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AN INTELLIGENT DEEP LEARNING BASED CLASSIFICATION OF ECG SIGNALS

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Abstract: The non-stationary impulses of an electrocardiogram (ECG) are widely utilized to assess the pace and frequency of heartbeats. An electrocardiogram (ECG) is a procedure that measures the heart's electrical activity to detect irregularities. Medical experts more widely use automatic ECG categorization in medical diagnostics and therapeutics. This work presents practical strategies for automatically classifying ECG data into two categories: standard and affected (abnormal) patients. To represent the ECG signal, morphological characteristics are retrieved for these classes. In this work, the signals are prepared with the normalization and filtering approaches, which minimizes the noise incidence. The preprocessed image is segmented, and feature vectors are selected using Ant Colony Optimization (ACO). With the assistance of feature vectors, abnormalities in the ECG signals are classified with the Bi-Long Term Short-Term approach (Bi-LSTM). The performance of the proposed approach is investigated using the performance metrics and acquired accuracy of 90%, which outperforms the existing ECG classification techniques.
Keywords: ECG, classification, clustering, classification, deep learning, optimization, and R-peaks.

Introduction

The electrocardiogram (ECG) signal offers a wealth of pathological data on the cardiac activities of the patient. The categorization of heartbeats, vital for diagnosing arrhythmias, is one of the most significant analyses in the ECG. Arrhythmias can be classified as life-threatening or non-life-threatening. A breakthrough has been made in the study of life-threatening arrhythmias. Although heartbeat categorization of long-term ECG recordings, essential for identifying non-life-threatening arrhythmias, can be time-consuming and inconvenient, computerized algorithms can significantly assist. As a result, it's essential to look at the automatic heartbeat classification of the latter arrhythmias. The electrocardiogram (ECG), which shows the heart's rhythm and activity, is an essential non-invasive clinical technique used by cardiologists to identify various cardiac problems. Cardiovascular diseases (CVDs) are the leading cause of mortality from heart disease around the globe. One of the primary causes of CVD fatalities is Coronary Artery Disease (CAD). If not detected and treated early enough, the CAD disease can worsen quickly, leading to an irreversible state of heart muscle death known as Myocardial Infarction (MI). Usually, the electrocardiogram (ECG) signal is the primary indicator of the existence of certain heart disorders. Manually interpreting the minor changes occurring in the ECG waveforms, on the other hand, is complex and takes much skill. To circumvent these constraints, various automated diagnostic methods have been created.

Computational intelligence has been used to study several automated ECG arrhythmia categorization algorithms. Three required methods are sometimes included in a successful ECG arrhythmia

classification: feature extraction, clustering, and classification. Feature extraction is a critical operation that significantly impacts any ECG arrhythmia classification system's classification ability. As a result, the primary stage for ECG arrhythmia classification challenges has extracted relevant features and reduced their dimensions for classifiers to produce the best classification outcome. However, the categorization of considerably distinct arrhythmias is restricted since various forms are not visibly different when heart rate variability (HRV) data is utilized alone but are prevalent in patients.

The arrhythmias should be classified as accurately as possible to detect potentially significant cardiac disorders early. Higher classification accuracies can be obtained by readjusting the used kernel parameters of the classifier: machine learning (ML) techniques, optimization approaches and deep learning approaches.

The remaining part of the paper is systemized into five sections. The literature review is detailed in Section 2, the proposed ECG classification methodology is elucidated in Section 3, the acquired classification results are illustrated in Section 4, and the article is finished with future suggestions in Section 5.

Related Work

An effective hybridized strategy for categorizing electrocardiogram (ECG) samples into important arrhythmia classes to identify heartbeat irregularities using a deep learning-based cuckoo search algorithm (DL+CSO). The most common and widely recognized automated identification system for monitoring heart health is physiological identification, utilizing electrocardiogram (ECG) data. Arrhythmia beat categorization is also essential in electrocardiogram (ECG) assessment, which determines cardiac health status by evaluating heart rhythm. The authors want to use discrete wavelet transformation (DWT) to accurately categorize ECG samples into main arrhythmia classifications by reducing the latent noise in ECG signals during the preprocessing step. The leading training information acquired from the Support vector machine (SVM) is utilized for training the feed-forward back-propagation neural network (FFBPNN) to categorize signals into five classes [13].

Electrocardiogram (ECG) signals diagnose and monitor patients with various cardiovascular diseases (CVDs). This research aims to create a reliable system that can reliably categorize ECG signals even when there is noise in the surroundings. A one-dimensional convolutional neural network (CNN) containing two convolutional layers, two down-sampling layers, and a fully connected layer is utilized for classification. The identical 1D data was turned into two-dimensional (2D) pictures to increase the model's classification accuracy. The 2D CNN model, consisting of input and output layers, three 2D-convolutional layers, three down-sampling levels, and a fully linked layer, was then used to categorize ECG signals [14].

Cardiovascular disorders have been identified as the primary cause of death worldwide. Researchers are particularly interested in Myocardial Infarction (MI), famous as "heart attack," since early detection might avert life-threatening cardiac disorders and save human lives. The electrocardiogram (ECG) can identify many forms of cardiac arrhythmias and give crucial diagnostic data. Real-time ECG monitoring devices that employ powerful machine learning approaches give users real-time information about their health condition and a better user experience. However, because of their high

computational needs, modern machine learning algorithms have placed a strain on wearable and portable devices. An enhanced, less complicated Convolutional Neural Network (CNN)-based classifier system detects numerous arrhythmia categories in real-time, utilizing a two-dimensional representation of the ECG wave. The suggested model is a three-layer ECG signal analytical method that might be used in real-time wearable electronic monitoring devices in the future [15].

