Neural Network Based Method for Automatic ECG Arrhythmias Classification

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ABSTRACT:
Automatic classification of electrocardiogram (ECG) arrhythmias is essential to timely and early diagnosis of conditions of the heart. In this paper, a new method for ECG arrhythmias classification using Wavelet Transform (WT) and neural networks (NN) is proposed. Here, we have used a discrete Wavelet Transform (DWT) for processing ECG recordings, and extracting some time-frequency features. In addition, we have combined the features extracted by DWT with ECG morphology and heartbeat interval features, to obtain our final set of features to be used for training a Multi-Layer Perceptron (MLP) neural network. The MLP Neural Network performs the classification task. In recent years, many algorithms have been proposed and discussed for arrhythmias detection. the results reported in them, have generally been limited to relatively small set of data patterns. In this paper 26 recordings of the MIT-BIH arrhythmias database have been used for training and testing our neural network based classifier. The simulation results of best structure show that the classification accuracy of the proposed method is 94.72% over 360 patterns using 26 files including normal and five arrhythmias.

KEYWORDS: Electrocardiogram (ECG), Arrhythmia, Discrete Wavelet Transform (DWT), Neural network (NN), Principal Component Analysis (PCA).

1. INTRODUCTION

The electrocardiogram, also called ECG signal, is an important signal among all bioelectrical signals. The ECG reflects the treatment of human heart. The most significant characteristic features of the ECG are the P, Q, R, S and T waves. Any physical disturbances to the normal smooth rhythmic contraction are shown on the ECG, and are referred as an arrhythmia. The amplitude and duration of each wave in ECG signals are often used for the manual analysis. Thus, the manual analysis is a very time-consuming and erroneous process. Therefore, automated arrhythmia detection has been developed in the past few years. The methods proposed in the previous studies for automatic classification of arrhythmias, differ in the algorithms employed for feature extraction as well as the type of the classifier. The features used in the past include ECG morphology [1-3], heart beat interval features [1]-[4], and Hermit polynomials [5]. In addition, the employed classifiers include linear discriminators [1], neural networks [1]-[3], [6]-[8], [27], [28], self-organizing maps with learning vector quantization [4, 9].

Mathematical transformations are applied to the signals to obtain further information from the signal that is not available in the time- domain. However, time-domain and frequency-domain constitute two alternative methods for signal processing. One of the most well-known of these is Fourier analysis, which breaks down a signal into constituent sinusoids with different frequencies. Several researchers have used the Fourier transform for feature extraction from ECG [10]. However, the Fourier transform is very useful for the analysis of stationary signals. Wavelet Transform is a useful tool for analyzing ECG signals, because it can be used for the analysis of non-stationary signals. The Results of previous work show that time-frequency features give better results for the classification of the heartbeat. Therefore, many researchers have used the Wavelet Transform for feature extraction of the ECG signals [10-14], [27]. Moreover, the previous researches employed their classifiers using a small set of data patterns leading to relatively high classification accuracy. For example, Shyu [7] have achieved very high accuracy (97.04%) on a small data set (7 files) from the MIT/BIH arrhythmia database. In addition, many researchers have used larger data set, but they have achieved relatively lower classification accuracy. Chazal and Reilly [1] used 44 files from the MIT/BIH, but they obtained an accuracy of 89%. Other researchers have tested their classifiers over a larger Set of data patterns, and they have obtained relatively higher classification accuracy. However, they have detected only a few arrhythmia types. Inan [8] employed their method for classification of only 2 types of arrhythmias. In the previous work [9], we only used the statically features of wavelet coefficients and neural network to detection the 4 type of arrhythmias. In this method high accuracy (97%) was presented. Mohan Rai and et.al [10] employed the 21 point of the ECG signal as the feature vector of RBF neural network for 5 type of arrhythmias classification. Although many techniques have been investigated in this field, but because of improper features extraction, they can't classify significant number of the arrhythmias. In addition, small records from the MIT/BIH arrhythmia database are used.

In this paper, we propose a neural network based method for classification of RBBB (Right Bundle Branch Block), LBBB (Left Bundle Branch Block), PVC (Premature Ventricular Contraction), PB (Paced Beat) and APB (Atrial Premature Beat) arrhythmias as well as the normal signal. Here, we extract some important features from the coefficients of the Wavelet Transform to achieve both an accurate and a robust neural network based classifier by using a small number of training patterns. The simulation results using a large number of testing patterns are very encouraging.

