ECG Cardiac arrhythmias Classification using DWT, ICA and MLP Neural Networks

*M.Ramkumar*, C.Ganesh Babu, Vinoth Kumar K, Hepsiba D, A. Manjunathan, R.Sarat Kumar

'Assistant Professor, Department of Electronics and Communication Engineering, Sri Krishna College of Engineering and Technology, Coimbatore

'mrakumar0906@gmail.com

'Professor, Department of Electronics and Communication Engineering, Bannari Amman Institute of Technology, Sathyamangalam

'bits_babu@yahoo.co.in

'Associate Professor, Department of Electrical and Electronics Engineering, New Horizon College of Engineering, Bengaluru

'kvinoth_kumar84@yahoo.in

'Assistant Professor, Department of Biomedical Engineering, Karunya Institute of Technology and Sciences, Coimbatore

'hepsibavijay23@gmail.com

'Assistant Professor, Department of Electronics and Communication Engineering, K.Ramakrishnan College of Technology, Trichy, India

'manjunathankrcst@gmail.com

'Assistant Professor, Department of Electronics and Communication Engineering, Sri Krishna College of Engineering and Technology, Coimbatore

'sarathkumar@skcet.ac.in

Abstract: Recognizing ECG cardiac arrhythmia automatically is an essential task for diagnosing the abnormalities of cardiac muscle. The proposal of few algorithms has been made for classifying the ECG cardiac arrhythmias, however the system of classification efficiency is determined on the basis of its prediction and diagnosis accuracy. Hence, in this study the proposal of an efficient system has been made for classifying the ECG cardiac arrhythmia as an expertise. Discrete Wavelet Transform (DWT) is being utilized for the preprocessing mechanism of ECG signal, Independent Component Analysis (ICA) is being utilized for dimensionality reduction and Feature Extraction process of ECG signal and Multi-Layer Perceptron (MLP) neural network is being utilized for performing the task of classification. As an outcome of classification, the results have been acquired on categorizing Normal Beats under the class of Non-Ectopic beat, Atrial Premature Beat under the class of Supra-Ventricular ectopic beat and Ventricular Escape beat under the class of Ventricular ectopic beat on the basis of standardization given by ANSI/AAMI EC57: 1998. For the acquisition of ECG signal, MIT-BIH physionet arrhythmia database is being utilized in this study added to that its being utilized for training process and testing process of the classifier on the basis of MLP-NN. The results obtained from the simulation has been inferred that the accuracy of classification of the proposed algorithm is 96.50% on utilizing 10 files inclusive of normal beats, Atrial Premature Beat and Ventricular Escape beat.

Keywords: ECG, Cardiac Arrhythmia, DWT, ICA, MLP-NN, MIT-BIH Arrhythmia database.

1. Introduction

An ECG signal is considered as an essential signal among all the electrically measured biological signals. The analyzing process of ECG signal is broadly utilized in diagnosing many disorders of cardiac muscles. Its recording could be made acquired from the signal propagation happening during the state of repolarization and depolarization process in the cardiac muscle. The conduction of potential in the cardiac tissues to the surface of the body where its measurement is made utilizing the electrodes.

Figure 1 depicts the normal ECG waveform along with its time period. The P peak, QRS peak and T peak are denoted as the most essential features characterized for ECG waveform. For an ECG beat, peak representation associated with the waveform is denoted as QRS complex along with its previous existence of P peak and the preceding T peak. For undergoing the clinical diagnosis these sections of data are the most relevant information for doctors to
undergo suitable treatment. Other essential data is inclusive of the S-T segment elevation, rate of heartbeat and R-R interval.

Fig 1: Representation of Normal ECG signal

The external pattern of ECG signal determines the most essential hidden data within its structure. The amplitude in terms of voltage and the time duration of each signal component in ECG are mostly utilized for making the analysis manually. Thus, being the data volume more enormous and the analysis carried out manually is considered to be very tough and the task of huge time-consuming part. Consequently, there is a large possibility of losing the most essential information by the analyst. Hence, the performance of clinical diagnostics could be made done by utilizing the computational analysis and implying the techniques of classification [1].

