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Deep Learning based DWT- Bi-LSTM Classifier for Enhanced Cardiovascular Arrhythmia Classification

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ABSTRACT- Nowadays heart diseases and their diagnosis have emerged as a prominent subject in health care systems, given that the heart performs a crucial role in the human body. Several computational techniques have been explored for the recognition and classification of cardiac diseases using Electrocardiogram (ECG) signals. Deep Learning (DL) is a present focus in healthcare solicitations, particularly in the classification of heartbeats in ECG signals. Many studies have utilized dissimilar DL models, including RNN (Recurrent Neural Networks), GRU (Gated Recurrent Unit), and CNN (Convolutional Neural Networks), to classify heartbeats using the MIT-BIH arrhythmia dataset. This article presents a methodical exploration of Bi-LSTM (Bi directional Long Short-Term Memory) based DL models for heartbeat classification using various quality metrics. Proposed variants include the Bi-LSTM model, demonstrating remarkable accuracy in classifying the heartbeats into five classes: Normal (N) beat, Supraventricular (S) beat, Ventricular contraction (V), Fusion beats (F), and Unclassifiable Beat (Q). The proposed technique outperforms present classifiers with Accuracy, Sensitivity, Specificity, and F1 score values of 98%, 96.9%, 97.4%, and 97.5% respectively. The simulations are conducted using MATLAB 2020a.

Keywords: Electrocardiogram; Discrete Wavelet Transform; Deep Learning; Gated Recurrent Unit; Bi-LSTM.

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1. INTRODUCTION

Heart abnormalities are increasing over time, causing global health concerns. ECG signals remain the most effective method for detecting irregular heart function. The rise in heart and cancer issues is attributed to a sedentary and sluggish routine. Healthy heart movement, identified through ECG and its corresponding waveforms like P, QRS, T, and QT interval, allows for the detection of abnormalities with precise medical knowledge.

Deep learning methods effectively observe heart conditions affecting the heart rate, indicating potential issues such as slow, fast, or irregular heart rates. Failure to seek proper treatment can lead to heart attacks and disorders. A regular, hale, and hearty ECG shows NSR (normal sinus rhythm), while CHF (congestive heart failure) represents an enduring condition impacting blood inflating and weakening the heart's functionality due to inappropriate blood circulation [1]. Identifying heart abnormalities and classifying ECG signals is crucial. Deep learning, with its multi-layered neural network, is an effective approach for rapid and accurate detection of ECG signals [2]. Acharya et al. introduced an analytic tool for MI (myocardial infarction), presenting a novel approach to detect normal and irregular ECG in both noisy and noiseless cases. Their method attained an accuracy of 93.53% with noise removal but attained a higher accuracy of 95.22% without such removal [3].

The initial section serves as an introduction, followed by a literature review in the second part, and concludes with the presentation of the method and results. The justification for this paper's purpose lies in the examination of the system design and assessment of the projected model. Ultimately, the

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concluding section assesses the overall concert of the model, considering the incorporation of pioneering transfer learning approaches [4].

LSTM (long short-term memory) replaces traditional RNNs, addressing the "gradient vanish/explode" issue in backpropagation for long dependencies. It uses gate units and memory cells to efficiently handle and transmit key data features during long-term calculations [5]. Hiriyannaiah et al. [6] conveyed a comparative investigation of LSTM-based DL (deep learning) models for the classification of heartbeats. In this analysis, Bi-LSTM-based DL model gives 95% sensitivity and 98% specificity, correspondingly, which is greater than the present works. Huang et al. [7] propose a new algorithm using 2D (two-dimensional) deep CNN for the classification of ECG abnormalities. First, time-domain ECG signals are converted into spectrograms both in time-frequency domains with the help of STFT (Short Time Fourier Transform) then it classifies ECG abnormalities.

Many techniques are projected to categorize and detect cardiac abnormalities. To obtain the features of ECG signals, several ML (machine learning) based models are developed by many investigators. QRS detection using DWT [8], RF (random forest) [9], PCA-SVM (principal component analysis-support vector machine), KNN (K- nearest neighbor) classifier [10], and numerous other ML algorithms are applied for the identification of heartbeat irregularities. An automated ECG signal classifier with CNN for the classification of cardiac arrhythmias is implemented [11-17]. Yildirim et al. [18] implemented RNN (recurrent neural network), GRU (gated recurrent units), and Bi-directional LSTM networks are used for the classification of cardiac anathemas.

