AUTOMATED CLASSIFICATION OF ECG SIGNAL USING CONVOLUTIONAL GATED RECURRENT NEURAL NETWORK FOR CARDIAC DISEASE DETECTION

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ABSTRACT

Early detection of unusual heart conditions is huge to recognize heart disappointment and maintain a strategic distance from unexpected death. The human with similar heart conditions nearly has practically identical using electrocardiogram (ECG) signals. By reviewing the ECG signals' models, one can anticipate heart disease.Since the standard techniques for heart disease disclosure depend after securing morphological features of the ECG signals, which are repetitious and tedious, the customized recognizable proof of cardiovascular disease is progressively perfect. Subsequently, the programmed identification of heart diseases a satisfactory strategy is required, which could arrange the ECG signals with dark features as appeared by the similitudes among them and the ECG signals with known characteristics. If this classifier can discover the similitudes, the likelihood of cardiovascular disease disclosure is broadened. This count can change into a significant procedure in research facilities. During this examination work, and another classification technique is brought into the Convolutional Gated Recurrent Neural Network classification methodology. All the more precisely, orders ECG signals that rely upon a powerful model of the ECG signal classification. With this proposed method, a convolutional gated recurrent neural network was constructed, and its simulation results show that this classification can partition the ECG with 97% accuracy.

Keywords: Electrocardiogram, myocardial infarctions, computer-aided diagnosis, arrhythmia detection, Convolutional Gated Recurrent Neural Network

1. INTRODUCTION

An electrocardiogram (ECG) is a complete depiction of the heart's electrical activity on the outside of the human body and comprehensively used in pharmacological testing of cardiovascular diseases [1, 2], which can be reliably used as an extent of the working of the cardiovascular system.ECG signals have been commonly used for diagnosing cardiovascular diseases in light of its ease and non-prominent nature.Features of ECG Signals and ECG models can be resolved and incorporates isolated using some reproduction programming software (Eg.matlab). For example, an enormous number of individuals suffer from irregular heartbeats, which can be dangerous now and then. Like this, low circulatory blood is significantly appealing to distinguish heart rate absolutely and economically [3].

A few investigations have created frameworks approaches dependent on robotized examination and ECG signaling to use as a classification of coronary illness. The significant components for the assessment and finding of cardiovascular diseases are the feature extraction, and classification of heart pulsates. Various techniques for requesting ECG signals have been proposed as of late and to achieve incredible results. The exhibition of the ECG framework classification firmly relies upon the portrayal intensity of the features that are gotten in the plan of the ECG signal and classifier (classification model). Automated classification of cardiac disease detection hasbeen recently accounted for by numerous investigators utilizing an assortment of features to speak to various ECG classification methods.

In existing, automated classification methods have a high false classification ratio. Therefore, this research introduced a new model based on the Convolutional Gated Recurrent Neural Network model for classification of ECG heartbeats to detect the cardiac disease, to significantly enhance the efficiency and effectiveness of the classification. The remaining part of this work is organized as follows:

Chapter 2: Discuss the literature survey based on existing ECG signal classification methods

Chapter 3: Presents the operation of the proposed cardiac disease detection system

Chapter 4: Presents the simulation results and performance analysis of the proposed method

Chapter 5: Presents the conclusion and feature work of cardiac disease detection method

2. LITERATURE SURVEY

The ECG signal identifies abnormal conditions and breakdowns by recording the potential bio-electric variety of the human heart. Precisely recognizing the clinical condition introduced by an ECG signal is a problematic errand [4]. In this way, cardiologists need to precisely predict and recognize the correct sort of abnormal heartbeat ECG wave before suggesting a specific treatment. This may require watching and examining ECG chronicles that may proceed for quite a long time (patients in essential consideration). To beat this test for the visual and physical clarification of the ECG signal, computer-supported indicative frameworkshave been created to naturally distinguish such signals, consequently [5].

The vast majority of the exploration in this field has been directed by consolidating various Machine Learning (ML) strategies for the productive distinguishing proof and precise assessment of ECG signals [6,7]. ECG signal grouping dependent on various methodologies has been introduced in writing including frequency examination [8], counterfeit neural networks (ANNs) [9], heuristic-based techniques [10], measurable strategies [11], Support Vector Machines (SVMs) [12], Wavelet Transforms [13], filter banks [14], concealed Markov models [15], and blend of-master techniques [16]. An artificial neural network-based technique got a normal exactness of 90.6% for the ECG wave arrangement into six classes [17]. In the interim, a feed-forward neural network was utilized as a classifier for identifying four sorts of arrhythmia classes and accomplished the greatest exactness [18].