The proposal of few algorithms has been made for classifying the heartbeat patterns of ECG signals on the basis of essential features extracted from the ECG waveform. Analysis over the Fourier transform gives the spectrum of signal or the frequency range of voltage amplitudes within the component of waveform itself. However, the technique of Fourier transform produces the frequency components and not the relationship of temporal characteristics. Wavelets could lend the representation of frequency versus time characteristics of signal and functions well on the data of non-stationary process [2][3][4]. Very few algorithms utilize the features of morphological characteristics [5], temporal intervals of heartbeat [6], features of frequency domain and perform the analysis over multifractal domain [7]. The algorithms of biomedical signal processing fields do require the subsequent appropriated classifiers in order to perform the best categorization of various ECG waveforms. In the year of 1976, Shortliffe has made the presentation over an earlier system of Computer aided diagnosis and preceding with treating the bacterial infection symptoms [8]. Classifying mechanisms of ECG signal pattern recognition is inclusive of Linear Discriminate Analysis [2], Artificial Feed Forward Neural Networks [9], Support Vector Machines [10], algorithms oriented to mixture of experts [12] and Probabilistic Markov Models [15] [16]. Added to that, the ECG waveform clustering mechanism under unsupervised learning has been analyzed utilizing Self-Organizing Maps [17].

Considering the fact that inspite of the raw acquired ECG signal is influenced with noisy component, the most important problem in performing the classification of ECG signal by the computational intelligent techniques is proposed to be of wide categorization of ECG beat shape is falling under the same category whereas the ECG beats
under same shape falls under different categories [18] [19]. Generally, the diagnosis on the basis of computational intelligent techniques is being done by three important sequential steps. They are Acquisition of ECG beat signal and detecting it, essential feature extraction process of various ECG beats and finally Classification of ECG beats under different categories.

In this proposed study, the algorithm on the basis of Artificial Neural Networks for classifying normal beats, Atrial Premature Beat and Ventricular Escape beat is being carried out. This proposed algorithm utilizes the features that are extracted by Discrete Wavelet Transform (DWT) technique along with the ECG timing features in order to perform the training of an Multi Layer Perceptron Neural Network (MLP NN). It is extracted with few essential features from the coefficients of wavelets in order to make the achievement on both robust and accurate Neural Network on the basis of classifier on utilizing the total count of training patterns.

The organization of this paper is made as follows. The second section makes the description of background data regarding DWT, ICA and MLP NN. The proposed dimensionality reduction technique, feature extraction process and classification study are presented in third section. Forth section determines the results over experimentation and the last section is ended with conclusion.

2. Background

A. Discrete Wavelet Transform

At the beginning, the presentation of wavelet transforms in made by Morlet in the year 1980s which was utilized for evaluating the seismic information [16]. Wavelets lend a variable solution for classical algorithms of Fourier transforms for single dimensional analysis and synthesis of informational data and produces enormous applications in the field of Physics, digital image processing, digital signal processing and mathematics. The application of wavelet transform could be made in both discrete time signal and continuous time signal. For instance, the representation of wavelet for the discrete signal X which possess N number of samples could be computerized by doing the convolution of X with the High Pass Filters and Low Pass Filters and decimating the output signal by second order and hence both the frequency bands each possess the samples of N/2.

This technique is on the basis of the wavelets usage as the basic functions for making the representation of other functions. Both in the frequency and time domain, the basic functions possess the support with finite numbers. The analysis over the achievement of multi resolution is made by utilizing the parent (mother) wavelet and the wavelet family generated by the dilations and translations of itself [20][21]. There are various approaches for implementing the two-dimensional DWT like the convolution based traditional methods and the scheme of lifting methods. The filtering is applied by the convolution algorithms by performing the multiplication of the filtering coefficients with the sample of inputs and proceeding with the accumulation of results. The implementation of the algorithms is done by utilizing the Finite Impulse Response (FIR) banks of filter. The proposal over the lifting scheme has been made for implementing the wavelet transform more efficiently. This technique possesses 3 phases. They are splitting, predicting and updating [22][23][24]. In the discrete wavelet transform of single dimensional technique, at the level of each decomposition state, the scaling function is made associated with the HPF which makes the production of detail data that relates high frequency components whereas the LPF which associates the scaling function makes the production of approximation data that are made in relation with the waveform’s low frequency components. The decomposition of the approximation section could be rendered in an iterative manner. The process of decomposition carried out in the second order is made depicted in figure 2. The segregation of the signal is made into many components of lower resolution. This mechanism is represented as the wavelet decomposition tree [24].
The wavelet transform is said to be as reversible one. The reversal mechanism of decomposition is said to be as reconstruction. The detail and the approximation coefficients of wavelet at each level are interpolated by the factor of 2, which gets passed through the Low Pass Filter and High Pass Filter and then it is summed up. The continuation of the process is undergone through the similar count of levels as in the process of decomposition in order to acquire the original signal and it is denoted in Figure 3.

