ARRHYTHMIA RECOGNITION USING ECG MORPHOLOGY BY TRAINED FEED FORWARD NEURAL NETWORK

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Abstract—
Analysis of ECG signal plays an important role in diagnosing cardiac diseases. In this work, a novel method is proposed for accurate recognition and classification of cardiac arrhythmias. Firstly, QRS components have been extracted from the noisy ECG signal by rejecting the background noise. Then it classifies the heart abnormalities according to previous extracted features. Trained feed-forward neural network has been selected for this research. Here, data used for the analysis of ECG signal are from database. Cardiac arrythmia indicates the abnormal electrical activity of the heart that can be a great threat to human which needs to be diagnosed.

***Index Terms*—ECG signal; QRS components; Trained feed-forward neural network.**

1. INTRODUCTION

The cases pertaining to Cardio Vascular Diseases (CVD) are increasing alarmingly nowadays. CVD's lead to or the root cause of death all over the world with 17.9 million deaths each year that forms around 30% of total deaths[8]. CVD deaths occur comparatively more in developing countries rather than developed ones. The main causes leading to CVD are unhealthy diet, obesity, lack of exercise, high blood pressure, tobacco abuse and stressed life style. Arrhythmia is a disease that comes under CVD, which is also fatal [3]. The problem has to be diagnosed in the earlier stages so as to prevent further cardiac complication and subsequent sudden death. Arrhythmia is most prevalent at present in which the electrical activity of the heart is either too fast (tachycardia) or too slow (bradycardia) that makes the heart beat irregular [10]. National Institutes of Health in 2010 reported that around 2.7 million people suffered from atrial fibrillation (AF), the most prevalent case of arrhythmia [10]. Electrocardiogram (ECG) is employed to record the electrical activity of the heart [3]. The graph obtained serves as a useful tool for initial screening in the diagnosis and subsequent treatment for many CVD [9]. The procedure is non-invasive and a low-cost method [9].

Continuous monitoring is essential to recognize arrythmia and classify it[3]. This process is a highly time-consuming one that also is error prone since human element is involved in the measurement[3]. To reduce this error, a computer assisted algorithm is proposed in this study for CVD diagnosis[3]. The mortality rate of people in different regions and number of persons dying due to CVD per million population are shown in figure 1.

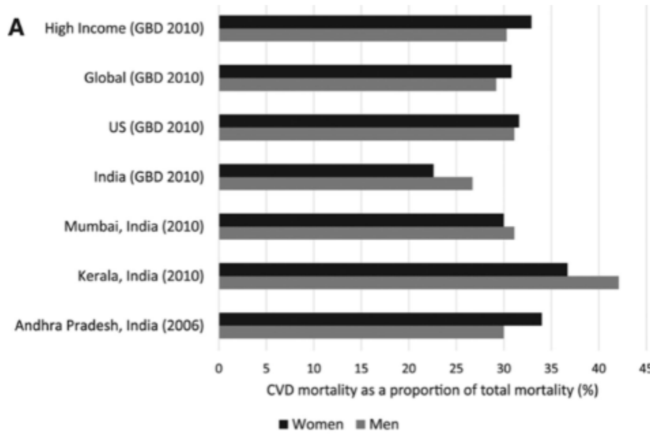


Figure 1.a

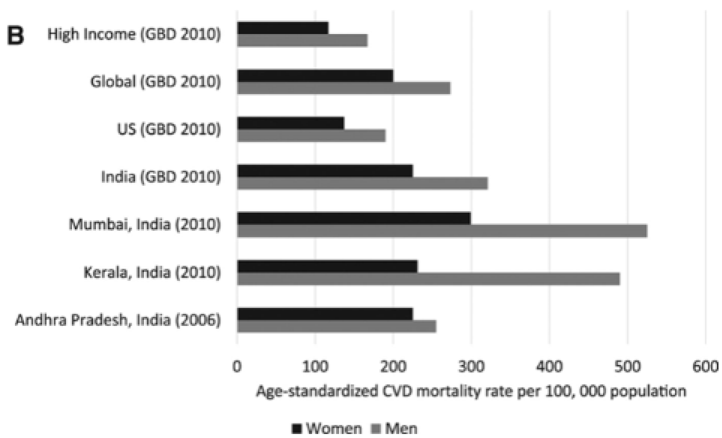


Figure 1.b

2. LITERATURE SURVEY

ECG signals are at present pre-processed manually for the purpose of noise filtration, feature extraction and reduction. Useful information is extracted from the ECG signal to identify and classify arrhythmia and subsequently to diagnose the cause of cardiac arrhythmias. The detection of PT and the wavelet algorithms (t

