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# Detection of abnormal heart conditions based on characteristics of ECG signals

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ABSTRACT

Heart diseases are one of the most important death causes across the globe. Therefore, early detection of heart diseases is crucial to reduce the rising death rate. Electrocardiogram (ECG) is widely used to diagnose many types of heart diseases such as abnormal heartbeat rhythm (arrhythmia). However, the non-linearity and the complexity of the abnormal ECG signals make it very difficult to detect its characteristics. Besides, it may be time-consuming to check these ECG signals manually. To overcome these limitations, we have proposed fast and accurate classifier that simulates the diagnosis of the cardiologist to classify the ECG signals into normal and abnormal from a single lead ECG signal and better than other well-known classifiers. First, an accurate algorithm is used for correcting the ECG signals from noise and extracting the major features of each ECG signal. After that, we simulated the characteristics of the ECG signals and created the proposed classifier from these characteristics. Two Neural Network (NN) classifiers, four Support Vector Machine (SVM) classifiers and K-Nearest Neighbor (KNN) classifier are employed to classify the ECG signals and compared with the proposed classifier. The total 13 features extracted from each ECG signal used in the proposed algorithm and set as input to the other classifiers. Our algorithm is validated using all records of MIT-BIH arrhythmia database. Experimental results show that the proposed classifier demonstrates better performance than other classifiers and yielded the highest average classification accuracy of 99%. Thus, our algorithm has the possibility to be implemented in clinical settings.

## 1. Introduction

Heart diseases in many developing countries (e.g. China) rose quickly. It is estimated at the "Report on Cardiovascular Disease (CVD) in China, 2011" that there are about 230 million patients with CVD, including 200 million patients with hypertension, 7 million patients with a stroke, 2 million patients with myocardial infarction, and 4.2 million patients with heart failure. There are 3 million cases of death of CVD each year, accounting for 41% of total [1]. So, early detection of abnormal heart conditions from the analysis of Electrocardiogram (ECG) signals is crucial to identify heart problems and avoid sudden cardiac death.

Arrhythmia is one of the CVDs types, which is an abnormal heartbeat. An arrhythmia occurs when electrical impulses, which direct and regulate heartbeats, don't function properly. This causes the heart to beat: too fast (tachycardia); too slow (bradycardia); too early (premature contraction) or too erratically (fibrillation) [2]. The diagnosis of arrhythmia is predicated on the identification normal versus abnormal heartbeats and their accurate annotation based on ECG morphology. Therefore, correct detection of arrhythmia is an imperative task for cardiologists in the diagnosis of cardiac diseases.

An ECG is a test that detects and records the heart's electrical activity through small metal electrode patches attached to the skin of person's chest, arms, and legs, this test shows how fast the heart is beating and its rhythm (steady or irregular). An ECG also records the strength and timing of electrical signals as they pass through the heart and it can be used to further investigate symptoms related to heart problems. The electrodes on the different parts of the body detect electrical impulses coming from different directions within the heart and there are normal patterns of each electrode. Various heart disorders produce abnormal patterns. The heart disorders that can be detected include:

- Abnormal heart rhythms. If the heart rate is very fast, very slow, or irregular. There are various types of irregular heart rhythm with characteristic electrocardiogram (ECG) patterns.
- A heart attack (myocardial infarction) and if it was recent or some time ago. A heart attack causes damage to heart muscle and it heals

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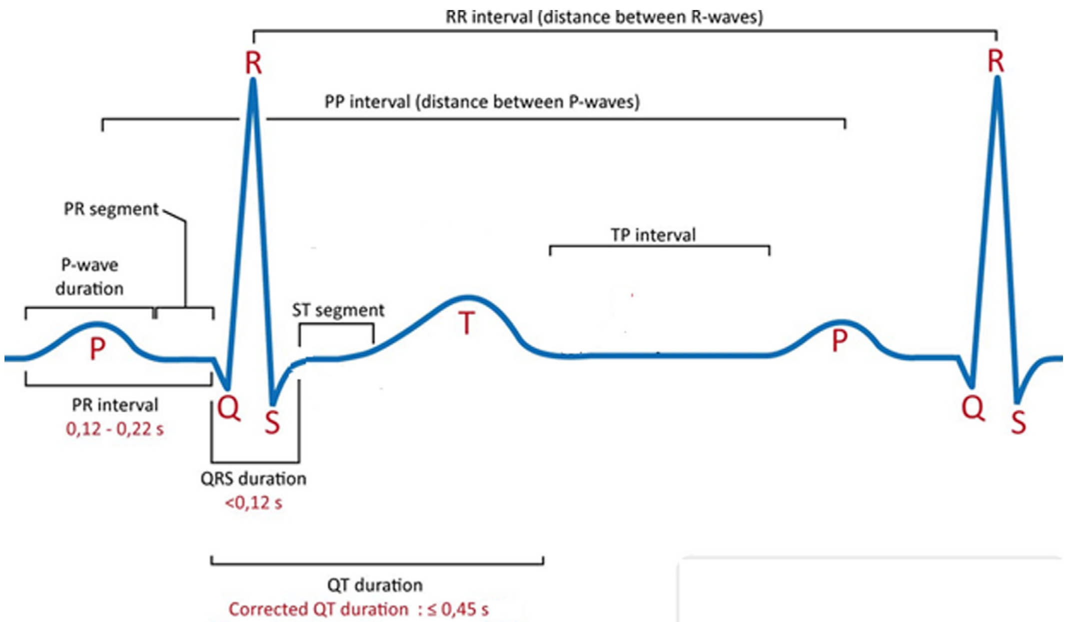


**Fig. 1.** Most common waveform of the classical ECG curve.

with scar tissue. These can be detected by abnormal ECG patterns.
- An enlarged heart. Basically, this causes bigger impulses than normal.

A complete ECG is taken using 10 electrodes capturing 12 leads (signals) to get a total picture of the heart. Each lead looks at the electrical activities from a different angle. 12 leads are required for accurate diagnosis purpose; however, one lead can offer important information for quick and initial assessment of the patient (lead II is used in this paper). Each ECG cycle consists of five waves: P, Q, R, S and T corresponding to different phases of the heart activities. The P-wave is the first positive deflection on the ECG, The QRS represents the simultaneous activation of the right and left ventricles, although most of the QRS waveform is derived from the larger left ventricular musculature and the T-wave should be concordant with the QRS complex. P-R interval measured from the beginning of the P-wave to the first deflection of the QRS complex and Q-T interval measured from the first deflection of QRS complex to end of T-wave at the isoelectric line as shown in Fig. 1.