The definition for different families of Wavelet in made in the literature survey. Daubechies wavelets are considered to be as the most widespread wavelet. The Daubechies wavelets are utilized in various applications. The selection of wavelet filters is made on the basis of their capability for analyzing the signal and its own shape in the respective application. Daubechies family with 9 elements is depicted in figure 4.
Fig 4: Daubechies family with 9 elements.

The consideration for the ECG signal is made as the representative signals of heart muscle’s physiology which is useful in making the diagnosis of heart muscle disorders. The most essential path in displaying this data is for performing the analysis of spectral components. The wavelet transform produces very generalized technique which could be determined for many applications oriented to signal processing. Computation of various features could be made and its manipulation is done over the domain of compression on utilizing the coefficients of wavelet. All it creates the fact that, the wavelet transform could be applied on the ECG signal and it could be converted to its wavelet parameters or coefficients. The acquired coefficients will produce the characterization as the ECG wave component behaves and the total count of these coefficients are considered to be as small than the total count of original ECG signal. The feature space reduction is most predominantly essential for the purpose of diagnosis and recognition [25].

B. Independent Component Analysis

The independent component analysis is too keenly correlated with the technique denoted as the Blind Source Separation (BSS). The representation of ECG signal is made by the current induced by myocardium in each and every individual heart beat. The considerations for the ECG signals could be made as the combinations of various sources of ECG. Thus, the representation of the signal could be made by the combination of few not known sources in linear fashion.

\[ S_{\text{ECG}} = \sum_{i=1}^{N} a_i s_i \]  

Where \( s_i \) is represented as single source and \( a_i \) is denoted as the coefficient.

The combinations which has been denoted in the linear fashion as in equation (1) is similar as that of the ICA basic model. On utilizing the notation of vector matrix, the model of mixing could be denoted as

\[ x = As \]

Where \( s \) is denoted as \( N \times 1 \) not known source signal column vector and \( A \) is denoted as \( N \times N \) combining matrix which has to be evaluated. On making the estimation of independent components equalizes determining the suitable linear combination \( s_i \).

\[ s = A^{-1}x \]

In this proposed study, the model of ICA is being utilized for finding effective notation of ECG signals. ICA based dimensionality reduction method has been utilized widely in very many fields such as image, video, hyperspectral and audio data along with real time extraction of biomedical signals such as ECG, EEG etc. The training of the basis functions over ICA is being done utilizing few samples selected randomly with the selection of null mean from various disease of cardiac muscle. 12 independent components have been chosen as the basis functions for processing into the computational intelligent classifiers.

C. Artificial Neural Networks

The Artificial Neural Networks (ANN) are the denoted as the tools which could be utilized for modelling neural biology or human cognition utilizing the operations of mathematics. An ANN is denoted as the elements of processing functions. It possesses few common performance characteristics with biologically associated neural networks. The characterization of neural network is as followed by its sequence.
a. The connection pattern in-between the neurons represented as the neural architecture
b. Its algorithm of weight determination on its connections termed as learning or training algorithms.
c. Its function of activation [26].

The Multilayer Perceptron (MLP) is denoted as the most generalized neural networks. This sort of neural network is termed to be as supervised neural network since its requirement is on the basis of desired expected output for creating the learning. The main purpose of Multilayer Perceptron is for creating a model which exactly performs the mapping of input data to the output by utilizing the historical information and hence the model could be utilized for producing the output data when the desired data of output is not known. The architecture of MLP with 2 hidden layers are depicted in figure 5.

