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Identification of Tachycardia from Ecg Signals Using Wavelet Transform and Feed Forward Neural Network

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Abstract

Heart disorders are very common among in recent days among all age group of people. Certain disorders are curable and some needs prolonged treatment. ECG is the primary tool used by the clinicians to analyze the heart disorders. The waveform of the ECG signal is used to identify the heart disorders. This signal analysis needs a human expertise in evaluating the heart disorders. In this scenario, a computer aided tool can aid the clinicians in better analysis and this will further lead to better treatment. This paper discusses one such tool developed to diagnose Bradycardia and Tachycardia from the ECG signals. The evaluation done with this tool on ECG signals has produced an accuracy of 88.8 % with minimal error rate of 11.8 %

Keywords: ECG, Signal analysis, computer aided process, machine learning.

1. Introduction

Disease related with heart is very common among the human beings. Life style, profession and food habits are the some of the major reasons for these disorders. The common procedure adopted in clinics to diagnose the heart disorder is analyzing the ECG signals. These ECG signals are acquired by placing electrodes in the standardized position of the human body. The nature of PQRST in the ECG waveform will furnish information related with heart disorders. The analysis of PQRST in ECG waveform is done manually. This manual analysis needs to be done with most care to identify the type of disorders in heart. In this juncture, implementing computer aided tool for ECG signal analysis can aid in error free diagnosis which can further lead to appropriate treatment. Many such methods have been developed and suggested globally by the researchers to diagnose heart disorders from the ECG wave from. A few of them have been discussed below.

ECG signal processing can also be done with wavelet transform techniques for the detection of RR interval, QRS complex, T wave and P wave. Initially pre-processing of signals is done for the removal of noise. Then features are extracted and detection algorithms based on soft computing techniques are implemented. The algorithm also analyzes the variability of heart rate and aids in detection of Bradycardia and Tachycardia [3][10].

Signal analysis can be performed with varied sampling rate of ECG [4]. Adaptive filtering is done with set sampling rate and widely increased window size. R point is attempted to detect in these types of analysis which is significant in detection of arrhythmia. R wave is separated from originally recorded signal using the given equation (2) median filter.

$$M_{i,n} = median_{r \in W}(S_{i+r,n}) \qquad (2)$$

It is inferred that if at least for 1 minute if there is abnormality in heart rate, then it is identified

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as Bradycardia and Tachycardia.

Soft computing techniques are widely used in detection of various arrhythmias. Instead of using ECG devices and its traditional signal analysis, signals are directly acquired using sensors and microcontroller which is followed by an analysis technique [5] [8]. The system is trained using back propagation neural network.

Power spectral analysis is used for detection of heart diseases. Diseases are identified by extracted R wave. Fast Fourier Transform (FFT) analysis is done for identification [9]. It is inferred that the R-R interval for ventricular Tachycardia is 0.6 and Bradycardia is 2. This is an attempt to develop a computer aided tool in ECG.

It is inferred that R-R peak gives significant results in detection of arrhythmia. Hence all work attempts to focus on extracting the features of R peak. Few works attempt to extract other features. Most of the work is performed with soft computing techniques or traditional filtration techniques [2]. This type of signal processing aids in identification of heart abnormalities and acts as a computer aided tool. This manuscript focuses towards studies and analysis of ECG signal by extracting the signal features using wavelet transform and classification using neural network.

Each of these discussed works supports the clinicians to analyze the ECG signals and identify the heart disorders. This paper discusses one such method developed using feed forward network to diagnose Tachycardia from the ECG signal. ECG signal is acquired from 17 subjects, of which 9 are normal signal and 8 are tachycardia signal are used in this study. The signals are Lead I, Lead II, Lead III, augmented Vector Foot (avF), augmented Vector left (avL), augmented Vector Right (avR), Chest leads V1, V2, V3, V4, V5 and V6 are continuously taken for the assessment. The extracted features from these signals are fed as input to the feed forward network. The method of feature extraction is described in section 2.

