ISSN: 2349-9141

Available online at http://www.ijirr.com

International Journal of Information Research and Review
Vol. 2, Issue, 05, pp. 695-700, May, 2015

OPEN ACCESS JOURNAL

Full Length Research Paper

IDENTIFICATION OF NORMAL AND ABNORMAL ECG USING NEURAL NETWORK

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Received 10th April 2015; Published 31th May 2015

Abstract

Classification of ECG involve various methods and techniques, which have given better performance and accuracy for the analysis of heart related diseases. Here we are using Neural Pattern recognition tool which is more powerful tool to identify normal and abnormal ECG. This proposed Artificial Neural Network is most efficient for identification of normal and abnormal ECG with 100% accuracy for normal ECG detection.

Keywords: Neural Network, Electrocardiogram (ECG), MIT-BIH database.

To cite this paper: *Ajeet Sharma and Kushagra Bhardwaj. 2015. Identification of normal and abnormal ecg using neural network. International Journal of Information Research and Review* ***Vol. 2, Issue, 05, pp. 695-700****.*

INTRODUCTION

Cardiac problems are increasing day by day. ECG is one of the most commonly used tests to diagnose the heart problem. Detection and treatment of arrhythmias have become one of the cardiac care unit's major functions. Few of the arrhythmias are Ventricular Premature Beats, a systole, Couplet, Bigeminy; Fusion beats (Shahanaz Ayub and Saini, 2011). For getting the best result toward the unknown and unseen data the size of the training database should be at least as large as the number of modifiable parameters in ANN. The literature survey in this topic reports several approaches to detection, including Bayesian (Willems and Lesaffre, 1987) and heuristic approaches (Talmon, 1983) expert systems (Gallin *et al.,* 1984) and Markov models (Coast *et al.,* 1990). Generally past approaches, as per published results, seem to suffer from common drawbacks that depend on high sensitivity to noise and unreliability to deal with new or ambiguous patterns.

Neural Pattern Recognition (NPR) have often been proposed as tools for realizing classifiers that are able to deal even with nonlinear discrimination between classes and to accept incomplete or ambiguous input patterns. Recently, the connectionist approach has also been applied to ECG analysis with promising results (Stamkopulos *et al.,* 1992; Frenster, 1990). Electrocardiogram (ECG) represents the electrical activity of the heart. Millions of ECGs are taken for the diagnosis of various classes of patients, where ECG can provide a lot of information regarding the abnormality in the concerned patient is analyzed by the physicians and interpreted depending upon their experience. The interpretation may vary by physician to physician. Hence this work is all about the automation and consistency in the analysis of the ECG signals so that they must be diagnosed and interpreted accurately irrespective of the physicians (Talmon, 1983). The recorded ECG waveform which is made of distinct electrical depolarization and repolarisation patterns of the heart. Any disorder of heart rate or rhythm, or change in the Morphological pattern is an indication of an arrhythmia, which could be detected by analysis of the recorded ECG waveform. A typical cycle of an ECG is shown in Fig. 1. Physicians locate such points as Q points, R points, and *S* points in the ECG from which they locate the P-complexes, QRS-waves, T-complexes, and U-waves in the ECG. These waves and complexes are defined in Fig. 1. Physicians then interpret the shapes of those waves and complexes. They calculate parameters to determine whether the ECG shows signs of cardiac disease or not. The parameters are the height and the interval of each wave, such as RR interval, PP interval, QT interval, and ST segment (Figure 1) (Yukinori Suzuki, 1995). In this paper we applied normal sinus ECG database and *abnormal* database, the normal sinus rhythm will not only give you an idea about the rhythm is normally generated from the sinus node and wandering in a normal manner in the heart. In most of the research paper single ECG bit taken for analysis, but in our research we have taken the 1 min complete ECG include of many ECG bit is taken for analysis which has taken a great care in case of heart beat variability. The normal value of heart bit rate depends upon age it is not same for all the normal people, normal heart rate for an infant is 150 beats in one minute maximum, even the heartbeat rate of child of five year age may 100 beats in a minute, the heart rate of adult is slower than the child, it is about 60-80 beats in one minute.