2. ECG ARRHYTHMIAS CLASSIFICATION METHOD

Figure 1, shows the block diagram of proposed method. The method consists of three stages: pre-processing, processing and classification. As shown in Figure 1, the digitized ECG signal is the input of pre-processing stage. In the preprocessing stage the Baseline and high frequency noises are removed from ECG signal. The second stage, consists of three structures: feature extraction using PCA, feature extraction using Wavelet Transform and combining Wavelet Transform and time domain features. In the classification stage, Multi-Layered Perceptron (MLP) neural network is employed as classifier.

2.1. Pre-processing

The ECG obtained from body electrodes has the following undesired components:

- Baseline wander, which may appear due to a number of factors arising from biological or instrument sources such as electrode skin resistance, respiration, and amplifiers thermal drift,
- 60Hz power-line interference,
- 100Hz interference from fluorescence lights [15].

The baseline wander is a low-frequency noise. First, the ECG signal is filtered using the moving average filter to eliminate the baseline wander. Moving average filter provides a simple filtering tool. This filter smoothes the data by replacing each data point with the average of the neighboring data points defined within a span. This process is equivalent to low pass filtering with the response of the smoothing given by the difference equation such as Equation 1:

$$y(i) = \frac{1}{2N+1}(x(i+N) + x(i+N-1) + ... + x(i-N)) \quad (1)$$

Where, y(i) is the smoothed value for the i^{th} data point, N is the number of neighboring data points on either side of y(i), and 2N+1 is the span[16]. Then, the Wavelet Transform (see Section 2.2.2) is employed to laminate the other noises. General de-noising procedure using wavelet involves three steps:

- Decompose Choose a wavelet; choose a level N. Compute the wavelet decomposition of the signals at level N.
- Threshold detail coefficients

For each level from 1 to N, select a threshold and apply soft thresholding to the detail coefficients. Thresholding can be done using two functions: Hard thresholding and soft thresholding. This functions are given in Equation 2 and Equation 3 respectively.

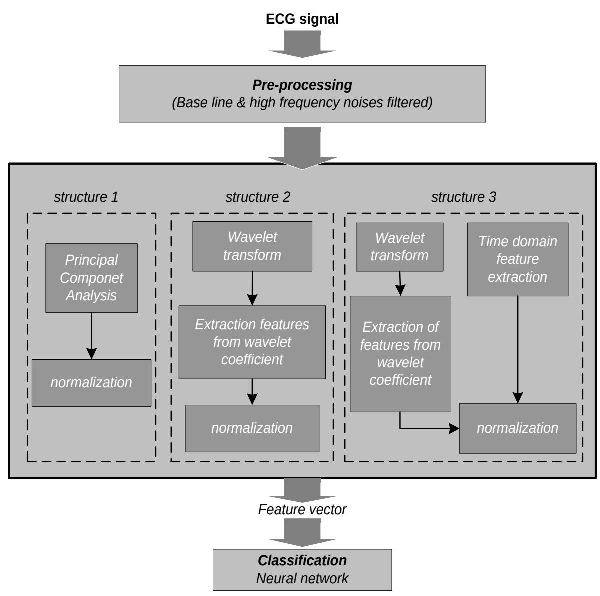

Fig.1. Block diagram of the proposed method

$$Y_H = \begin{cases} Y & , \ |Y| \geq T \\ 0 & , \ |Y| < T \end{cases} \quad (2)$$

$$Y_S = \begin{cases} sign(Y)(|Y| - T) & , \ |Y| \geq T \\ 0 & , \ |Y| < T \end{cases} \quad (3)$$

Where, Y_H is the hard threshold signal, Y_S is the soft threshold signal, Y is the original signal and T represents threshold value.

- Reconstruct

ECG signals reconstruct from the coefficients of each level.

2.2. Processing

The feature extraction is an important stage for designing a neural network based approach for pattern classification. Features are used to obtain some important information from the training patterns with the goal of minimizing the lost of information. Features are usually extracted based on either:

(a) Best representation of a given class of signals,
(b) Best distinction between classes[14].

In this paper three feature extraction methods were used. Principal Component Analysis (PCA) was applied in structure 1, Discrete Wavelet Transform in structure 2 and combined time domain features with wavelet coefficients in structure 3.