Anil Chacko and Samit Ari [16] said that the denoising technique for visual record signals supported by Empirical Mode Decomposition (EMD) is projected. The shrie visual record signal is ab initio rotten into a collection of Intrinsic Mode Functions (IMFs) exploitation EMD methodology. Within the projected technique, the IMFs that square {measure} dominated by noise are mechanically determined exploitation Spectral Flatness (SF) measure, then filtered exploitation Butterworth filters to eliminate the noise. This methodology is evaluated on visual record signals offered in MIT-BIH cardiac arrhythmia information. The experiment results show that the projected technique performs with a higher Signal to Noise magnitude relation (SNR) and lower Root Mean sq. Error (RMSE) than the ordinarily used moving ridge rework based primarily on denoising technique.

Galya Georgieva-Tsaneva and Krassimir Tcheshmedjiev [17] investigated a new adaptive thresholding method for denoising electrocardiography (ECG) signals using Wavelet Transform. The classical denoising technique has been improved by implementing a new subband-dependent threshold. The projected algorithmic rule has been tested with ECG signals (MITBIH cardiopathy Database) with additional commonplace Gaussian noise. Valuation parameters area unit calculated to see the effectiveness of the given algorithmic rule. The results showed that the proposed denoising algorithm could be applied to electrocardiography signals.

Mantosh Biswas and Hari Om [18] projected a replacement methodology of noise removal from a picture corrupted with Gaussian noise exploitation soft-thresholding. There is a unit of 2 varieties of thresholding: Soft and exhausting thresholding. The Universal thresholding methodology, i.e., VisuShrink, is predicated on Hardthresholding, and it's not acceptable for Soft-thresholding. Their projected methodology was straightforward and adaptational since the estimation of Thresholding parameters depends on the info of wave coefficients. According to the experimental results, this projected methodology has higher Peak S/N (PSNR) and visual effects than the VisuShrink.

Proposed Methodology

This section discusses the proposed methodology, where the drawbacks faced in literature are considered for formulating the proposed classification. The overall block diagram of the proposed approach is given in Figure 1.

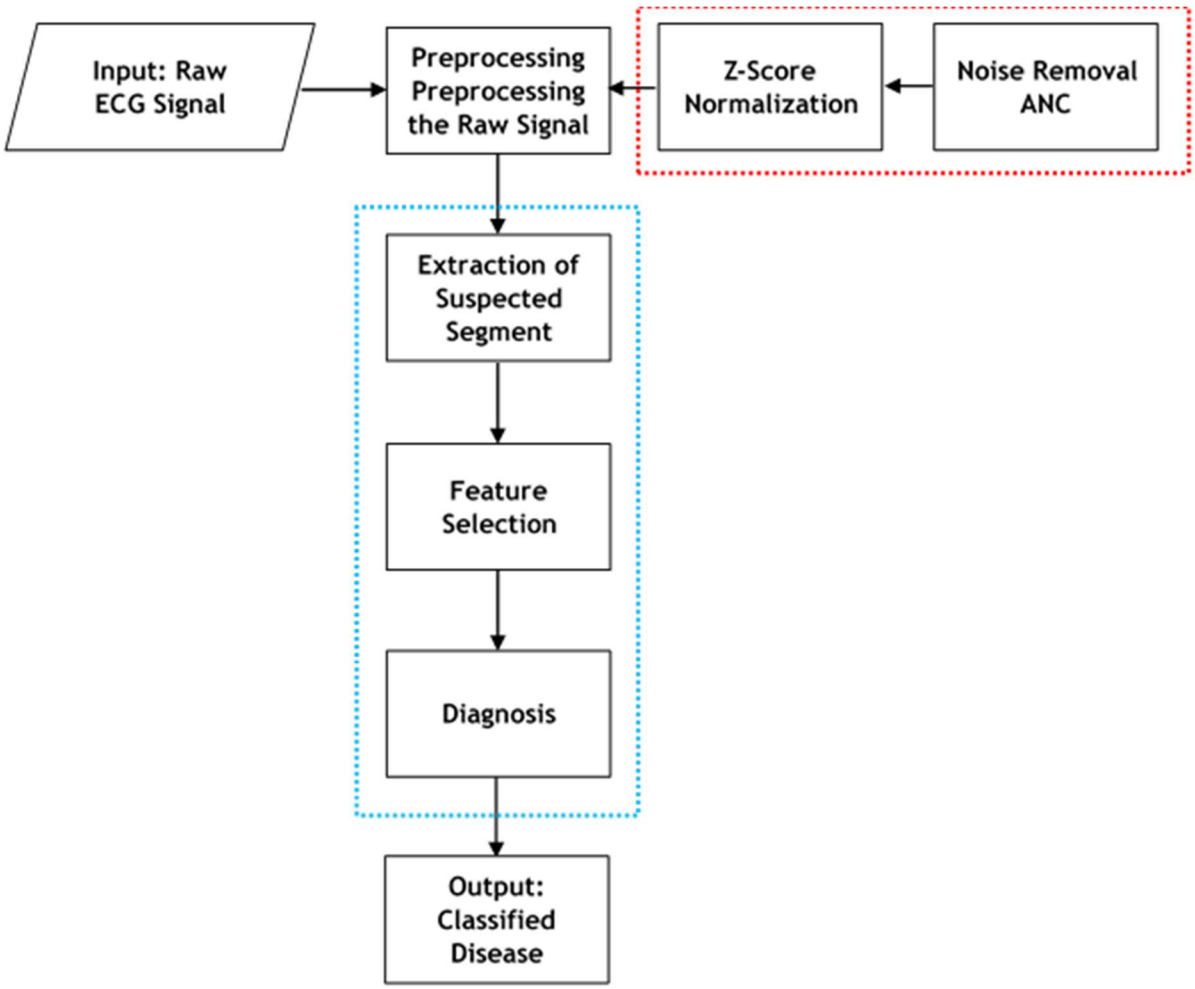


Figure 1. Overall block diagram of the proposed methodology

Pre-processing

The signal preprocessing is intended to acquire significant features with a greater probability of correlation. The preprocessing process is attained to the data before training and testing with Bi-LSTM. The process of preprocessing is displayed in section 4.

