layers, softmax layer, and classification layer. Finally, the performance evaluation of the proposed method is compared with the existing techniques using the quality metrics Accuracy, Sensitivity, Precision, Specificity, and F1-score.

The proposed algorithm consists of the following steps.

Step 1: Read the ECG samples from the MIT-BIH Arrhythmia Database.

Step 2: Apply EMD on both training data and testing data.

Step 3: Obtain the EMD reconstructed signal to attain the QRS complex.

Step 4: Decompose the EMD reconstructed signal by applying DWT for 3 levels using Daubechies 2 wavelet function to obtain the approximation and the detailed coefficients, to get the features of an ECG signal.

Step 5: Apply the EMD-DWT-based features to FFBPNN, and DNN with the Bi-LSTM layer to classify the ECG signal beats into five classes such as N, S, V, F, and Q.

Step: 6 Compare the performance of the proposed method with the existing methods.

2.5. Performance Evaluation

To assess the proposed CNN, we assumed that the class containing abnormal beats as the positive class, and hence the accuracy, sensitivity, and specificity are evaluated by using the equations (10), (11) & (12)

$$Accuracy = \frac{TP' + TN'}{(TP' + TN') + (FP' + FN')} \quad (10)$$

$$Sensitivity = \frac{TP'}{TP' + FN'} \quad (11)$$

$$Specificity = \frac{TN'}{FP' + TN'} \quad (12)$$

$$Precision = \frac{TP'}{TP' + FP'} \quad (13)$$

$$F1 - Score = \frac{2 TP'}{2 TP' + FP' + FN'} \quad (14)$$

Where

- (i) TP' indicates the number of correctly classified abnormal beats;
- (ii) TN' indicates the number of correctly classified normal beats;
- (iii) FP' indicates the number of incorrectly classified normal beats as abnormal;
- (iv) and FN' indicates the number of incorrectly classified abnormal beats as normal;

3. Results and Discussion

The performance of the proposed classification method based on EMD-DWT features with a DNN classifier using the Bi-LSTM layer is evaluated by conducting experiments on 48 ECG records from the MIT-BIH database. The proposed algorithm is implemented using Matlab 9.5 with Intel Core I3, 2.2-GHz Computer. The corresponding results are considered.

In this work, four methods are used for classification. They are EMD-DNN, DWT-DNN, FFBPNN, and EMD-DWT-DNN classifiers. The overall performance measures of various proposed classifiers are shown in Table 1.

Table 1. Performance measures of various proposed classifiers with 5 classes

Proposed Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)
EMD-DNN	90.80	85.71	97.30	91.13	85.97
DWT-DNN	94.50	86.33	98.37	95.59	90.25
FFBPNN	93.20	87.88	98.16	95.52	90.63
EMD-DWT-DNN	95.30	96.90	98.70	95.72	93.73

Among all the classifiers EMD-DWT-DNN classifier gives an outstanding performance than the remaining classifiers. Hence this method is considered my proposed method for the comparison of existing techniques and its visual representation is shown in Figure 4.