Several ECG detection methods have been developed during decades; these methods include instantaneous Hilbert phase which employed by Kota et al. [3], to identify QRS complexes in the ECG. Pandit et al. [4], proposed an algorithm using a lightweight real-time sliding window-based Max-Min Difference (MMD) for QRS detection from Lead II ECG signals. Yochum et al. [5], described a method based on the continuous wavelet transform to detect the QRS, P and T waves. Kumar et al. [6], proposed Total Variation Denoising (TVD) based approach to find the locations of R-peaks in the ECG signal. Finally, the Hilbert transform with the adaptive threshold technique which employed by Sahoo et al. [7], to explore an optimal combination to detect R-peaks more accurately and other methods [8–12]. Many approaches have been proposed in the literature for the classification of ECG signals; some of these approaches being Artificial Neural Network (ANN) [13], support vector machine (SVM) [14], Random Forests [15], k-nearest neighbor (KNN) [16], Bayesian networks [17] and others [18–24]. Chen et al. [25], presented a method to classify ECG beat using projected and dynamic features of ECG signals and using radial basis function (RBF-SVM) for classifying heartbeats. Sahoo et al. [26], proposed an improved algorithm to detect QRS complex features based on the multi-resolution wavelet transform to classify four types of ECG beats using Neural Network (NN) and SVM classifier. Khazaee et al. [27], are employed two different classifiers (SVM and SVMGA) for classifying five types of ECG signals. Rai et al. [13], proposed a technique to truthfully classify ECG signal data into two classes (abnormal and normal class) using Back Propagation Network (BPN), Feed Forward Network (FFN) and Multilayered Perceptron (MLP).

In this paper, we have proposed a classifier that simulates the diagnosis of cardiologist to classify ECG signal data into normal and abnormal classes from single lead ECG signals. The proposed algorithm is tested on 48 records from MIT-BIH database and compared with other seven classifiers: two NN classifiers, four SVM classifiers and KNN classifier. Experimental results show that the proposed classifier achieves competitive classification performance with other classifiers in terms of accuracy and computing time.

## 2. Methodology

### 2.1. Dataset

MIT-BIH arrhythmia dataset [28] is used in this paper. It contains 48 half-hour records obtained from 47 subjects and extracted from two leads (lead II (MLII) and lead V1). Each of the 48 records is slightly over 30 min long. The subjects were 25 men aged 32–89 years, and 22 women aged 23–89 years. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10-mV range. MIT–BIH arrhythmia database is divided into two classes, normal 25 ECG records and abnormal 23 ECG records. In this paper, the algorithm is tested on the ECG signals taken from lead II (MLII).

### 2.2. ECG feature extraction

The proposed classifier totally depends on the features that extract from each ECG signal, so accurate detection of ECG signal is vital and necessary for classifying individual's ECG to normal or abnormal cases. In this paper, an accurate algorithm has been used to extract the features of each ECG signal. Initially, ECG signals that obtained from MIT-BIH database contain noise and baseline drift. Due to this, it is so difficult to detect ECG waveforms from the signal that have noise or baseline drift. In this paper, the algorithm in [29] is used to bring the baseline drift to almost zero. The noise could be removed by implementing a band-pass (Butterworth) filter with 0.5 Hz and 40 Hz cutoff frequencies. Fig. 2 shows how band-pass filters effect on an ECG

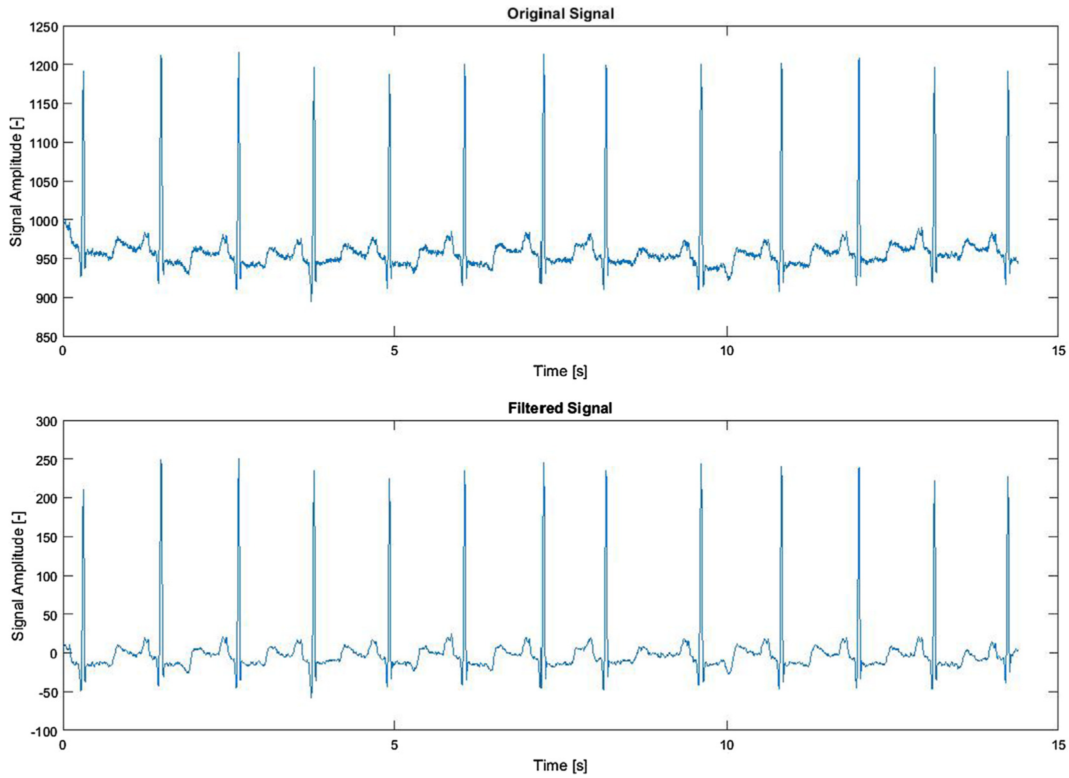


**Fig. 2.** Plot of original ECG signal (top signal) and the ECG signal after applying band-pass filter (bottom signal).

signal.

Second, R-peaks are determined by modifying Pan-Tompkins algorithm [30] and applying it to the filtered ECG signals. This algorithm comprises the following steps to extract R-peaks from ECG signal: First, we obtained the high slope using differentiation equation; the next step performed squaring the signal to detect R-peaks which is the high-frequency component; finally, we performed integration sum to extract the slope of R-wave. Fig. 3 shows an example for detecting all R-peaks from an ECG signal using the algorithm in [30]. In this paper, Pan-Tompkins algorithm has been used to detect R-peaks because it can quickly adapt to the signal changes and get a good detection furthermore, it is the most cited paper related to ECG detection.

To find all other peaks (P, Q, S and T peaks), after detected all R-peaks, we have used these peaks as reference points by calculating the corresponding value of each R-peak on the x-axis then we will calculate the value of one point before each R-peak value on the x-axis and one point after it. Within these time points, a minimum or a maximum value is detected which gives the P and T-peaks. Fig. 4 shows the result of the feature extraction algorithm after detecting PQST-peaks from an ECG signal. Finally, the features that used in this paper are P-peak, Q-peak, R-peak, S-peak, T-peak, the time duration of P-wave, the time duration of Q-wave, the time duration of R-wave, the time duration of S-wave, the time duration of T-wave, P-R interval, R-R interval and S-T interval, then the feature matrix is generated with size 48 × 13 ECG features. Where 48 is the number of input ECG signals. The total 13 extracted features are the averaged cardiac cycle features across the entire record.

