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Detection of Bundle Branch Blocks using Machine Learning Techniques

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ABSTRACT

The most effective method used for the diagnosis of heart diseases is the Electrocardiogram (ECG). The shape of the ECG signal and the time interval between its various components gives useful details about any underlying heart disease. Any dysfunction of the heart is called as cardiac arrhythmia. The electrical impulses of the heart are blocked due to the cardiac arrhythmia called Bundle Branch Block (BBB) which can be observed as an irregular ECG wave. The BBB beats can indicate serious heart disease. The precise and quick detection of cardiac arrhythmias from the ECG signal can save lives and can also reduce the diagnostics cost. This study presents a machine learning technique for the automatic detection of BBB. In this method both morphological and statistical features were calculated from the ECG signals available in the standard MIT BIH database to classify them as normal, Left Bundle Branch Block (LBBB) and Right Bundle Branch Block (RBBB). ECG records in the MIT- BIH arrhythmia database containing Normal sinus rhythm, RBBB, and LBBB were used in the study. The suitability of the features extracted was evaluated using three classifiers, support vector machine, k-nearest neighbours and linear discriminant analysis. The accuracy of the technique is highly promising for all the three classifiers with k-nearest neighbours giving the highest accuracy of 98.2%. Since the ECG waveforms of patients with the same cardiac disorder is similar in shape, the proposed method is subject independent. The proposed technique is thus a reliable and simple method involving less computational complexity for the automatic detection of bundle branch block. This system can reduce the effort of cardiologists thereby enabling them to concentrate more on treatment of the patients.

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1. INTRODUCTION

The Electrocardiogram indicates the electrical activity of the heart recorded non-invasively from various locations of a person’s body. It is the most commonly used biological signal to study the functioning of the heart. ECG consists of several deflections named P wave, QRS complex, and T wave. The electrical conduction system of the heart regulates the heart’s pumping action and coordinates the contraction of the various chambers of the heart. An important part of the cardiac system is the Bundle branches. Bundle Branch block is a common cardiac disorder in which there is a blockage in the pathway of the electrical impulses of the heart which leads to an irregular heartbeat. The LBBB and the RBBB are the two types of BBBs which are caused by the delayed activation of the left and right ventricles respectively. LBBB is often associated with serious heart disease and can be the result of extensive strain, myocardial injury, or hypertrophy. RBBB can be caused due to heart attack, blood clot in the lungs, high blood pressure etc. The presence of BBB causes an uncoordinated contraction of the heart and can make it harder for it to efficiently pump blood through the body. The LBBB and RBBB are found in normal subjects also, but they can be taken as a sign of risk due to cardiac disorders. Therefore early detection of LBBB and RBBB is very important for clinical practice. Also automatic classification of heart beats into various categories can help cardiologists by reducing the diagnosis time.

Fig 1 shows the general block diagram for the classification of ECG signal into the three classes, namely, normal sinus rhythm, LBBB, RBBB.

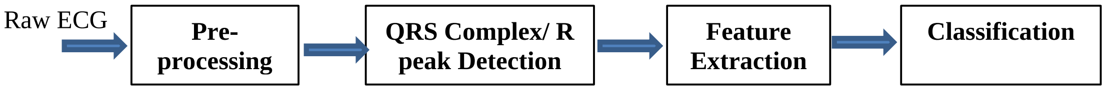


Figure 1. General block diagram for BBB classification

1.1. The Pre-processing Stage

Electrocardiographic signals may be corrupted by various kinds of noise or artefacts. Artefacts are unwanted signals that are incorporated with the ECG signal and in their presence sometimes a true diagnosis becomes difficult for the physician. Proper signal processing methods are needed to eliminate them from the ECG signals. Powerline interference, baseline wandering, electromyogram noise and electrode motion artefacts are the four main types of artefacts encountered in ECG signal processing. The pre-processing stage is used to remove various noise and artefacts from the raw ECG signal [1]. Several methods have been proposed for pre-processing such as adaptive filters [2], bandpass filters [3], [4], wavelet transform based methods [5], [6], [7], empirical mode decomposition [7] etc. For example, [7] proposed a method based on Discrete Wavelet Transform and empirical mode decomposition for noise removal in ECG signals.