2. Feature Extraction

The input consists of large data, feature extraction is used to reduce the number of resources and take out the key characteristics of the signal. Various methodologies are available for feature extraction and wavelet transform is one such tool. Wavelet transform provides information on the signal with respect time as well as frequency. In wavelet transform decomposition is performed by sequentially applying the signal to a series of low pass and high pass filters. Output of each high pass filter is fed to high pass and low pass filter. Hence, the decomposition occurs till the least frequency component of the signal and in turn that many level of decomposition. Detailed coefficients are derived from the high pass filter and approximation coefficients are derived from the low pass filter. From these coefficient, statistical features are extracted which specifies the characteristics of the signal.

Since significant signal decomposition occur upto 6th level, the signal is decomposed into 6 levels using Haar wavelet transform. The detailed coefficient is equal to the number of level chosen. Figure 1 shows the 6 level decomposition signals using Haar wavelet transform for normal subject and Figure 2 shows the 6 level decomposition signals using Haar wavelet transform for abnormal subject. The statistical features are extracted for the decomposed signal. Mean, median, mode, standard deviations, and mean absolute deviation, median absolute deviations, L1 norm, L2 Norm are the extracted features. Distinguishable changes between the normal and abnormal signal are observed with standard deviation, median absolute deviations,

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hence these are considered for classification. The training dataset has been given in Table 1 where 7 abnormal (affected by tachycardia) and 10 normal subjects are present.