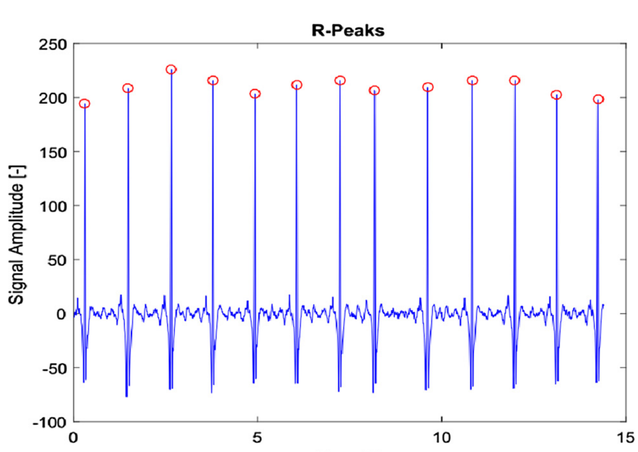


**Fig. 3.** Detected R-peaks from an ECG signal.

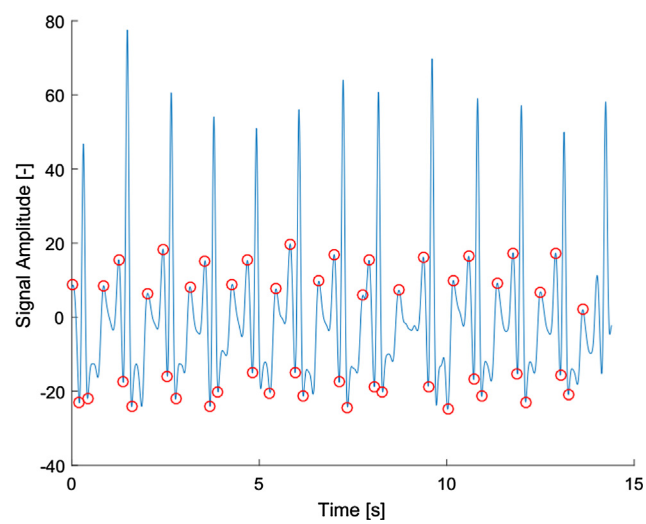


**Fig. 4.** Detected PQST-peaks from an ECG signal.

## 3. Characteristics of the normal ECG signals (classification)

The appearance of a normal ECG depends on several major things

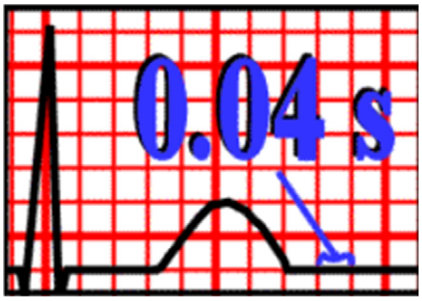


**Fig. 5.** A small square is 0.04 s.

one of these the lead we are looking at, where each lead gives a slightly different view of the electrical events in the heart, so the output from each lead will look a little different. In this paper, Lead II from the database is used to assess arrhythmia, normally in Lead II, the P-wave is positive and the QRS is predominantly positive (R-wave).

After extracting the ECG features, it is conventional to record the ECG using standard measures for the amplitude of the electrical signal and for the periods [31]. The amplitude, or voltage, is expressed on an ECG in the vertical dimension and is measured in millivolts (mV). On standard ECG paper, 1 mV is represented by a deflection of 10 mm. Standard ECG paper moves at 25 mm per second during real-time recording. This means that when looking at the printed ECG a distance of 25 mm along the horizontal axis represents 1 s in time. ECG paper is marked with a grid of small and large squares. Each small square represents 40 ms (ms) in time along the horizontal axis and each larger square contains 5 small squares, thus representing 200 ms as shown in Fig. 5. Standard paper speeds and square markings allow easy measurement of cardiac timing intervals. This enables calculation of heart rates and identification of abnormal electrical conduction within the heart.

A normal ECG is illustrated in Fig. 6 and according to medical experts the heart is beating in a regular sinus rhythm between 60 and 100 beats per minute (specifically 82 bpm) and the normal values for waves and intervals in Lead II are as shown in Table 1.

Where 1 mm corresponds to 0.1 mv on standard ECG grid.

In this paper, we simulated the previous characteristics and created the proposed classifier from these characteristics. According to these characteristics, the proposed classifier can simulate the diagnosis of the cardiologist to classify ECG signal data to normal and abnormal signals, so, we can use the proposed classifier as a diagnostic tool in places where access to a cardiologist is difficult.

**Table 1**
Characteristics of normal waves and intervals.

| Waves and intervals | Duration | Amplitude | Comments |
|---|---|---|---|
| P-waves | $< 0.11$ s | $< 2.5$ mm | Must be upright and followed by a QRS complex |
| QRS-complex | $< 0.12$ s | $> 0.5$ mV | Upright R and R-wave amplitude $< 20$ mm |
| T-waves | N/A | N/A | Always upright |
| P-R interval | 0.12–0.22 s | N/A | – |
| S-T interval | N/A | $> 0.5$ mm | Isoelectric, slanting upwards to the T-wave |
| Q-T interval | $< 0.45$ s | N/A | – |

Fig. 7 shows pseudo-code of the proposed classification algorithm based on the previous normal characteristics of ECG signals. All medical information (e.g. labeling the data to normal and abnormal, determining the correct duration and amplitude of waves and intervals etc.) were initially done by a group of certified cardio-graphic technicians and then verified by a cardiologist.

### 3.1. Neural network (NN)

#### 3.1.1. Feed forward neural network (FFNN)

A feed-forward neural network is a biologically inspired classification algorithm; it is the first type of artificial neural network devised. In this network, the information moves only from the input layer directly through any hidden layers to the output layer without cycles/loops. In this paper, *tansig* function is used as a transfer function for the hidden layer, *purelin* function is used as a transfer function for the output layer, these functions work better in Neural Network (NN) where speed is more important and *trainlm* function is used as a training function of FFNN, where this function supports training with validation and test vectors. The validation vectors are used to stop training early when the network is reached to the maximum epochs or to the performance that is minimized to the goal, the test vectors are used to check whether the network generalizes well. Finally, this network is created with 13 features for input layer, one hidden layer and one output layer.