1.2. QRS Complex/ R peak Detector

ECG signal processing algorithms are effective only if they can detect the presence and time of occurrence of a heartbeat. Since QRS complex is the most differentiable feature of the ECG waveform, QRS complex detection is equivalent to beat detection. Therefore the design of the QRS complex or the R peak detector is the most crucial step as poor detection will propagate to subsequent steps, thus limiting the system overall performance. The popular methods for QRS complex detection include derivative based digital filtering methods [8],[9],[10], Hilbert transforms [11], wavelet transforms [12],[13],and deep learning[14].

1.3. Feature Extraction

Feature extraction stage should extract the best possible features that can be used to distinguish a signal from another. Maximum information about the signal should be contained in these features. Efficient automatic classification of cardiac disorders therefore highly depends on these extracted features. Several features have been proposed in literature which can be grouped into time domain, frequency domain and morphological features. The inter-beat R wave interval is the most commonly used time domain feature. A classification accuracy of 96.0% has been reported by Venkatesan et al. [15] using RR parameters as features from the ECG signal. Morphological features like amplitude, durations, and slopes of the various waves in the ECG signal have also been used in literature [16], [17]. Marinho et al. [16] extracted morphological features using Structural Co-Occurrence Matrix to obtain an accuracy of 94.3% in the classification task and the system was faster by several factors. In the frequency domain, the discrete wavelet transform [11], [12], [13], fractional wavelet transform [18], have been used for feature extraction. Other methods like principle component analysis [19] and independent component analysis [20] have also been used for feature extraction.

1.4. Classification

It is the final stage for arrhythmia classification. Cardiac disorders must be classified based on the location where they originate in the heart, how they manifest themselves and the affected cardiac functions. Different classifiers have been used in literature for the classification task like the neighborhood linear discriminant analysis [21] support vector machine [22], neural networks [23], [24], Hidden Markov Models [25] etc.

In the proposed method, a subject- independent classification of BBB is implemented using simple statistical and morphological features extracted from the ECG signal. Since the computational complexity is low for the proposed method, it is easy to implement it in hardware and can perform faster than other methods used in literature.

2. RESEARCH METHOD

The Figure 2 shows the detailed block diagram for the proposed work.