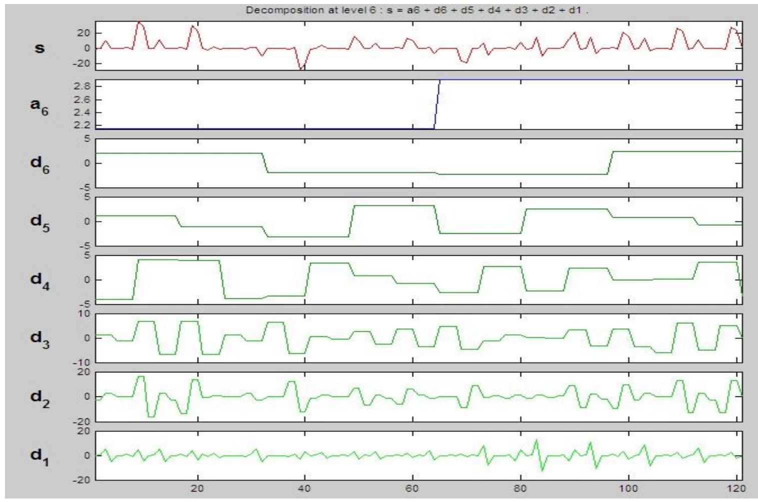

Figure 1. Signal Decomposition of Normal Subject– A Sample

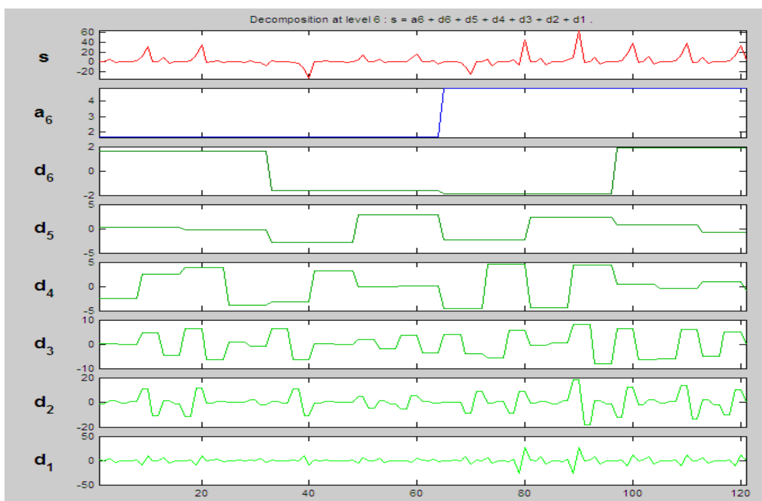

Figure 2. Signal Decomposition of Abnormal Subject – A Sample

Table 1. Training data for classification

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Subject	Standard Deviation	Median absolute deviation	Category
1	4.925	0.6	Normal
2	7.715	0.5	Normal
3	8.825	0.6	Normal
4	6.789	0.7	Normal
5	7.986	0.5	Normal
6	6.125	0.7	Normal
7	4.825	0.6	Normal
8	3.939	0.5	Normal
9	11.38	1.1	Abnormal
10	12.2	1.1	Abnormal
11	10.14	0.8	Abnormal
12	8.93	0.9	Abnormal
13	13.56	1	Abnormal
14	13.98	1	Abnormal
15	6.65	0.7	Normal
16	13.56	0.7	Abnormal

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17	9.54	0.7	Normal

3. Classification

Feed forward back propagation algorithm is used for classification where the network has input layer, hidden layer and output layer. The input layer contains 2 neurons and that of hidden layer 4 neurons with an output layer of one neuron. Figure 3 shows the network architecture. The Levenberg-Marquardt back propagation training which is also called as Error Back Propagation (EBP) is adopted for minimal error convergence.

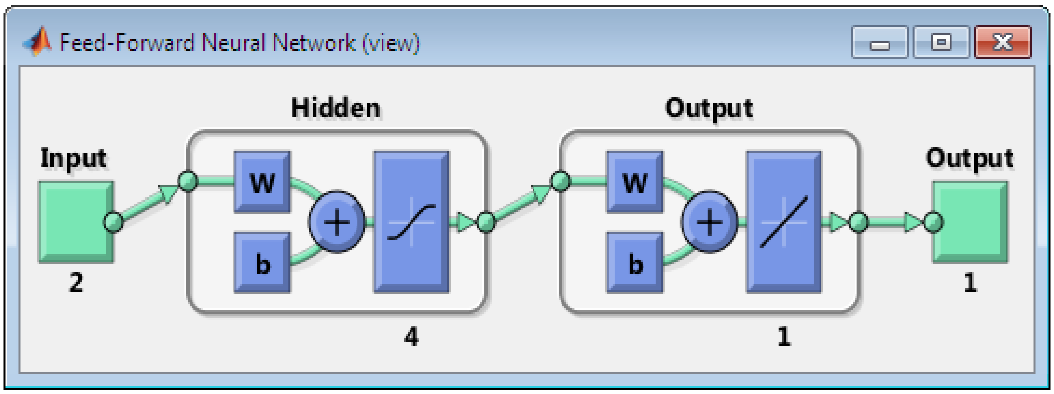

Figure 3. Architecture of Neural Network

Figure 4 shows the performance of the feed forward neural network, it is observed that best validation occurred at 6th epoch where the mean square error value meets the best fit value. The performance of training and testing data set is validated by taking in to consideration all values of regression value R. As the regression R converges towards 1 the training of the net is best fit.

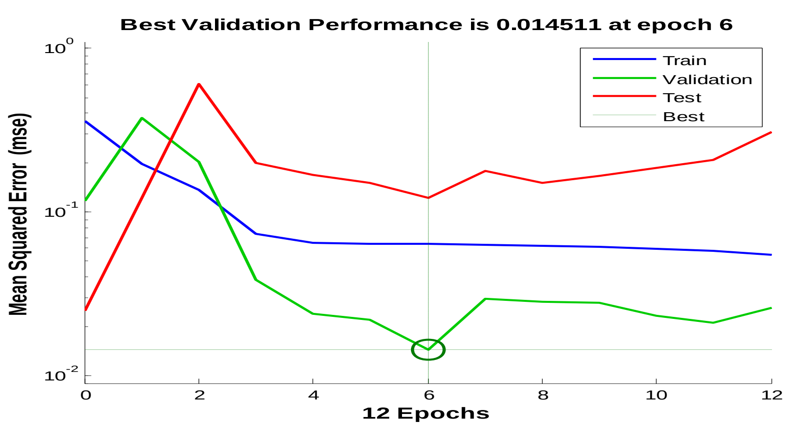

Figure 4. Performance of Feed Forward Neural Network

Figure 5 shows the overall averaged regression values for training, validation and testing

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and found to be 0.87. For training only R value of 0.85 could be achieved, whereas for validation the R value is 0.989 which is satisfactory. The regression value of 0.87 outperforms better in identification of normal and abnormal subjects.

