Research Journal of Computer Systems and Engineering
ISSN: 2230-8571, 2230-8563
Volume 02 Issue 01 - 2021 (January to June)
Page 06:10

ECG Signal Analysis for Myocardial Disease Prediction by Classification with Feature Extraction Machine Learning Architectures

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Article History	***Abstract***
Received: 22 January 2021 Revised: 14 April 2021 Accepted: 19 May 2021	An effective method for early diagnosis of numerous cardiovascular disorders is the electrocardiogram (ECG) signal. This method is particularly useful for detecting arrhythmias, which are irregular heartbeats. This research proposes novel technique in ECG signal analysis for myocardial disease prediction using machine learning architectures-based feature extraction and classification. Here the input is taken as ECG signal for detecting myocardial disease and process the signal for noise removal. The processed signal features are extracted using principal component analysis and classified using fast fourier vector machine. The objective of the work, the algorithms used, and the outcomes are the qualitative and qualitative parameters used to compare and contrast the existing methodologies. The experimental analysis has been carried out in terms of accuracy, precision, recall, F_1 score, SNR and RMSE. Keywords: Electro cardiogram, myocardial disease prediction, machine learning, feature extraction, classification

1. Introduction:

A medical test called an electrocardiogram (ECG) measures the electrical activity the heart produces to look for signs of cardiac abnormalities. Small electrical impulses from the heart go throughout the heart muscle. An ECG machine can identify these impulses. The electrical activity of the heart is captured by an ECG machine, which then plots this information as a trace on paper. A medical professional interprets this data after that. ECG aids in identifying the source of symptoms like chest pain and aids in the detection of irregular cardiac (heart) rhythms [1]. Due to difficulties in the classification process, classifying ECG signals is a difficult problem. Lack of standardisation of ECG features, variability among ECG features, individuality of ECG patterns, absence of ideal classification methods for ECG classification, and variability in patient ECG waveforms are major problems [2] in ECG classification. Another challenge in the classification of ECG arrhythmias is creating the best classifier that can classify arrhythmia in real-time. Applications of ECG signal categorization include diagnosing a new patient more accurately than by hand and determining the type of abnormality [3].

2. Related works:

The categorization of ECG signals has been a focus of numerous studies. They used several feature extraction approaches, classifiers, and pre-processing techniques. Work [4] has used DWT to extract the RR interval and Z score to standardise the RR interval. They categorised ECG beats using FCM.They had a 99.05% accuracy rate. Using DWT, the RR interval and R point position are features that were retrieved in [5]. FCM was used for preclassification, and 3-layer MLPNN for final classification.They obtained 99.99% accuracy. In [6], DWT is used to extract the R peak and RR interval. Using MLPNN, ECG classification was carried out. 0.00621 was the measured Mean Squared Error (MSE).Work [7] used DWT to extract the RR interval. In this research, the performance of MLPNN and SVM were compared. The R peak and RR interval were manually retrieved by the author of [8] from the MIT-BIH arrhythmia database's annotation file. Features are reduced using FCM and normalised using Zero mean. As a classifier, a 3-layer FFNN with a back propagation technique is employed [9,10].

3. System model:

This section discussnovel technique in ECG signal analysis for myocardial disease prediction using machine learning architectures based feature extraction and classification. Here the input is taken as ECG signal for detecting myocardial disease and process the signal for noise removal. The processed signal features are extracted using principal component analysis and classified using fast fourier vector machine. Figure 1 shows overall architecture

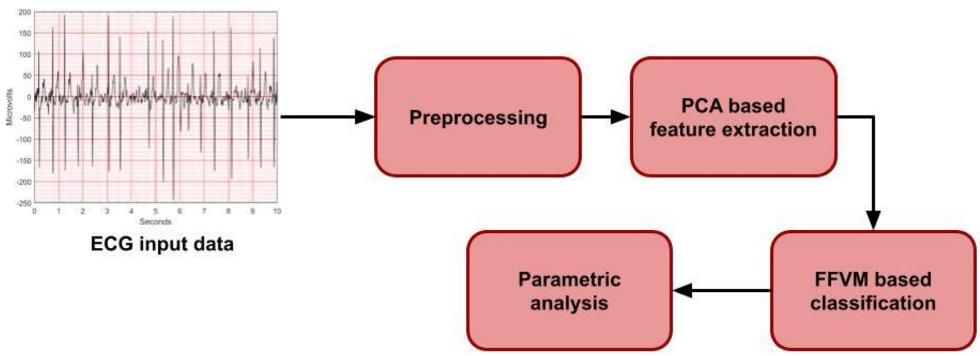

Figure 1: overall architecture

The dataset was filtered to remove ECGs that were not divided into diagnostic classifications. The ECGs with a probability of categorization less than 100% were subsequently filtered out. In the following stage, ECGs from subclasses with less than 20 occurrences in the dataset were filtered out. For the investigation, a sampling period of 10 seconds at a frequency of 100 Hz was chosen. The training, validation, and test sets were split up into the dataset in the following ratios: 70%, 15%, and 15%, respectively. The validation set was used to choose the model, the training set was used to train the network, and the test set was used to evaluate the performance of the network.