In this exploration, we applied DWT (discrete wavelet transform) for the preprocessing of ECG signals and then classified the altered signals into five classes N, S, V, F, and Q. Finally, the performance metrics of various classifiers like DWT-Bi-LSTM and DWT-GRU are compared with existing classifiers. GRU and Bi-LSTM can analyze ECG signals by capturing temporal patterns and dependencies for the diagnosis of diseases from sequential medical data instead of CNN.

2. MATERIALS AND METHODS

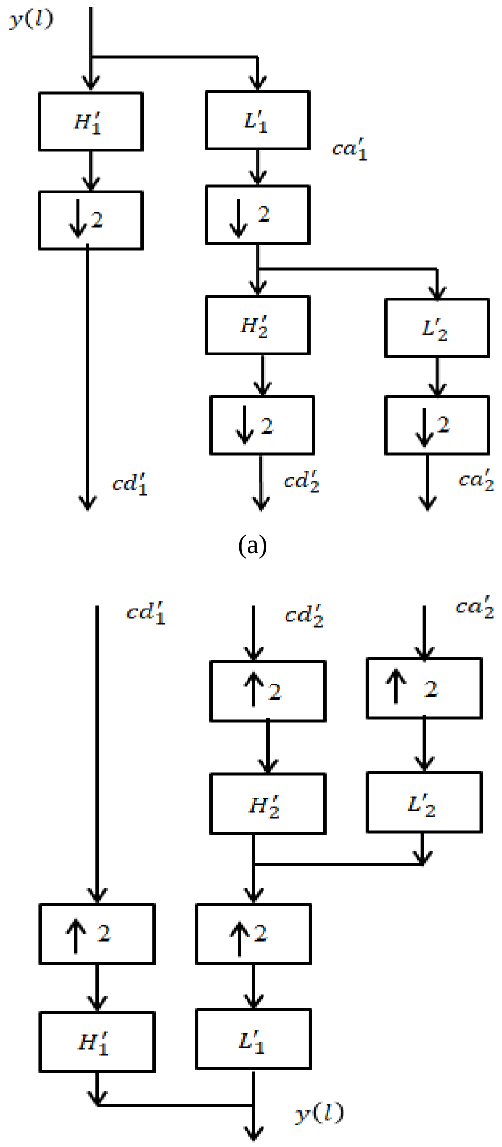
The recommended model requires two phases in ECG signal extraction. They are denoising and classification.

2.1 Discrete Wavelet Transform

Signal amendment is frequently possible in temporal and spectral perspectives. DWT is a good choice in spectral perspective technique. DWT decomposes the signal into both low (approximation (ca_1') coefficients) and high (detailed (cd_1') coefficients) spectral components. The first level ca_1' coefficients are again alienated into approximations (ca_2') and detailed coefficients (cd_2') in second-level decomposition and displayed in figure 1(a). Here, $y(l)$ indicates input data, symbols L_1' &L_2' indicates LPFs (low-pass filters) and H_1' &H_2' denotes HPFs (high-pass filters) [16]. After passing through a filter, down sampling is applied to lower the sampling rate by a factor of 2. *Figure 1(b)* indicates the synthesis process which is the reverse of decomposition. The applicable mathematical equations are given in *equations (1) and (2)*.

$$[\mathrm{ca}_1', \mathrm{cd}_1'] = \mathrm{DWT}\big(\mathrm{y}(\mathrm{l})\big) \tag{1}$$

$$[\mathrm{ca}_2', \mathrm{cd}_2'] = \mathrm{DWT}(\mathrm{ca}_1') \tag{2}$$



(b)

Figure 1. (a) Two-level decomposition by DWT; (b) Two-level synthesis by DWT

2.2 Gated Recurrent Unit

GRU is an amended form of LSTM that has a much rapider training procedure. It is not as much of complicated as LSTM and has the lowest computational complexity. GRU is made up of gates that work together to balance the data flow inside units. The input and forget gates are fused to make an update gate which is mostly combined with balancing the situations of both the preceding & applicant activation. *Figure 2* displays the GRU architecture.