#### 3.1.2. Multilayered perceptron (MLP)

An MLP is a network of simple neurons called perceptron. The perceptron computes a single output from multiple real-valued inputs by forming a linear combination according to its input weights and then

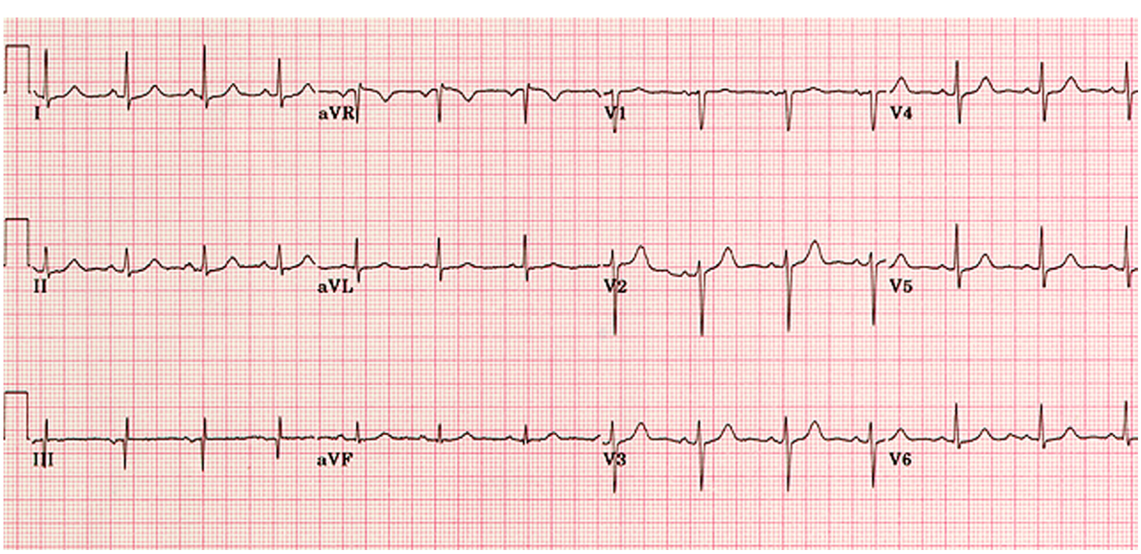


**Fig. 6.** Normal 12 lead ECG.

*Classification Algorithm:*

**Get** *P, Q, R, S and T peaks*
**Get** *P, Q, R, S and T time duration*
**Get** *P-R intervals*
**Get** *Q-T intervals*
**Get** *QRS time duration*
**If** *P, T and R peaks are negative then*
    The signal is ***Abnormal***
  **Else**
    **If** *P-peak is greater than 2.5mm and P time duration is greater than 0.11s then*
      The signal is ***Abnormal***
    **Else**
      **If** *R-peak is greater than 20mm and QRS time duration is greater than 0.12s then*
        The signal is ***Abnormal***
      **Else**
        **If** *P-R interval is less than 0.12s and greater than 0.22s then*
          The signal is ***Abnormal***
        **Else**
          **If** *Q-T interval is greater than 0.45s then*
            The signal is ***Abnormal***
          **Else**
            The signal is ***Normal***
          **End If**
        **End If**
      **End If**
    **End If**
**End If**

**Fig. 7.** Algorithm of proposed classifier.

possibly putting the output through some nonlinear activation function [32]. Mathematically this can be written as Eq. (1):

$$y = \varphi\left(\sum_{i=1}^{n} w_i x_i + b\right) = \varphi(w^t x + b) \tag{1}$$

where $\boldsymbol{w}$ denotes the vector of weights, $\boldsymbol{x}$ is the vector of inputs; $\boldsymbol{b}$ is the bias and $\varphi$ is the activation function.

In this paper, MLP is used with one input-layer that contains 13 nodes represent the feature vector, three hidden-layers and one output-layer that represents the pattern class which must be classified.

### 3.2. Support Vector Machine (SVM)

Support Vector Machines are one of the most popular statistical classification algorithms that classify data by separating two classes with the help of a functional hyperplane. SVM is known for good performance on noisy and high dimensional data [33]. The idea behind SVM classifier is that it creates a feature space using the attributes in the training data, then tries to identify a decision boundary or a hyperplane that separates the feature space into two halves where each half contains only the training data points belonging to a category. There are two types of SVMs, (1) Linear SVM, which separates the data points using a linear decision boundary and (2) Non-linear SVM, which separates the data points using a non-linear decision boundary.

Linear SVM performs well on datasets that can be easily separated by a hyperplane into two parts. But sometimes datasets are complex and are difficult to classify using a linear kernel. Non-linear SVM classifiers can be used for such complex datasets. The concept behind non-linear SVM classifier is to transform the dataset into a high dimensional space where the data can be separated using a linear decision boundary. In the original feature space, the decision boundary is not linear. The main problem with transforming the dataset to a higher dimension is the increase in complexity of the classifier. Also, the exact mapping function that can separate data linearly in a higher dimensional space is not known. To overcome this, a concept called kernel trick is used to transform the data to a higher dimensional space. In this paper, four most commonly kernel functions are used [34].

Linear kernel function as Formula (2):

$$K(x,x_i) = x^T x_i \tag{2}$$

Polynomial kernel function as Formula (3):

$$K(x,x_i) = (x^T x_i)^n \tag{3}$$

Gaussian kernel function (RBF) as Formula (4):

$$K(x,x_i) = \exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right) \tag{4}$$

Quadratic kernel function as Formula (5):

$$K(x,x_i) = (x^T x_i + 1)^2 \tag{5}$$

where $\sigma$ is a real value standard variance of Gaussian distribution and each $x_i \in R^p$ is a p-dimensional real vector. Linear kernel, polynomial kernel (with degree of 2), Quadratic kernel and radial basis functions

**Table 2**
Extracted P-peaks of the feature extraction algorithm for all records of the database.

| Record number | Se (%) | +P (%) | DER (%) |
|---|---|---|---|
| 100 | 100 | 100 | 0 |
| 101 | 100 | 100 | 0 |
| 102 | 99.95 | 100 | 0.04 |
| 103 | 100 | 100 | 0 |
| 104 | 100 | 100 | 0 |
| 105 | 100 | 100 | 0 |
| 106 | 100 | 100 | 0 |
| 107 | 100 | 100 | 0 |
| 108 | 100 | 100 | 0 |
| 109 | 99.92 | 100 | 0.07 |
| 111 | 100 | 100 | 0 |
| 112 | 100 | 100 | 0 |
| 113 | 100 | 100 | 0 |
| 114 | 100 | 100 | 0 |
| 115 | 100 | 100 | 0 |
| 116 | 100 | 100 | 0 |
| 117 | 100 | 100 | 0 |
| 118 | 100 | 100 | 0 |
| 119 | 100 | 100 | 0 |
| 121 | 100 | 100 | 0 |
| 122 | 100 | 100 | 0 |
| 123 | 100 | 100 | 0 |
| 124 | 100 | 100 | 0 |
| 200 | 100 | 100 | 0 |
| 201 | 100 | 100 | 0 |
| 202 | 100 | 100 | 0 |
| 203 | 99.66 | 99.93 | 0.40 |
| 205 | 100 | 100 | 0 |
| 207 | 100 | 100 | 0 |
| 208 | 99.72 | 99.89 | 0.37 |
| 209 | 100 | 100 | 0 |
| 210 | 100 | 100 | 0 |
| 212 | 100 | 100 | 0 |
| 213 | 100 | 100 | 0 |
| 214 | 100 | 100 | 0 |
| 215 | 99.97 | 100 | 0.02 |
| 217 | 100 | 100 | 0 |
| 219 | 100 | 100 | 0 |
| 220 | 100 | 100 | 0 |
| 221 | 99.95 | 100 | 0.04 |
| 222 | 100 | 100 | 0 |
| 223 | 100 | 100 | 0 |
| 228 | 99.80 | 100 | 0.19 |
| 230 | 100 | 100 | 0 |
| 231 | 100 | 100 | 0 |
| 232 | 100 | 100 | 0 |
| 233 | 99.83 | 99.96 | 0.19 |
| 234 | 100 | 100 | 0 |
| Total/Avg | 99.97 | 99.99 | 0.0275 |

with ($\sigma = 0.2$) were implemented to map the training data into a kernel space.