Normalization – Z-Score

Generally, Normalization is utilized in carrying the two signals to a similar or a predefined series. A typical example of a predefined series is the statistical discernment of the Normalization, converting the signal where the mean value is 0 and the standard deviation value is 1. In this proposed scheme, the z-score technique is utilized for the Normalization, which unveils the performance by flattening the signal [19]. The value of the z-score is equated as,

$$z - score = \frac{score - mean}{standard\ deviation}$$

This Normalization preserves the correlation between the normalized and original ECG signal, whereas it considerably minimizes the selection bias. After completing the normalization process, deep learning approaches are incorporated, and the Normalization makes the learning approach

easier.

Noise Removal- Least Mean Square Adaptive Noise Cancellation (ANC)

The noise greatly influences the ECG's high quality, which is a huge enemy of the ECG signal. The incidence of noise is decisive for the proper investigation of ECG. The incidence of noise in the ECG signal is removed by the Least Mean Square Adaptive Noise Cancellation (ANC). The unwanted information in the power line of the ECG signal is removed successfully by the ANC scheme [20].

Segmentation- K-means clustering

The images prepared by preprocessing are utilized in the process of segmentation that is done by k-means clustering. Image segmentation disintegrates a digital image into various subsets known as Image segments to decrease the image's complexity and facilitate subsequent processing or assessment. Segmentation is the process of allocating numbers to pixels in essential words [21]. This is the suggested method, in which K-means is used as a search methodology, and the final clusters' centers are based on a group of original centers. Having well-chosen starting centers is a crucial aspect of clustering. To discover excellent starting centers that split data collection across the data axis with the most significant variability, the research used the methods described in k means clustering.

Finding an unmounting position with both the most significant variance on the data axis and the lowest total segmentation distortion is a primary task. The unmonitored K-Means clustering approach separates the region of interest from the surrounding environment. The data is clustered or partitioned into K-clusters or K-centroid-based parts. The median filtering technique involves sliding a frame over most files. The filtered image is created by centering the frequency median of the output picture in the input frame.

The median is the maximum frequency estimate of location in a Laplacian distribution. When long-tailed noise is identified, the median filter estimates the gray-level value for reasonably uniform areas, and it is quite effective. When an edge is crossed, either side of the window is occupied, or the display suddenly switches among the values. The bottom, on the other hand, isn't hazy. The median filter value is g(x, y)=med{f(x-i, y-j),i, j, jw where the original image & reference image are f(x, y) g(x, y) respectively.

Feature Selection-Ant colony optimization

The images are fine-tuned by segmentation, and it is utilized in feature vector generation with the assistance of a bio-inspired approach. The behavior of ants is the basis for this algorithm. With the aid of the pheromone left by the former ants, all ants pursue the same course. Successive ants use this pheromone to locate their way. As a result, each ant gradually builds a solution to the challenge [22]. Similarly, each ant builds the feature of the input picture repeatedly to acquire the characteristics of the ECG signal. The below formula shows the probability calculation to choose the next feature based on the base attractiveness, τ, and visibility η,

$$pro(\,feature, f) = \frac{\tau(f) * \eta(\mathrm{f})}{\sum_{available_features_f'} \tau(f') * \eta(f')}$$

The procedure of Ant Colony Optimization is given in Algorithm 1.

Algorithm 1: ACO

```
Input: ECG Signal
Output: Feature vector
Begin
Initialize the base attractiveness, τ, and visibility, η,
for each feature for i < IterationMax do:
        for each ant, do:
                choose probabilistically (based on the previous equation) the next state to
                move into;
                add that move to the list for each ant
                repeat until each ant completed a solution
        end
        For each ant that completed a solution, do:
                update attractiveness τ for each feature that the ant traversed
        end
        if (local best solution better than a global solution)
                save local best solution as a global solution
        end
end
```

Classification- Bidirectional Long Term Short Term Memory Bi-LSTM

Bi-LSTM is a diversified form of standard network in that it takes a sequence vi=(vi1,vi2,…..,viT) as input, and the process of iteration is accomplished from it=1 to T that generates the following,

$$q_{ti} = \Phi(y_{qit} + W_{hi}h_{ti-1} + W_{at^{vt}})$$

where q is a vector encoding the concealed unit q = (q1, q2, ..., qT). Bias vectors are the b terms (e.g., yq denotes bias of the hidden layer). The nonlinear function Φ varies depending on the situation; however, in the case of a generic RNN, it is generally the adoption of the element-wise sigmoid (σ), as shown following equation [23]. When a Bi-LSTM is utilized, however, this is calculated with Φ.

The acquired features are passed to the first two layers, whereas the values are elected randomly, which minimizes the error. After processing the data in the preceding layers, the output returns, and the softmax activation function estimates probability. The RNN elects the data that is remembered or forgotten. At a sequence of time ti, the learning network is updated as,

$$i_{ti} = \sigma(W_{ai}a_{ti} + W_{hi}h_{ti-1} + y_i)$$

$$f_{ti} = \sigma(W_{af}a_{ti} + W_{hf}h_{ti-1} + y_f)$$

$$g_{ti} = \tanh\,(W_{ac}a_{ti} + W_{hc}h_{ti-1} + y_c)$$

$$c_{ti} = i_{ti} \odot g_{ti} + f_{ti} \odot c_{ti-1}$$

$$o_{ti} = \sigma(W_{ao}a_{ti} + W_{hi}h_{to-1} + y_o$$

$$h_{ti} = o_{ti} \odot \tanh\,(c_{ti})$$

where the activation function is signified as σ, the multiplication with element-wise is signified as ⊙, the input vector value at the time it is signified as ati, and the hidden states in the network are signified as the weight matrix for the diverse layers are signified as Wai, Waf, Wac, Wao for ati, weight matrix for the diverse layers are signified as Whi, Whf, Why, Who for hti, the bias in the layer is signified as yi, yf, yc, yo, the input layer is signified as i, the forgotten layer is signified as f, memory layer is signified as c, and the output layer is signified as o. LSTM memory cells are effective in identifying and exploiting long-range contexts.