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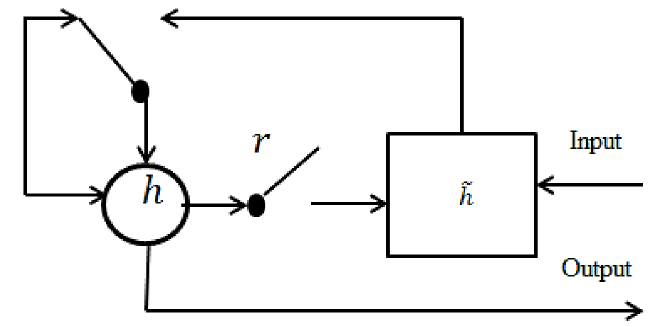

Figure 2. Internal Architecture of GRU [6]

2.3 Short-Term Memory (LSTM)

Conventional neural networks struggle to recognize long and short-term dependencies when dealing with sequential input, especially in ECG signals to get precise results. RNNs use internal memory to train through backpropagation and may compute short-term dependencies. The vanishing gradient problem may make it difficult to capture long-term interdependence.

To alleviate this issue, the LSTM network (gated RNN) has been developed, consisting of LSTM cells with input, forget, and output gates, as displayed in *figure 3*. This LSTM cell determines how much amount of information has to be transferred through recapitulations depending on the input, output, and forget gates. In the cell x_i indicates the present input; h_i gives the cell's hidden information and C_{i-1} rises the preceding cell state of the LSTM. The main purpose of the forget gate is to decide how much the quantity of data is required from the prior cell state and the input gate computes the stimulus of the present input to the cell. Hence these gates play a major role in preserving the cell state at any specified interval. The final output gate o_i can be used to estimate how much data about the cell state will be continued to the subsequent moment of instance.

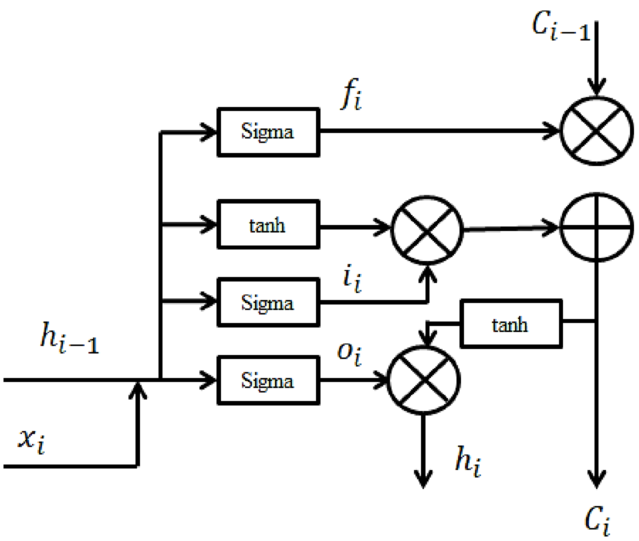

Figure 3. Internal Architecture of LSTM [6]

In conventional LSTM data travels only in either forward or backward movement but in Bi-LSTM, it flows in two directions. In the proposed system, the network has one input layer that carries sequence information, a Bi-LSTM layer, and five hidden layers in front of the output layer. This network improves the model's ability to acquire temporal dependencies. However, this leads to a rise in the attribute quantity and training period for every epoch, and the Adam optimizer is utilized in the model, and the hidden layers are activated via the ReLu function. The network's ultimate result includes a soft-max regressor with an appropriate number of classes.

2.4 Dataset

In this investigation, MIT-BIH arrhythmia dataset from Physionet is employed for classification purposes. It involves ECG records recorded at a sampling rate of 360 Hz. Accessible on Kaggle in [17, 18], a csv file is provided, with a composition of 87,554 training and 21,892 testing samples.

2.5 Methodology

The envisioned classification comprises denoising based on DWT, feature extraction, and classification, as illustrated in *figure 4*.

