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Human Identification Using Electrocardiogram Signal as a Biometric Trait

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ABSTRACT

Biometrics is an interesting study due to the incredible progress in security. Electrocardiogram (ECG) signal analysis is an active research area for diagnoses. Various techniques have been proposed in human identification systems based on ECG. This work investigates in ECG as a biometric trait which is based on uniqueness. In this paper, a proposed non-fiducial identification system is presented with comparative study using radial basis functions (RBF) neural network, back propagation (BP) neural network, and support vector machine (SVM) as classification methods. The discrete wavelet transform method is applied to extract features from the ECG signal. The experimental results show that the proposed scheme achieves a high identification rate compared to the existing techniques. Furthermore, the two classifiers, RBF and BP, are integrated to achieve higher rates of human identification.

KEYWORDS

Biometric, ECG, Fiducial, Identification, Non-Fiducial, Verification

1. INTRODUCTION

Science is the basis of life since its inception, and the technologies produced which in turn led to the development of various inventions to facilitate human life and raise its well-being. Therefore, science is the basis of the technology that has entered the details of human life. The importance of science lies in being the cornerstone of many practical applications that contribute to providing the basic needs of human beings and improving their standard of living. Various sciences and the technology that they have produced have always contributed to making the life of the individual easier, such as the techniques using systems dynamics which facilitate the life of the hypothesis (Guma, et al., 2018; Aslani, et al., 2018; Iqbal, & Abdullah, 2018; Omamo, et al., 2018).

Security became an interesting area for creativity due to the incredible progress in information technology. Three available approaches to prove a person's identity are something you have (physical object as magnetic card, keys, and so on), something you know (a pre-defined knowledge, as a password) and something you are (measurable personal traits as biometric). Secure increasing for identity proof by using a combination of these approaches.

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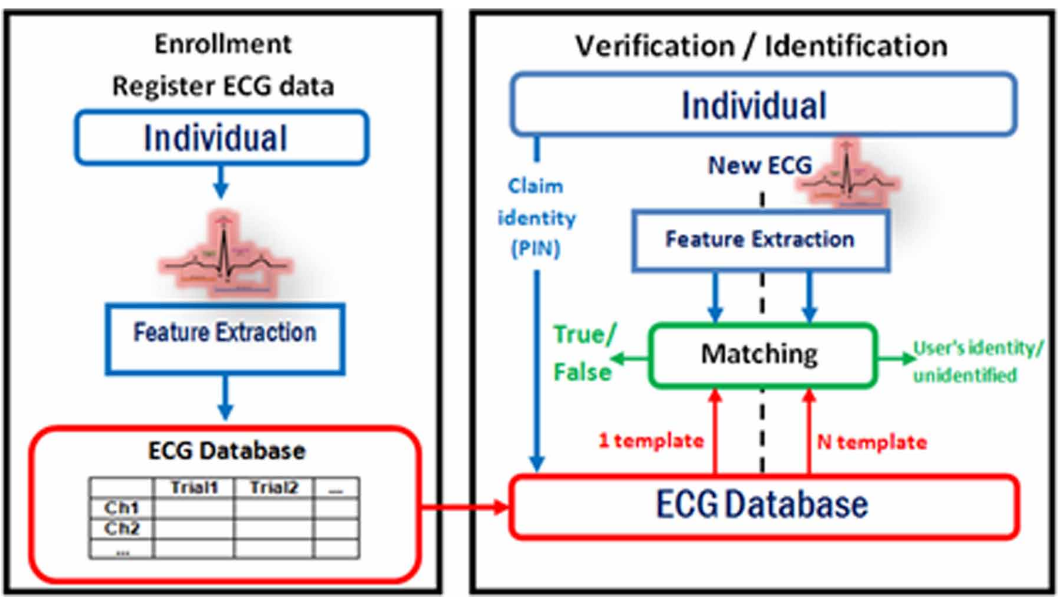
Biometrics is a method of recognizing a person based on physiological or behavioral characteristics; therefore, it is difficult to be lost or forgotten and cannot be stolen or mimic. There are physiological characteristics that are related to the shape of the body such as face, electrocardiogram (ECG), fingerprints, hand geometry, DNA, and iris. While there are behavioral characteristics that are related to the behavior of the person such as handwriting, voice, and gate (Harshit, et al., 2014).

Medical biometrics considers another category of new biometric recognition method that includes signals which are used in clinical diagnostics. Examples of medical biometric signals are the electrocardiogram (ECG), phonocardiogram (PPG), electroencephalogram (EEG), blood volume pressure (BVP) (Agrafioti, et al., 2011).

The biometric system operates in one of two modes verification or identification after the enrollment process for database building as shown in figure 1. In verification mode, the captured biometric characteristic of the person compared with the individual biometric template of a given Personal Identification Number (PIN), which is stored in the system database and retrieved using the PIN (one to one comparison). In identification mode, the system recognizes an individual by searching the entire template database for a match (one-to-many comparison) (Prabhakar, et al., 2003).

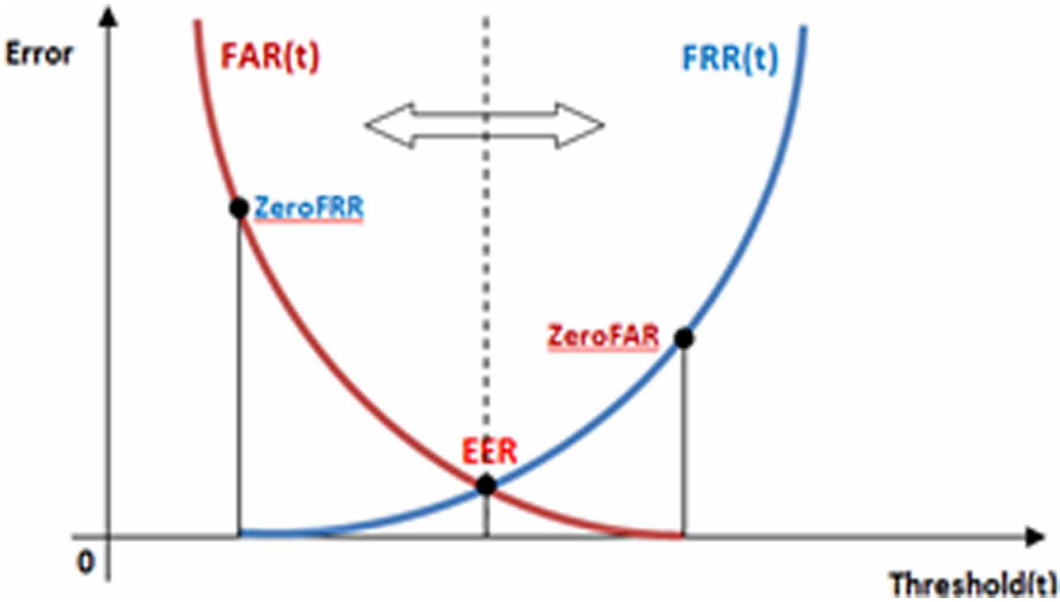
Figure 1. Enrolment, verification and identification processes



False Rejection Rate (FRR(t)) and False Acceptance Rate (FAR(t)) are two common types of errors companion to the biometric systems which are functions on the desired security level (acceptance threshold t). FRR (t) is the frequency of rejections for verifiable persons and it is an increasing function, while FAR(t) is the frequency of accesses for imposters and it is a decreasing function. Equal Error Rate (EER) denotes the system error when FRR equals FAR while Zero FAR denotes FRR when FAR equals zero and Zero FRR denotes FAR when FRR equals zero as shown in figure. 2.