Algorithm 2: Bi-LSTM

Generation of subset and instance from the whole training process

The iteration generation process $q_{ti} = \Phi(y_{qit} + W_{hi}h_{ti-1} + W_{at^{vt}})$

Random generation of variables

Training individual Bi-LSTM classifier where the training process of the classifier is initiated

$$i_{ti} = \sigma(W_{ai}a_{ti} + W_{hi}h_{ti-1} + y_i)$$

Accomplishing the prediction process and final prediction with overall score generation

Result and Discussion

In this section, ECG signals are classified, and the proposed methodology outcomes are evaluated by the performance metrics, namely accuracy, precision, recall, and f-measure. The images are acquired from the publicly available dataset [24]. The proposed approach is compared with the existing approaches, namely DL+CSO, hybrid deep CNN, 2D CNN, and Bi-LSTM. The input ECG signals are given in Figure 2.

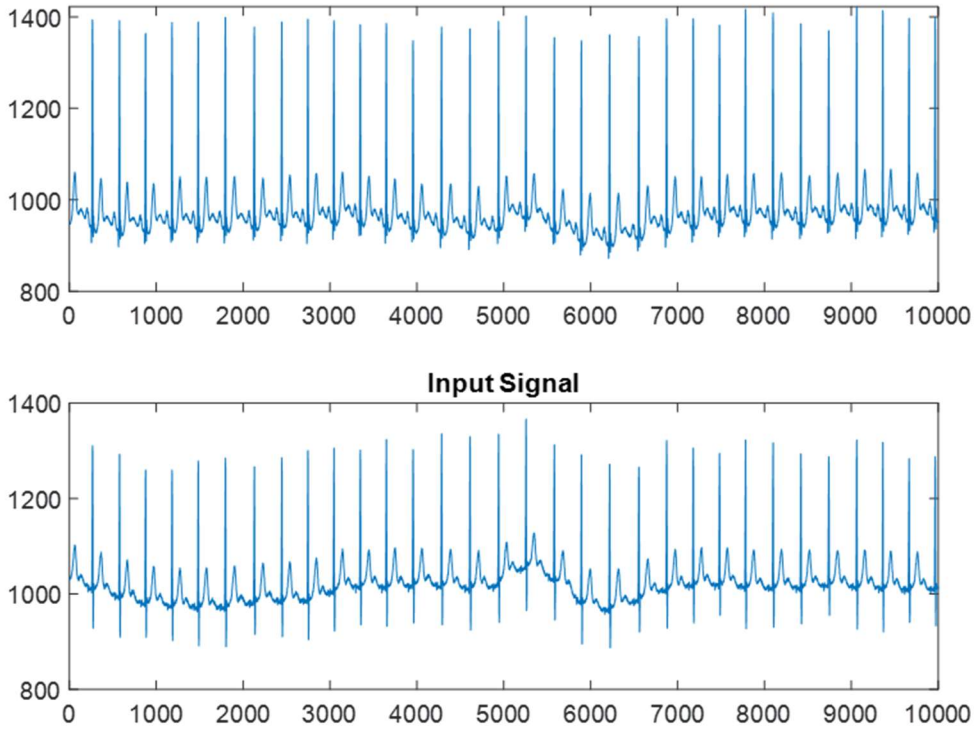


Figure 2. Input ECG signals

The input format of ECG signals is given in Figure 2, showing the general form of input signals without any processing or enhancements.

Pre-processing

This section discusses the process of preprocessing considered in this research work. The actions taken to prepare pictures before they are utilized in model training and inference are known as image preprocessing. This covers downsizing, aligning, and color adjustments, among other things.

Z-Score Normalization

Normalization is an image processing procedure that alters pixel intensities' spectrum. For example, images with low contrast owing to glare might be used. Normalization is also known as histogram shifting or contrast adjustment. The normalized images and their spectrums are given in Figures 3 and Figure 4.

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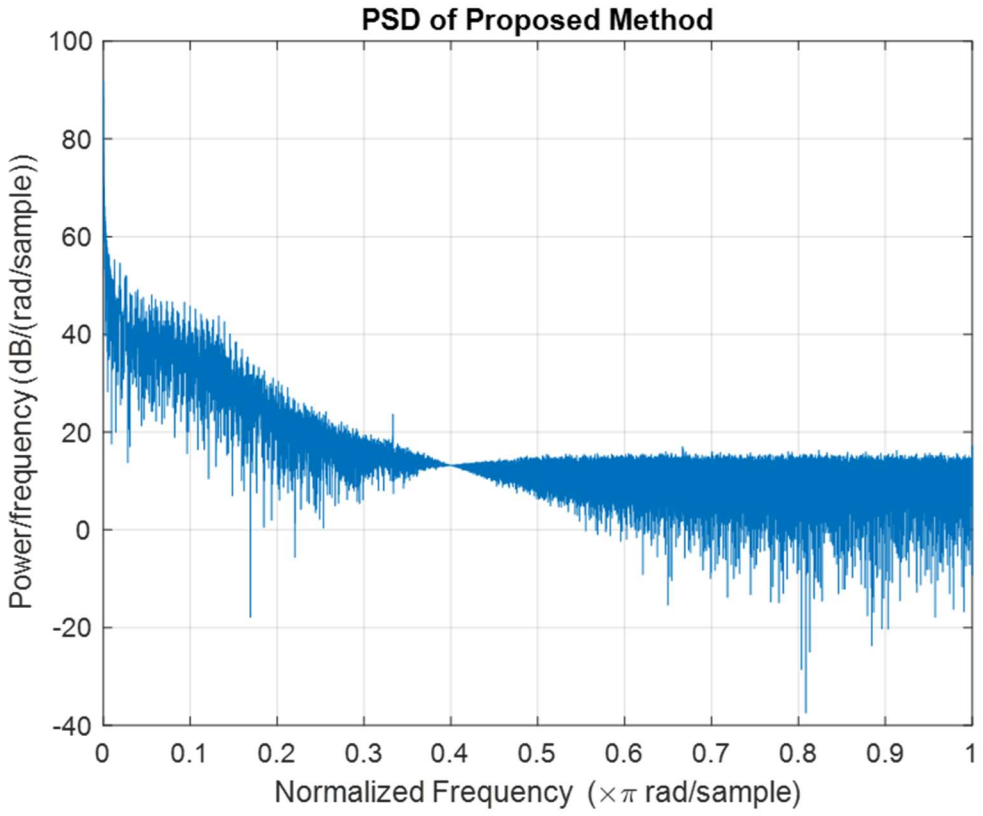