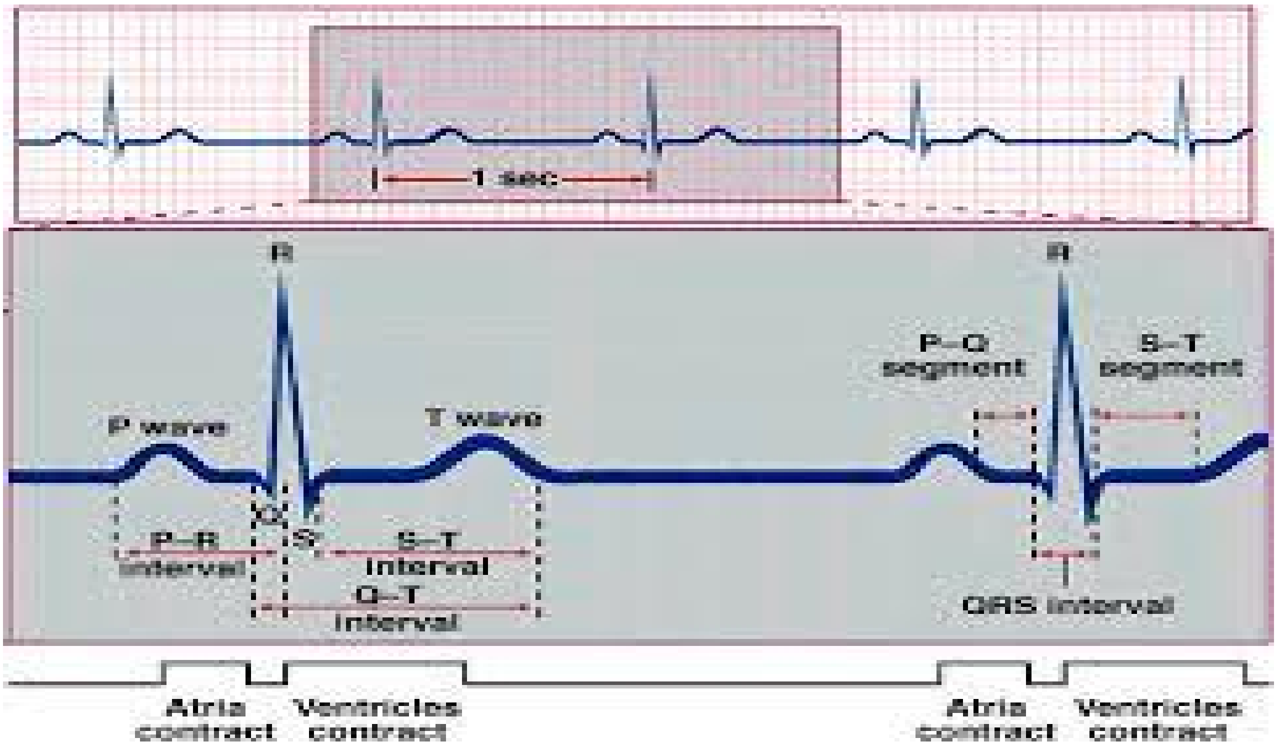

Figure 1. The ECG signal and its different components

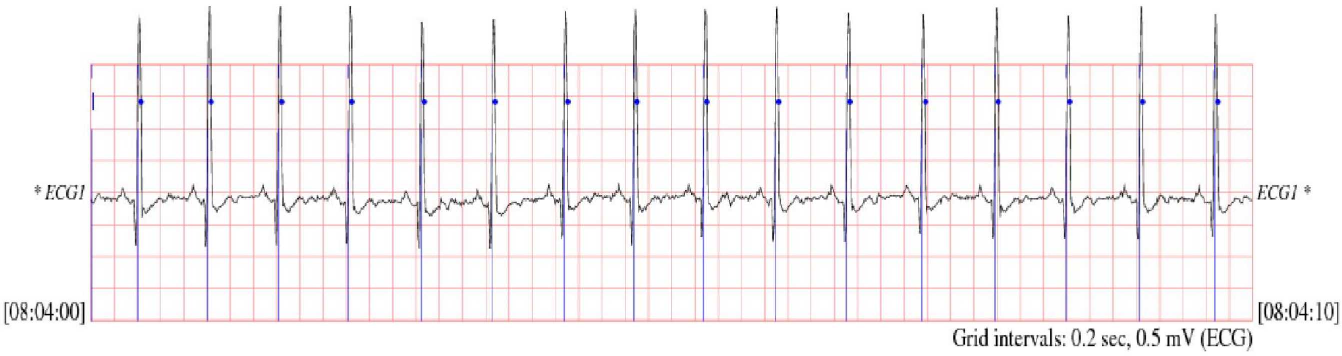

Figure 2a. normal sinus 16265 signal of MIT-BIH

Figure 2b. *Supraventricular* Arrhythmia 800 signal of MIT- BIH

In normal sinus rhythm of heart p-waves are pursued after a short gap. By a QRS complex followed by a T-wave of ECG the cause of Supraventricular Arrhythmia is a quick heart rhythm of the upper chambers of the heart. In Supraventricular Arrhythmia electrical signals or the electrical potential move through the upper chambers to lower chambers of the heart.Supraventricular Arrhythmia are usually 150-250 beats per minute but it can be both slower or faster.

The most common types of supraventricular tachycardia are caused by a re-entry phenomenon producing accelerated heart rates. Normally, Supraventricular Arrhythmia results in symptoms such as frequent heart beating, dizziness, shortness of breath and chest discomfort.

MIT BIH Database

The database was the first generally available set of standard test material for evaluation of arrhythmia detectors, and has been used for that purpose as well as for basic research into cardiac dynamics at more than 500 sites worldwide. The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. The image of the normal sinus rhythm database (16265) and supraventicular Arrhythmia (801) duration of 10 Sec and 128 Hz sampling rate of MIT-BHI is shown in the Figure (2a, 2b) (Massachusetts Institute of Technology, ?).

NPR

A neural network is an interconnected group of nodes, akin to the vast network of neurons in a brain. Here, each circular node represents an artificial neuron and an arrow represents a connection from the output of one neuron to the input of another. In machine learning