hat form QRS complexes) serves a main role in dissecting the ECG signal[4]. The idea of detecting QRS complex and P wave from positive and negative amplitude signals, removing false QRS complex using certain criteria and by using adaptive P wave search approach, the detection performance is improved under noisy conditions[1]. A new routine is suggested for the classification of ECG signals obtained for a longer period from the same patient. This routine is constructed by modifying a procedure called vector quantization[5]. A systematic procedure for screening the arrhythmias by employing a learning-based intelligent classifier has been framed. The proposed method can be used as an assisting tool built in a portable monitoring device that is employed in screening cardiac arrhythmias and related diseases[2]. In the automated screening routine of cardiac arrhythmias, the SVM classification is done after conducting the ECG morphology and extraction of segment feature of the ECG signals. The accuracy can be improved further by employing Neural Networks[3]. This will also help to see if the classification is stable when the level of tolerance is changed. In this proposed method, the ECG signals in the time domain are transformed into ECG spectrograms of two-dimensional time-frequency types[6].For low complexity and high accuracy, wavelet-based classification method is used for time-frequency ananlysis[7]. The resultant ECG spectrograms were made as input to identify the ECG arrhythmia and classify using General Regression Neural Network (GRNN). The suggested GRNN can provide better ECG arrhythmia classification accuracy without the need for manual pre-processing of the ECG signals for parameters like feature extraction, noise filtering and feature reduction.

3. PROPOSED METHOD

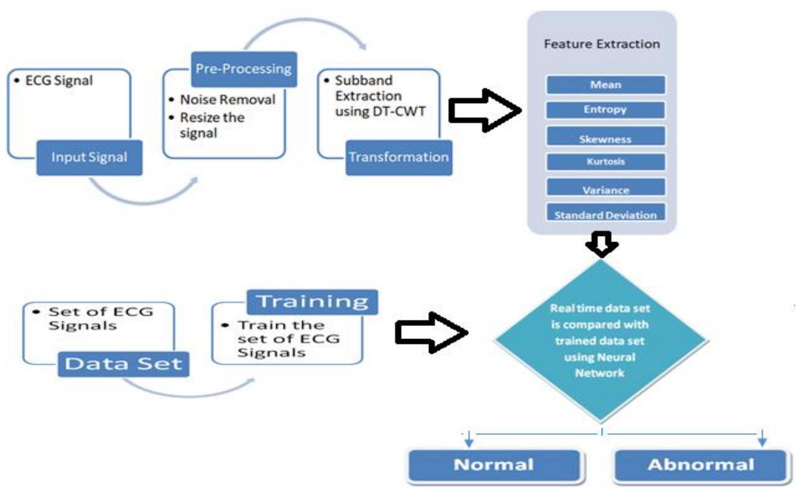


Fig 3.1 Block diagram of the proposed system

Trained feed-forward neural network has been chosen in this proposed method. The data used for analysis in this work for analyzing the ECG signal were taken from the existing databases. Since high frequency noises like electromyogram noise, additive white Gaussian noise, and power line interference or low frequency noises like baseline wandering noises contained in the ECG signals can lead to erroneous interpretation, the signals have to be preprocessed. Carrying out preprocessing function by high pass or low pass filters are ineffective since it can because high pass can only remove low frequency noises and low pass can only eliminate high frequency noises. So in this method, MEDIAN 2 FILTER is used. This filter utilizes the median value to smoothen the signals, which are then processed using Dual Tree-Complex Wavelet Transform. The waveform offers multi-resolution, useful characterization and sparse representation of an image structure. The CWT uses dual tree mechanisms to extract the sub-bands. Since the input signal is ECG, the sub-bands which possess required information pertaining to only ECG are retained and then subjected to Feature Extraction. The details that were extracted from the ECG Signals were mean, kurtosis, entropy, skewness, variance, standard deviation. Mean is the feature obtained by averaging all the values obtained from feature extraction process. Entropy points to disorderliness whereas kurtosis shows the shape of frequency distribution and skewness points to its asymmetricity. Variance provides the divergence and standard deviation shows the deviation of the signals from the rest. The features were obtained in real time and got compared with the available trained data set. GRNN, a one-pass learning algorithm possesses a high degree of parallel structure that facilitates smooth transition from one observed value to another one where there is only sparse data in a multidimensional space. GRNN is resorted decision making by mapping the extracted features of real time data on the trained data, to arrive at an objective conclusion, Normal or Abnormal. Performance metrics like specificity, sensitivity and accuracy could be determined if needed. The sensitivity is the proportion of patients with disease who test positive to patients without diseases who test negative. This capability of this method enhances the results that could be obtained using this test.