Principal component analysis-based feature extraction:

The method necessitates training, which calls for the input of several data sets from diverse testing scenarios. Each data set from an observation is converted into a column vector, Gn, whose length N depends on the number of variables employed, in order to create eigensignals. We shall have an array matrix G with a dimension of M £ N for M observations. Consequently, we have by eq. (1)

$$r = [\Gamma_1, \Gamma_2, \Gamma_3, \dots, \Gamma_M]$$

$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n$ (1)

The average signal is subtracted from each training signal to calculate the difference signals eq. (2):

$$\Phi_i = \Gamma_i - \psi \qquad (2)$$

Principal components analysis is now being applied to these vectors. The covariance matrix C should be calculated in order to determine the orthogonal eigenvectors by eq. (3).

$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n \cdot \Phi_n^T = \frac{1}{M}\mathbf{A}\cdot\mathbf{A}^\top$ (3)

where$\mathbf{A} = [\Phi_1, \Phi_2, \dots, \Phi_M]$.

$$\mathbf{A}^\mathrm{T}\mathbf{A}\nu_i = \mu_i V_i$$

Eigensignals are the name given to this UI. After obtaining the eigensignals, the biggest corresponding eigenvalues are used to select the M eigensignals that are the most important. A linear combination of the eigensignals can be used to identify any signal.

Fast Fourier vector machine:

In the proposed strategy while applying the Fast Fourier Transformation - FFT, every ECG signal is Fourier Transformed but before registering the Fourier change, Hamming window is utilized with Fourier Change as it has better side flap concealment attributes [10]. The length of the window is taken as the quantity of tests inside the chosen 3 second intervals. The choice of the FFT coefficients that utilized in the characterization is a basic subject. In this way, the best number of FFT coefficients will be controlled by experimentation. We found that we get best outcomes with 80 coefficients of FFT. Computerized signal processors use FFT for wide uses. Be that as it may, it is a calculation done at a lot higher speed than what a Continuous-Time Fourier Transform would require in processing time. This makes the FFT thought for microprocessor-based instruments used to separate periodic waveforms, for example, heart rhythms from a noisy source. The noise source on account of the ECG instrument is inalienable broadband noise that exists on the ECG leads as got on the patient's body and the encompassing electromagnetic vitality field in the instrument.

4. Experimental analysis:

This paper's preprocessing was put into practise using MATLAB 2021a. Based on Python 3.6, the enhanced SVM network model was created. The operating system was Windows 64-bit, and it had an Intel(R) Core(TM) i7-5500U CPU running at 2.40 GHz and 8.00 GB of RAM.

Table-1 Comparative analysis of MIT-BIH dataset

Parameters	MLPNN	SVM	ECG_MDP_FEMLA
Accuracy	85	88	91
Precision	71	73	75
Recall	64	68	71
F-measure	51	53	55
RMSE	38	41	43