Failure to Enrol rate (FTE) error happens when obtaining data cannot enter into the biometric system because it is considered as boor quality or invalid. Failure To capture rate (FTC) error happens during data acquisition where the system sensor fails to detect the biometric trait (Sareen, 2014).

Figure 2. The relation between threshold and False Acceptance Rate (FAR) and False Rejection Rate (FRR)



There are several existing schemes for using ECG signal as a biometric. These schemes have been exploited various techniques such as Discrete Wavelet Transform, Fourier Transform, and Autocorrelation and Discrete Cosine Transform for feature extraction while RBF neural network, BP neural network, Multilayer Perceptron neural network and support vector machine have exploited as classifiers. Generally, using a Fourier transform is not appropriate for the non-stationary signal like ECG. The accuracy of any biometric system should be calculated for authorized and unauthorized together. Accordingly, the accuracy in Tantawi et al. (2012) is indistinct while there is no testing for the unauthorized persons Yarong & Gang (2015), Gawande & Ladhake (2015) and Bassiouni et al. (2016). Diab et al. (2018) show how many subjects are used in testing authorized and unauthorized subjects.

Researchers are using data mining techniques as machine learning algorithms, Support Vector Machines (SVM) and artificial neural networks (ANN) to solve any problem from various fields. Modelling classification problems were solved using ANN, SVM, and PNN which became effective classifiers due to their capability to capture complex nonlinear relationships among variables. (Majhi, 2018).

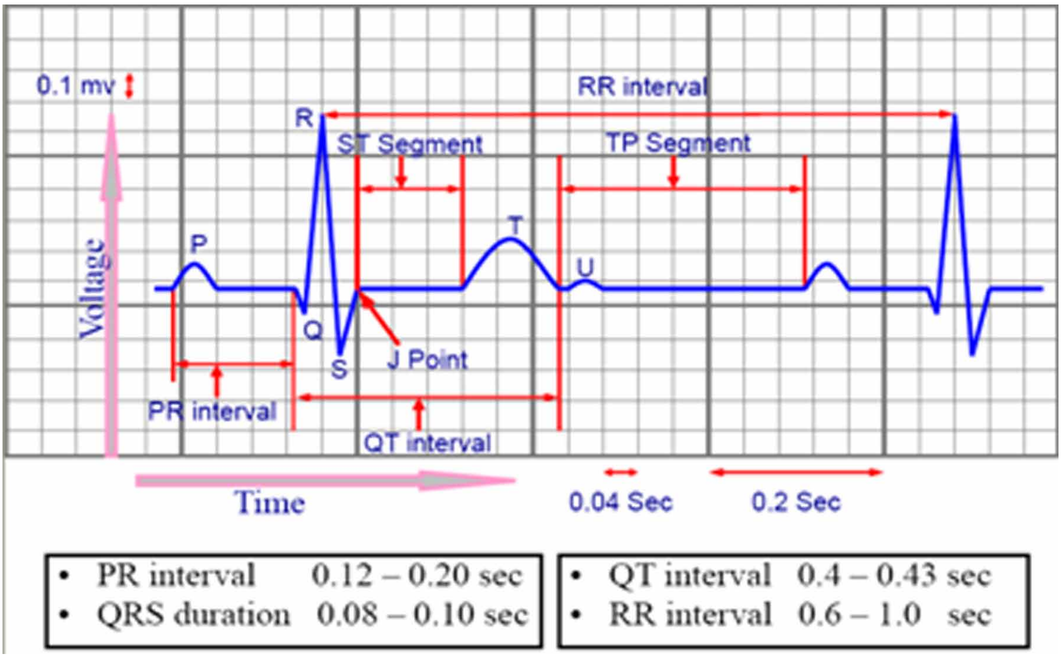
In this paper, a non-fiducial identification system using ECG signal as human biometric is proposed. Discrete Wavelet Transform is used as feature extraction. While Radial Basis Functions (RBF) neural network, Back Propagation (BP) neural network, and Support Vector Machine (SVM) are used as classifiers.

This paper is organized as follows. In Section 2, ECG signal as a biometric and ECG feature extraction approaches are shown. The basic steps required for ECG processing are presented in Section 3. Section 4 describes the related work. The proposed system architecture is described in Section 5. In section 6, experiments and results are shown. Finally, Section 7 concludes this paper.

1.1 ECG Signal as a Human Biometric

ECG signal is a method to measure the change in electrical potential of the heart by the depolarization and repolarization of ventricles and atria over time; therefore, it is considered as a physiological trait. ECG was used many years ago as a medical diagnostic data to analyze the contraction of heart occurring normally or not in an individual. Nevertheless, from the last few years, it was used as a new biometric feature (Verma & Rana, 2014; Belgacem, et al., 2012). Each beat in the ECG signal contains three main waves, the P wave, the QRS complex, and the T wave, as shown in figure 3 (Umer, et al., 2014).