### 3.3. k-Nearest neighbor (KNN)

The k-nearest neighbor (KNN) algorithm is a non-parametric lazy learning algorithm that stores all available cases and classifies new cases by calculating its distance to the nearest neighbor by training samples in the feature space. The classifier is defined by its parameters. Setting parameter k depends on the data and affects the performance of the classifier. Parameter 'k' must be large enough to reduce misclassification of an example point and must be small enough so that the sample point is close to the neighboring points, which results in the better estimation of the point's class. For pattern classification, the k-NN algorithm only requires a set of labeled samples k, and a metric to measure distance [35]. In this paper, KNN classifier is used with parameter $K = 1$.

## 4. Experimental results

### 4.1. Experimental setup

In the experiments, the proposed method is evaluated using 48 records from the first channel (MLII) of MIT-BIH arrhythmia dataset, which divided into two classes, normal class which contains 25 ECG records and abnormal class which contains 23 ECG records. The proposed method is compared with other classification algorithms and several popular methods in ECG classification tasks. All the experiments are executed on a PC with 4 Intel Core i5 CPUs (2.50 GHz) and 4 GB RAM and the algorithm was implemented using MATLAB software R2016a. We randomly selected the ECG samples for the training and the testing data sets in all cases and we evaluated the final statistical results after 5 runs. The average result of all five-runs gives the total performance of the system.

### 4.2. Performance metrics

To assess the performance of the feature extraction and classification algorithm many parameters are used:

1. The sensitivity (Se) is defined as (6):

$$Se = \frac{TP}{TP + FN} \times 100\% \tag{6}$$

2. The positive predictivity (+P) is defined as (7):

$$+P = \frac{TP}{TP + FP} \times 100\% \tag{7}$$

3. Detection error rate (DER) is defined as (8):

$$DER = \frac{FP + FN}{TP} \times 100\% \tag{8}$$

4. The most crucial metric for determining overall system performance is usually Accuracy (Acc), which is the proportion of the total number of predictions that were correct. We calculated the overall accuracy as (9):

$$\text{Accuracy(Acc)} = \frac{\textit{Correctly classified samples}}{\textit{Total number of samples}} = \frac{TN + TP}{TP + FP + FN + TN} \times 100\% \tag{9}$$

Where:

False Negative (FN) denotes the number of missed detections or the number of abnormal ECG signals that classifies as normal, False Positive (FP) represents number of extra detections peaks or the number of normal ECG signals that classifies as abnormal, True Negative (TN) is the number of normal ECG signals that classifies as normal and True Positive (TP) is the number of peaks that correctly detected or the number of abnormal ECG signals that classifies as abnormal.

### 4.3. Results

The feature extraction algorithm that used in this paper was evaluated using 48 records from the first channel (MLII) of MIT-BIH arrhythmia dataset. To demonstrate the ability of the feature extraction algorithm for detecting all features from all ECG signals in the database, +P and Se are used to differentiate between true and false detections also DER is used to test the accuracy as shown in Tables 2–6 for all records of the database.

The obtained results show the overall Se of 99.98% and +P of 99.99 with detection error rate of 0.018% in detecting all ECG records from the database. To assess the performance of the feature extraction

**Table 3**
Extracted Q-peaks of the feature extraction algorithm for all records of the database.

| Record number | Se (%) | +P (%) | DER (%) |
|---|---|---|---|
| 100 | 100 | 100 | 0 |
| 101 | 100 | 100 | 0 |
| 102 | 100 | 100 | 0 |
| 103 | 100 | 100 | 0 |
| 104 | 100 | 99.95 | 0.04 |
| 105 | 100 | 100 | 0 |
| 106 | 99.80 | 100 | 0.19 |
| 107 | 100 | 100 | 0 |
| 108 | 100 | 100 | 0 |
| 109 | 100 | 100 | 0 |
| 111 | 100 | 100 | 0 |
| 112 | 100 | 100 | 0 |
| 113 | 100 | 100 | 0 |
| 114 | 99.78 | 100 | 0.21 |
| 115 | 100 | 100 | 0 |
| 116 | 100 | 100 | 0 |
| 117 | 100 | 100 | 0 |
| 118 | 100 | 100 | 0 |
| 119 | 100 | 100 | 0 |
| 121 | 100 | 100 | 0 |
| 122 | 100 | 100 | 0 |
| 123 | 100 | 100 | 0 |
| 124 | 100 | 100 | 0 |
| 200 | 100 | 100 | 0 |
| 201 | 100 | 100 | 0 |
| 202 | 100 | 100 | 0 |
| 203 | 99.96 | 99.93 | 0.10 |
| 205 | 100 | 100 | 0 |
| 207 | 100 | 100 | 0 |
| 208 | 99.83 | 100 | 0.16 |
| 209 | 100 | 100 | 0 |
| 210 | 99.96 | 100 | 0.03 |
| 212 | 100 | 100 | 0 |
| 213 | 100 | 100 | 0 |
| 214 | 100 | 100 | 0 |
| 215 | 100 | 100 | 0 |
| 217 | 100 | 100 | 0 |
| 219 | 100 | 100 | 0 |
| 220 | 100 | 99.95 | 0.04 |
| 221 | 100 | 100 | 0 |
| 222 | 100 | 100 | 0 |
| 223 | 100 | 100 | 0 |
| 228 | 100 | 100 | 0 |
| 230 | 100 | 100 | 0 |
| 231 | 100 | 100 | 0 |
| 232 | 100 | 100 | 0 |
| 233 | 100 | 100 | 0 |
| 234 | 100 | 100 | 0 |
| Total/Avg | 99.98 | 99.99 | 0.0160 |