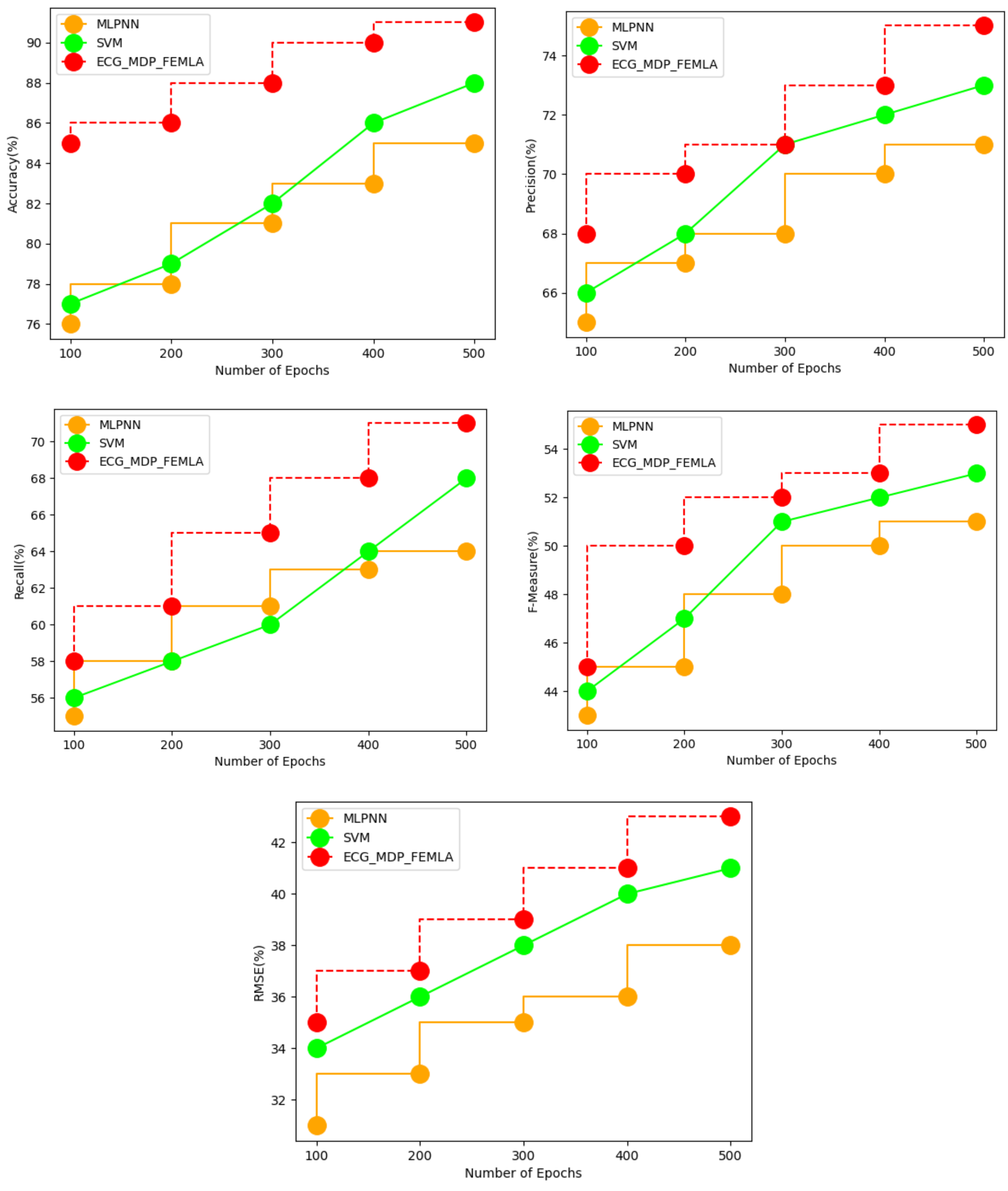

Figure- 2 Comparative analysis of MIT-BIH dataset in terms of (a) Accuracy, (b) precision, (c) Recall, (d) F-measure, (e) RMSE

The above table-1 and figure 2 (a)- (e)shows the comparative analysis for MIT-BIH dataset based on accuracy, precision, recall, F_ measure and RMSE. Here the proposed technique attained accuracy of 91%, precision of 75%, recall of 71%, F_ measure of 55% and RMSE of 43%which is optimized when compared to existing technique for MIT-BIH dataset. One metric for measuring classification model performance is accuracy. Informally, accuracy is percentage of predictions that our method correctly predicted. Accuracy is defined as follows in formal language: Accuracy is the quantity of accurate forecasts. sum of all projections. How frequently an algorithm successfully classifies a data point can be determined, for example, by looking at the accuracy of the algorithm. The percentage of projected data points that really occurred is known as accuracy. One measure of a ML methods effectiveness is precision, or standard of a successful prediction the model makes. Ratio of overall number of true positives to total number of positive forecasts is known as precision. F1-score combines precision and recall of a classifier into one metric by computing their harmonic means. It is mostly used to evaluate the performance of two classifiers.

5. Conclusion:

This research propose novel technique inin ECG signal analysis for myocardial disease prediction using machine learning architectures based feature extraction and classification. Here the input is taken as ECG signal for detecting myocardial disease and process the signal for noise removal. The processed signal features are extracted using principal component analysis and classified using fast fourier vector machine. The experimental analysis has been done in terms of RMSE, F 1 score, recall, accuracy, and precision. Because heart disease classification accuracy has improved, using entropy-based characteristics has been advantageous. The inclusion of entropy-based features to data preparation has promise for improving other signal-processing-related activities.

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