Figure 3. Electrocardiogram (ECG) signal (Advances in Bioscience and Biotechnology, 2014)

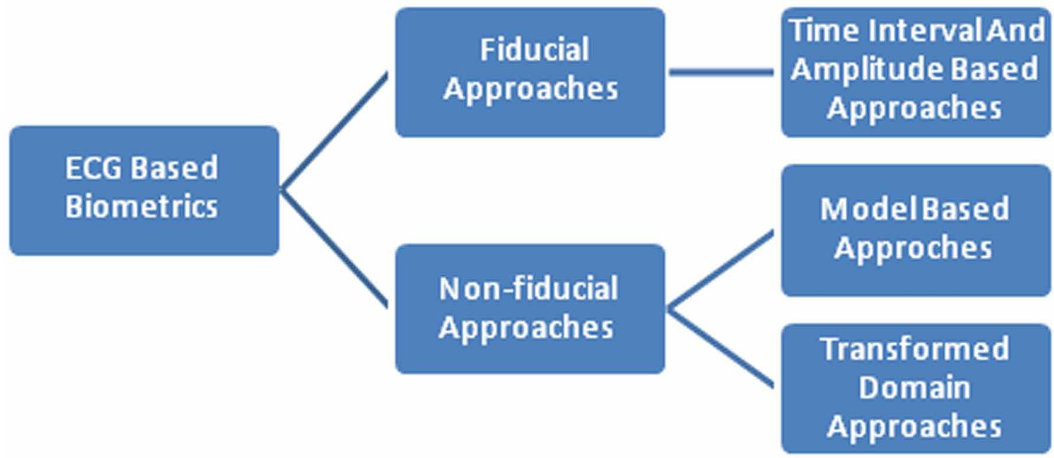


A segment is a line that connects two waves without including either one of them as PR Segment which is the line that connects the end of the P wave with the beginning of the QRS complex. While the interval is a Portion of the ECG signal that includes a segment and one or more waves as PR interval starts from the beginning of the P wave until the beginning of the QRS complex that is including the P wave (Gacek & Pedrycz, 2012).

Fiducial and non-fiducial approaches are two ECG based biometric techniques used to deduce the distinctive features of ECG signals according to the feature extraction methods as shown in figure 4. Fiducial techniques fix fiducial features from P, QRS and T waves for every heartbeat. These features are the temporal and amplitude distances between fiducial points, and angle features as prominent heights, onsets and offsets, the depression between peaks, the local maxima and minima, of a single ECG waveform (Umer, et al., 2014).

Some fiducial features require the detection of eleven fiducial points from each heartbeat. The eleven fiducial points represent the three peak points (P, R and T), two valleys (Q and S) and the six onsets and offsets for the three waves. Non-fiducial systems usually investigate the ECG frequency content. Non-fiducial features are used to get the discriminative clues from ECG waveform without getting intermediate features like wavelet coefficients, discrete cosine transform coefficients and so on. The R peak is the easiest point to detect due to its strong sharpness and is needed for fiducial detection while for some non-fiducial approaches no fiducial detection is needed (Umer, et al., 2014; Tantawi, et al., 2012).

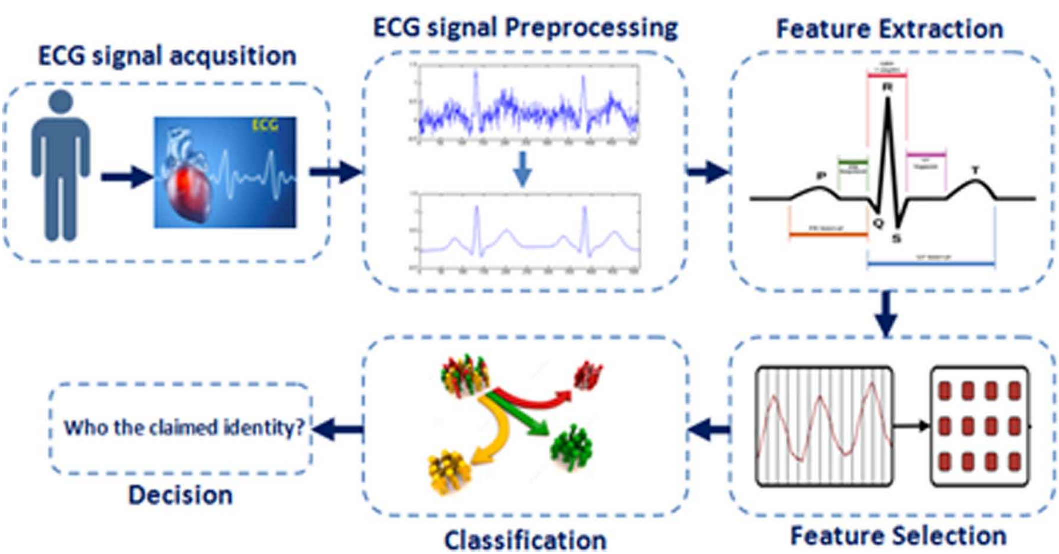
Figure 4. ECG feature extraction approaches



1.2 ECG Signal Analysis

The basic steps required for ECG processing are pre-processing, feature extraction, feature selection and classification, as shown in figure 5. Noise removal should be performed at first in the preprocessing stage of ECG signal analysis. The presence of noise makes a lot of errors companion to the biometric system. The filter selection for noise removal depends on the noise type. After pre-processing, the feature extraction process is applied to detect certain features of ECG signals mostly QRS complex, P and T waves. These features are used as inputs to the classifier in the classification stage that enables acceptable classification rates to be achieved to identify a subject or to verify an identity from the sensor observations (Ahuja & Shrivastava, 2016).

Figure 5. Basic steps for ECG processing



2. RELATED WORK

Fiducial and non-fiducial approaches are two ECG based biometric techniques. To overcome the disadvantages of the fiducial approaches, non-fiducial approaches have been conducted. In what follows, some non-fiducial studies are presented.

Tantawi et al. (2012) presented a non-fiducial identification system based on Wavelets and Radial Basis Function (RBF) neural network. The PTB, MIT-BIH and Fantasia datasets were used in this work. They achieved 100% identification accuracy for PTB database using full wavelet structure and reduced wavelet structure. Generalizing the results using Fantasia database achieved 95.89% average heartbeat recognition rate (HR) using a reduced wavelet structure. Moreover, this work achieved 100% subject identification rate for test known subjects, for testing unauthorized subjects they calculate Heartbeat Recognition accuracy (HR), FRR, and FAR and it is not clear the value of subject identification rate for testing authorized and unauthorized subjects together. Yarong and Gang (2015) introduced a human identification method based on ECG frequency domain features. Fourier transform was used for feature extraction. Correlation coefficient and Back Propagation (BP) neural network were used to classify respectively. The dataset used in this paper collected as following five people from MIT database and ten people from PTB database. The result of human identification by ECG signal based on the correlation coefficient shows that the FRR is higher FAR is acceptable. Since the method is feasible, the accuracy was 96.4% for using neural network as a classifier. However, there is no enough dataset for learning and testing also the MIT-BIH contains only one record for each person that was divided into parts for learning and testing.