2.2.1. Principal component analysis (PCA)

PCA is a one of techniques for feature extraction and dimensionality reduction. In some situations, the dimension of the input vector is large, but the components of the vectors are highly correlated (redundant). It is useful in this situation to reduce the dimension of the input vectors. An effective procedure for performing this operation is principal component analysis. This technique has three effects: it orthogonalizes the components of the input vectors (so that they are uncorrelated with each other), it orders the resulting orthogonal components (principal components) so that those with the largest variation come first, and it eliminates those components that contribute the least to the variation in the data set.

The steps for PCA algorithm are given follow [17]:

- Consider the input data as X
- calculate $\overline{X}$ that $\overline{X}$ is the mean of X
- calculate the covariance matrix using Equation 4

$$\text{cov} = \frac{\sum_{i=1}^{n} (X_i - \overline{X})(X_i - \overline{X})}{n-1} \quad (4)$$

- Calculate the eigenvectors and eigenvalues of the covariance matrix
- Arrange eigenvectors based on eigenvalues and form a matrix (E)
- calculate final features matrix(P) by the Equation 5

$$P = E^T (X - \overline{X}) \quad (5)$$

Where, E^T is the transpose of E.

2.2.2. Discrete Wavelet Transform (DWT)

The Wavelet Transform was introduced at the beginning of the 1980s by Morlet, who used it to evaluate seismic data[18]. Wavelets provide an alternative to classical Fourier methods for one and multi-dimensional data analysis and synthesis, and have numerous applications both within mathematics (e.g., to partial differential operators) and in areas as diverse as physics, seismology, medical imaging, digital image processing, signal processing and computer graphics and video [19].

This technique is based on the use of wavelets as basis functions for representing other functions. These basis functions have a finite support in time and frequency domain. Multi-resolution analysis is achieved by using the mother wavelet, and a family of wavelets generated by translations and dilations of it [18],[19]. Calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates an awful lot of data. An efficient way to implement this scheme using FIR filter banks was developed in 1988 by Mallat [20]. In fact, The Mallat algorithm is a classical scheme known in the signal processing community as a two-channel sub-band coder [21]. Discrete Wavelet Transform (DWT) can be realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by the filtering operations, and the scale is determined by up-sampling and down-sampling (sub-sampling) operations [22].

Wavelet analysis is a windowing technique with variable-sized regions. The wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information. In the wavelet analysis, we often use of approximations and details. The approximations are the high-scale, low-frequency components of the signal. The details contain the low-scale, high-frequency components [23]. The ECG signals are decomposed into time-frequency representations using discrete Wavelet Transform (DWT). The DWT uses two filters, a low pass filter (LPF) and a high pass filter (HPF) to decompose the signal into different scales. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. Each stage consists of two digital filters and two down samplers by 2. The procedure for decomposition an input signal using the DWT is shown in Figure 2.The down-sampled outputs of high pass filters and low pass filters provide the detail coefficient (CD) and the approximation coefficient (CA). The first approximation is decomposed again and this process is continued as shown in Figure 2.

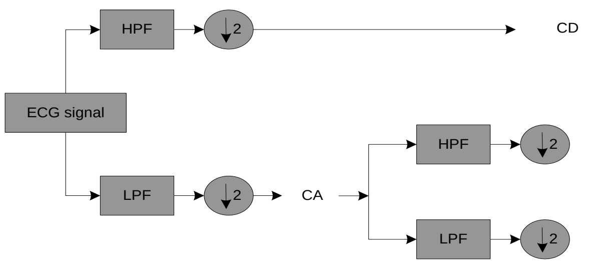

Fig. 2. Sub-band decomposition of discrete wavelet transforms implementation

To reconstructing a signal, we used the wavelet coefficients as you see in Figure 3.

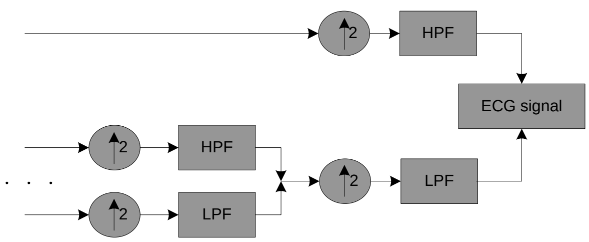

Fig. 3. Wavelet reconstruction process

This is called the inverse discrete Wavelet Transforms (IDWT). Where wavelet analysis involves filtering and down-sampling, the wavelet reconstruction process consists of up sampling and filtering. Each stage consists of two digital filters and two up-samplers by 2. Up-sampling is the process of lengthening a signal component by inserting zeros between samples [23]. Figure 4, shows this process.