Machine learning is a subset of artificial knowledge utilized with top of the line symptomatic apparatuses [19-23] for the prediction and conclusion of various kinds of ailments [24]. Deep learning, as a subset of ML, has numerous applications in the prediction and counteraction of deadly disorders, especially Cardiac attacks. The various procedures of deep learning utilized for the examination of bioinformatics signals have been introduced in [25-27]. Be that as it may, there are a few disadvantages to these classification techniques. For example, master frameworks require a lot of earlier information, which may fluctuate for various patients. Another issue lies in the manual element choice of the heartbeat signal for some machine learning techniques. Therefore, this research introduced a new model based on the Convolutional

Gated Recurrent Neural Network model for classification of ECG heartbeats to detect the cardiac disease, to significantly enhance the efficiency and effectiveness of the classification.

3. MATERIALS AND METHOD

A block diagram of the proposed convolutional gated recurrent neural network-based cardiology disease detection is shown in which the three major stages of operation of the proposed system are classified as ECG signal pre-processing, feature extraction, and classification (shown in Figure 1). By using Pre-processing artifacts or noise is removed using the dual-tree discrete wavelet transform method. Followed by features are extracted from Artifacts or Noise removed signal. Finally,Convolutional Gated Recurrent Neural Network (CG-RNN) classifier analysis the extracted features and find out whether the disease is present or not from the Electrocardiogram signal.

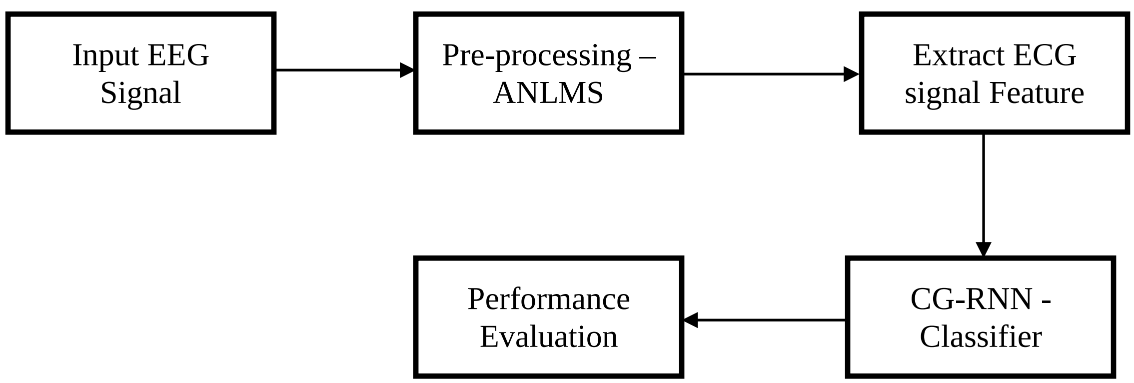

Figure 1: Proposed system architecture

3.1 ECG Signal Pre-processing-Adaptive Normalized Least Mean Squared Filter

The exhibition of the classification, not just base anyway it is additionally founded on the features and upgraded ECG signal Adaptive Normalized Least Mean Squared (ANLMS) Filter and assembled the noise segment simultaneously safeguarding the space features. This algorithm works by normalizing the intensity of the info and hence balancing out the filter. In this calculation step size, a boundary isn't steady, choosing the normalized step size boundary. The step size boundary μ changes to μ(n).The weight refreshing condition for this algorithm was

$$w(n+1) = w(n) + \mu(n)X(n)e(n) \text{ .... (1)}$$

Where,

μ = correction factor or step size for the filter coefficients

w = Weight factor

e = error

The advantage of the planned LMS algorithm is that step size can be picked freely of the information signal power and number of tap weights. Thus the ANLMS algorithm has a combined rate and a consistent state error rate superior to the LMS algorithm. The algorithm steps of ANLMS as Follows

3.1.1 Algorithm: Adaptive Normalized Least Mean Squared

Step 1: Begin

Step 2: Obtain the signal pattern

Step 3: Read the input signal from the dataset

Step 4: For Each Signal E at Time Ti From Ie

E = ANLMS (E)

If Ei>minTh then

Add to the signal pattern E.

