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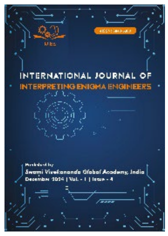
BIDIRECTIONAL LSTM BASED HYBRID DEEP LEARNING FRAME WORKS FOR CARDIAC ARRHYTHMIA CLASSIFICATION



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Original Article

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Abstract

In this paper, implemented a hybrid approach to ECG classification by combining a Deep Neural Network andBi-directional Long Short Term Memory (Bi-LSTM) layer. We substantially improved denoising by preprocessing ECG signals with a mix of Empirical Mode Decomposition and Discrete Wavelet Transform, resulting in higher signal quality for classification. The suggested method successfully classified ECG signals into five unique classes, with 95.3% accuracy, 96.9% sensitivity, and 98.7% specificity, respectively, using the MIT-BIH database as an evaluation benchmark. Our results show that the proposed hybrid technique outperforms existing classifiers, highlighting its potential for real-world clinical applications at cardiac arrhythmia diagnosis. Future research can concentrate on enhancing the model for real-time processing and expanding its application to different physiological datasets in order to improve its adaptability and generalizability in cardiovascular disease diagnoses.

Keywords: Electro cardiogram, Empirical Model Decomposition, Discrete Wavelet Transform, Deep Neural Networks.

Introduction

The electrocardiogram one of the important clinical test for analyzing significant electrical disturbances such as cardiac arrhythmia, as well as providing insights into mechanical and metabolic difficulties such as myocardial infarction and hypertrophies. Several signal processing approaches have been used to predict features from ECG data, which aid in the diagnosis of cardiac problems. These methodologies serve as the foundation for more accurate and efficient identification and classification of cardiac diseases.

Deep learning-base methods for widely used in classifying medical application to find the cardiovascular illnesses and decease classification [1]. The automatic identification of myocardial infarction [2], and detection of heart rate, rhythm, and location using ML and DL have all been effective results. ECG signal classification through CNN with Empirical Model Decomposition(EMD) techniques are implemented to measure of classification accuracy[1].Arrhythmia classification using modified features through Discrete Wavelet Transform (DWT) [4] and the combination of EMD-DWT [3]diagnosis of cardiac arrhythmia with deep learning algorithms using CNN, Recurrent RNN & CNN-RNN etc. [5].

To enhance the accuracy of wavelet-based features, methods such as kNN classifiers[7][8],wavelet packet entropy, and random forests (RF)[9] are employed. Various ECG beat classification techniques, including artificial neural networks and deep neural networks, have also been explored. K. Malik et al. [11] proposed A straightforward approach for distinguishing between normal and abnormal ECGs, using wavelet decomposition and an SVM classifier[10]. Banerjee et al.[12] sugested a unique Recurrent Neural Network (RNN) topology gives two LSTM networks. This network is designed to analyze temporal parameters like as RR and PR intervals in the ECG data.

Martiset et al. [13] investigated many ECG beats such as Normal, RBBB, LBBB, APC, and VPC. Principal Component Analysis (PCA) is used to reduce dimensionality in retrieved features. These components are fed into four-layer FFNN and Least Squares-SVM suggested for automatic pattern detection. The author presented separate bispectrum and bicoherence charts for each cardiac class.

Karthiketal.[14] devised an efficient feature extraction technique for detecting and classifying cardiac anomalies. This proposed approach is used to classify cardiac abnormalities. Runnanet al[15] explains the limitations of the standard automatic classification detection methods in cardiac disorders based on the features of medical signal.

There are various types of signals and images are applied for wavelet technique4 for decomposition of images, same as Multimodality image registration refers to applications in which moving and fixed images are captured using various imaging modalities, sometimes in distinct dimensions. Supervising and unsupervising classification algorithms are also choosen for better classification results, which are act as better far with wavelets for large data set using dimensional reduction technique with PCA and ICA algorithms[18][19][20][21].

Material and Methods

This paper developed by implemented with methodology has two phases in ECG signal extraction.

Empirical Model Decomposition

EMD decomposes into intrinsic model functions (IMFs)[1]. To get upper and lower envelope, combine the maxima and minima points of the original signal(n),is a combination of oscillation components of IMF's $c_i(n)$ with zero mean and Nth residual or noisy part$r_N(n)$which is represented as

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

Here N=6.