![Architecture of MLP with two hidden layers.](image)

In the initial step, MLP is utilized for learning the input informational behavior on utilizing the back-propagation algorithm. This sequence is represented as the phase of training. As the preceding step, the trained network of MLP is utilized for testing using the unknown informational sequence. The comparison over the result is made by back propagation algorithm which is acquired in this sequence with the expected result. This sort of classification is represented as supervised system of classification. The computation of the error signal is made by the MLP utilizing the desired and the acquired output. The signal with error which is computed is then connected to the neural network through an adaptive mechanism and it is utilized for weight adjustment that undergoes the iterative process which results in the decrease of error and the model of neural network are tuned to be précised in order to determine the desired output. The learning algorithm of neural network is depicted in figure 6.

![Learning algorithm of Neural Network](image)

There are various algorithms utilized for training, whereas it is very hard for knowing and analyzing the faster training algorithms to be selected from the cluster for a specific problem. In order to make the determination over the fastest algorithm of training, the consideration of many parameters has to be done. For example, the problem
complexity, the total count of training set data points, the total count of weights, network biases and the evaluation of goal for the error should be made.

3. Proposed System of Classification

The functional block diagram of proposed system of classification is depicted in figure 7. This system is on the basis of wavelet transform and artificial neural networks. This system is consisting of 2 different phases. They are dimensionality reduction combined with the feature extraction phase and next is the phase of classification and these were discussed in the subsequent sections.

![Functional Block Diagram of Proposed System of Classification](image)

A. First Phase of ECG Signal Processing

The initial phase consisting of the subsequent stages of acquisition of Raw ECG signal from MIT-BIH arrhythmia physionet database, Pre-Processing of ECG waveform, Dimensionality Reduction using ICA and the feature extraction. Preprocessing makes the improvement in accuracy of classification of any of the defined algorithms since it is processed with the adequate and the accurate form of features.

The acquired ECG signal from the surface of the electrodes stick on the surface of the body has the noise associated with the baseline. Hence the baseline wander, which might appear because of large number of factors that arise from instrumental or biological sources like the skin resistance from the electrode, thermal drift of amplifiers and respiration. It is considered as the noise of low frequency. In the stage of preprocessing, the filtration of the ECG signal is made utilizing the moving average filter for establishing the elimination of baseline wander. This elimination of baseline wander is equalized with the Low Pass Filter impulse response which aids in smoothening of signal.

\[
y(i) = \frac{1}{2N+1}(x(i + N) + x(i + N - 1) + \cdots + x(i - N))
\]

where \(y(i)\) is denoting smoothened value of data point in ith order, \(N\) denotes the total count of adjacent data points on both the side of \(y(i)\), \(2N + 1\) denotes the span and \(x\) denotes the vector of input [25].

Figure 8 denotes the original ECG signal in presence of noise and Figure 9 denotes the ECG signal with the elimination of baseline wander and results as noise free signal.
In the post-processing stage, the extraction for the features of ECG is being made by utilizing the selection of two seconds of ECG plot from its record. For the dimensionality reduction the Independent Component Analysis is being utilized and for feature extraction the discrete wavelet transform is being utilized. As previously mentioned, there are so many filters of wavelet that can be applied on the signal. The selection of Daubechies Wavelet in the 6th order is being made in the form of db6. This is done since the family of Daubechies Wavelet is of same external shape as that of QRS complex of ECG signal and their concentration over the spectrum of energy are captured to be surrounding the lower frequencies. The total count of decomposition level is being set with the value of 8. In other words, it could be represented as the decomposition of ECG signals have been designated from D1 to D8 level of details. In order to make the reduction of dimensions for the extracted vectors of features, the probabilistic 24 sets of
the wavelet coefficients are being utilized from 1\textsuperscript{st} level to 8\textsuperscript{th} level along the Independent Component Analysis. The feature sets are listed below.