E=Σ(E+Ei).

End

Step 5: stop.

3.2 Feature Extraction -Dual-Tree Discrete wavelet transform

An electrocardiogram contains different time areas and space area features; they are the amplitudes and intervals of various sectors. In this work,extract the features of the P-wave interval, P-waveAmplitude,T-wave interval, T-waveAmplitude, QRS-Wave interval, values of PQRST waves. Each element extracted and stored in the database for additional control. In this work,the dual-tree wavelet transform method is used for feature extraction.

3.2.1 Algorithm for Feature Extraction:

Step 1: Read Input ECG signal with Transformation Ds

Step 2: Extract the following features:

Pr=P-wave interval

Tr = T-wave interval

QRS = QRS-wave interval

PA- P wave Amplitude

TA - Q wave Amplitude

Construct vector V_i and add to vector set V_s

$V_s = \sum V_i(Pr,Tr,QRS,PA,TA)$

End.

Step 3: Stop

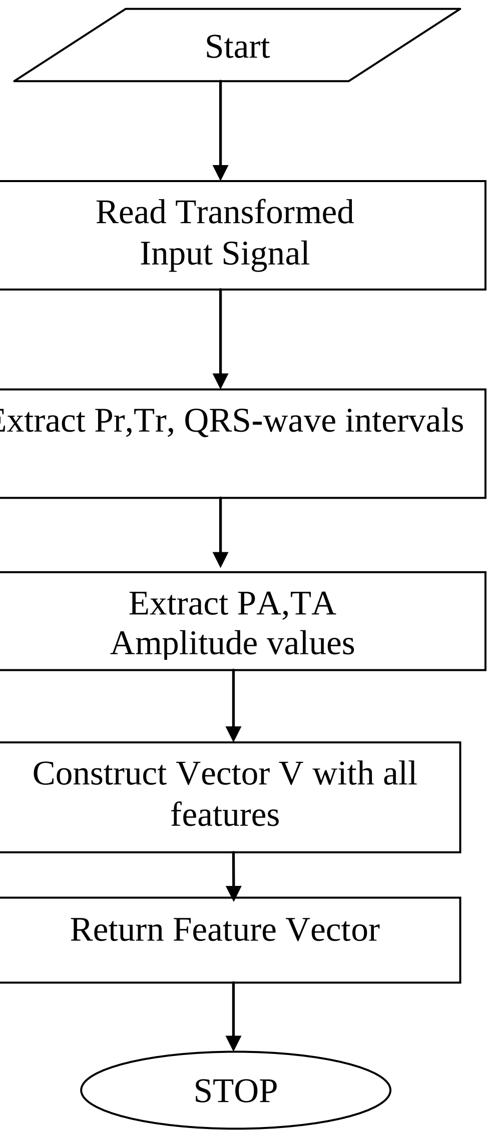

Figure 3 Flowchart of feature extraction

Figure 3 shows the feature extraction procedure to disengage the features of the information from the ECG signal. The recognized component peaks are utilized to perform characterization and assessment utilizing a stochastic example. The created designs from the pre-processed signal are utilized as information, and the pre-computed pattern set is retrieved from the data set. We calculate the similarity measure with each segment in the existing pattern group database with the extracted feature peaks. It has a pattern set that is more similar in each pattern and is identified. The components based on the ECG signal are separated and classified and constructed from the input pattern to form a determined value for each signal value of the waveform. The patterns generated from different dimensions and the generated patterns will be used to calculate the sequence similarity measure.

3.3 CONVOLUTIONAL GATED RECURRENT NEURAL NETWORK

Convolutional Gated Feed-Forward Neural System (CG-FFN) has developed as a fundamental device for classification. It is a computational model that has the appearance of the human neural system. The design of a convolutional gated is prepared to do any rough capacity.Along these lines, convolutional gated is the correct decision when the capacity to be educated isn't known ahead of time. Convolutional Gated feed-forward neural network frameworks are data-driven and self-flexible strategies in which they can change themselves to the data, with no definite detail of practical or distributional from with the fundamental model. The convolutional gated comprises three layers: the input layer, hidden layer, and output. A simple structure of multiclass convolutional gated, as outlined in Figure 4. In the given convolutional gated, inputs are taken as Ip and Is. The data of each node are assigned to each node of the hidden layer.