To reconstruct the ECG signal, bye the sum of the first three IMFs.

The modified and noise free ECG signal c$(n)$is defined as

$$c_i(n)=c_1(n)+c_2(n)+c_3(n) \qquad [2]$$

Discrete Wavelet Transform

This transform used in many signal and image processing applications, which decomposes the information into both low and high frequency signals [16][17]. The second level approximation and detailed coefficients CA2and CD2 are shown in Figure1, and the corresponding expressions are given in equations (3) and (4).

$$[CA_{1,1}]=(y(n)) \qquad [3]$$

$$[CA_{2,2}]= (CA_1) \qquad [4]$$

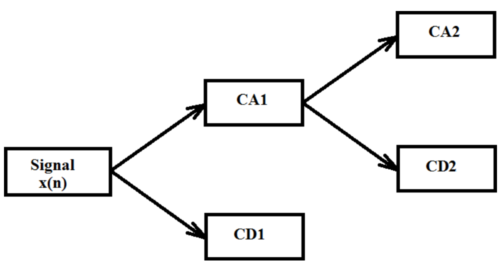

Fig.1.Twoleveldecomposition of DWT

Bidirectional Long Short Term Memory Networks

Bidirectional Long Short-Term Memory (BiLSTM) Networks are an advanced type of LSTM network that processes input sequences in both forward and backward orientations. Unlike typical LSTMs, which only examine the sequence from past to future, BiLSTMs combine two distinct LSTM layers: one analyzes the sequence in the standard forward direction, while the other processes it in reverse.

The block diagram of the Bi-LSTM network is shown in Figure2.

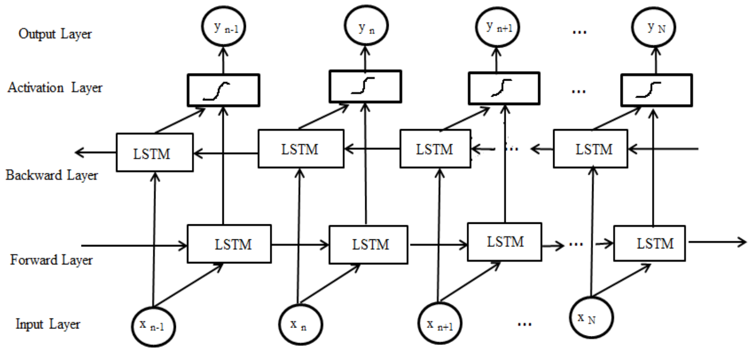

Fig: 2.Bi-LSTM Architecture

The first two layers handle feature extraction, and fully connected layers handle categorization.

Methodology

This dataset has been downsampled, cropped, and segmented into 87,554 training and 21,892 testing samples, from Kaggle [17]. Figure 3 shows the workflow of the suggested categorization approach. ECG signal categorization is a three-stage technique. They include denoising, feature extraction, and classification steps.

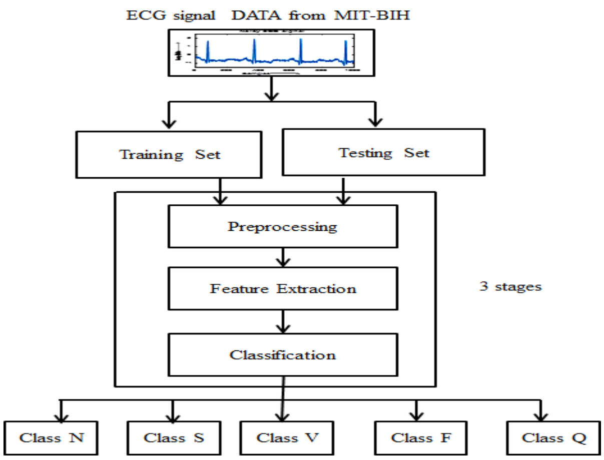

Fig: 3.Work flow of the proposed classification method

The EMD algorithm [12] applied for preprocessing ECG signals for the data set, which divide as both training and testing phases. This algorithm decomposes the signal into intrinsic mode functions. The discrete wavelet transform (DWT) is applied to the reconstructed EMD signal using the Daubechies2 (Db2) wavelet at three levels. DNN has used in this study consists of five layers: a sequence input layer (with an input size of 1), a Bi-LSTM layer (with 100 hidden neurons), five fully connected layers, a softmax layer, and a classification layer. The proposed method's performance is then compared to existing techniques using evaluation metrics such as accuracy, sensitivity, precision, specificity, and F1-score.