Figure 3. Normalized Frequency of ECG

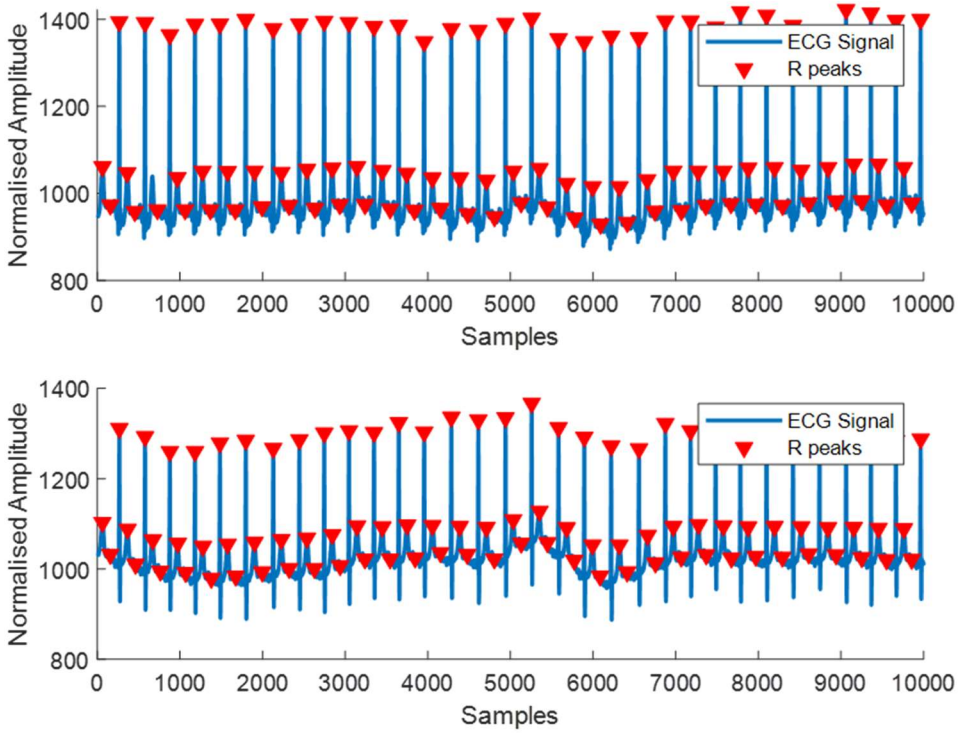


Figure 4. Normalized amplitude with R peaks

The above images show the power spectral density analysis and R-peaks of normalized ECG signals.

Least Mean Square Adaptive Noise Cancellation (ANC)

An adaptive filtering system employs a noise cancellation concept to reduce as much noise as feasible. Two inputs are used in the adaptive filtering system. One input comprises the noise-corrupted speech signal. A noise reference input is the second source. The signal noise is processed using ANC, shown in Figure 5.

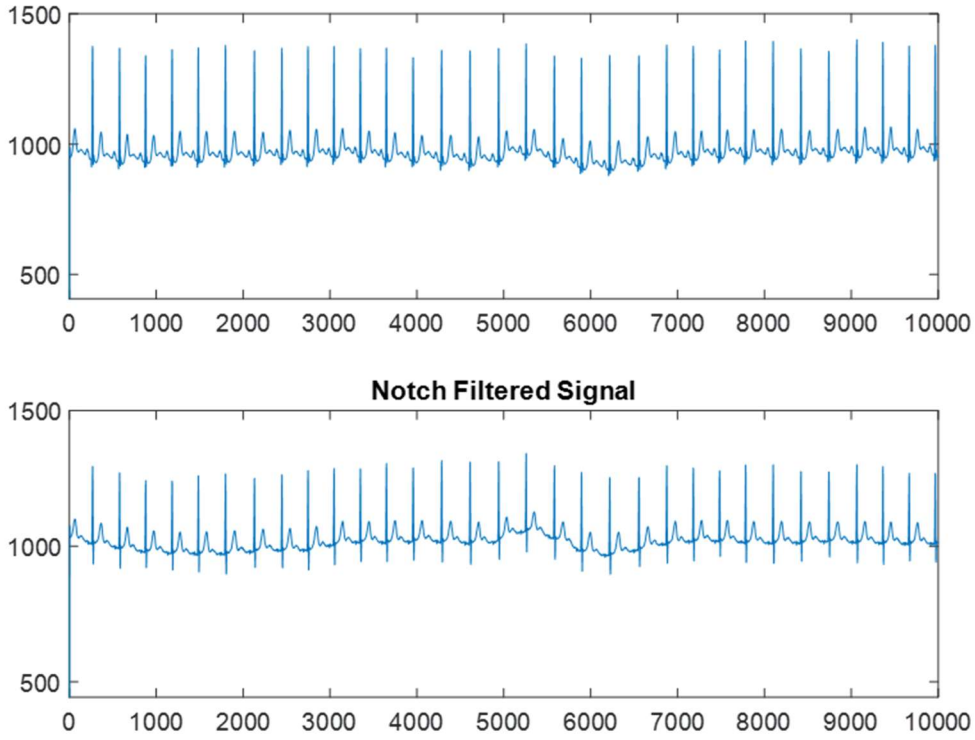


Figure 4. ECG signal processed using ANC

Figure 4 shows the ECG signals after applying the ANC filter, whereby the filter-applied image is utilized for further feature extraction.