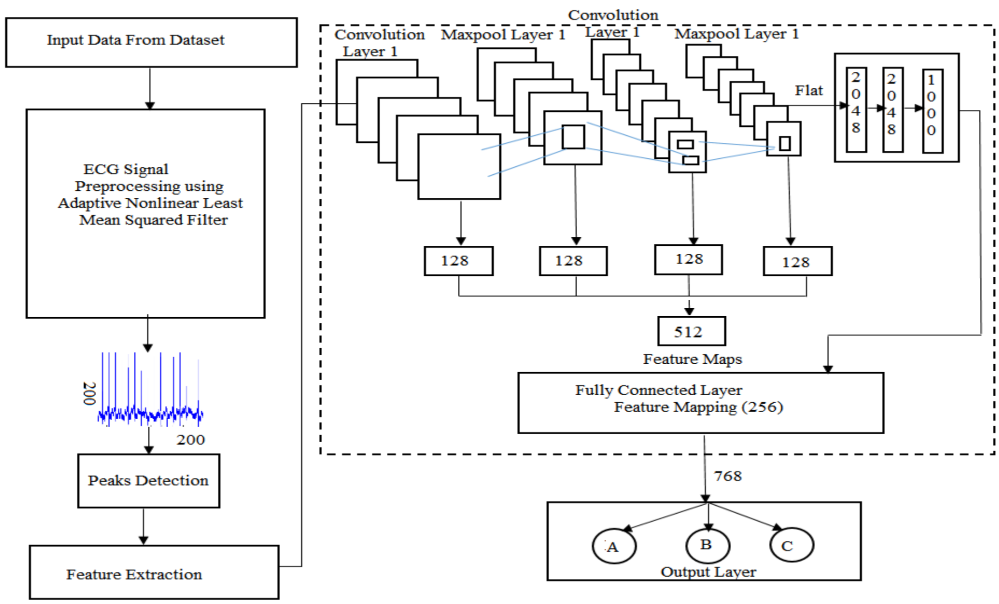

Figure 5.The architecture of Convolutional Gated feed-forward neural network

Figure 5 shows the **architecture of the Convolutional Gated feed-forward neural network**. The reference picture has been founded on the source of the "convolution gated feed-forward neural system" to help comprehend this in a disentangled way. In CG-FFN, there are three parts, notwithstanding the input and output layers, to be specific to the convolution, pool, and complete associated layers. The accompanying steps are performed during the classification procedure:

3.4.1 Convolutional Gated Feed-Forward Neural Network Algorithm

Step1: Select the Input Data from the dataset

Step2: Remove the noise using Adaptive Nonlinear Least Mean Square Filter.

Step 3: Detect the peaks from the pre-processed signal

Step 4: Extract ECG feature (P,Q,R,S,T)

Step6: Compare features of the query signal with tested data from the database by Euclidean Distance (E.D.)/ Canberra Distance (CD) technique. In this distance illustrates the root of the sum for the square differences between opposite values in vectors.

$$ED(x, y) = \sqrt{\sum_{i=1}^{n} |x_i - y_i|^2} \ldots (2)$$

Where x, y = Numeric Vectors

Step 7: Store the result and classify what type of medicinal disease.

Step 8: Perform the sorting of the result.

Step 9: Display the corresponding ECG signal.

A proficient investigation of estimating execution for classification capacities is introduced with regards to sensitivity, specificity,and accuracy, which are usually utilized assessment measurements, and proposed proportions of these measures are utilized to assess the presentation. These measures give the best point of view on the classifier's execution for classification.

Table 1: Confusion matrix for classification

EVALUATION METRIC	PREDICTED OUTCOME	
	POSITIVE	NEGATIVE
POSITIVE	TP	TN
NEGATIVE	FP	FN

The confusion matrix contains data on the genuine and anticipated classifications of a classification framework, where T.P. and T.N. are the quantities of true positive and true negative forecasts for the specific class. F.N. and F.P. are the quantities of false negatives and false positives for the particular class. The sensitivity, specificity, and accuracy are measure using equations 3, 4, and 5, respectively.

$$\text{Sensitivity} = \frac{T_p}{T_p+F_n} * 100 \quad (3)$$

$$\text{Specificity} = \frac{T_n}{T_n+F_p} * 100 \quad (4)$$

$$\text{Accuracy} = \frac{T_p+T_n}{T_p+T_n+F_p+F_n} * 100 \quad (5)$$

Where

T_p = True positive,T_n = True negative, F_p = false positive, F_n = False negative.