**Table 4**
Extracted R-peaks of the feature extraction algorithm for all records of the database.

| Record number | Se (%) | +P (%) | DER (%) |
|---|---|---|---|
| 100 | 100 | 100 | 0 |
| 101 | 100 | 100 | 0 |
| 102 | 100 | 100 | 0 |
| 103 | 100 | 100 | 0 |
| 104 | 99.91 | 100 | 0.08 |
| 105 | 100 | 100 | 0 |
| 106 | 100 | 100 | 0 |
| 107 | 100 | 100 | 0 |
| 108 | 99.94 | 100 | 0.05 |
| 109 | 100 | 100 | 0 |
| 111 | 100 | 100 | 0 |
| 112 | 100 | 100 | 0 |
| 113 | 100 | 100 | 0 |
| 114 | 100 | 100 | 0 |
| 115 | 100 | 100 | 0 |
| 116 | 100 | 100 | 0 |
| 117 | 100 | 100 | 0 |
| 118 | 99.78 | 100 | 0.21 |
| 119 | 100 | 100 | 0 |
| 121 | 100 | 100 | 0 |
| 122 | 100 | 100 | 0 |
| 123 | 100 | 100 | 0 |
| 124 | 100 | 100 | 0 |
| 200 | 100 | 100 | 0 |
| 201 | 100 | 100 | 0 |
| 202 | 100 | 100 | 0 |
| 203 | 99.83 | 100 | 0.16 |
| 205 | 100 | 100 | 0 |
| 207 | 100 | 100 | 0 |
| 208 | 100 | 100 | 0 |
| 209 | 100 | 100 | 0 |
| 210 | 100 | 100 | 0 |
| 212 | 100 | 100 | 0 |
| 213 | 100 | 100 | 0 |
| 214 | 100 | 100 | 0 |
| 215 | 100 | 100 | 0 |
| 217 | 100 | 100 | 0 |
| 219 | 100 | 100 | 0 |
| 220 | 100 | 100 | 0 |
| 221 | 100 | 100 | 0 |
| 222 | 100 | 100 | 0 |
| 223 | 100 | 100 | 0 |
| 228 | 100 | 100 | 0 |
| 230 | 100 | 100 | 0 |
| 231 | 100 | 100 | 0 |
| 232 | 100 | 100 | 0 |
| 233 | 100 | 100 | 0 |
| 234 | 100 | 100 | 0 |
| Total/Avg | 99.98 | 100 | 0.0104 |

algorithm, a comparative study is done with state-of-art feature extraction algorithms using MIT-BIH database and summarized in Table 7.

As shown in Table 7, it is evident that the feature extraction algorithm in this study provides a good accuracy with less error detection rate.

The total 13 features are extracted from each ECG signal using the feature extraction algorithm and used in the proposed classification algorithm also these features given as input to other classifiers. In this experiment, the performance of the proposed classifier is tested by shuffling the proportion of training samples and testing samples by 95%/5%, 85%/15%, and 75%/25%, on MIT-BIH database. The comparison results of the proposed classification algorithm with Two NN classifiers (FFN and MLP), four SVM classifiers (Linear-SVM, RBF, Polynomial-SVM and Quadratic-SVM) and KNN classifier are shown in Figs. 8 and 9.

Figs. 8 and 9 are shown the detail performance results in terms of class accuracy and the average total time of various classifiers respectively. In case of NN classifiers, different numbers of neurons are used and for SVM classifiers the same parameters are used to get the best performance. For NN classifiers, the number of neurons in the hidden layer that used in training and testing for FFNN are 5, 10, 15 and 20 and for MLP network the combination of neurons (5,5,5), (10,5,5), (10,10,10) and (20,10,10) are used. The *tansig* transfer function is applied for hidden layers, the *purelin* transfer function is applied for output layer and the network training function is the *trainlm* function. For SVM classifiers, after lots of experiments, the scaling factor σ of RBF is assigned to 0.2 and degree to 2 in the polynomial-SVM. For KNN classifier, we use the parameter K = 1 in all training and testing cases.

Figs. 10–12 show the variation of the accuracy of different classifiers during different runs (five-runs) on the three different cases.

The confusion matrix of the two classes obtained after five-runs is presented in Table 8. According to Table 8, it can be noted that 2.4% of the normal ECG signals are wrongly classified as abnormal ECG signals and all abnormal ECG signals are classified correctly using the proposed classifier. 5.6% of the normal ECG signals are wrongly classified as abnormal ECG signals and 5% abnormal ECG signals are classified as normal ECG signals using FFNN classifier. 8% of the normal ECG signals

**Table 5**
Extracted S-peaks of the feature extraction algorithm for all records of the database.

| Record number | Se (%) | +P (%) | DER (%) |
|---|---|---|---|
| 100 | 99.91 | 100 | 0.08 |
| 101 | 100 | 100 | 0 |
| 102 | 100 | 100 | 0 |
| 103 | 100 | 100 | 0 |
| 104 | 100 | 100 | 0 |
| 105 | 100 | 100 | 0 |
| 106 | 100 | 100 | 0 |
| 107 | 100 | 100 | 0 |
| 108 | 100 | 100 | 0 |
| 109 | 100 | 100 | 0 |
| 111 | 100 | 100 | 0 |
| 112 | 100 | 100 | 0 |
| 113 | 100 | 100 | 0 |
| 114 | 100 | 100 | 0 |
| 115 | 99.79 | 99.94 | 0.25 |
| 116 | 100 | 99.95 | 0.04 |
| 117 | 100 | 100 | 0 |
| 118 | 100 | 100 | 0 |
| 119 | 99.89 | 99.89 | 0.20 |
| 121 | 100 | 99.94 | 0.05 |
| 122 | 100 | 100 | 0 |
| 123 | 100 | 100 | 0 |
| 124 | 100 | 100 | 0 |
| 200 | 100 | 99.96 | 0.03 |
| 201 | 100 | 99.89 | 0.10 |
| 202 | 100 | 100 | 0 |
| 203 | 99.96 | 100 | 0.03 |
| 205 | 100 | 100 | 0 |
| 207 | 100 | 100 | 0 |
| 208 | 99.93 | 99.96 | 0.10 |
| 209 | 100 | 100 | 0 |
| 210 | 100 | 100 | 0 |
| 212 | 100 | 100 | 0 |
| 213 | 100 | 100 | 0 |
| 214 | 100 | 100 | 0 |
| 215 | 100 | 100 | 0 |
| 217 | 100 | 100 | 0 |
| 219 | 100 | 100 | 0 |
| 220 | 100 | 100 | 0 |
| 221 | 99.91 | 99.95 | 0.12 |
| 222 | 100 | 100 | 0 |
| 223 | 100 | 100 | 0 |
| 228 | 100 | 100 | 0 |
| 230 | 100 | 100 | 0 |
| 231 | 100 | 100 | 0 |
| 232 | 99.94 | 100 | 0.05 |
| 233 | 100 | 100 | 0 |
| 234 | 100 | 100 | 0 |
| Total/Avg | 99.98 | 99.98 | 0.0218 |