4. SOFTWARE REQUIRED

MATLAB is employed to perform math and computation, algorithm development, modeling, simulation, and prototyping, data analysis, exploration, and visualization, scientific and engineering graphics and application development including graphical user interface building. The software does not require dimensioning, which allows solving many technical computing problems like matrix and vector formulations quickly. MATLAB Toolboxes contains collections of functions (M-files) to obtain solutions to various problems in neural networks, fuzzy logic, wavelets, simulation, signal processing, control systems, etc. The MATLAB system consists of five main parts:

- **DEVELOPMENT ENVIRONMENT:** This contains MATLAB desktop and Command Window, a command history, and browsers for viewing help, the workspace, files, and the search path.
- **MATLAB MATHEMATICAL FUNCTION LIBRARY**: Functions like sum, sine, cosine, complex arithmetic, matrix inverse, matrix eigen values, Bessel functions, and fast Fourier transforms are available here.
- **MATLAB LANGUAGE**: It has control flow statements, functions, data structures, input/output, and object-oriented programming features.

- **HANDLE GRAPHICS: H**igh-level commands for two-dimensional and three-dimensional data visualization, image processing, animation, and presentation graphics are included here.
- **MATLAB APPLICATION PROGRAM INTERFACE (API):** A library that permits writing programs in C or FORTRAN that invokes routines from MATLAB (dynamic linking) for processing MAT-files.

5. RESULTS AND DISCUSSION

The Specificity, Sensitivity and Accuracy are obtained as

Specificity:

The proportion of patients without disease who test negative.

Specificity = [(number of true negatives) / (number of true negatives + number of false positives)]

Sensitivity:

The proportion of patients with disease who test positive.

Sensitivity = [(number of true positives) / (number of true positives + number of false negatives)]

Accuracy:

To find average value of measurements.

Accuracy = [(True Positive + True Negative) / (True Positive + True Negative + False Positive + False Negative)]

The performance metrics obtained from this test are shown in figure 5.1.

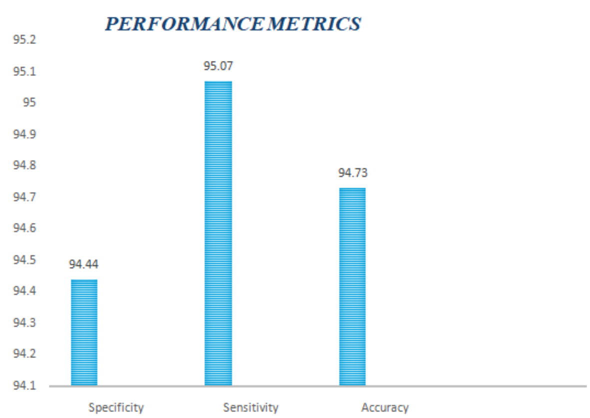


Fig 5.1. Performance metrics

The input ECG signal has a frequency range of about 0.5-100Hz is detected from holter devices from the patient.This ECG signal is then given to Median-2 to remove noises, which results in filter signal.

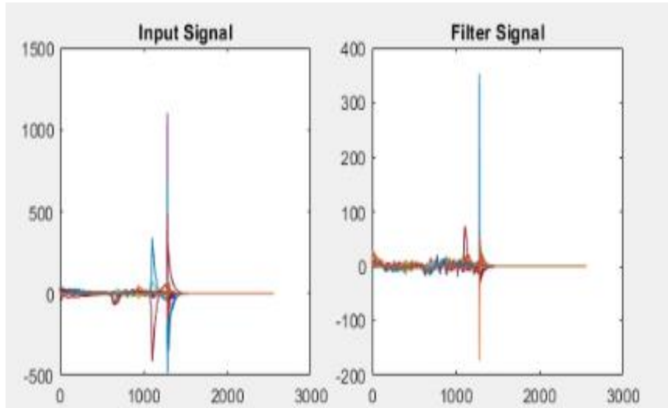


Fig 5.2 Input And Preprocessing

Using DT-CWT, the sub bands are extracted from the filtered signal as low pass filter signal and high pass filter signal. Only low pass filter signal has essential information and using this information features are extracted.