4. SIMULATION RESULTS AND DISCUSSION

The proposed cardiac disease detection based ECG approach using a convolutional gated recurrent neural network technique has been implemented and tested for its efficiency. The exhibition of the proposed framework is contrasted and past techniques. This area shows the outcomes created by the proposed strategy.

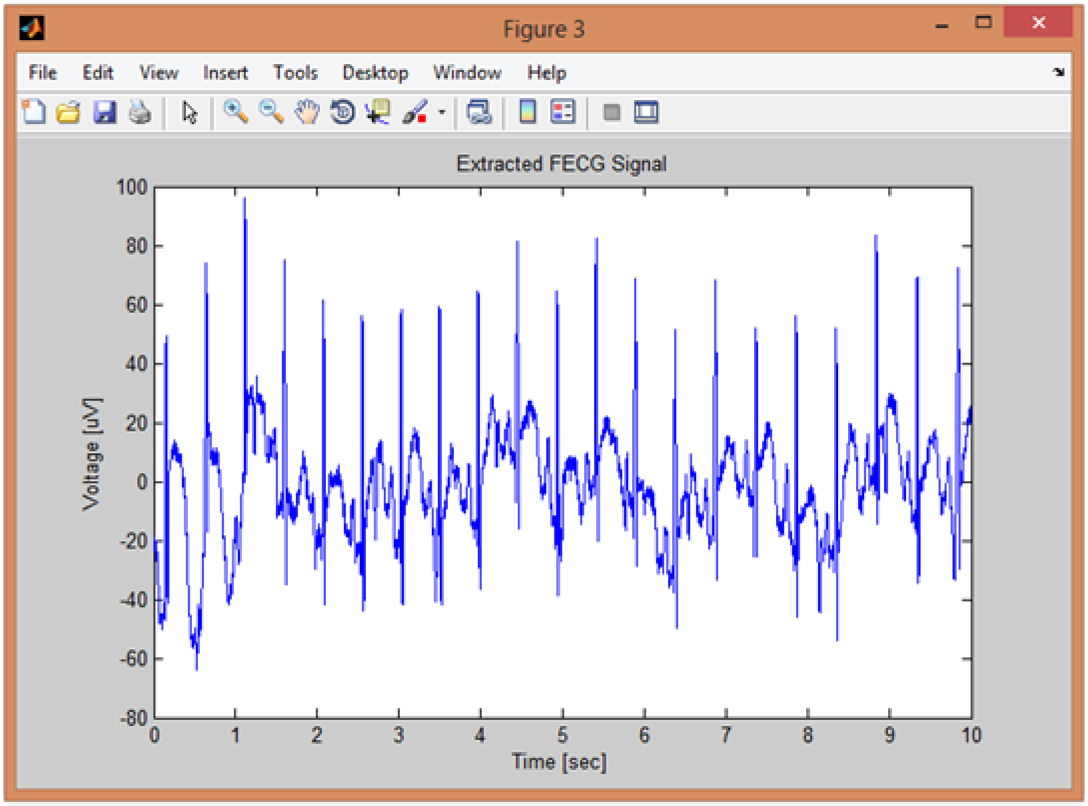

Figure 4: shows the input ECG-Subject-1.

Figure 4 shows the input ECG waveform of the subject-1 with noise been removed. Figure 5 shows the simulated drowsy detected waveform for the Theta band.