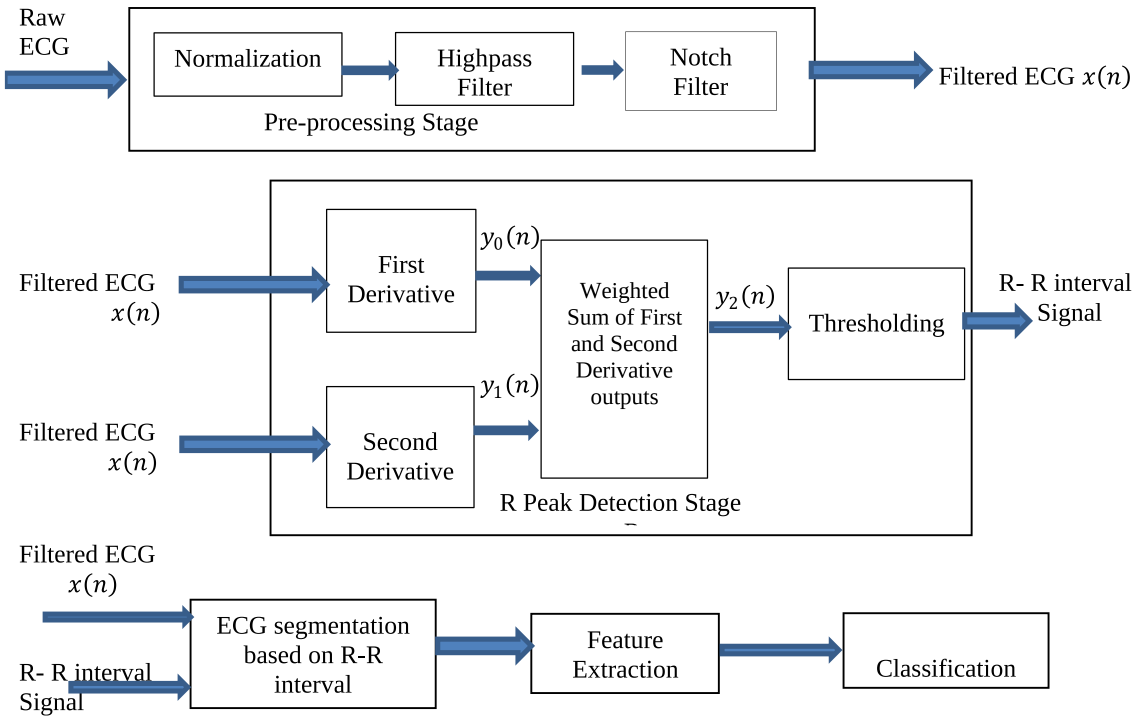


Figure 2. Detailed block diagram of the proposed technique

The proposed method involves pre-processing the ECG signal to remove noise, a derivative-based algorithm for R peak detection from the QRS complex, segmenting the signal, feature extraction and classification. Each of the processes are explained in detail in the following sections. The MIT – BIH Arrhythmia database was used for verifying the results [26].

2.1. Materials

The raw ECG signal is acquired from the MIT- BIH Arrhythmia database. This database consists of two channel (MLII and V1) ambulatory annotated recordings of 47 subjects suffering from various arrhythmias. This was studied by the BIH Arrhythmia Laboratory between 1975 and 1979 and was digitized at 360 Hz. There are 48 recordings and each is of approximately 30 minutes with 11-bit resolution over a 10 mV range. Table 1 presents the MIT- BIH Database record for each beat type used in the study.

Table 1. MIT- BIH Database Record Number used in the study

Arrhythmia	MIT- BIH Database record number used
Normal Sinus Rhythm	101, 103, 220, and 234
Left Bundle Branch Block (LBBB)	109, 111, 207, and 214
Right Bundle Branch Block (RBBB)	124, 207, 212, 231, and 232

2.2. Pre-processing Stage

The pre-processing stage is needed to remove noise and other artefacts that can corrupt ECG signals while they were recorded. Even though the ECG signal data acquired from the MIT-BIH arrhythmia database doesn’t contain significant noise as that acquired directly from the patient, it still has some amount of artefacts which need special attention so that the performance of the system can be improved. Since the features extracted from the ECG signals are negatively affected due to the presence of noise and artefacts, feature extraction should be done only after noise removal.

The most common types of noise in the ECG signal are the powerline interference and the baseline wandering noise. The power supply to the measurement system or other electrical equipments in the environment can set up electromagnetic fileds which interferes with the ECG signal creating powerline interference noise. The frequency spectrum of this noise lies around the frequency of 50Hz (or 60Hz) and is possibly accompanied by a number of harmonics, which comes in the spectral band of ECG signal [27]. Baseline wandering is a low frequency artefact which due to respiration. The frequency content of baseline wandering lies around 0.5Hz. The proposed work addresses only these two artefacts.

The pre-processing stage thus consists of:

- the normalization block,
- a highpass filter to remove baseline wandering noise and
- a notch filter to remove powerline interference.

Normalization is used to change the range of signal amplitude values in the ECG records to a constant range which is consistent throughout all the records. In the proposed work, each sample value of a record selected from the MIT- BIH database is divided by the maximum value in that record to obtain the normalized signal such that the maximum value in the range will be 1.The highpass filter with cutoff at 1Hz is used to remove low frequency noise and baseline wandering noise. Next a notch filter at 60Hz is used for eliminating powerline interference. The output of the preprocessing block is the filtered ECG signal.

2.3. R peak Detection Stage

In the proposed work, the presence of a heartbeat is automatically detected by identification of the R peak in the ECG signal. A derivative based algorithm is used for R peak detection. In this method, a weighted sum of the first and the second derivative of the filtered ECG signal is used to detect the R peak [28]. The R peak detection stage consists of the following blocks as shown in Fig. 2: first derivative block, second derivative block, weighted sum block and thresholding block.

The three-point smoothed first derivative $y_0(n)$ of the filtered ECG signal $x(n)$ is approximated as:

$$y_0(n) = |\, x(n) - x(n-2)\, | \tag{1}$$

The second derivative $y_1(n)$ is approximated as

$$y_1(n) = |\, x(n) - 2x(n-2) + x(n-4)\, | \tag{2}$$

The two results are combined as follows to obtain $y_2(n)$, a weighted sum of the first and the second derivative of the filtered ECG signal

$$y_2(n) = 1.3y_0(n) + 1.1y_1(n) \tag{3}$$

The result $y_2(n)$ is scanned with a threshold of 0.8. When the threshold is met, the adjacent ten samples are also checked and the highest sample is taken as an R peak. The advantages of using the derivative based method is that the algorithm can analyse the amplitude and slope of the ECG signal even in the presence of noise and can recognize the R peak reliably.