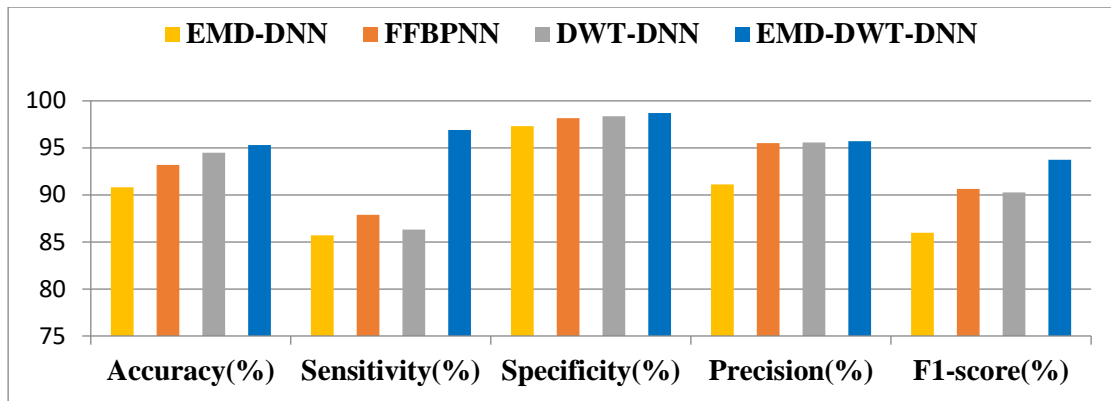


Figure 4. Comparison of performance metrics of various proposed classifiers for five classes.

The confusion plot of the proposed method is shown in Figure 5. It gives detailed information about various performance metrics based on the target class and the output class. The overall accuracy of the proposed EMD-DWT based DNN classifier is 95.3%. The comparative analysis of the overall accuracy, sensitivity, specificity, precision, and F1-score of the proposed classifier with existing works is shown in Table 2.

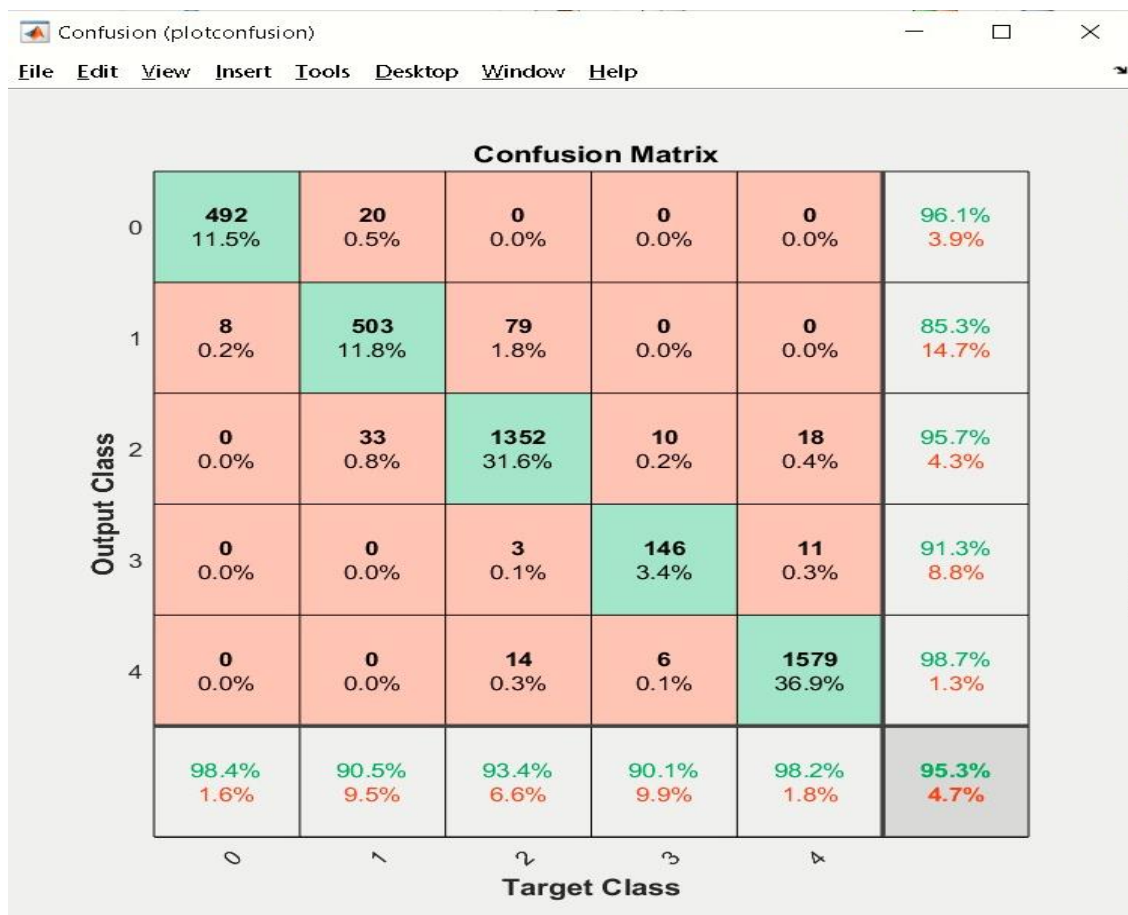
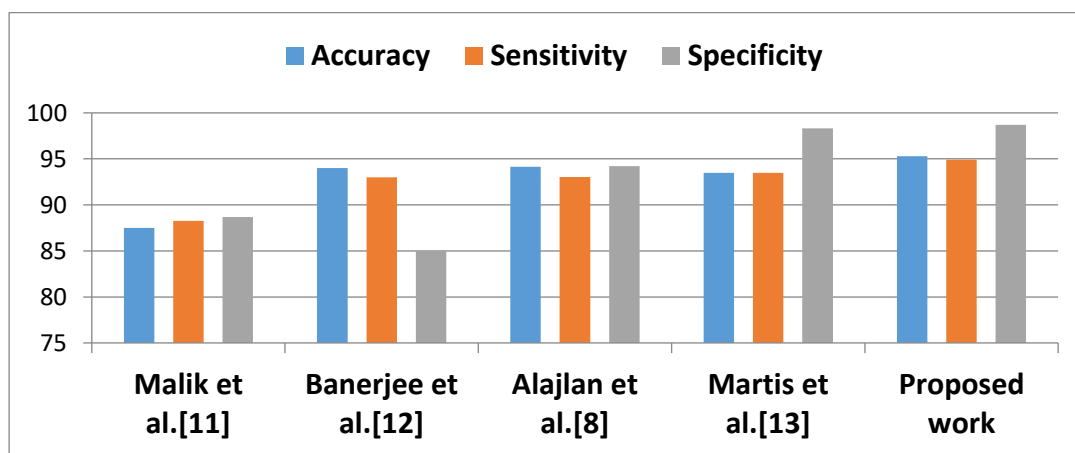