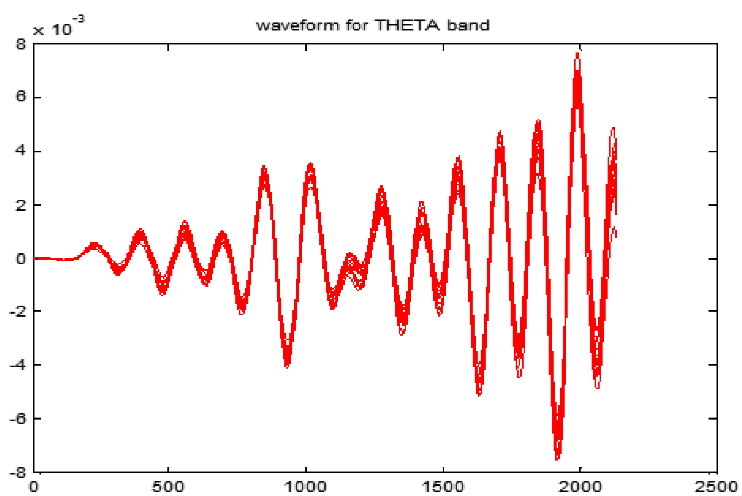

Figure 5: Simulated tired detected waveform for the Theta band

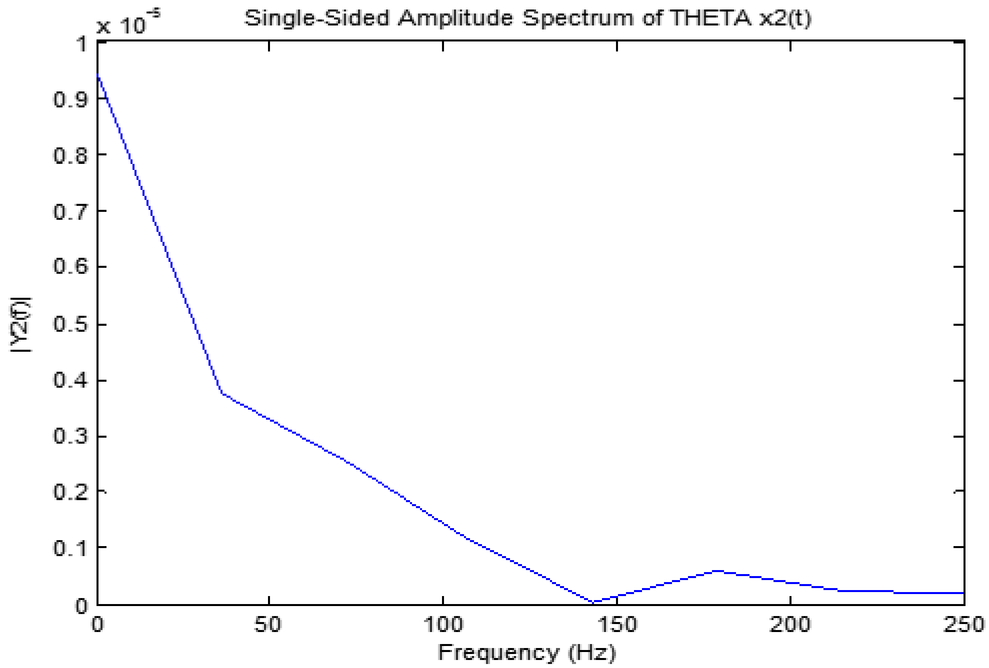

Figure 6: Amplitude power spectrum for the Theta band

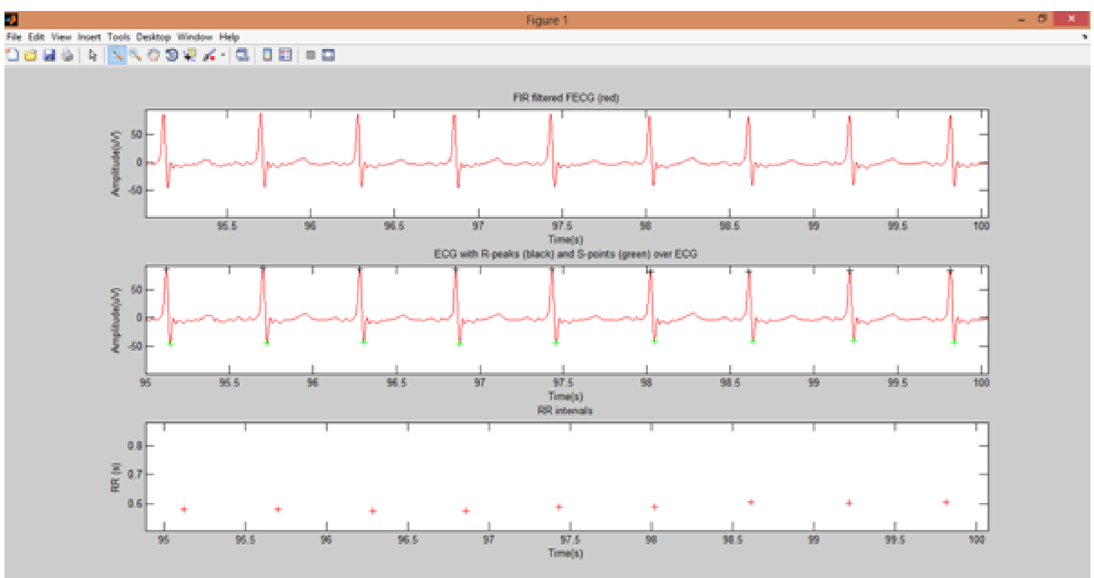

Figure 7 Disease detected results in the ECG cycle.