Performance of Classification

Accuracy

Accuracy is a measure of how near a value calculated from categorized ECG signals is to the true value and a representation of systematic mistakes or statistical bias. Accuracy refers to the closeness of determining true positive and actual negative values from the signal classes under investigation. Differences in genuine value investigative outcomes cause the occurrence of low accuracy. The ratio of incidence of epilepsy in the ECG signal is the total count of the signal investigated. The value of accuracy is equated as,

$$Acy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}$$

Table 1. Comparison of Accuracy

Number of Images	Existing Algorithm			Proposed Algorithm
	DL+CSO	Hybrid Deep CNN	2D CNN	Bi-LSTM
10	80.4	82.7	86.3	90
20	78.1	83.3	85.2	87.4
30	75.6	81.2	86.2	90

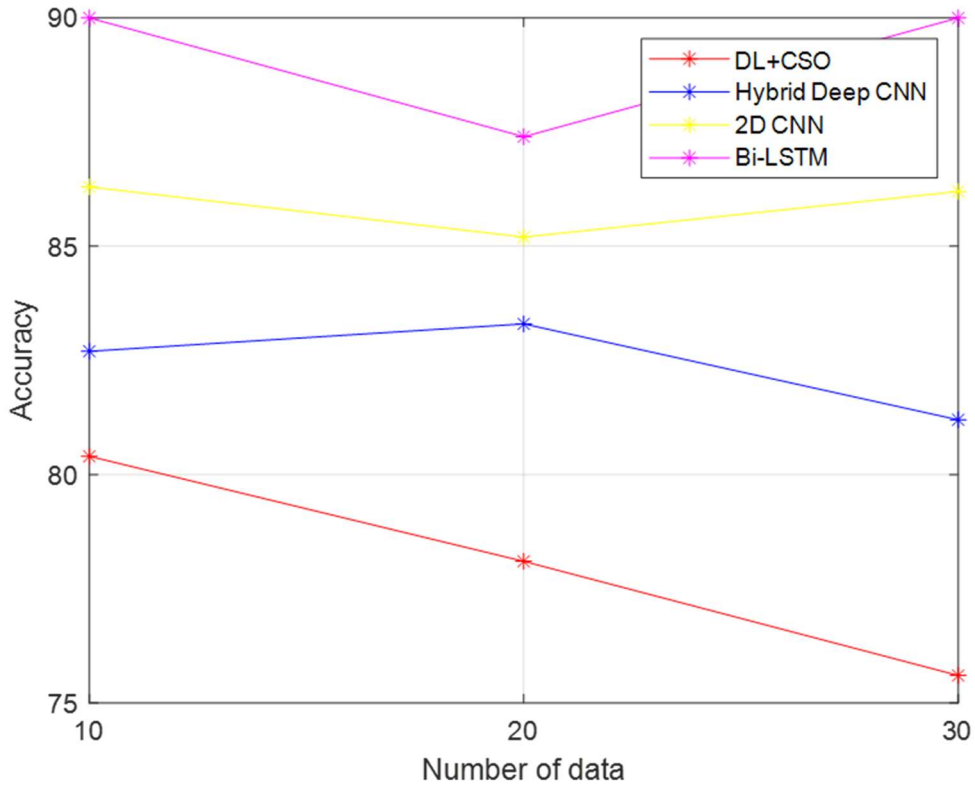


Figure 5. Comparison of Accuracy

Figure 5 shows the accuracy acquired from the proposed Bi-LSTM compared with the existing DL+CSO, Hybrid Deep CNN, and 2D CNN algorithm. The accuracy rate of Bi-LSTM is {9.6%, 7.3%, and 3.7%} higher than {DL+CSO, Hybrid Deep CNN, and 2D CNN} existing algorithm for 10 images. The accuracy rate of Bi-LSTM is {9.3%, 4.1%, and 2.2%} higher than {DL+CSO, Hybrid Deep CNN, and 2D CNN} existing algorithm for 20 images. The accuracy rate of Bi-LSTM is {14.4%, 8.8%, and 3.8%} higher than {DL+CSO, Hybrid Deep CNN, and 2D CNN} existing algorithm for 30 images. The acquired high F-Measure illustrates the effectiveness of the proposed Bi-LSTM.

Precision

The analytical rate with positive results, also known as precision, reflects the accuracy of the measurement and the relevance of the signals found. The frequency of random mistakes is expressed as precision, which is expressed using statistical variables. Accuracy and precision are the same concepts for acquired signal values. Typically, binary or decimal digits are used to represent the accuracy of a signal. True Positive (TP) and False Positive (FP) rates are used to calculate them. The fraction of positive readings in the ECG signal determines the precision value. The count of fundamental positive values (i.e., the count of items accurately labeled as positive classes of ECG signals) is the accuracy number for a specific issue in the classification stage. The algorithm's high precision shows a resulting value that achieves more desired data than the incorrect data. It's likened to

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Table 2. Comparison of Precision

Number of Images	Existing Algorithm			Proposed Algorithm
	DL+CSO	Hybrid Deep CNN	2D CNN	Bi-LSTM
10	79.1	81.1	84.7	85
20	77.1	82.4	84.2	86
30	77.5	82.3	86.4	87.5