2.4. ECG Segmentation and Feature Extraction

After the detection of the R-peaks, the filtered ECG signal is segmented based on the R peaks. Each segment consists of signal samples between 5 R-R intervals. Various features can be extracted from each of these segments. The presence of LBBB or RBBB, causes delay in the respective ventricle contraction and this changes the total time for ventricular depolarization. This is manifested as a change in the shape of the QRS complex i.e., it widens. Therefore statistical features are very effective for classification and so we have used the following morphological and statistical features in the feature extraction stage.

- Mean of R peak Amplitudes in each segment
- Mean of R- R intervals for each segment
- Mean of Heart rates for each segment
- Mean value of the sample amplitudes for each segment
- Mean of Variance values for each segment
- Mean of Energies for each segment

2.5. Classification

Three different machine learning classifiers were used for the comparative study of the features extracted: k- nearest neighbours (kNN), support vector machines and linear discriminant analysis (LDA). The kNN algorithm is an easy-to-implement, simple-but- efficient supervised machine learning algorithm. Given a test sample, the k nearest neighbours of this sample from the training set are considered to evaluate its class. The predicted class for the test sample is based on the class label of its majority k nearest neighbours. Support vector machine (SVM) is one of the most popular supervised machine learning algorithms which is commonly used for classification and outlier detection. It is highly effective in multidimensional spaces. The SVM algorithm finds the optimal hyperplane in an N-dimensional space that distinctly classifies the data points. It is memory-efficient as it uses a subset of the training set as support vectors or decision vectors. Different Kernel functions can be specified for the support vectors, even custom-made can be specified instead of common kernels, which make the SVM highly versatile. The LDA is a linear classifier usually used in pattern recognition problems. It can also be used for feature reduction thus reducing the computing cost. LDA obtains a linear combination of features which best classifies two or more classes.

The classifier results were validated by employing a 10-fold cross-validation method. In the 10-fold cross-validation, the dataset is partitioned into 10 equal parts. In each step, training of the system is conducted using 9 out of 10 parts and the remaining one part is used for validation. After each iteration, the confusion matrix is recorded and at the end of 10 iterations, the average of the calculated values corresponds to the classification. The final confusion matrix gives the overall performance of the system.

3. RESULTS

The pre-processing, R peak detection, and feature extraction steps were performed using MATLAB software. Fig. 3 shows the waveforms from the various stages of ECG signal processing namely, the ECG signal from the MIT- BIH database record (record number 111 (LBBB) has been shown) and the output waveforms of the pre-processing and the derivative-based R peak detection stages.