Gawande and Ladhake (2015) have used a multilayer perceptron neural network and support vector machine for classification. Ten hybrid features were extracted using wavelet transform. A database of 10 normal persons (self-collected) was used in this work. The accuracy was 98.86% for using SVM and 98.05% for using MLP NN. This work achieved high accuracy; however, the used dataset is not enough for training and testing also there is no test for the unauthorized subjects. Bassiouni et al. (2016) introduced a machine learning technique for human identification based on electrocardiograms (ECG). Autocorrelation and Discrete Cosine Transform (AC/DCT) were used for feature extraction (non-fiducial feature). Artificial Neural Network (ANN) was used for classification. The dataset used in this research is30 subjects that were collected from MIT_BIH database. The classification accuracy was 97%. However, the MIT_BIH database contains only one record for each person that was divided into parts for training and testing. Also, there is no testing for unauthorized persons. Yadav et al. (2017) proposed an ECG biometric identification system. Statistical features like mean, variance and standard deviation, other features like PQRST wave's amplitude and DWT mean intervals are extracted from the recorded ECG. Artificial Neural Network (ANN) was used for classification. Ten healthy subjects were used. The accuracy of the identification system is 100%. Diab et al. (2018) suggested an identification system based on ECG signal. This work forms a comparative study between different identification techniques and their performances. The multilayer perceptron neural network was used as a classifier. This study shows a comparison of the same data using a fiducial feature set and a non-fiducial feature set based on statistical calculation of wavelet coefficient. The non-fiducial using Discrete Meyer (dmey) wavelet achieved the highest identification rate of 98.65. This work achieved a high identification rate; however, features extracted from five different heartbeats and this not enough for training. In addition, the authors used 52 healthy subjects from PTB database, and it is not clear how many subjects are used in training and testing unauthorized subjects. The system tested only on healthy subjects.

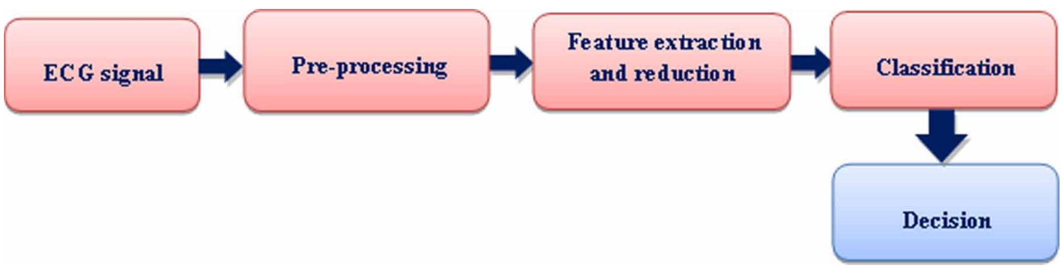
Guven et al. (2018) presented a biometric identification method based on three different feature sets. The first feature set was extracted using the AC/DCT method, while the second feature set (cepstral features) was extracted using adapting Mel-Frequency Cepstral Coefficients (MFCC) extraction algorithm, and for the third feature set the authors determined the QRS beats for each ECG signal. Both LDA and 5-NN were used as classifiers. Three databases were used; the first database contains 30 healthy subjects, while the second database and third databases were composed of 45 and 60 subjects. The recognition rate was 100% for the first and the second datasets, while it is 98.33% for the third dataset. Hanilçi and Gürkan, (2019) presented an ECG biometric identification method based on a two-dimensional convolutional neural network. AC/DCT features, and cepstral features were extracted from ECG signals. 42 subjects were used from the PTB database. The system achieved an identification rate of 90.48%.

In this paper, the proposed scheme achieves a high identification rate compared to the existing techniques. In addition, the two classifiers RBF and BP are integrated to achieve a higher rate of human identification.

3.THE PROPOSED SYSTEM ARCHITECTURE

The proposed non-fiducial identification system consists of three main steps pre-processing, feature extraction and reduction, and classification, as shown figure 6.

Figure 6. Block diagram of the proposed system



3.1 Pre-Processing

The first dataset is filtered so we used it directly. For the second dataset, the Butterworth filter of second order with cut off frequencies of 0.8 and 40 Hz was applied for noise reduction and to eliminate baseline wandering. Figure7 shows a signal for a person from the first dataset. Figure 8 and figure 9 show the original and the filtered signal for a person from the second dataset.

Pan-Tompkins algorithm is a real-time algorithm for the detection of the QRS complexes of ECG signals developed by Jiapu Pan and Willis J. Tompkins. The algorithm is implemented as follow, the signal is passed through a bandpass filter composed of successive high-pass and low-pass integer filters. Then the signal is differentiation, squaring, moving window integration, and finally peak is detected by applying threshold (Pan & Tompkins, 1985).

Then, the Pan and Tompkins algorithm was applied for R peak detection. We select 10 R-R cycles for each person is used in training. Since feature vectors must have equal length each cycle length was fixed at 200 samples. The amplitude of all points for each R-R cycle was normalized into the range from 0 to 1.

3.2 Feature Extraction

Discrete Wavelet Decomposition was applied as a feature extraction method to select R-R cycles by using Daubechies wavelets (db8). The number of decomposition levels is chosen depending on the dominant frequency components of the signal. In this work, the number of decomposition levels is chosen to be five. The obtained wavelet coefficient’s structure contains six parts (from d1 to d5 and a5), five parts (from d1 to d5) are the coefficients obtained from the details region for each level and one part (a5) is the coefficients obtained from the remaining approximation region in the last level, as shown figure 10.