- Maximum Value of the coefficients of wavelets in each desired level
- Minimum value of the coefficients of wavelets in each desired level
- Variance value of the coefficients of wavelets in each desired level

B. Second Phase of ECG Signal Processing (Classification)

For the phase of classification, Multi-Layer Perceptron Neural Network has been utilized. The MLP-NN’s best architecture is generally acquired utilizing the trial and error mechanism [26] [27][28]. Hence after the series of simulations, MLP-NN is being chosen with twenty-four number of input neurons, single hidden layer and two output neurons of linear fashion. The outputs of bipolar utilizing +1 and -1 numbers were utilized as the target of outputs for the selected 3 number of classes. The testing of performance for the proposed MLP-NN is being carried out by the parameter of Mean Square Error (MSE). The computation of this error is made utilizing the differences obtained between the outputs that has been resulted actually and the trained Neural Network output.

In the model of Neural Network, with which the implementation is being carried out using the programming tools of Matlab, there are several algorithms of training which possess a variety of various requirements of computational analysis and storage. However, it is very tedious for finding an algorithm which is very well suited for most of the applications. In this proposed study, the implementation is tried by utilizing the algorithm possessing high performance characteristics like traindx or Variable Learning Rate, trainrp or Resilient Backpropagation, trainlm or Levenberg-Marquardt with reduced memory as the part of training algorithms. The outputs with 2 bipolar neurons were utilized as the network target. For the three patterns of classification, the targets used are, for normal signal it is [1,1]; for Atrial Premature Beat (APB) it is [-1,-1] and for Ventricular Escape Beat (VEB) it is [-1,1]. The techniques of heuristic algorithms were utilized by the trainrp and the traindx algorithms. The development of heuristic techniques was made utilized by the performance analysis of the steepest descent algorithm which is standardized. The standardized techniques of numerical optimization were utilized by the algorithm of trainlm [29]. The best training performance of 0.18306 at 50000 epochs of the proposed MLP neural network is denoted in the figure 10.

![Best Training Performance is 0.18306 at epoch 50000](image)

**Fig 10: The best training performance of the proposed MLP-NN**

4. Experimentation and Simulation Results

The MIT-BIH physionet arrhythmia database is consisting of 48 recordings of ECG signal. Each of the individual records is comprising of several signals, few files, few annotations and the signal attribute specifications. Individual records acquired from MIT-BIH arrhythmia database is of half an hour recording out of 24 hours. The frequency of sampling for the ECG signal is 360 Hz and all the records are followed with suitable annotations. Consequently, for a single record of ECG from MIT-BIH arrhythmia database, it is consisting of nearly 2000 annotations of beats and smaller count of rhythms along with the annotations of realizing the signal quality.

In this proposed study, classification is made under Normal beats, Atrial Premature Beat and Ventricular Escape beat. Totally 10 records have been chosen from MIT-BIH database for the realization of
classification by using MLP Neural Network. The training for the MLP neural network has been utilized by 90 vectors of training from the 10 files of ECG MIT-BIH database. The testing for the trained neural networks of MLP has been made under forty-five patterns with which fifteen testing patterns were utilized for each individual class inclusive of normal and two different clusters of arrhythmias. In order to make the testing of trained MLP-NN performance, 2 different criteria have been utilized for comparing the samples of recognition, trained networks and rate of recognition. The definition for the rate of recognition is as follows.

\[ A = 100 \left( \frac{N_c}{N_T} \right) \]  

(5)

Where A is termed to be as the rate of recognition, Nc is the total count of patterns that are classified correctly and Nt denotes the total pattern count. The results over simulation is depicted in table 1, 2 and 3. The results over the testing are acquired by performing the training over the proposed MLP-NN by the utilization of various number of neurons updated in the hidden layer.