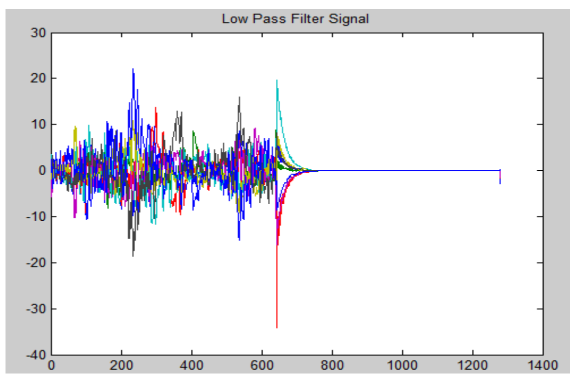


Fig 5.3.1 Sub-Band Extraction – Low Pass filter

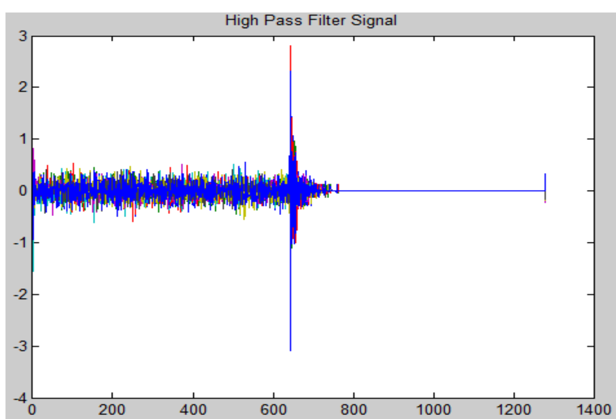


Fig 5.3.2 Sub-Band Extraction – High pass filter signal

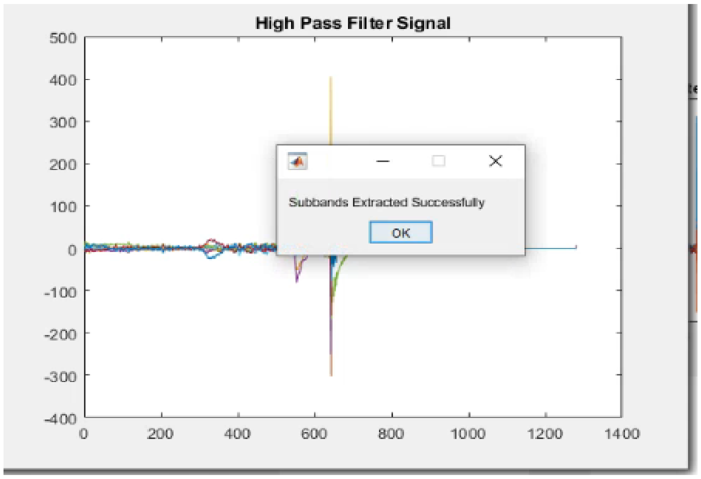
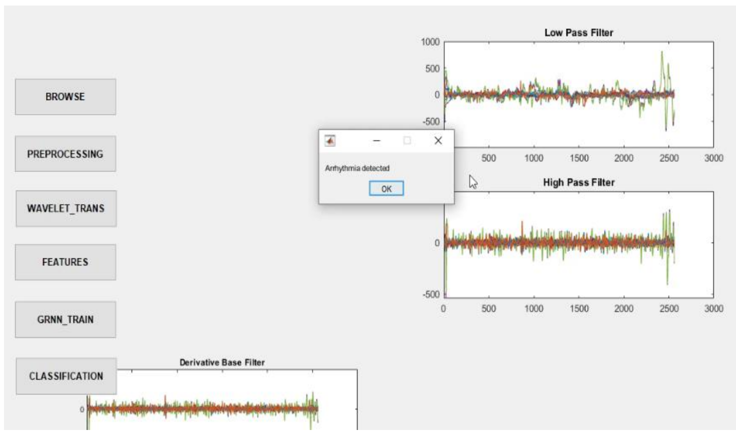


Fig 5.4 Detection Of Arrhythmia

After comparing the real time data with trained data-set using GRNN, arrhythmia is detected based on the results as

- If the output is 1, it indicates normal.
- If the output is 2, it indicates arrhythmia detected.



6. CONCLUSION

ECG signals offer a vital role to diagnose the abnormalities that are present in the heart. ECG signal provides abundant valuable information about the cardiac state. Using the signals one can classify and take further course of action against cardiac arrythmias. In this work, a General Regression Neural Networks for classification after performing the combination of pre-processing and feature extraction has been proposed. By using GRNN to the real time data, an appropriate decision can be arrived at which makes this process very useful with an accuracy of about 94.77%. Since a high efficiency is provided by this method one can adopt this method than following the traditional SVM Classification and K-means Clustering to GRNN.

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