**Table 6**
Extracted T-peaks of the feature extraction algorithm for all records of the database.

| Record number | Se (%) | +P (%) | DER (%) |
|---|---|---|---|
| 100 | 100 | 100 | 0 |
| 101 | 100 | 100 | 0 |
| 102 | 100 | 100 | 0 |
| 103 | 99.95 | 100 | 0.04 |
| 104 | 100 | 100 | 0 |
| 105 | 100 | 100 | 0 |
| 106 | 100 | 100 | 0 |
| 107 | 100 | 100 | 0 |
| 108 | 100 | 100 | 0 |
| 109 | 100 | 100 | 0 |
| 111 | 100 | 100 | 0 |
| 112 | 100 | 100 | 0 |
| 113 | 100 | 100 | 0 |
| 114 | 100 | 100 | 0 |
| 115 | 100 | 100 | 0 |
| 116 | 100 | 100 | 0 |
| 117 | 100 | 100 | 0 |
| 118 | 100 | 100 | 0 |
| 119 | 100 | 99.89 | 0.1 |
| 121 | 100 | 100 | 0 |
| 122 | 100 | 100 | 0 |
| 123 | 100 | 100 | 0 |
| 124 | 100 | 100 | 0 |
| 200 | 100 | 100 | 0 |
| 201 | 100 | 100 | 0 |
| 202 | 100 | 100 | 0 |
| 203 | 99.83 | 99.93 | 0.23 |
| 205 | 100 | 100 | 0 |
| 207 | 100 | 100 | 0 |
| 208 | 99.86 | 100 | 0.13 |
| 209 | 100 | 100 | 0 |
| 210 | 100 | 100 | 0 |
| 212 | 100 | 100 | 0 |
| 213 | 100 | 100 | 0 |
| 214 | 100 | 100 | 0 |
| 215 | 100 | 100 | 0 |
| 217 | 100 | 100 | 0 |
| 219 | 100 | 100 | 0 |
| 220 | 100 | 100 | 0 |
| 221 | 100 | 100 | 0 |
| 222 | 100 | 100 | 0 |
| 223 | 100 | 100 | 0 |
| 228 | 100 | 100 | 0 |
| 230 | 100 | 100 | 0 |
| 231 | 100 | 100 | 0 |
| 232 | 100 | 100 | 0 |
| 233 | 99.80 | 99.80 | 0.39 |
| 234 | 100 | 100 | 0 |
| Total/Avg | 99.98 | 99.99 | 0.0185 |

are wrongly classified as abnormal ECG signals and 4.3% abnormal ECG signals are classified as normal ECG signals using MLP classifier. 4.8% of the normal ECG signals are wrongly classified as abnormal ECG signals and 8.8% abnormal ECG signals are classified as normal ECG signals using SVM classifier. 8% of the normal ECG signals are wrongly classified as abnormal ECG signals and 8.6% abnormal ECG signals are classified as normal ECG signals using KNN classifier.

## 5. Discussion

From results, it is evident that the accuracy of the proposed classification algorithm is better than most of the other classifiers also the proposed algorithm has less computation time than other classifiers. The accuracy of MLP in some cases is better than the proposed algorithm and other classifiers but take a long time for computation. In this paper, we also compared the classification performance of the proposed classifier with some well-known methods using different classifiers as shown in Table 9.

Table 9 shows that, the accuracy of the classification algorithm in [25] using RBF-SVM is 98.5%, in [24] the authors obtained average classification accuracy of 93.48% using LS-SVM with Radial Basis Function (RBF) kernel, the accuracy of the classification algorithm in [26] using NN is 96.7% and using SVM is 98.4%, the accuracy of the classification algorithm in [27] using SVMGA is 96%, the accuracy of the classification algorithm in [13] using BPN is 97.8%, FFN is 97.8% and MLP is 100% in case of using neurons (20,20,10) in the hidden layers and the accuracy of the proposed classifier is 99%. From results of Table 9, it is evident that the proposed classification algorithm has the distinguish performance than the other well-known classification algorithms.

The main highlights of our proposed algorithm are summarized below:

- The implementation time of the proposed algorithm is very low (few seconds), which is acceptable for real-time application.
- The computational cost of the proposed algorithm is relatively low.
- The proposed algorithm overcomes the over learning problem that confronted most of previous algorithms.

**Table 7**
Comparison of proposed algorithm and several detection algorithms.

| Detection algorithm | Numb of records | Features | Se (%) | +P (%) | DER (%) |
|---|---|---|---|---|---|
| Ref. [6] | 48 records | R-peaks | 99.91 | 99.89 | 0.20 |
| Ref. [7] | 19 records | QRS-peaks | 99.71 | 99.72 | 0.52 |
| Ref. [8] | 48 records | QRS-peaks | 99.90 | 99.88 | 0.23 |
| Ref. [10] | 48 records | R-peaks | 99.50 | 99.56 | 0.93 |
| Ref. [11] | 48 records | QRS-peaks | 99.76 | 99.95 | 0.29 |
| Ref. [26] | 48 records | QRS-peaks | 99.87 | 99.69 | 0.42 |
| This study | 48 records | P, QRS and T peaks | 99.98 | 99.99 | 0.01 |

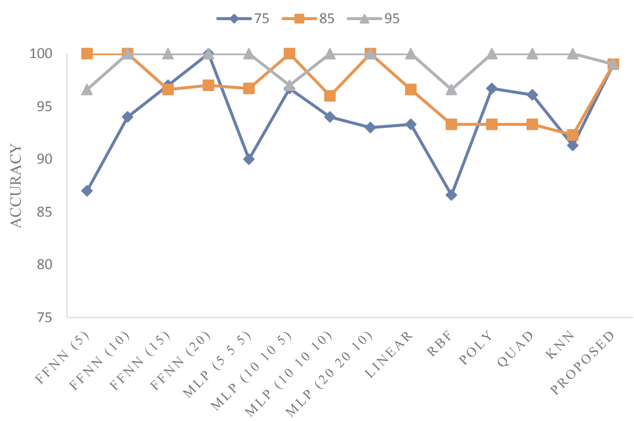


**Fig. 8.** Comparative result of ECG signal classifier in terms of accuracy.

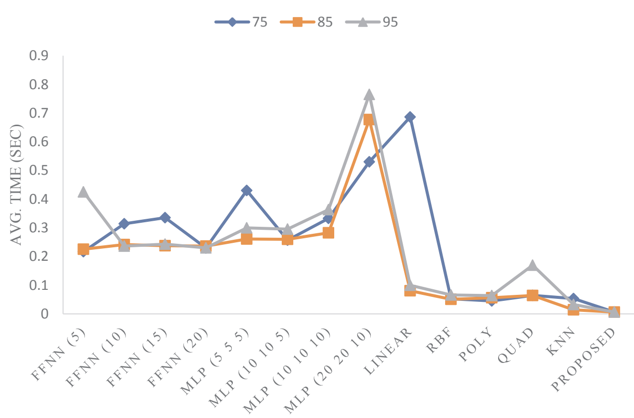


**Fig. 9.** Comparative result of ECG signal classifier in terms of average total time.

- The proposed algorithm achieves superior results compared with the previous algorithms.
- The proposed method is very simple and easy to use.

The drawbacks of our proposed algorithm are as follows:

- The proposed algorithm is sensitive to the ECG signal quality.
- It totally depends on the features values that extract from the feature extraction stage.

Recently, deep learning has been employed in the automated classification of ECG signals with a good performance and more types of abnormal ECG signals as in [36]. Thus, we intend to employ deep learning in our future study to increase the performance and to classify more types of abnormal ECG signals.