Table 1. Simulation Result with the algorithm of traingdx

| Data  | Total Number of samples | Total Number of hidden neurons | Total Number of hidden neurons | Total Number of hidden neurons |
|-------|-------------------------|--------------------------------|--------------------------------|--------------------------------|
|       |                         | 12 | 13 | 14 | 12 | 13 | 14 |                           |
| Normal| Train                   | 32 | 32 | 32 | 32 | 100.0 | 100.0 | 100.0 |
|       | Test                    | 17 | 15 | 16 | 16 | 88.2 | 94.1 | 94.1 |
| APB   | Train                   | 32 | 32 | 32 | 32 | 100.0 | 100.0 | 100.0 |
|       | Test                    | 17 | 17 | 17 | 17 | 100.0 | 100.0 | 100.0 |
| VEB   | Train                   | 32 | 32 | 32 | 32 | 100.0 | 100.0 | 100.0 |
|       | Test                    | 17 | 14 | 15 | 14 | 82.4 | 88.2 | 82.4 |
| Total |                         | 147 | 142 | 144 | 143 | 96.6 | 98.0 | 97.3 |

Table 2. Simulation Result with the algorithm of trainrp

| Data  | Total Number of samples | Total Number of hidden neurons | Total Number of hidden neurons | Total Number of hidden neurons |
|-------|-------------------------|--------------------------------|--------------------------------|--------------------------------|
|       |                         | 10 | 11 | 12 | 10 | 11 | 12 |                           |
| Normal| Train                   | 32 | 32 | 32 | 32 | 100.0 | 100.0 | 100.0 |
|       | Test                    | 17 | 14 | 15 | 14 | 82.4 | 88.2 | 82.4 |
| APB   | Train                   | 32 | 32 | 32 | 32 | 100.0 | 100.0 | 100.0 |
|       | Test                    | 17 | 17 | 17 | 17 | 100.0 | 100.0 | 100.0 |
| VEB   | Train                   | 32 | 32 | 32 | 32 | 100.0 | 100.0 | 100.0 |
|       | Test                    | 17 | 14 | 15 | 15 | 82.4 | 88.2 | 88.2 |
| Total |                         | 147 | 141 | 143 | 142 | 95.9 | 97.3 | 96.6 |

Table 3. Simulation Result with the algorithm of trainlm

| Data  | Total Number of samples | Total Number of hidden neurons | Total Number of hidden neurons | Total Number of hidden neurons |
|-------|-------------------------|--------------------------------|--------------------------------|--------------------------------|
|       |                         | 13 | 14 | 15 | 13 | 14 | 15 |                           |
| Normal| Train                   | 32 | 32 | 32 | 32 | 100.0 | 100.0 | 100.0 |
|       | Test                    | 17 | 15 | 15 | 14 | 88.2 | 88.2 | 82.4 |
| APB   | Train                   | 32 | 32 | 32 | 32 | 100.0 | 100.0 | 100.0 |
|       | Test                    | 17 | 17 | 17 | 17 | 100.0 | 100.0 | 100.0 |
| VEB   | Train                   | 32 | 32 | 32 | 32 | 100.0 | 100.0 | 100.0 |
|       | Test                    | 17 | 14 | 14 | 15 | 80.0 | 82.4 | 88.2 |
| Total |                         | 147 | 145 | 142 | 142 | 98.6 | 96.6 | 96.6 |
Table 1 depicts the results which has been acquired utilizing the algorithm of training “traingdx”. 12, 13 and 14 neurons has been utilized for the hidden layers. It could be inferred that the best training performance is acquired utilizing 13 neurons in the hidden layer. The exact learning rate setting is very essential for traingdx algorithm because of its sensitivity with respect to its performance. For instance, if the rate of learning is set with very higher value the oscillations could be produced in the algorithm and results with unstable condition, whereas if the rate of learning is very small, then algorithm takes more time for converging. It is very tedious to make the determination over the optimal setting prior to training phase. This happens since at the time of training process; the rate of optimal learning will be varied.

Table 2 determines the results with which the calculation is being made utilizing the trainrp algorithm. It makes the utilization of 10, 11 and 12 neurons which has been utilized in the hidden layer. The best performance has been resulted when it is being utilized with 11 neurons in the hidden layer. The gradient might possess very smaller value of magnitude when the steepest descent has been utilized for training the ANN with the functions of tan sigmoid. This results in the smaller bias variations and the weight vector even if the weights and biases are quite distant from their optimal values. The ultimate aim of trainrp algorithm is to determine the removal of partial derivative magnitudes and harmful effects.