Results and Discussion

The suggested classification method, which combines EMD and DWT features with a Deep Neural Network (DNN) classifier based on a Bi-LSTM layer, was tested on 48 ECG records. The results show how effective the technique is. A confusion plot, as depicted in Figure 4, provides extensive insights into the performance parameters by comparing the target and output classes. The overall accuracy rate of 95.3%. Table 1 shows the comparison of the proposed classifier's accuracy, sensitivity, and specificity to existing approaches, demonstrating its improved performance.

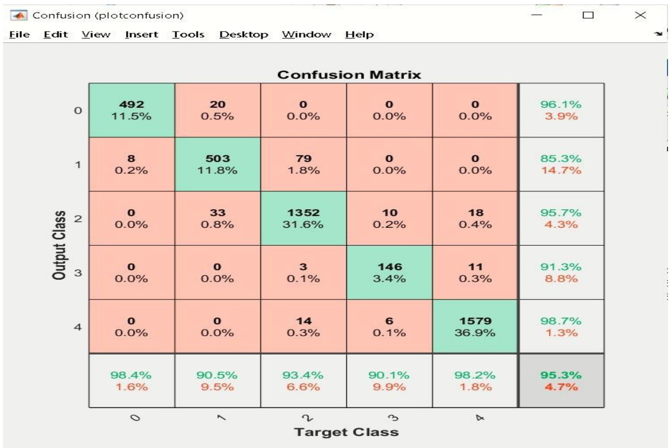

Figure 4.Confusioin matrix for proposed method

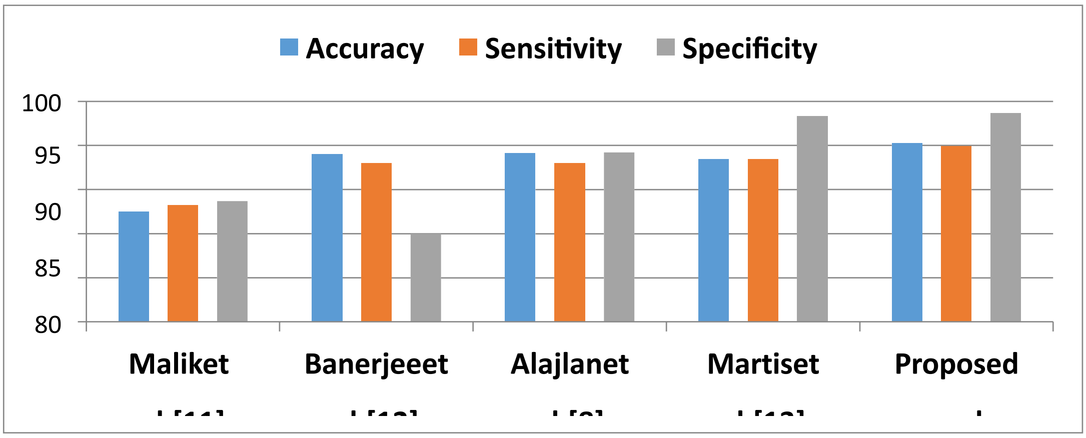

Fig: 5.Comparision results.

The performance metrics of the proposed EMD-DWT based DNN classifier are compared with theexistingstate-of-theartworksinFigure5.

Conclusion

This paper developed classification technique that combines a Deep Neural Network (DNN) with a Bi-LSTM architecture. The classification procedure is broken down into three stages: ECG signal preprocessing, feature extraction, and classification. To extract features, the ECG data is first preprocessed using Empirical Mode Decomposition (EMD) and then wavelet decomposed with the Db2 wavelet. These attributes are then supplied into a DNN with Bi-LSTM architecture, which classifies ECG data into five categories: normal (N) beats, supraventricular premature beats (S), premature ventricular contractions (V), fusion of ventricular and normal beats (F), and unclassifiable beats (Q). The proposed EMD-DWT-DNN technique performs well, with an accuracy of 95.3%, sensitivity of 94.9%, and specificity of 98.7%.

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