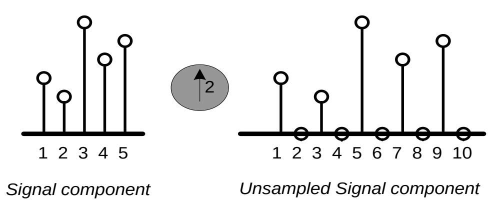

Fig. 4. Up-sampling process

2.3. Classification

An artificial neural network (ANN) is an information-processing system that has certain performance characteristics in common with biological neural networks. The ANNs have been developed as generalizations of mathematical models of human cognition or neural biology. A neural network is characterized by 1) its pattern of connections between the neurons (called its architecture), 2) its method of determining the weights on the connections (called its training, or learning algorithm), and 3) its activation function [24].There are four reasons to use an artificial neural network as a classifier:

- The ANN weights are found by using an iterative training algorithm,
- The ANN has a simple structure for physical implementation,
- The ANN can easily map complex class distributions,
- The generalization property of the ANN produces appropriate results for the input vectors not used in the training phase, i.e., testing input vectors [15].

Here, we have employed a Multi Layered Perceptron (MLP) neural network for classification as shown in Figure 5. MLP neural network consists of an input layer (parameters characterizing an object), one or two hidden layers and an output layer providing the class of the object [25]. We choose to use an architecture of neural networks for receive better performance of classification.

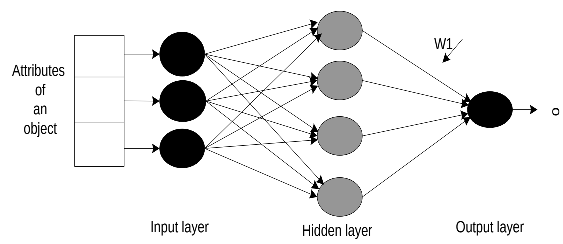

Fig. 5. An example of neural network with an adaptive structure; when a neuron is added to the hidden layer (in gray), the links are updated and all weights are initialized in a random way[25]

3. EXPERIMENTS AND SIMULATION RESULTS

In this study, ECG data from the MIT/BIH arrhythmia database has been used. This database is comprised of 48 files; each containing 30-minECG segments selected from 24-hr. The sampling frequency of the ECG signals in this database is 360Hz.We used 26 records from this database listed in Table 1.

The preprocessing of ECG signal improves the classification accuracy of any method; because, the pre-processing stage gives us more accurate features. In Figure 6, an example of an original ECG signal along with its baseline noise and high frequency noises is shown. In Figure 7, you can see a baseline eliminated ECG signal before high frequency noises elimination. Figure 8, shows an ECG signal after using the mentioned filters in section 2.1.

Table 1. Selected ECG records from the MIT/BIH arrhythmia database

Class	Record Numbers
NORMAL	100-101-103-112-115-117-121-123-202-234
PVC	200-208-213-233
RBBB	212-118-124
LBBB	109-111
PB	104-107-217
APB	209-220-222-223

3.1. Feature extraction

Although we used Wavelet Transform for ECG filtering, the signals should reconstruct without loss of information for time domain feature extraction. After reconstruction, the ECG signal is ready for feature extraction. Features were extracted by selecting 5Sec from the ECG records.

For feature extraction, we used three structures. PCA was used in first structure. In PCA, feature vector was performed using MATLAB. This vector consists of 97 elements which are the input of the classifier. In second structure we used DWT for feature extraction. The selection of an appropriate wavelet and the number of decomposition levels is very important in analysis of the signals using DWT. We can select a suitable number of levels based on the nature of the signal, or a suitable criterion such as entropy. In the present study, the number of decomposition levels was chosen to be 8. Thus, the ECG signals were decomposed into the details D1-D8. There are a large number of known wavelet families and functions. The wavelet families include Biorthogonal, Coiflet, Harr, Symmlet, Daubechies wavelets, etc. The choice of the wavelet function depends on the application. The Daubechies wavelet families are similar in shape to the QRS complex and their energy spectrums are concentrated around low frequencies. The features of the Daubechies wavelet of order 6 (db6) makes it more suitable for detection of the changes in the signals under study. Therefore, we selected db6 for feature extraction. Here, the discrete wavelet coefficients computations were performed using MATLAB [23]. The computed discrete wavelet coefficients for each record were used as the feature vectors. In order to reduce the dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients was used. The sets of features are given bellow:

- Maximum of the wavelet coefficients in each level
- Minimum of the wavelet coefficients in each level
- Variance of the wavelet coefficients in each level

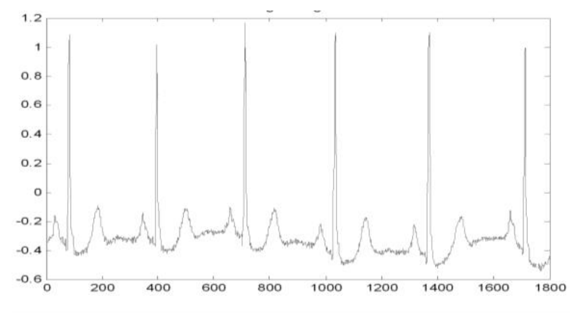

Fig.6. Original ECG signal with baseline and high frequency noises

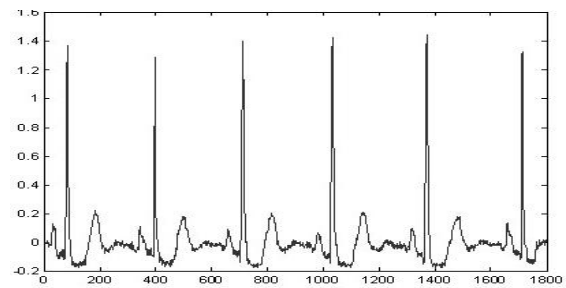

Fig.7. Baseline eliminated ECG signal

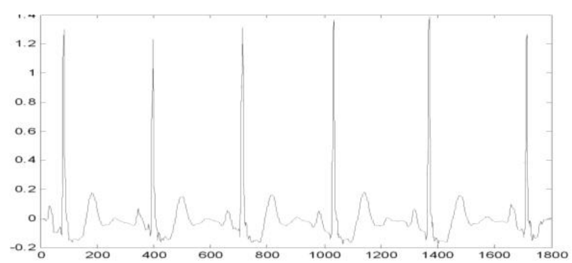

Fig. 8. Baseline and other high frequency noises eliminated ECG signal

To receive the best result, we compared obtained features and selected above-mentioned features from five levels: 2^{th},3^{th},4^{th}, 7^{th} and 8^{th}. This leads to reduction of size of the NN input vector.

In third structures, before using DWT, time domain technique was applied and following features were extracted

- Maximum of the original ECG signal
- Variance of the original ECG signal
- Minimum of the original ECG signal
- Standard deviation of the original ECG signal

- Five RR interval duration

RR interval duration is defined as the difference between the QRS peaks of the present beat, and the previous beat. It is well known that the RR interval duration has high efficiency. A group of researches explored the RR interval duration signal for classifying categories of arrhythmias [26].

Both the above-mentioned features and the obtained features from second structure were used as the input vector for classifier. Then the feature vectors from each structure were normalized. They fall in range [-1,1].

3.2. Classification

Multi-Layer Perceptron (MLP) neural network have been used for classification in all of structures. The best architecture of an MLP neural network is obtained using a trial-and-error procedure [19]. Therefore after running many simulations we chose an MLP neural network with one hidden layer.

Bipolar outputs using +1 and -1 numbers were used as the output target for the six selected classes. These bipolar outputs were (1,1,1), (1,1,-1), (1,-1,1), (1,-1,-1) , (-1,1,1) and (-1,1,-1) for six classes.

The proposed MLP neural networks were trained using 78 training vectors from 26 files of the MIT/BIH arrhythmia database listed in Table 1.

The performance of the proposed MLP neural network was tested using Mean-Squared Error (MSE) between actual targets and the outputs obtained using neural network. Variable Learning Rate (or "traingdx") algorithm in MATLAB neural network toolbox [27], was employed to train the MLP neural networks.