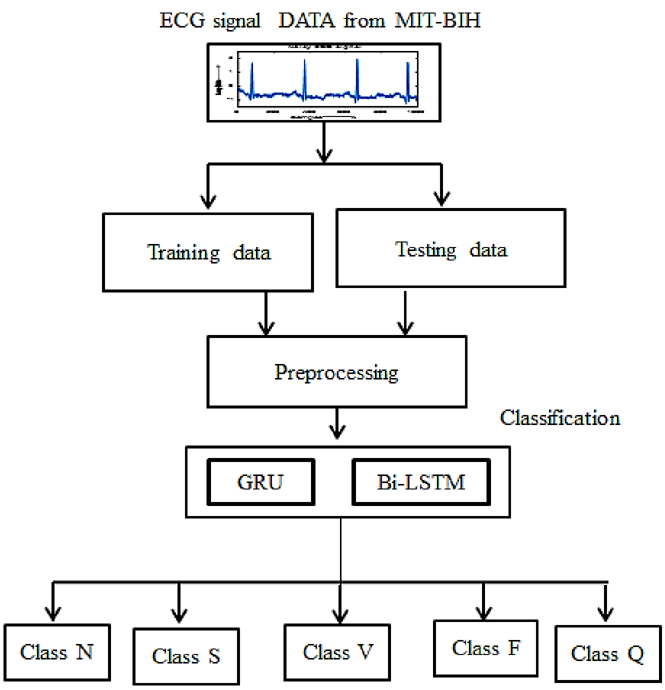

Figure 4. Flow chart of projected classifier

The proposed system comprises the following steps.

1. Retrieve ECG records from [18].
2. Employ the Db2 wavelet family for 3 levels of DWT to obtain the preprocessed signal.
3. Utilize GRU and Bi-LSTM architectures for classification with the altered ECG signal.
4. Evaluate and compare the efficiency of the projected technique against present techniques.

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2.6 Performance Metrics

To appraise the suggested DNN, the accuracy, sensitivity, specificity, and F1-score are determined by the *equations (3), (4) (5) & (6)*.

$$\text{Accuracy (Acc)} = \frac{t'_p + t'_n}{t'_p + t'_n + f'_p + f'_n} \quad (3)$$

$$\text{Sensitivity (Se)} = \frac{t'_p}{t'_p + f'_n} \quad (4)$$

$$\text{F1} - \text{Score} = \frac{2 \times t'_p}{(2 \times t'_p) + f'_p + f'_n} \quad (5)$$

$$\text{Specificity (Sp)} = \frac{t'_N}{t'_n + f'_p} \quad (6)$$

Where t'_p=Number of erroneous beats properly classified; t'_n=Number of regular beats accurately classified; f'_p=Number of normal beats wrongly categorized as irregular; and f'_n = Erroneous beats that were wrongly classed as normal.

3. IMPLEMENTATION RESULTS

Experimental trials are carried out with 48 ECG recordings from the MIT-BIH database to measure the efficacy of the suggested classification strategy based on the DWT-Bi-LSTM classifier. The recommended system is implemented in MATLAB. The confusion matrix of two models DWT-GRU and DWT-Bi-LSTM are displayed in *figures 5 & 6*. It is an outcome of training a suggested model for sorting five different categories of cardiac abnormalities. As demonstrated through the confusion plot, we concluded that the recommended model outperforms in the classification of N, V, S, F, and Q beats.