Figure 7 shows the waveform of drowsy detected ECG from the input waveform. Figure7 demonstrates the snapshot of a result produced at each ECG cycle considered.

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On the premise that Variability control may contain nonlinear parts, there is an expanding enthusiasm to consider ECG utilizing techniques other than the standard straight strategies, i.e., time-space and ghostly examination. It has been shown that loss of Inter Beat Interval (IBI) signal complexity and loss of fractal-like scaling behaviors may be a general feature of signal processing. Optimization Plot analysis, entropy-based measures, and fractal-based standards are but a few Variability analysis techniques used.

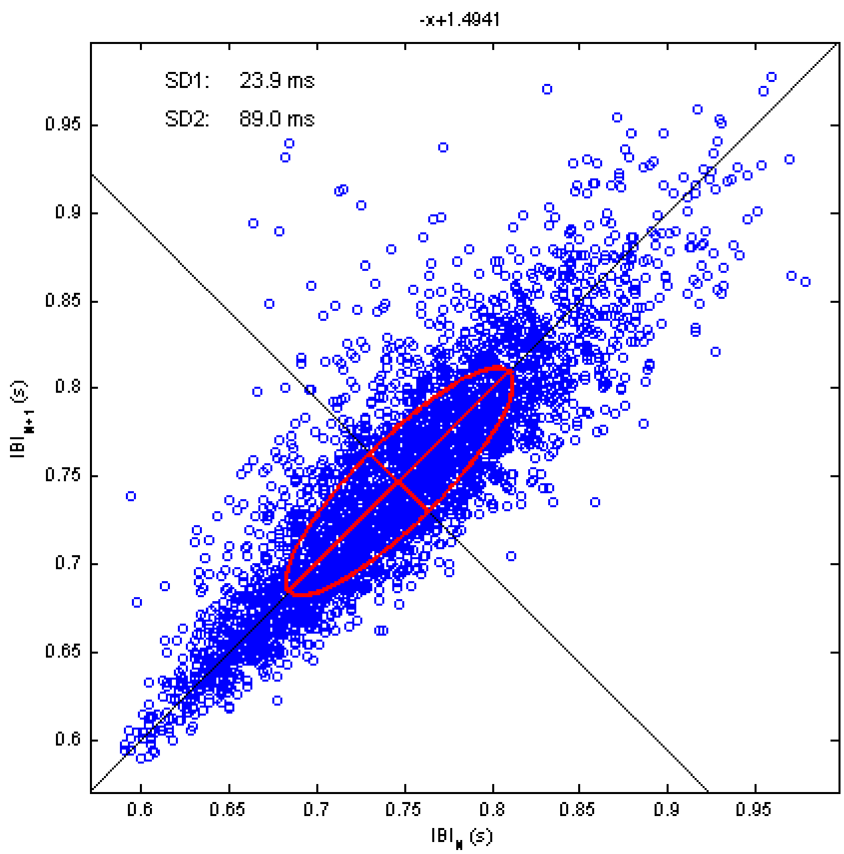

Figure 8– Nonlinear Analysis of ECG.

The performance of various classifiers is shown in Table 1. The accuracy-related and the false-rate-related measures are computed for comparing input and processed ECG signal with true positive, true negative false positive and false negative signal not available.

Table 1: Performance Analysis in terms of per unit

MEASURES	*Proposed CG_RNN*	*EXISTING [NVDN]*	*EXISTING [PCA]*	*EXISTING [LDA]*
Precision	0.96	0.94	0.90	0.83
Recall	0.71	0.63	0.56	0.53
F-Measure	0.87	0.73	0.67	0.63
Accuracy	0.93	0.67	0.57	0.52
Sensitivity	0.91	0.60	0.56	0.51
Specificity	0.92	0.78	0.61	0.59
FDR	0.02	0.06	0.10	0.16
FNR	0.21	0.27	0.43	0.48
FPR	0.18	0.21	0.26	0.39
FAR	1.95	2.16	3.06	5.10
FRR	12.03	15.01	20.25	21.03
MCC	0.21	0.29	0.20	0.07