and cognitive science, neural networks (NNs) are a family of statistical learning algorithms inspired by biological neural networks (the central nervous systems of animals, in particular the brain) and are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. Artificial neural networks are generally presented as systems of interconnected "neurons" which can compute values from inputs, and are capable of machine learning as well as pattern recognition thanks to their adaptive nature. A neural network for handwriting recognition is defined by a set of input neurons which may be activated by the pixels of an input image. After being weighted and transformed by a function (determined by the network's designer), the activations of these neurons are then passed on to other neurons. This process is repeated until finally, an output neuron is activated. This determines which character was read and the weights of neurons as it outputs. The BPA is a supervised learning algorithm, in which a sum square error function is defined, and learning process aims to reduce the overall system error to a minimum.

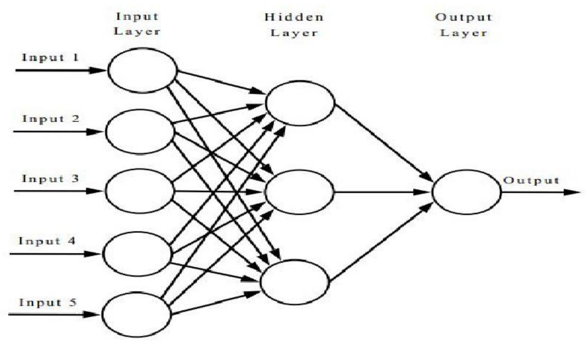

Figure 3. Architecture of Neural Network

The output units have weights $W^3_{i,j}$ and the hidden units have weights $W^2_{i,j}$ and $W^1_{i,j}$. During the training phase each output neuron compares its computed activation *YK* with its target value d_k to determine the total square error E for the pattern with that neuron,

$$E = 1/2\sum_{k=1}^{m}(d_k - y_k)^2$$

Where m is the number of output neurons, k represents the k[th] neurons. By using Back propagation Algorithm the network has been trained with moderate values of learning rate and momentum .the weights will be terminated when the sum square error reaches a minimum values.