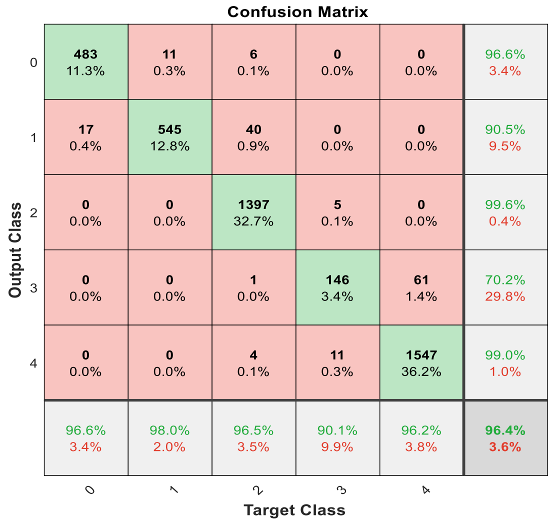

Figure 5. Confusion plot for DWT-GRU classifier

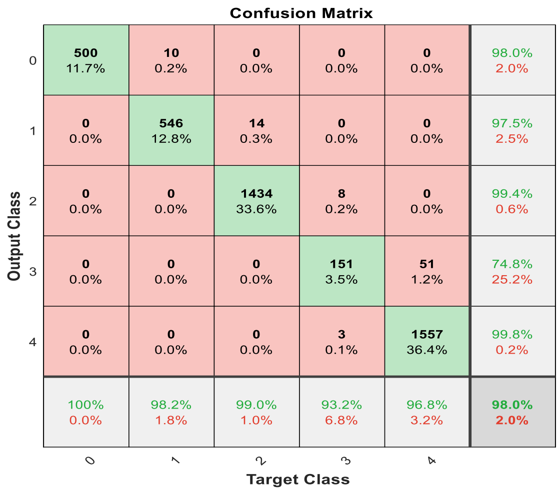

Figure 6. Confusion plot for DWT-Bi-LSTM classifier

Table 1: Performance measures of DWT-GRU and DWT-Bi-LSTM classifiers

Classes	t'_p	t'_n	f'_p	f'_n	Acc (%)	Se (%)	Sp (%)	F1-score (%)
DWT-GRU Classifier								
N	483	3774	0	0	99.6	100	100	100
S	556	3720	0	0	100	100	100	100
V	1405	2824	43	2	98.9	99.9	97.0	98.4
F	61	3925	101	187	93.3	24.6	37.7	29.7
Q	1421	2524	187	142	92.3	90.9	88.4	89.6
DWT-Bi-LSTM Classifier								
N	500	3764	0	10	99.8	98.0	100	99.0
S	546	3704	10	14	87.9	97.5	98.2	97.8
V	1434	1711	14	8	73.6	99.4	99.0	99.2
F	15	4064	11	51	98.6	74.8	93.2	82.9
Q	1557	2666	51	3	98.8	99.8	96.8	98.3

Table 2: A Comparative analysis of employed techniques with conventional approaches

Author	Classifier	Acc (%)	Se (%)	Sp (%)	F1-score (%)
Dinesh et al. [11]	Optimized CNN	93.2	93.9	95.0	86.9
Oliver et al. [12]	CNN	93.2	95.0	94.3	64.9
Bhekumuzi et al. [13]	CNN	95.3	94.2	95.0	86.9
Acharya et al. [14]	11-layer CNN	96.0	95.5	94.2	95.9
Proposed	DWT-Bi-LSTM	98.0	96.91	97.4	97.5

Further, we assessed two different studies such as DWT-GRU and DWT-Bi-LSTM for the classification of ECG signal abnormalities. DWT-GRU produces an accuracy of 96.4% and DWT-Bi-LSTM produces an accuracy of 98%. Results of both trial methods are presented in Table 1. Among those two methods, our proposed DWT-Bi-LSTM method has an average accuracy of 98%, sensitivity of 96.91%, specificity of 97.4%, and F1-score of 97.5% respectively, (Referenced from *Table 2*).

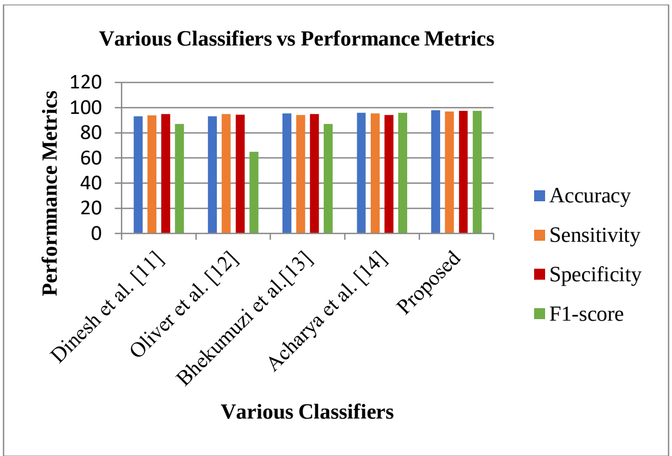

Figure 7. Comparison of several classifiers vs performance metrics

The assessment of the suggested DWT-Bi-LSTM classifier is associated with the existing techniques revealed in Figure 7 in terms of Quality metrics.

4. CONCLUSIONS

In this paper, Bi-LSTM and GRU classifiers are employed with the denoising technique DWT to classify the ECG signals. The employed classifiers are DWT-GRU and DWT-Bi-LSTM. The attained simulation outcomes confirm that the proposed DWT-Bi-LSTM classifier gives an outstanding classification performance compared to challenging methods for different standard quality metrics. In the proposed approach, DWT is used for preprocessing then the modified ECG signals are fed to GRU and Bi-LSTM networks to classify the data into five classes N, S, V, F, and Q. The outcomes of DWT-Bi-LSTM are compared with several classification methods and have an accuracy of 98%, Sensitivity of 96.91%, Specificity of 97.4%, and F1 score of 97.5% correspondingly as employed through the present modern classifiers.

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Conflicts of Interest: "There is no conflict of interest."

Human and Animal Related Study: This manuscript does not involve the use of human/animal subjects.

Informed Consent: This is our original research work.

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