3.3. Testing results

The trained MLP NNs were tested using 360 Patterns (60 Testing Patterns for Each Class) Using 26 Files Including Normal and Five Arrhythmias**.** As an index for testing the trained MLP neural networks, we used an accuracy metric index that was chosen in many papers before [8, 22, 23]. This index is given in Equation 5.

$$A = 100 * \left(1 - \frac{Ne}{Nt}\right) \tag{5}$$

Where, A is the accuracy index, N_e is the total number of classification errors, and N_t represents the total number of testing patterns. The simulation results are listed in Table 2. As shown in Table 3, the third structure has demonstrated better testing results. The results show that the obtained accuracy index for this structure is 94.72%. since, in this paper we have used the random selection of test for training the network, for more accurate and more confinable results, the Cross-validation is used, and finally the average of obtained results for the 10 sets of test and training, not the best results, is presented as the final solution. In addition, Table 2 summarizes the results obtained by the other methods proposed in the literature. As it can be seen in Table 3, the proposed method in this paper has high performance in compared with the other methods for ECG arrhythmias classification. Also, the best determined structure by simulation results (structure 3) was tested with RBF neural network and the classification accuracy was obtained 92.35%.

Therefore, this method can be used for fast classification of the arrhythmias with a good degree of accuracy.

4. CONCLUSION

In this paper, A multi-layered perceptron (MLP) neural network based method has been presented for automatic ECG arrhythmias classification. In the proposed method, we used the combination of time specifications with the specifications resulted from Wavelet Transformation to determine 6 types of arrhythmias. This method is novel and can classify 6 types of classes which is much more than the other methods in the literature. In other words, the number of classes of the proposed method is so considerable. Moreover, the method tested 360 samples with the precision 94.72.

A preprocessing stage is employed to remove the noises from the ECG signals. In addition, a processing stage is used to obtain the required inputs for the MLP neural network. In processing stage, we combined some statistical features obtained by the Wavelet Transform with timing interval features and morphology features from ECG, and used them to train an MLP neural network. The advantages of the MLP neural network classifier include its simplicity and ease of implementation. Due to preprocessing stage and extraction of some suitable features, the total number of neural network inputs, and the total number of training data patterns are considerably reduced. In fact, by extraction suitable features for the proposed neural network, the required time for classification of testing pattern is reduced. In this paper, we have used a large set of data patterns (26 recordings from the MIT-BIH arrhythmias database) for training as well as testing our classifier, while many other researchers have employed only a small set of data patterns. The simulation results confirmed the validity of this method. Then the proposed method can be used as a tool for fast classification of ECG arrhythmias with a good degree of accuracy.

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Table 2.The simulation results obtained using MLP neural network for three structures

Architecture	Classification classes	N0. of training data	No. of testing data	No. of Miss-classified	% Accuracy index
Structure1: PCA-NN	Normal	13	60	8	90
	PVC	13	60	15	81.66
	RBBB	13	60	12	85
	LBBB	13	60	11	86.66
	PB	13	60	13	81.88
	APB	13	60	9	88.34
	Total	78	360	68	81.11
Structure 2: DWT - NN	Normal	13	60	3	95
	PVC	13	60	8	86.66
	RBBB	13	60	6	90
	LBBB	13	60	5	91.67
	PB	13	60	7	88.34
	APB	13	60	3	95
	Total	78	360	31	91.38
Structure 3: DWT+ time domain features- NN	Normal	13	60	1	98.33
	PVC	13	60	5	91.67
	RBBB	13	60	4	93.33
	LBBB	13	60	3	95
	PB	13	60	4	93.33
	APB	13	60	2	96.66
	Total	78	360	19	94.72

Table 3.Performance of several methods for ECG arrhythmias classification in comparison with the proposed method

Ref.	Method	Database	Arrhythmia types	Accuracy %
(6)	Multi stage Neural network	10 files	6 types of Arrhythmia	88.33
(8)	Combining wavelet and timing interval / neural network	22 files	PVC – Normal – Other beat	95.16
(7)	Wavelet / neural network	7 files	PVC and Non PVC	97.04
(9)	Wavelet/ neural network	20 files	4 types of Arrhythmia	97
(28)	PCA and wavelet / neural network	40 files	PVC – Normal – Other beat	97
(29)	DFT, DCT and wavelet / neural network	-	4 types of Arrhythmia	95
(30)	Maximum margin clustering/ Immun evolutionary algorithm	7 files	4 types of Arrhythmia	95.9
This work	Feature extraction from wavelet coefficients and time-domain information/ neural network	26 files	6 types of Arrhythmia	94.72