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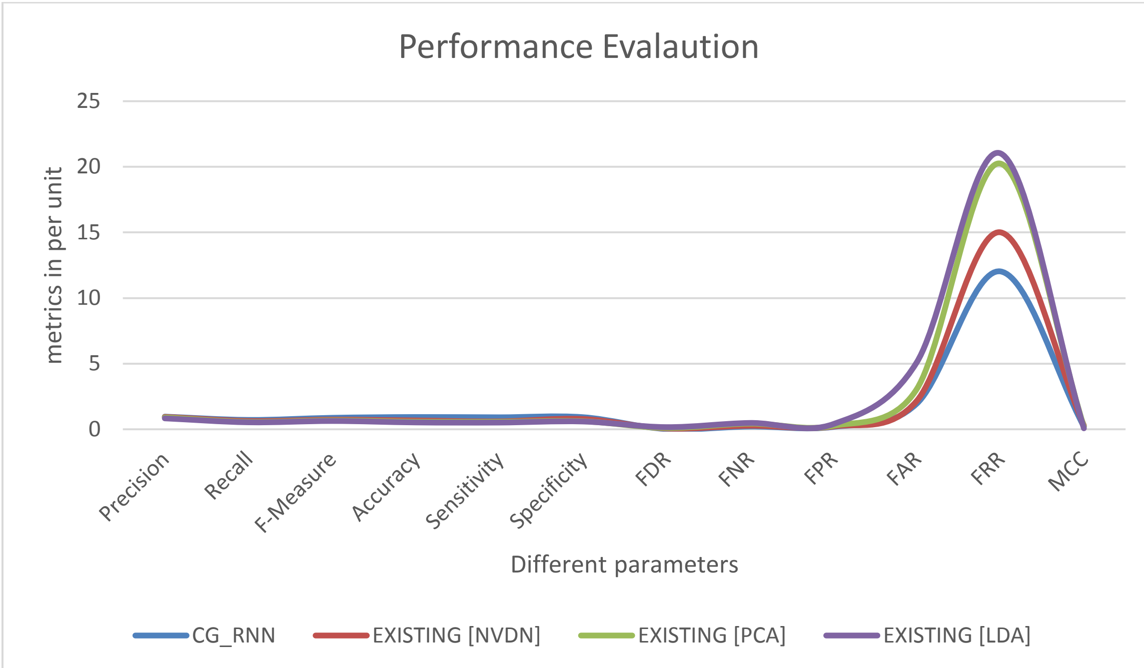

Figure 9. Performance Evaluation Metrics

From the comparison table 1 and Figure 9 it has been shown that the precision, recall, F-measure, accuracy, sensitivity, a specificity of the proposed techniques such as CG_RNN are 0.96, 0.71, 0.87, 0.93, 0.91, 0.92respectively which is higher than the existing method PCA and LDA.Similarly,From the comparison table 1, it has been shown that the false discovery rate, False-negative Rate, False Positive Rate, False Acceptance Rate, False Rejection Rate and Mathew's Correlation coefficients of the proposed techniques such as CG-RNNare 0.02, 0.21, 0.18, 1.95, 12.03,0.21respectively are also considerably reduced when compared to the existing method PCA,LDA, and ICA.

5. CONCLUSION

The problem of the difference in the central electrocardiogram of heart patients with the same condition will affect the heart rate classifier's performance. In this study, complex QRS and statistical parameters were omitted to cover important analysis data covering cardiac events. The feature extraction standard improves reliability and reduces the structural complexity of the ECG classifier. In this work, a new classification method is proposed to more accurately classify ECG signals based on the dynamic model of ECG signals. In this research work, a new classification strategy is proposed for a more accurate model of ordering ECG signals to rely on ECG signals.The method proposed here was developed by Convolution Gated Recurrent Neural Network (CG-RNN), and its simulation results show that the classification can isolate the electrocardiogram with high productivity. This proposed technique expands the accuracy of ECG classification regarding increasingly accurate arrhythmia findings. This proposed method increases the accuracy of the ECG classification regarding more precise arrhythmia detection.For example, precision, recall, F-measure, accuracy, sensitivity, specificity of the proposed technique are 0.96, 0.71, 0.87, 0.93, 0.91 and 0.92 respectively

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