The weights are assigned randomly at the beginning and progressively modified backward from the output layer to the input layer to reduce overall system error. The weight update is in the direction of negative descent to maximize the speed of error reduction. For effective training, it is desirable that the training data set be uniformly spread throughout the class domains. The available ECG data were used repetitively until the error converges to its minimum. Hence an algorthim containing three steps that are (i) setting random weights, (ii) training recursion and (iii) Detection of ECG (Kuo-Kuang Jen and Yean-Ren Hwang, ?; Mehmet Korurek, 2010; Sadaphule *et al.,* 2012; Shanxiao Yang and Guangying Yang, 2010). The block diagram of the ANN system is shown in the figure-4; two arrows indicate the training data and testing data that applied to the cascade feed forward type ANN system. Training data used for preparing the network architecture and decide the input and output range according to the training function, number of hidden layer, the method used for optimization and training functions is used for training. After this test data is applied, on the basis of proposed ANN network output is determined in the form of 0 and 1 here 0 for supraventricular ECG and 1 for normal sinus ECG.

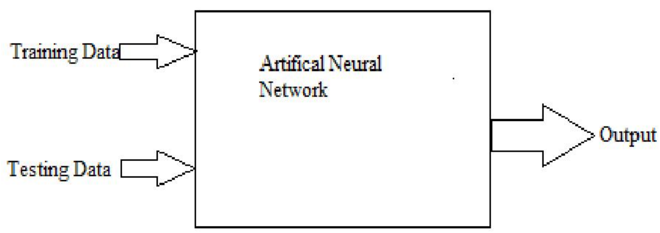

Figure 4. Artificial Neural Network Systems

MATERIALS AND METHODS

The MIT-BIH Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. The recordings of normal sinus ECG (ECG1) database and Supraventricular ECG (ECG1) database were digitized at the rate of 128 samples per second per channel with the resolution of 11-bits over a span of 10 mV (Massachusetts Institute of Technology, ?). In our method we use 18 ECG Signal of normal sinus database, out of 18 we use 14 in training and 4 in testing. The duration of one ECG is 10 Sec with sampling rate 128 Hz and total sample of an ECG signal is 1280 some of the abnormal ECG is called arrhythmia in our paper we have taken supraventricular database. In abnormal database we take supraventricular arrhythmia database of 66 ECG signal out of 66 ECG signal 14 signal used for training and 52 used for testing. The sampling rate of supraventricular ECG signal is same as a normal ECG signal.

Input Data

The input database is given in the matrix from shown in the table,

Name	Total	Training	Testing
Normal ECG Database	18	14	4
Supraventricular ECG database	66	14	52

From the above table the total 84 ECG signals are used for analysis, out of 84, 28 are used for training and remaining 56 used for testing.

Training Function

Levenberg-Marquardt (trainlm): Like the quasi-Newton methods, the Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feed-forward networks), then the Hessian matrix can be approximated as

$$H = J^T J$$

And the gradient can be computed as

$$g = J^T e$$

Where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and **e** is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix. The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$X_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way the performance function will always be reduced at each iteration of the algorithm (http://radio.feld.cvut.cz/matlab/toolbox/nnet/backpr11.html; http://www.mathworks.in/help/nnet/ref/trainlm.html).

Analysis

Levenberg-Marquardt function also known as DLS (damped least squares) is used for training the neural network. The proposed neural network diagram, algorithm and process diagram is given below:

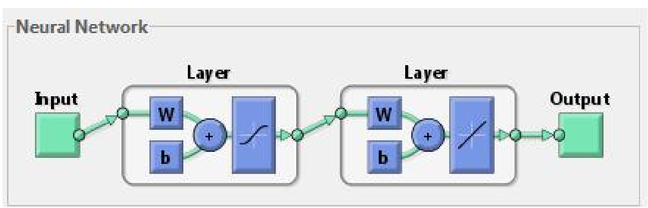

Figure 5. Neural Network

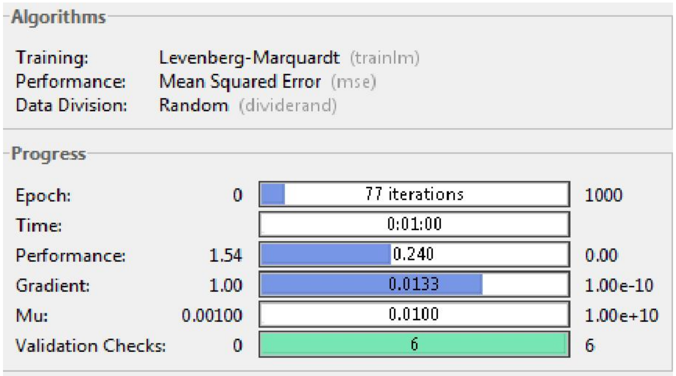

Figure 6. Algorithm and process

The given neural network has two hidden layer between the input layer and output layer. The performance graph of the neural network is plot between the mean square error and the epoch. Here the blue line stand for training data, green for the validation and red line for the test data. Performance graph, training state graph and the regression diagram is given below:

The coding of Neural Network is done with the help of book MATLAB "An Introduction with Applications" written by Amos Gilat on MATLAB 7.10.0 (2010a) software.