Figure 7. Subject 31 original signal (filtered) from the first dataset

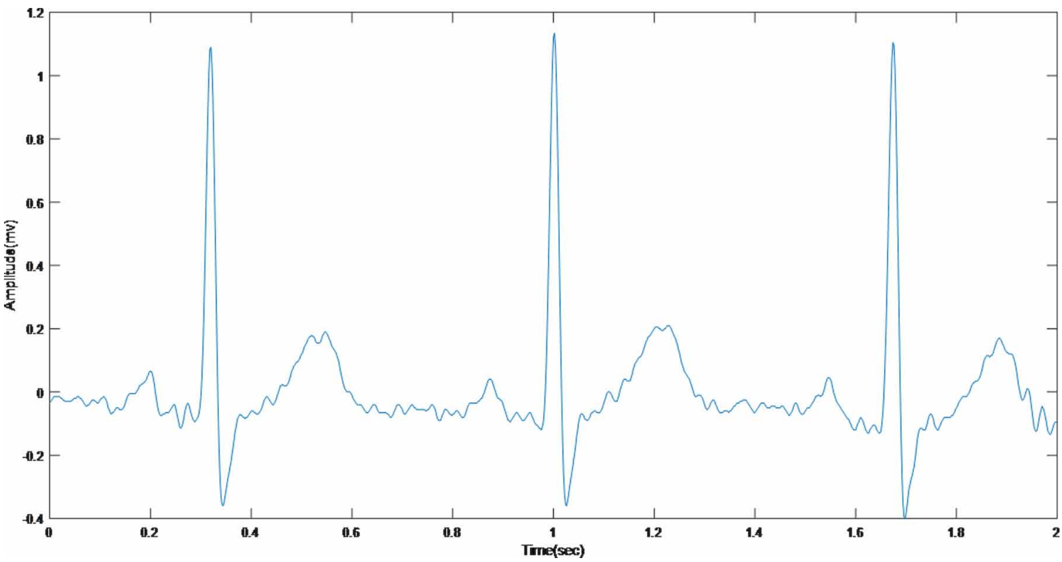


Figure 8. subject 103 original signal from the second dataset

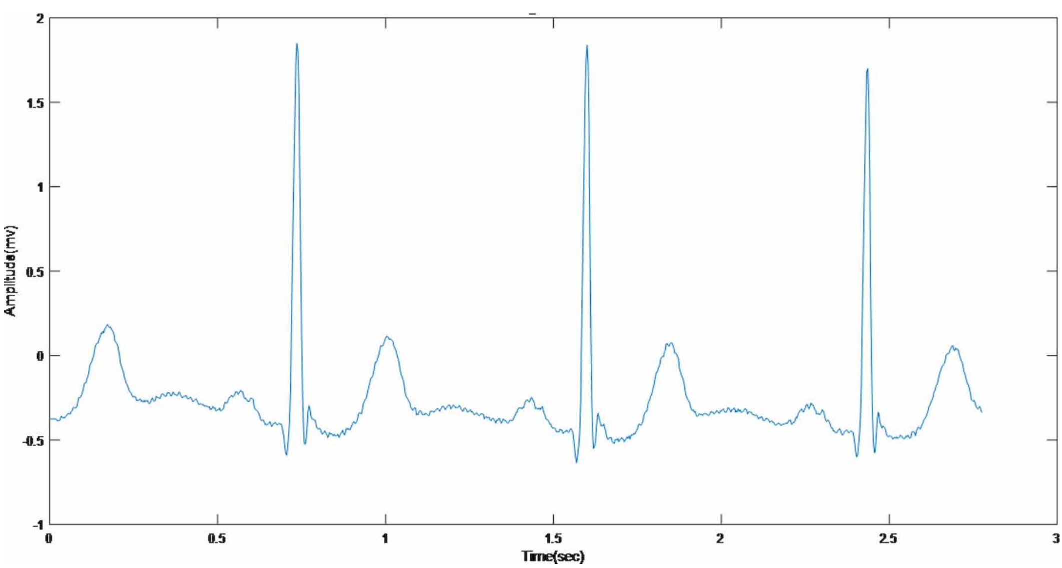


Figure 9. subject 103 filtered signal from the second dataset

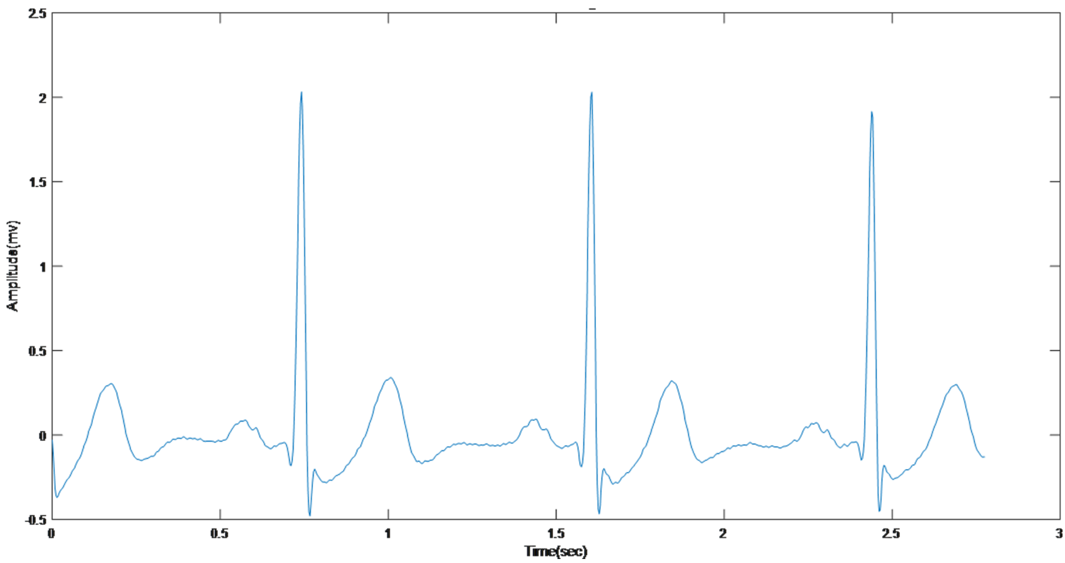


Figure 10. The 5-level discrete wavelet decomposition using Daubechies wavelets ‘db8’

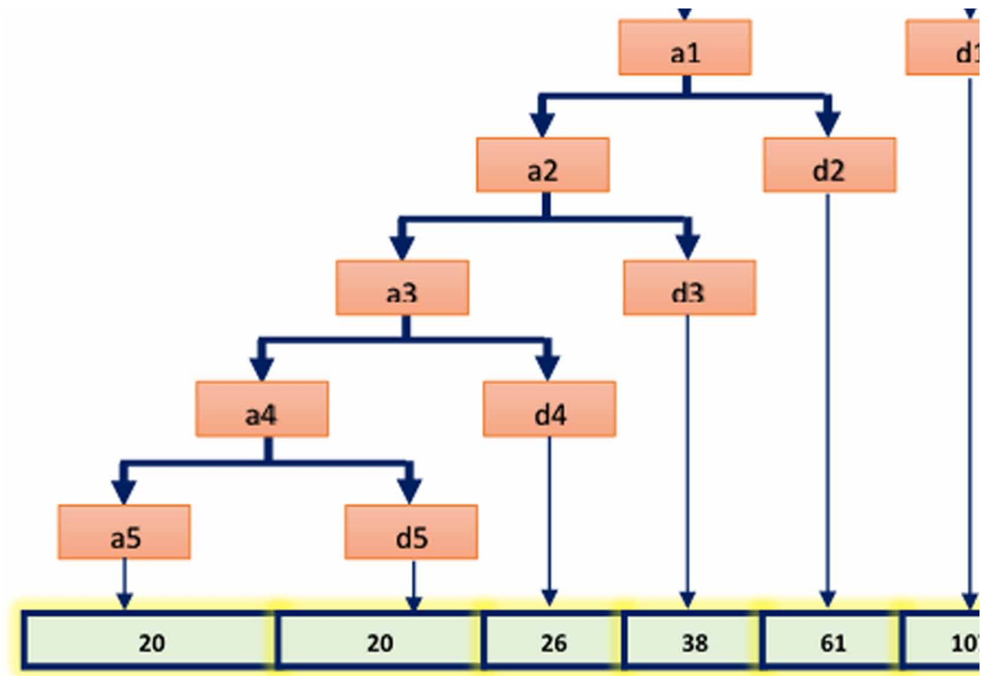


Figure 11 and figure 12 show an R-R interval and its wavelet coefficient structure using Daubechies wavelet ‘db8’. The detail information of levels 1 and 2 (d1, d2) are discarded because the frequencies covered by these two levels were higher than the frequency content of the ECG signal after filtering, so its wavelet coefficients are around zero which have no effect to be used as features