The acquired results utilizing the trainlm algorithm is being represented in table 3. The best performance has been resulted when it is being utilized with 14 neurons, rather than utilization of 13 and 15 neurons in the hidden layer. This algorithm is determined to be as the fastest algorithm and has the disadvantage of storage of vectors that induce parallel processing. And overall, the best rate of recognition of the proposed MLP-NN with all the 3 trained algorithms has been resulted with 98.6%.

5. Conclusion
Thus, in this proposed study, the system on the basis of neural networks for classifying ECG arrhythmias automatically has been realized. 10 recordings have been utilized from MIT-BIH arrhythmia database for performing the training process and the testing process of the classifier. It has been analyzed under the phase of feature extraction along with the dimensionality reduction and the phase of classification. In the initial phase the moving average filter is being employed for the elimination of baseline wander from ECG wave component. Later on, the application of DWT is being utilized over the filtered signal and it is utilized for the extraction of wavelet coefficient features. As the next phase, the dimensionally reduced extracted features has been utilized for training the MLP-NN classifier. The demonstration over the simulation results of MLP-NN for categorizing the ECG arrhythmias with the rate of recognition of 98.6% has been resulted with the utilization of 13 neurons in the hidden layer with traingdx, 11 neurons with trainrp and 14 neurons in the algorithm of trainlm respectively.

6. References
1) R. Acharya, P. S. Bhat, S. S. Iyengar, A. Roo and S. Dua, (2002) “Classification of heart rate data using artificial neural network and fuzzy equivalence relation”, The Journal of the Pattern Recognition Society, vol. 130, pp. 101–108
2) K. Minami, H. Nakajima and T. Toyoshima, (1999) “Real-Time discrimination of ventricular tachyarrhythmia with fourier-transform neural network”, IEEE Trans. on Biomed. Eng, vol. 46, pp. 179-185.
3) Romero and L. Serrano, (2001) “ECG frequency domain features extraction: A new characteristic for arrhythmias classification”, in Proc.23rd Annual Int. Conf. on Engineering in Medicine and Biology Society, pp. 2006-2008.
4) P. de Chazal, M. O’Dwyer and R. B. Reilly, (2000) “A comparison of the ECG classification performance of different feature sets”, IEEE Trans. on Biomed. Eng, vol. 27, pp. 327-330.
5) P. de Chazal, M. O’Dwyer and R. B. Reilly, (2004) “Automatic classification of heartbeats using ECG morphology and heartbeat interval features”, IEEE Trans. on Biomed. Eng, vol. 51, pp. 1196-1206.
6) Alexakis, H. O. Nyongesa, R. Saatchi, N. D. Harris, C. Davis, C. Emery, R. H. Ireland and S. R. Heller, (2003) “Feature extraction and classification of electrocardiogram (ECG) signals related to hypoglycemia”, Proc. Computers in Cardiology, vol. 30, pp. 537-540.

7) P. Ivanov, M. QDY, R. Bartsch, et al, (2009) “Levels of complexity in scaleinvariant neural signals”, Physical Review.

8) S. Z. Mahmoodabadi, A. Ahmadian, M. Abolhasani, P. Babyn and J. Alirezaie, (2010) “A fast expert system for electrocardiogram arrhythmia detection”, Expert system, vol.27, pp. 180-200.

9) T. H. Linh, S. Oosowski and M. Stodolski, (2003)“On-line heart beat recognition using hermite polynomials and neuro-fuzzy network”, IEEE Trans. on Instrumentation and Measurement, vol. 52, pp. 1224-1231.

10) S. Oosowski, L. T. Hoai and T. Markiewicz, (2004) “Support vector machine-based expert system for reliable heartbeat recognition”, IEEE Trans. on Biomed. Eng, vol. 51, No. 4, pp. 582-589.

11) T. H. Linh, S. Oosowski and M. Stodolski, (2003)“On-line heart beat recognition using hermite polynomials and neuro-fuzzy network”, IEEE Trans. on Instrumentation and Measurement, vol. 52, pp. 1224-1231.