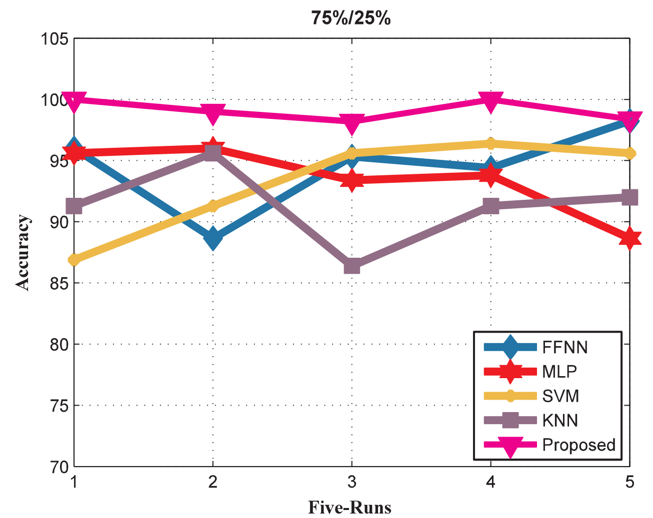


**Fig. 10.** Plot of accuracy (%) versus different runs (five-runs) for different classifiers.

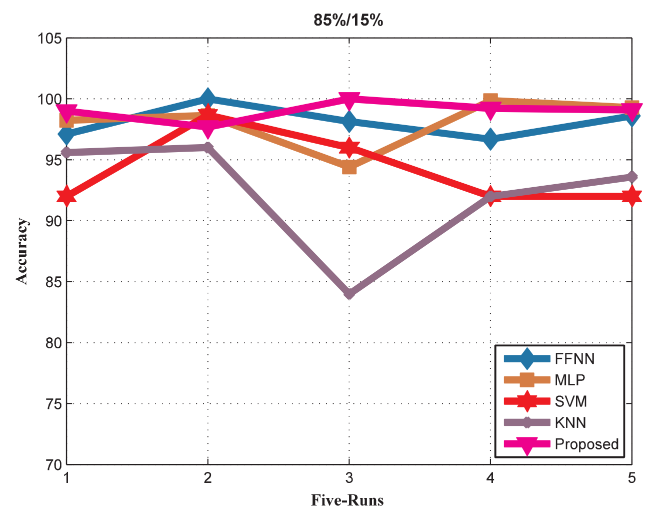


**Fig. 11.** Plot of accuracy (%) versus different runs (five-runs) for different classifiers.

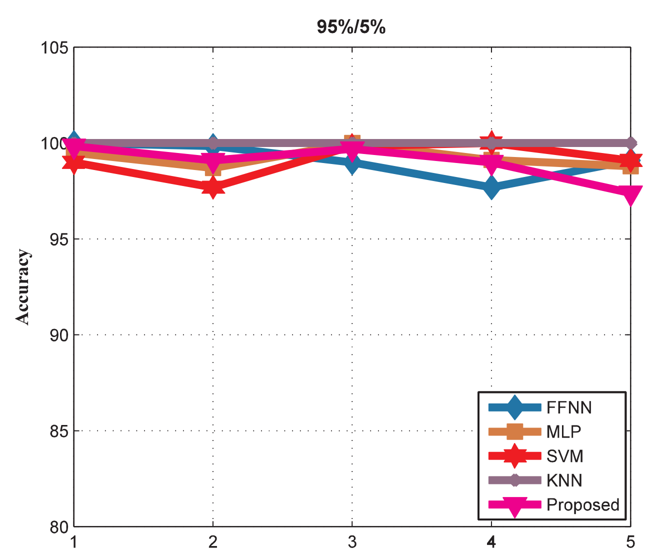


**Fig. 12.** Plot of accuracy (%) versus different runs (five-runs) for different classifiers.

**Table 8**
Confusion matrix of all classifiers used in this study.

| Classifier | Output/target | Normal class | Abnormal class | Accuracy (%) |
|---|---|---|---|---|
| | Normal class | 24 | 1 | 94 |
| FFNN | Abnormal class | 1 | 22 | 95.18 |
| | Total/Avg | 25 | 23 | 94.59 |
| | Normal class | 23 | 1 | 91.20 |
| MLP | Abnormal class | 2 | 22 | 95.62 |
| | Total/Avg | 25 | 23 | 93.41 |
| | Normal class | 24 | 2 | 95.20 |
| SVM | Abnormal class | 1 | 21 | 91.30 |
| | Total/Avg | 25 | 23 | 93.25 |
| | Normal class | 23 | 2 | 91.20 |
| KNN | Abnormal class | 2 | 21 | 91.42 |
| | Total/Avg | 25 | 23 | 91.31 |
| | Normal class | 24 | 0 | 98 |
| Proposed | Abnormal class | 1 | 23 | 100 |
| | Total/Avg | 25 | 23 | 99 |

**Table 9**
Classification performance of the proposed classifier compared with some well-known methods.

| Algorithm | Classifier (s) | Classes | Accuracy (%) |
|---|---|---|---|
| Ref [25] | RBF-SVM | 5 | 98.5 |
| Ref [24] | LS-SVM | 5 | 93.48 |
| Ref [27] | SVMGA and SVM | 5 | 96 |
| Ref [26] | NN and SVM | 4 | 96.7 and 98.4 |
| Ref [23] | KNN | 3 | 98.5 |
| Ref [13] | BPN, FFN and MLP | 2 | 97.8, 97.8 and 100 |
| Proposed | Characteristics of ECG signals | 2 | 99 |

RBF-SVM: Radial Basis Function-Support Vector Machine, LS-SVM: Least Square-Support Vector Machine, SVMGA: Genetic Algorithm and Support Vector Machine, SVM: Support Vector Machine, NN: Neural Network, KNN: K-Nearest Neighbor, BPN: Back Propagation Network, FFNN: Feed Forward Network, MLP: Multilayered Perceptron.

## 6. Conclusion and future work

This paper presents a classification method based on characteristics of ECG to classify ECG signals data into normal and abnormal classes. Out of 48 records from MIT-BIH arrhythmia database, 25 records are chosen as a normal class and 23 records are considered as abnormal class. An accurate algorithm is used for extracting the features of each ECG signals. The total 13 features extracted from each ECG signal used in this study to classify the signals. The performance of the proposed classifier is comprehensively better than that of other NN, SVM and KNN classifiers and the other well-known methods. The overall accuracy of the proposed classifier is 99% with an average computation time equal 0.006203 s. The proposed classifier solved most of classification problems and overcomes the misdiagnosis problems that face many cardiologists. Results show that we can use the proposed classifier to perform real-time classification of ECG signal. Hence, it is evident that our algorithm has the possibility to be implemented in clinical settings, which can serve as a tool to help clinicians in confirming their diagnosis. In the future, we can expand this work to classify many types of abnormal ECG signals such as left bundle branch block (LBBB), right bundle branch block (RBBB) and Paced beats (P) with good performance results.

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