Figure 11. A selected R-R interval from subject 103 (second dataset)

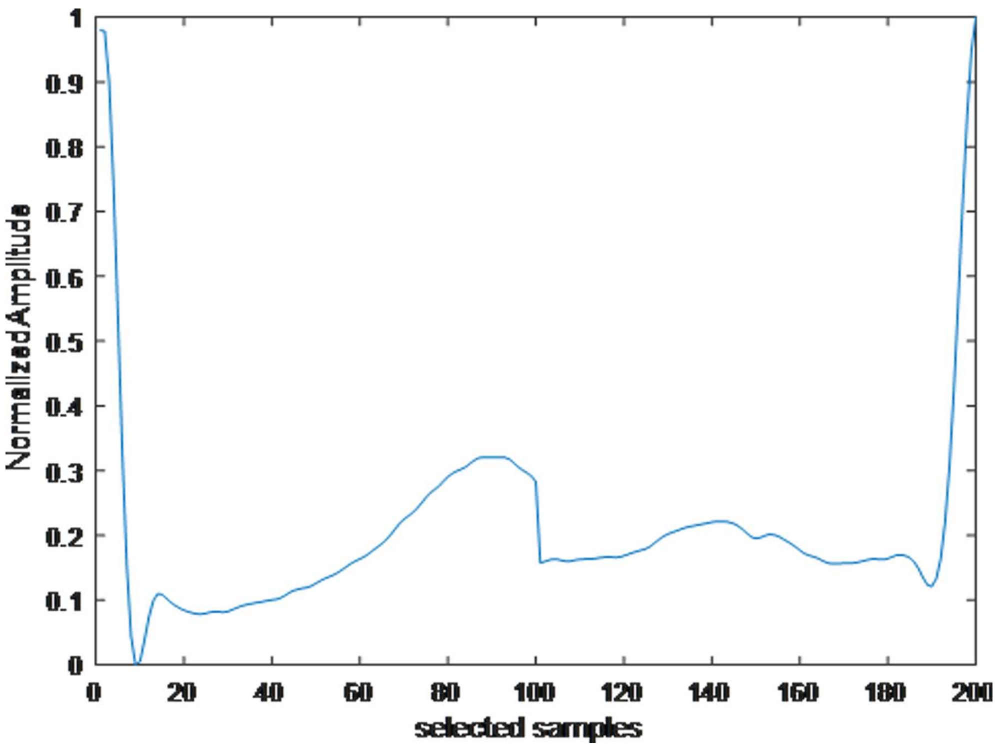
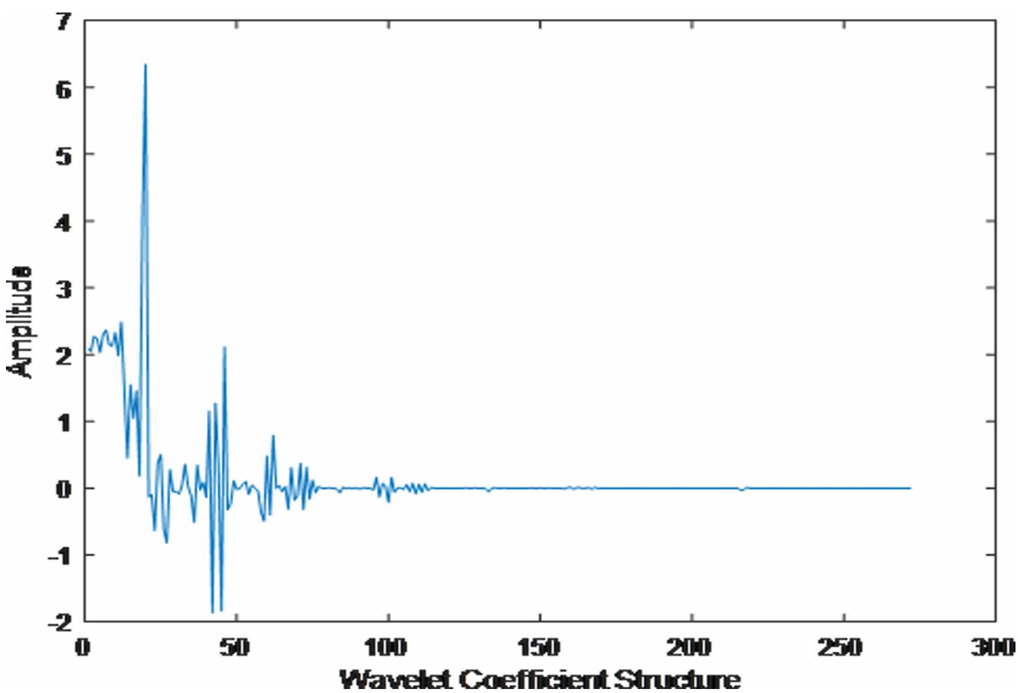


Figure 12. Wavelet coefficient structure of the selected R-R interval



in the identification process. The number of the wavelet coefficients after 5-level discrete wavelet decomposition is 272 coefficients. After (d1, d2) are discarded we use 104 coefficients.

3.3 Classification

Radial Basis Functions (RBF) neural network was used as a classifier. The Gaussian activation function was used for RBF networks which is given by:

$$\varnothing\left(\mathrm{r}\right)=\mathrm{e}^{-\mathrm{r}^2/2\tilde{\mathrm{A}}^2} \tag{1}$$

where r > 0 denotes the distance from a data point $\vec{\mathrm{x}}$ to a center $\vec{\mathrm{c}}$. For input $\vec{\mathrm{x}}$, the output of the RBF network is given by:

$$y_i\left(\vec{x}\right)=\sum_{k=1}^{J2}\omega_{ki}\varnothing\left(\vec{x}-\overrightarrow{c_k}\right) \tag{2}$$

Where $\mathrm{y}_{\mathrm{i}}\left(\vec{\mathrm{x}}\right)$ is the ith output, $\acute{\mathrm{E}}_{\mathrm{ki}}$ is the connection weight from the kth hidden unit to the ith output unit, and . denotes the Euclidean norm.