12) Y. H. Hu, W. J. Tompkins, J. L. Urrusti and V. X. Afonso,( 1994) “Applications of artificial neural networks for ECG signal detection and classification”, The Journal of Electrocardiology, vol. 26, pp. 66-73.

13) A. Coast, R. M. Stern, G. G. Cano and S. A. Briller, (1990) “An approach to cardiac arrhythmia analysis using hidden markov models’, IEEE Trans. on Biomed. Eng, vol. 37, pp. 826-836.

14) M. Fernández-Delgado and S. B. Ameneiro, (1998) “MART: A Multichannel ART-based neural network”, IEEE Trans. on Neural Networks, vol. 9, pp. 139-150.

15) S. B. Ameneiro, M. Fernández-Delgado, J. A. Vila-Sobrino, C. V. Regueiro and E. Sánchez, (1998)”Classifying multichannel ECG patterns with an adaptive neural network”, IEEE Engineering in Medicine and Biology, vol. 17, pp. 45-55.

16) Y. Hu, S. Palreddy and W. J. Tompkins,( 1997) “A patient-adaptable ECG beat classifier using a mixture of experts approach”, IEEE Trans. on Biomed. Eng, vol. 44, pp. 891-900.

17) R. V. Andreao, B. Dorizzi and J. Boudy, (2006) “ECG signal analysis through hidden markov models”, IEEE Trans. on Biomed. Eng, vol. 53, pp. 1541-1549.

18) S. Oosowski, T.H. Linh, (2001) “ECG beat recognition using fuzzy hybrid neural network”, IEEE Trans. Biomed. Eng, Vol. 48, pp. 1265-1271.

19) M. Lagerholm, C. Peterson, G. Braccini, L. Edenbrandt and L. Sörnmo, (2000) “Clustering ECG complexes using hermite functions and self-organizing maps”. IEEE Trans. on Biomed. Eng, vol. 47, pp. 838-848.

20) L. Shyu, W. Hu, (2008) “Intelligent Hybrid Methods for ECG Classification-A Review,” Journal of Medical and Biological Eng., Vol. 28, pp. 1-10.

21) Mertins,( 1999) Signal analysis wavelets, filter Banks, time-frequency transforms and applications, Wollongong.

22) M. Jansen and P. Oonincx,( 2005) Second generation wavelets and applications, Springer.

23) S. Mallat, (1989) “A theory for multiresolution signal decomposition: the wavelet representation”, IEEE Pattern Anal. and Machine Intell Ii, pp. 674-693.

24) G. Strang and T. Nguyen, (1996) Wavelets and filter banks. Wellesley Cambridge Press.

25) D. Uebelyi, (2008) “Implementing wavelet transform/mixture of experts network for analysis of electrocardiogram beats”, Expert system, Vol. 25, pp. 150-162.

26) M. Misiti, Y. Misiti and G. Oppenheim, J-M. Poggi, (2006) Wavelet toolbox for use with MATLAB.

27) (2006) Digital signal processing toolbox user’s guide for use with MATLAB.

28) Fausett, (1994) Fundamentals of neural networks, Prentice Hall, New Jersey.

29) S.Heykin, (1999) Neural networks: a comprehensive foundation, Prentice Hall, New Jersey.

30) H. Demuth, M. Beale and M. Hagan, (2006) Neural network toolbox For Use with MATLAB.

31) T. Inan Omer, L. Giovangrandi, and T. A. Kovacs Gregory, ( 2006) “Robust neural-network-based classification of Premature Ventricular Contractions using wavelet transform and timing interval features”, IEEE Trans. on Biomed. Eng, Vol. 53, pp. 2507- 2515.
32) M. Engin, (2004) “ECG beat classification using neuro-fuzzy network”, Pattern Recognition Letters, Vol. 25, pp. 1715–1722.
33) H. G. Hosseini, K. J. Reynolds, and D. Powers, (2001) “A multi-stage neural network classifier for ECG events”, In Proc. of 23rd Int. Conf of IEEE EMBS, Vol. 2, pp.1672-1675.
34) http://library.med.utah.edu/kw/ecg/mml/ecg_533.html
35) http://library.med.utah.edu/kw/ecg/mml/ecg_533.html