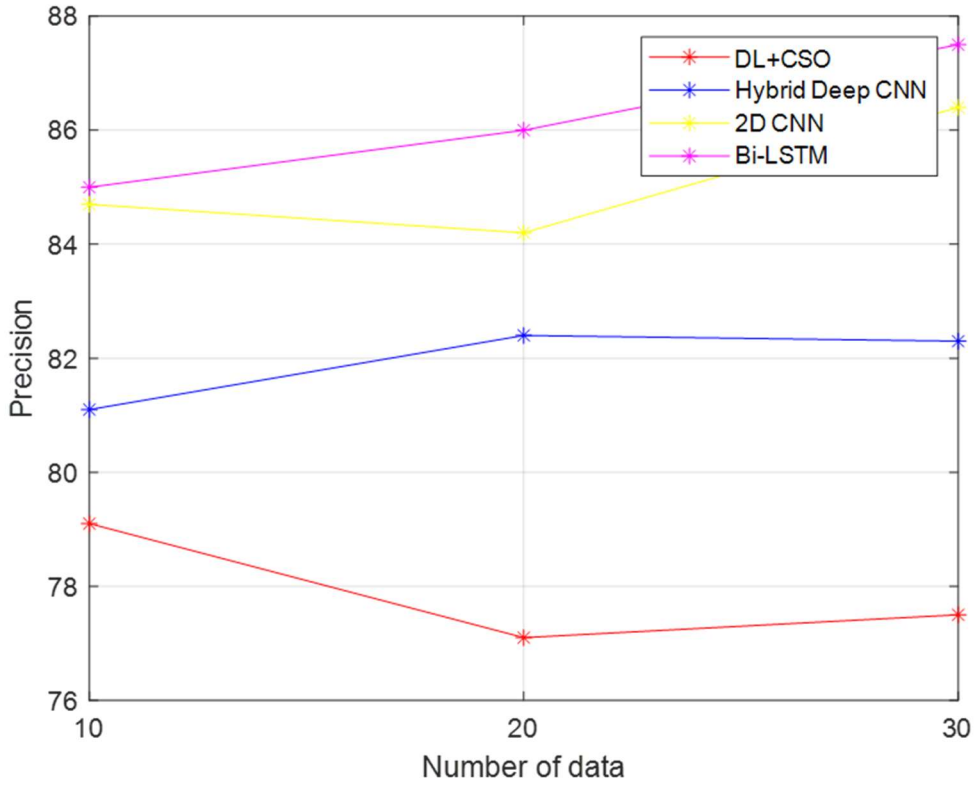


Figure 6. Comparison of Precision

In Figure 6, the precision acquired from the proposed Bi-LSTM is compared with the existing DL+CSO, Hybrid Deep CNN, and 2D CNN algorithm. The rate of precision of Bi-LSTM is {5.9%, 3.9%, and 0.3%} higher than {DL+CSO, Hybrid Deep CNN, and 2D CNN} existing algorithm for 10 images. The rate of precision of Bi-LSTM is {8.9%, 3.6%, and 1.8%} higher than {DL+CSO, Hybrid Deep CNN, and 2D CNN} existing algorithm for 20 images. The rate of precision of Bi-LSTM is {10%, 5.2%, and 1.1%} higher than {DL+CSO, Hybrid Deep CNN, and 2D CNN} existing algorithm for 30 images. The acquired high F-Measure illustrates the effectiveness of the proposed Bi-LSTM.

Recall

The associated ECG signals among the reclaimed episodes make up the recall rate. The estimated recall measure is the successful predicting rate, and recall is the count of associated events. The count of adequately spotted values is multiplied by the count of TP and FP values in the ECG signals to calculate recall. Epilepsy in the ECG signal identification at TP and False Negative (FN) rates are used to assess precision. It is computed as follows:

$$Recall = \frac{TP}{TP + FN}$$

Table 3. Comparison of Recall

Number of Images	Existing Algorithm			Proposed Algorithm
	DL+CSO	Hybrid Deep CNN	2D CNN	Bi-LSTM
10	84.3	85.5	89.2	92
20	83.2	87.2	88.8	95
30	80.8	87.2	91.4	100