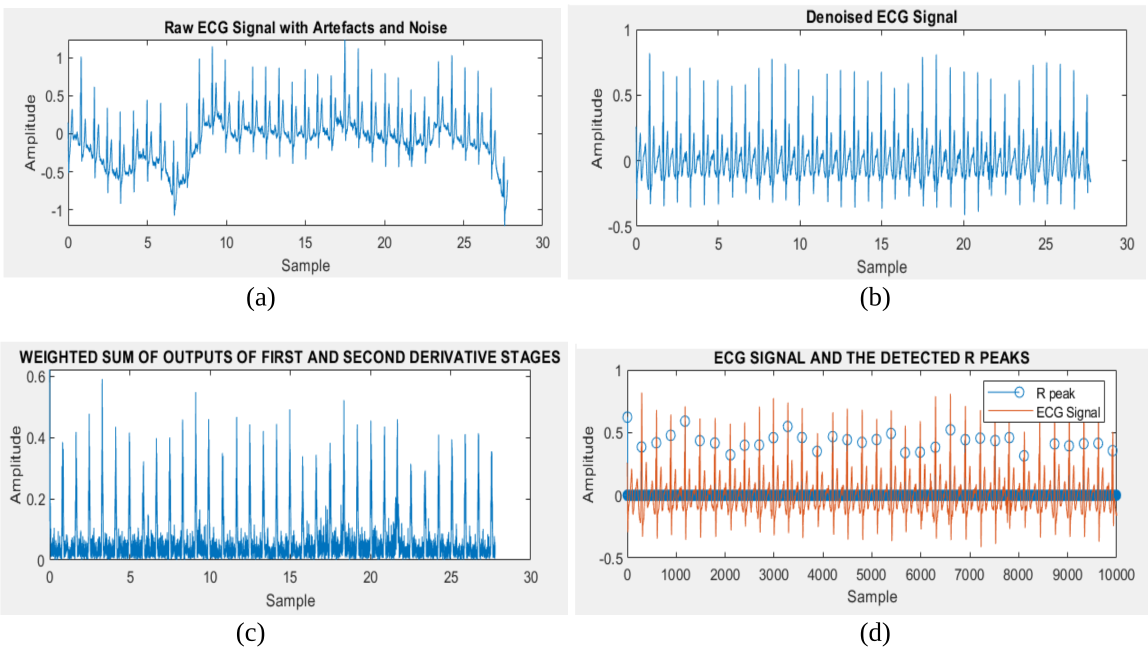
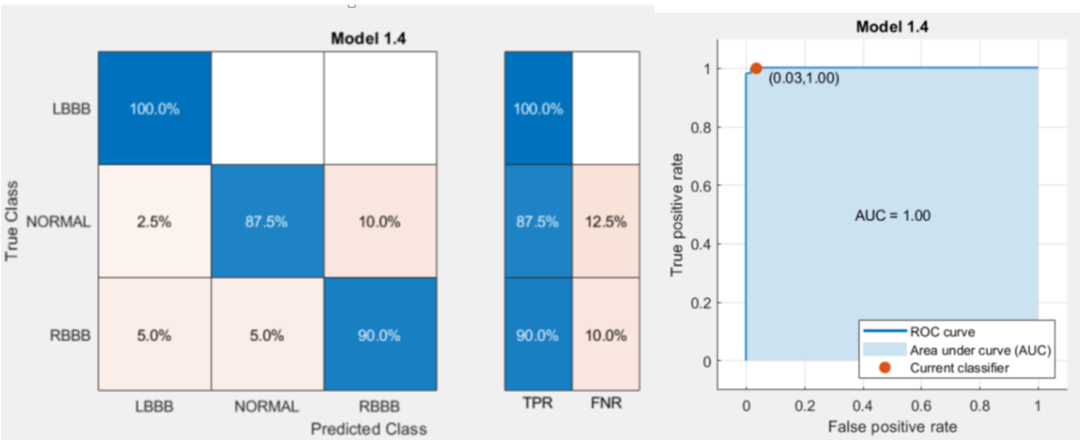
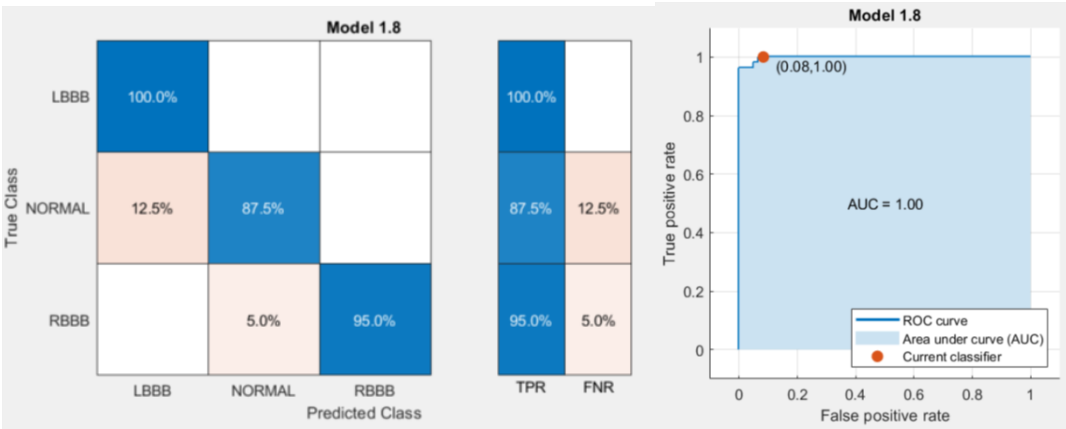


Figure 3. The waveforms from the various stages of ECG signal processing in the proposed technique (a) raw ECG signal from the MIT-BIH arrhythmia database record number 111. It is corrupted by baseline wandering noise. (b) ECG signal after pre-processing (c) output waveform of the derivative stage (d) R peaks detected