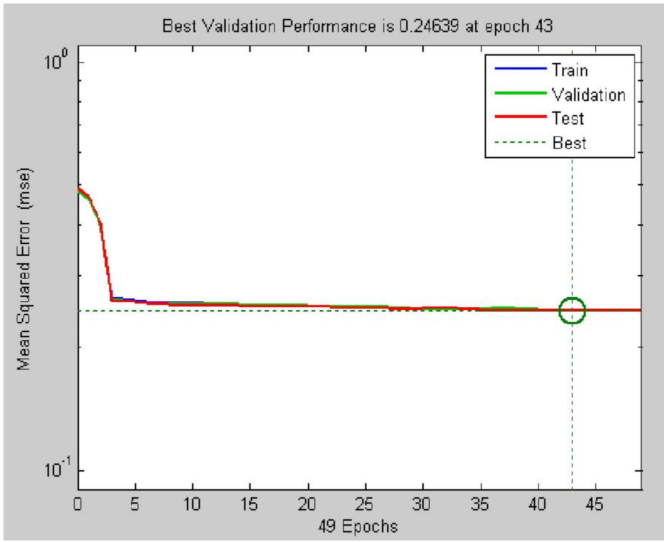

Figure 7. Performance plot

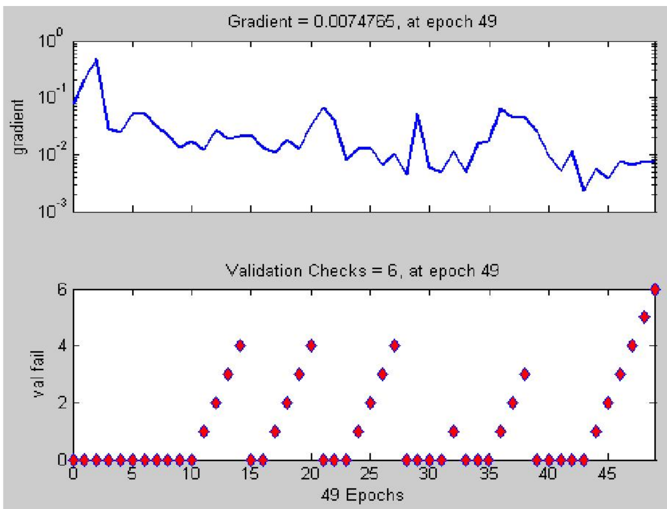

Figure 8. training state

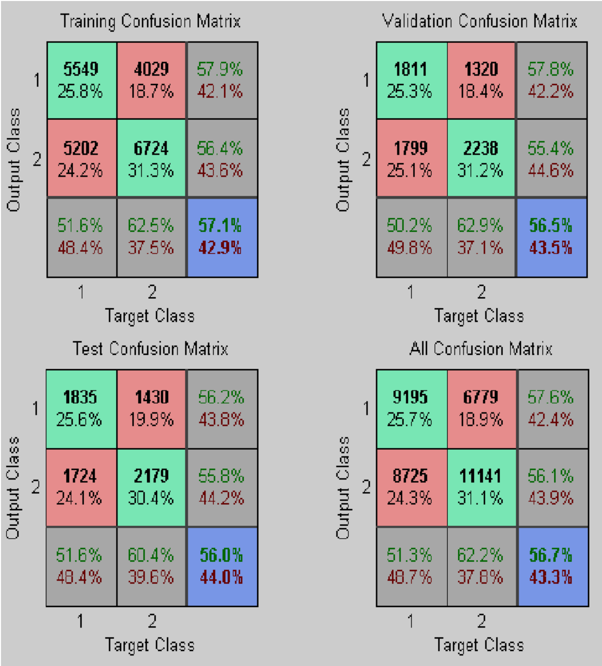

Figure 9. Confusion matrix

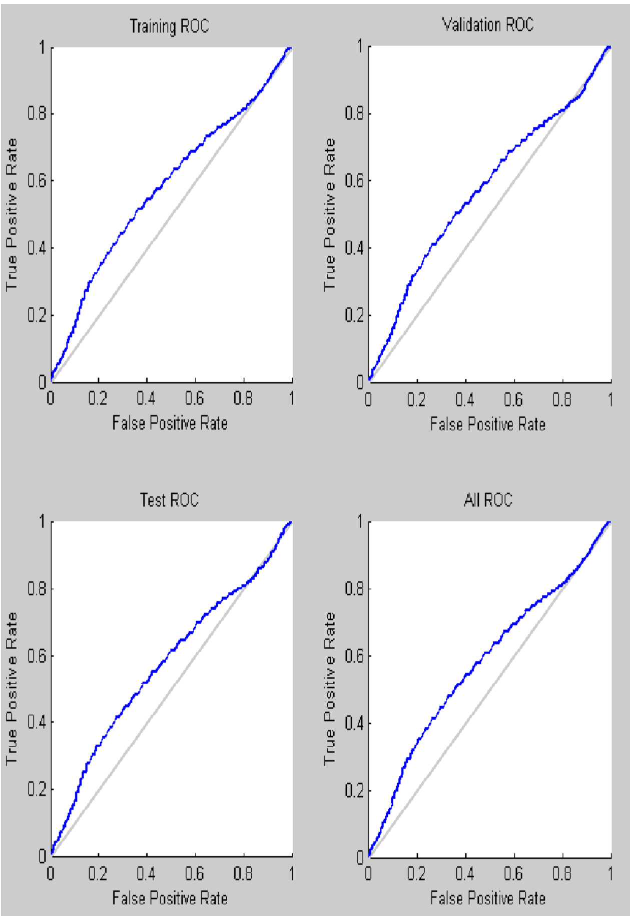

Figure 10. ROC plot

RESULTS

Result of processing of normal and abnormal ECG signal is shown in tabular form

Name	*Testing signal number*	*Testing Result*	*Overall Test Accuracy*
Normal sinus database	19093	Verified	100%
	16265	Verified	
	19539	Verified	
	19830	Verified	
Supraventricular Arrhythmia database	822	Verified	
	823	Not Verified	
	825	Verified	
	826	Verified	
	828	Verified	
	829	Verified	
	840	Verified	
	844	Verified	
Supraventricular Arrhythmia database	845	Verified	
	846	Verified	
	848	Verified	
	851	Verified	
	852	Verified	
	853	Verified	
	854	Verified	
	855	Verified	
	856	Verified	
Supraventricular Arrhythmia database	857	Verified	
	858	Verified	
	859	Not Verified	
	860	Verified	
	861	Verified	
	862	Verified	
	863	Not Verified	
	864	Verified	
	867	Verified	
	868	Not Verified	
	869	Verified	
	870	Not Verified	
	871	Verified	
	872	Verified	
	873	Not Verified	
	874	Verified	
	875	Verified	84.615%
	876	Verified	
	877	Verified	
	878	Verified	
	879	Verified	
	880	Verified	
	881	Verified	
	882	Verified	
	883	Verified	
	884	Verified	
	885	Verified	
	886	Not Verified	
	887	Verified	
	888	Verified	
	889	Verified	
	890	Not Verified	
	891	Verified	
	892	Verified	
	893	Verified	

Conclusion

The conclusion resulting from this work is that, by using MATLAB based the Neural network recognition some better networks can be prepared which have the capability to understand all types of ECG database. In most of the research paper single ECG bits taken for analysis, but in our research we have taken the 10 Sec complete ECG include of many ECG bits is taken for analysis which has taken a great care in case of heart beat variability. This type of network can be very reliable as neural network provides a better and understandable set of tools so that the network parameters can be adjusted and precisely easily, such type of network can handle a large amount of database and can work easily with unseen database. The accuracy obtained by such network is comparatively good. The above Neural network method for analysis of ECG signal gives 100 % accuracy for normal sinus database. Proposed network model used for detection normal ECG and arrhythmia is proving to be a very reliable precise method of analyzing each signal.

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