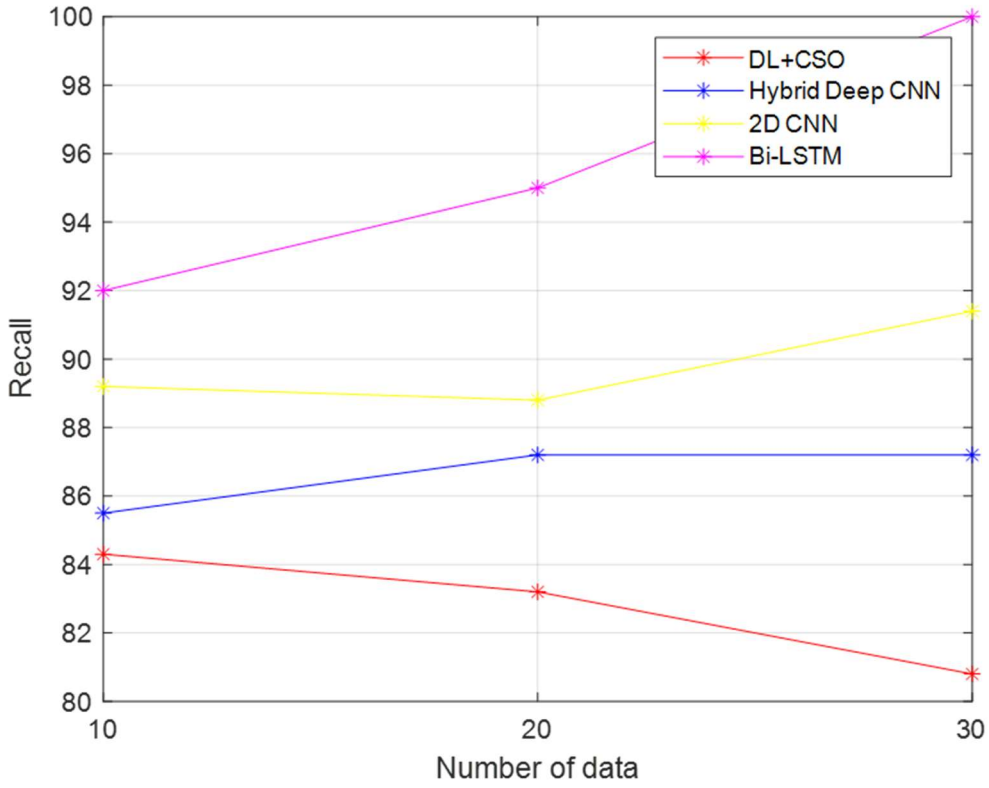


Figure 7. Comparison of Recall

In Figure 7, the recall acquired from the proposed Bi-LSTM is compared with the existing DL+CSO, Hybrid Deep CNN, and 2D CNN algorithm. The rate of recall of Bi-LSTM is {7.7%, 6.5%, and 2.8%} higher than {DL+CSO, Hybrid Deep CNN, and 2D CNN} existing algorithm for 10 images. The rate of recall of Bi-LSTM is {11.8%, 7.8%, and 6.2%} higher than {DL+CSO, Hybrid Deep CNN, and 2D CNN} existing algorithm for 20 images. The rate of recall of Bi-LSTM is {19.2%, 12.8%, and 8.6%} higher than {DL+CSO, Hybrid Deep CNN, and 2D CNN} existing algorithm for 30 images. The acquired high F-Measure illustrates the effectiveness of the proposed Bi-LSTM.

4.2.4. F-Measure

The F-measure or F-score determines the accuracy of the examination of the categorization problem.

The method achieves the optimum f-measure value by achieving the highest accuracy and recall value. The F-measure value improves the retrieval of relevant information from the ECG and provides a realistic representation of the algorithm's performance. It's calculated as follows:

$$F - measure = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

Table 4. Comparison of F-Measure

Number of Images	Existing Algorithm			Proposed Algorithm
	DL+CSO	Hybrid Deep CNN	2D CNN	Bi-LSTM
10	81.5	83.3	86.9	90
20	80.3	84.6	86.4	92.5
30	79.1	84.5	88.6	93.3

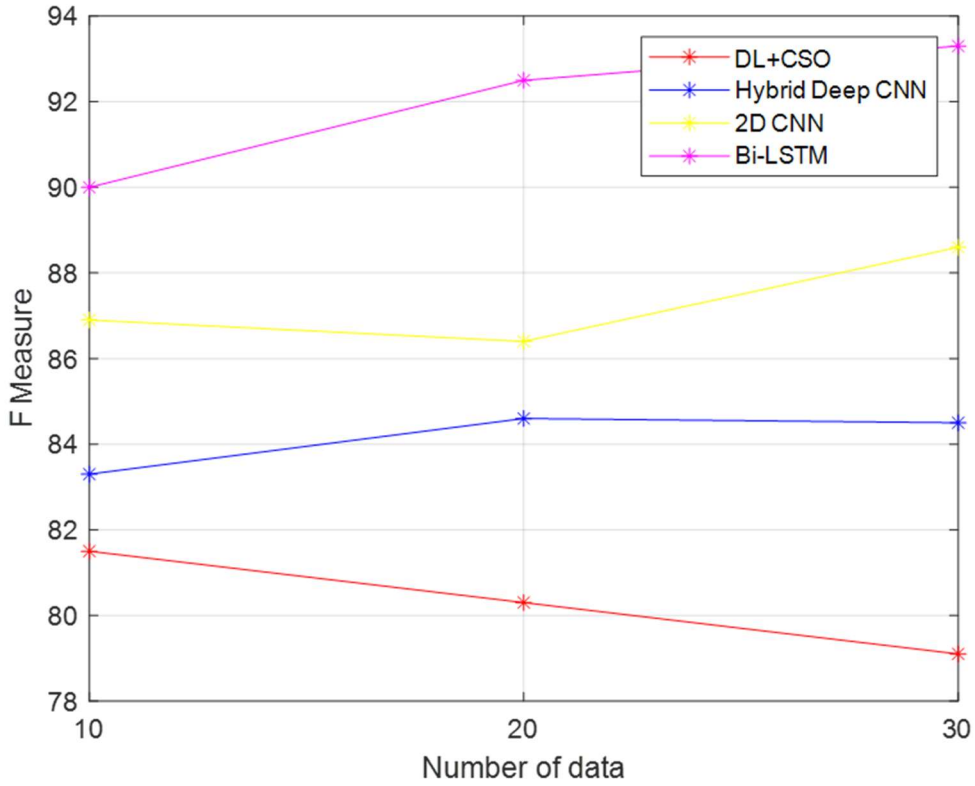


Figure 8. Comparison of F-Measure

In Figure 8, the F-Measure acquired from the proposed Bi-LSTM is compared with the existing DL+CSO, Hybrid Deep CNN, and 2D CNN algorithm. The rate of fmeasure of Bi-LSTM is {8.5%, 6.7%, and 3.1%} higher than {DL+CSO, Hybrid Deep CNN, and 2D CNN} existing algorithm for 10 images. The rate of fmeasure of Bi-LSTM is {12.2%, 7.9%, and 6.1%} higher than {DL+CSO,

Hybrid Deep CNN, and 2D CNN} existing algorithm for 20 images. The rate of fmeasure of Bi-LSTM is {14.2%, 8.8%, and 6.7%} higher than {DL+CSO, Hybrid Deep CNN, and 2D CNN} existing algorithm for 30 images. The acquired high F-Measure illustrates the effectiveness of the proposed Bi-LSTM.

Conclusion

Medical professionals are increasingly using automatic ECG classification in medical diagnoses and therapies. This paper outlines excellent methods for automatically categorizing ECG data into two groups: normal and abnormal. These classes' morphological qualities are used to represent the ECG signal. The signals are produced in this study using normalization and filtering techniques, which reduce the amount of noise. Ant Colony Optimization is used to segment the preprocessed picture and pick feature vectors (ACO). The Bi-Long Term Short Term method classifies anomalies in ECG data using feature vectors (Bi-LSTM). The suggested approach's performance is evaluated using performance measures and achieves a 90% accuracy rate, which exceeds the existing ECG classification techniques' accuracy.

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