In addition, the feed-forward neural network is trained using backpropagation algorithm as a classifier. The backpropagation neural is a multilayered feed-forward neural network and works by approximating the non-linear relationship between the input and the output by adjusting the weight values internally (Wu, et al., 2012; Lee & To, 2010).

Support Vector Machine (SVM) is a supervised learning used for classification and regression. It is a useful technique for data classification. SVM constructs a hyperplane or set of hyperplanes in a high dimensional space that can be used for classification or regression (BURGES ,1998).

3.4 Datasets Description

Two datasets are used in our experiments; the first dataset is collected from the ECG-ID Database. This database contains 310 ECG recordings, obtained from 90 persons (44 men and 46 women aged from 13 to 75 years). Each recording contains ECG lead I, recorded for 20 seconds, digitized at 500 Hz, and the second dataset is collected from the MIT-BIH Arrhythmia Database. This database contains 48 ECG recordings, obtained from 47 subjects were 25 men aged from 32 to 89 years and 22 women aged from 23 to 89 years. (Records 201 and 202 came from the same male subject). In most records, the upper signal is a modified limb lead II (MLII) obtained by placing the electrodes on the chest. Each record is sampled at 360 HZ. Each of the 48 records is slightly over 30 minutes long (https://archive.physionet.org/cgi-bin/atm/ATM).

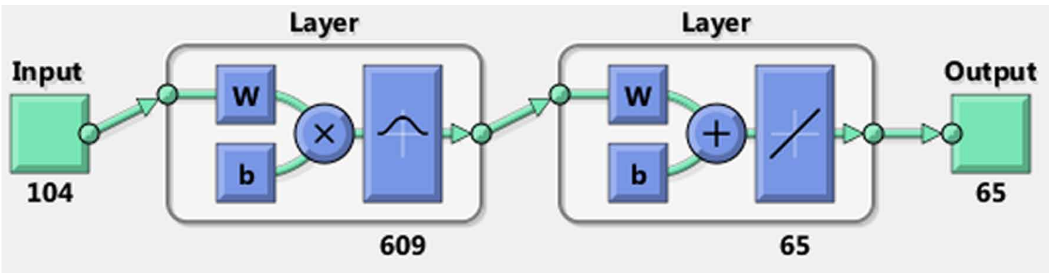
For the first dataset, in our study 65 subjects are used to train the ANN. Forty subjects are used for testing. Among these 32 subjects are used for testing known (authorized) persons, and 8 subjects are used for testing unknown (unauthorized) persons. In our experiments, we used a record for training and another one for testing.

For the second dataset, we used 25 subjects that were recorded using lead II (MLII). We used different ECG types. Forty subjects are used for testing. Among these 25 subjects are used for testing known (authorized) persons, and15 subjects are used for testing unknown (unauthorized) persons (12 subjects from the first dataset and 3 subjects from the second dataset).

4. EXPERIMENTS AND RESULTS

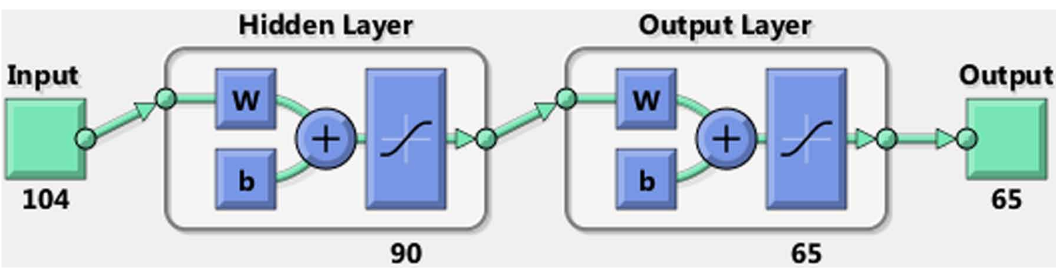
Daubechies wavelet 'db8' as feature extraction method is used. For the first dataset, the wavelet coefficients of the training set are fed into an RBF neural network. The number of input nodes is 104 (input vector size). The number of hidden nodes is 609 and the number of output nodes is 65 (number of persons to be classified) as shown in figure 13.

Figure 13. Radial Basis Neural Network for the first dataset



Using backpropagation neural network as a classifier, the number of input nodes is 104 (input vector size). The number of hidden nodes is 90 and the number of output nodes is 65 (number of persons to be classified) as shown in figure 14.

Figure 14. Back Propagation Neural Network for the first dataset



Also, we used SVM as a classifier. The proposed system is generalized using the second dataset. The effectiveness of the proposed system was determined by the accuracy, false acceptance rate (FAR) and false rejection rate (FRR).

$$\text{Accuracy}\left(\%\right) = \frac{\text{correctly classified subjects}}{\text{total number of subjects}} * 100 \tag{3}$$

In addition, some metrics are used such as recall, precision and F-score to evaluate the proposed system performance.

$$\text{Recall}\left(\%\right) = \frac{\text{TP}}{\text{TP} + \text{FN}} * 100 \tag{4}$$

$$\text{Precision}\left(\%\right) = \frac{\text{TP}}{\text{TP} + \text{Fp}} * 100 \tag{5}$$

$$\text{F} - \text{score} = \frac{2 * \text{Recall} * \text{Precision}}{\left(\text{Recall} + \text{Precision}\right)} \tag{6}$$

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. Recall or Sensitivity is the ratio of correctly predicted positive observations to all observations in the actual class. F- Score is the weighted average of Precision and Recall. It takes both false positives and false negatives into account (Godil, et al.,2014).

Where TP: denotes the number of true positive samples.

TN: denotes the number of true negative samples.
FP: denotes the number of false-positive samples.
FN: denotes the number of false-negative samples.

Table (1) contains comparison between classification methods for the first and the second datasets using Daubechies wavelet 'db8'as feature extraction.

Table 1. Comparison between the used classification methods for the first and the second datasets

Dataset	Methods	Subject Recognition Accuracy (%)	FRR (%)	FAR (%)	Precision (%)	Recall (%)	F-score (%)
ECG-ID	**RBNN**	**97.5**	**0**	**2.5**	**96.97**	**100**	**98.46**
	BPNN	95	2.5	2.5	96.87	96.87	96.87
	SVM	80	12.5	7.5	90	84.37	87.09
MIT-BIH Arrhythmia	**RBNN**	**97.5**	**0**	**2.5**	**96.15**	**100**	**98.04**
	BPNN	95	0	5	92.59	100	96.15
	SVM	72.5	5	22.5	71.87	92	80.7

Figure 15 and figure16 show the percentage values of accuracy, precision, recall and f-score for the first and the second datasets using Daubechies wavelet'db8' as feature extraction technique and classification methods (RBNN, BPNN and SVM).