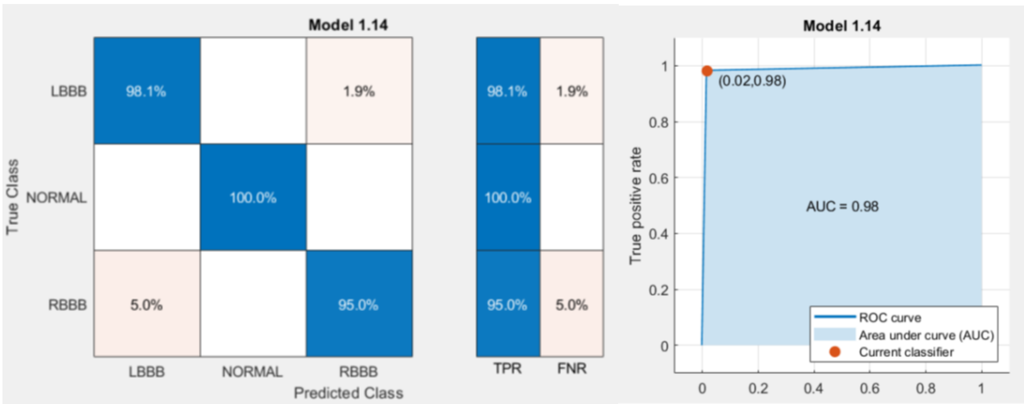
The Classification Learner App was used to train and test the three classifiers. All the classifiers used in this study namely, kNN, SVM and LDA have performed well with respect to the extracted features. The kNN classifier achieved the highest accuracy value of 98.2%. Fig. 4 shows the confusion matrix and the ROC curves for the three classifiers used. Table 2 shows the accuracy of the classifiers used in this method.



(a)



(b)



(c)

Figure 4. Confusion matrix and ROC curves of the three classifiers (a) LDA (b) Linear SVM (c) KNN

Table 2. Accuracy of the classifiers used in the proposed technique

Classifier used	ACC (in %)
LDA	93.8
Linear SVM	94.7
KNN	98.2

4. DISCUSSION

This paper presents a method for the automatic detection and classification of two types of bundle branch blocks. The performance of this method is evaluated using the ECG records available in the MIT-BIH arrhythmia database. Table 3 presents the comparison of the proposed method with that of the existing methods for BBB detection.

Table 3. Performance comparison with related works

Technique	ACC (in %)
This work	98.2
BFPSO [28]	98.1
Neural Network [29]	88.7

Kora et al. [29] presents a combination of two heuristic methods for feature selection using bacterial forging and particle swarm optimizations. They have used various classifiers like kNN, neural networks and SVM. Yang et al. [30] presents an automatic algorithm based on 5-layer neural network for the detection of strict left bundle branch block. Our suggested technique has better accuracy than these methods.

5. CONCLUSION

Computer aided automatic detection of BBB drastically reduces the effort of cardiologists thereby permitting them to focus more on treatment. In this paper, a highly effective and automatic diagnostics method for the detection and classification of BBB is realized by classifying ECG signal into three different cardiac conditions; normal sinus rhythm, left bundle branch block and right bundle branch block.

The ECG signal records in the MIT- BIH arrhythmia database were used in this study. After acquiring the data, filtering was implemented to remove noise and artefacts. A three step derivative process was used to detect the R peak. The signal was segmented taking the R peaks as the reference. Later, various statistical and morphological features were extracted from the signal. We have used three classifiers, namely LDA, kNN, and SVM to distinguish between Normal Sinus rhythm and BBB beats. The classification accuracy achieved for the BBB detection is very promising. The kNN classifier achieved the highest classification accuracy of 98.4% in this study. The results show that the proposed scheme for the detection of BBB heartbeats can be transformed to a computer- assisted diagnostics system. Simple features are extracted which makes this a straightforward method for implementing in hardware. Also, since the ECG waveform looks similar for individuals with the same cardiac disorder, subject independent automatic detection is possible.

As a future work, the proposed system can be used to detect other arrhythmia types. More morphological features like the shape and duration of the various waves from the ECG signal can be extracted. Also the performance of other classifiers like the neighborhood linear discriminant analysis and the Hidden Markov Models for the proposed system can be evaluated as future work. Finally, the proposed methos can be implemented in hardware on an embedded platform.

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