Figure 5. Confusion plot for the proposed EMD-DWT features-based DNN classifier for five classes.

Table 2. Performance measures of various proposed classifiers with 5 classes

Proposed Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)
Banerjee <i>et al.</i> [12]	94.00	93.00	85.00	-	89.00
Alajlan <i>et al.</i> [8]	94.15	93.02	94.23	-	-
Malik <i>et al.</i> [11]	87.51	88.25	88.67	-	-
Martis <i>et al.</i> [13]	93.48	92.5	98.31	-	-
Proposed work	95.30	94.90	98.70	95.72	93.73

**Figure 6. Comparison of the overall accuracy, sensitivity, and specificity of the proposed classifier with existing works.**

The performance metrics of the proposed EMD-DWT based DNN classifier are compared with the existing state-of-the-artworks in Figure 6.

4. Conclusions

In this article, a novel, classifying technique using a Deep Neural Network with Bi-LSTM architecture is proposed. In this paper, three stages are there in the classification process. They are ECG signal preprocessing, feature extraction, and then classification. First, preprocess the ECG data using EMD and apply wavelet decomposition with the Db2 wavelet to get the features of the ECG signal. Then the modified signal is given to a Deep neural network with Bi-LSTM architecture to classify the data into five classes Normal (N) beat, Supraventricular premature beat (S), Premature ventricular contraction (V) beat, Fusion of ventricular & normal beat (F), and Unclassifiable Beats (Q). The results of the proposed EMD-DWT-DNN approach are compared with various classification techniques. The proposed method has a high accuracy of 95.3%, Sensitivity of 94.9%, Specificity of 98.7%, Precision of 95.72%, and F1 score of 93.73% respectively as compared with the other classifiers. In this paper, we used the MIT-BIH Arrhythmia dataset to classify the heartbeats. All the simulations are carried out through MATLAB.

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