The experimental results show that using RBF neural network gives higher identification rate than other used classifiers. Also, we found that the system accuracy by using the neural network as

Figure 15. Comparison between the used classification methods (RBNN, BPNN and SVM) for the first dataset

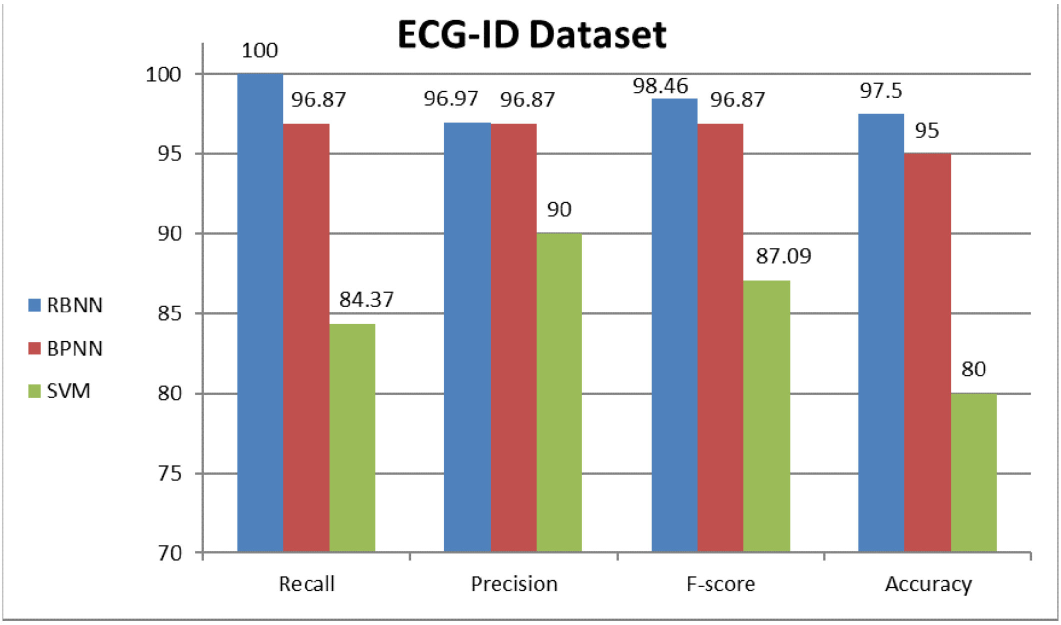
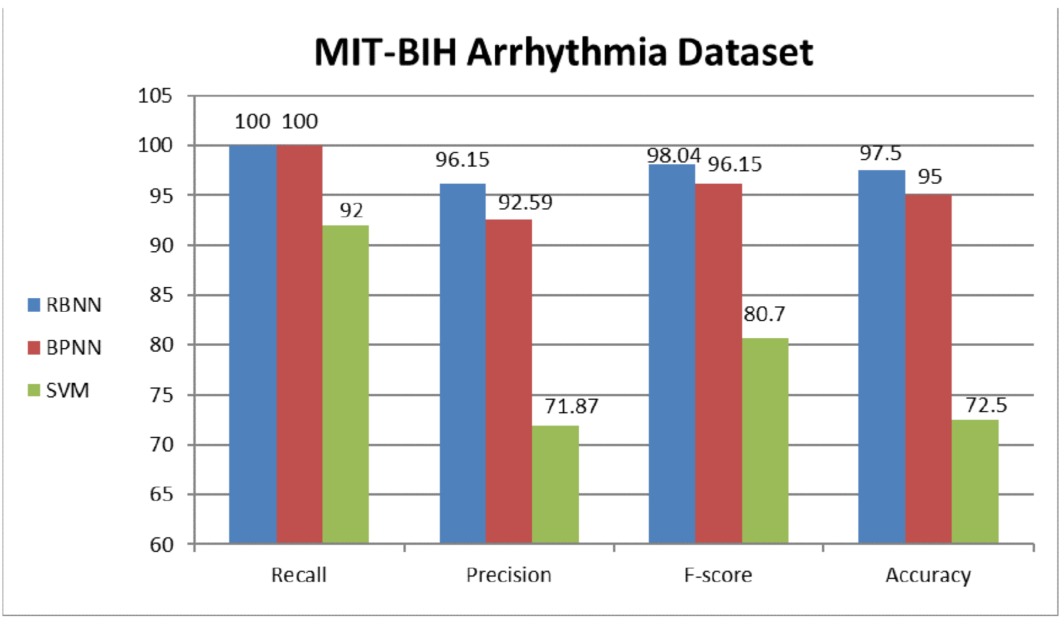


Figure 16. Comparison between the used classification methods (RBNN, BPNN and SVM) for the second dataset



a classifier is better than that using the support vector machine for the first and the second datasets. We found that the system performance using SVM is improved by decreasing the number of subjects. Also, SVM as classifier has been used even when prediction of unknown samples is not necessary.

The results show that some unknown subjects accepted as known; accordingly, this problem is solved by combining the two classifiers (RBFN and BPNN), the Subject Recognition Accuracy for the first dataset is 97.5% and 100% for the second dataset, see Table (2).

Table 2. System performance for the first and the second datasets using the two combining classifiers

Dataset	Methods	Subject Recognition Accuracy (%)	FRR (%)	FAR (%)	Precision (%)	Recall (%)	F-score (%)
ECG-ID	RBNN + BPNN	97.5	2.5	0	100	96.87	98.41
MIT-BIH Arrhythmia		100	0	0	100	100	100

5. CONCLUSION

This paper proposes an efficient identification biometric system based on ECG signal. A comparative study is presented between the RBFN, BPNN and SVM as classification methods. ECG is considered a non-stationary signal, so using wavelets as feature extraction method is more suitable than other transformed methods. The results show that Daubechies wavelet'db8' gives high identification rate 98.46%by RBF network as classifier. In addition, BP network gives a good identification rate, for the first dataset f-score is 96.87% and for the second dataset f-score is 96.15%. While the RBF network gives a high f-score than the BP network and the Support Vector Machine for the first and the second datasets. By combining the two classifiers (RBFN and BPNN), the identification rate for the first dataset is 98.41% and 100% for the second dataset. In the future work, a comparative study will be conducted to compare different feature extraction methods.

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