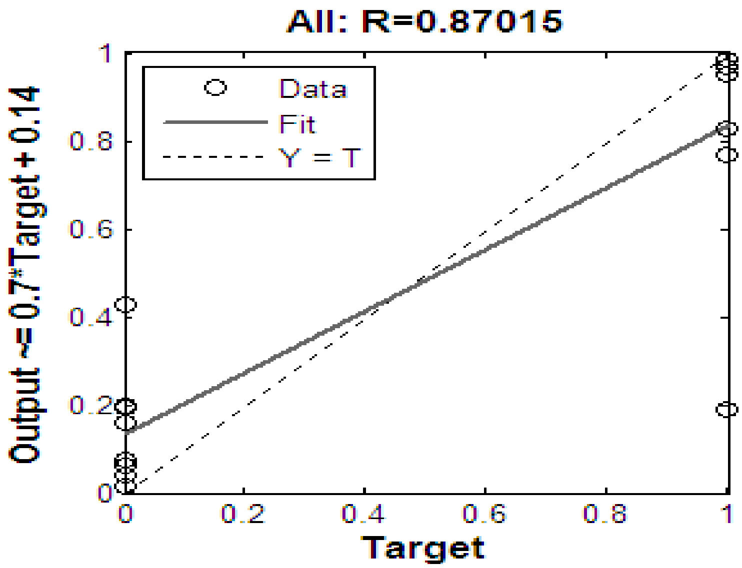

Figure 5. Average Regression

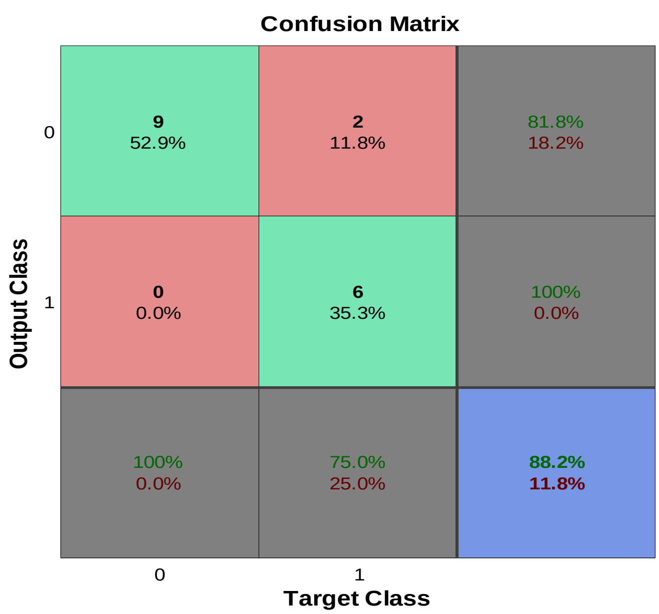

Figure 6. Confusion matrix

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Figure 6 shows the confusion matrix from which sensitivity and other measuring metrics are estimated. The performance metrics of the network is given by sensitivity, specificity, False positive rate, precision, True positive rate and classification error as shown in equation (3 -8).

The classification accuracy is achieved to be 88.2 %.

Sensitivity = TP/(TP+FN) (3)

Specificity = TN/ (TN+FP) (4)

False positive rate = FP/(TN+FP) (5)

Precision = TP/ (TP+FP) (6)

True positive rate = TP/(TP+FN) (7)

Classification error = (FP+FN)/ (TP+TN+FP+FN) (8)

Where

TP – True Positive: Correctly identifying the Normal subject

TN – True negative: Correctly identifying the Abnormal subject

FP – False positive: Wrongly identifying the Normal subject

FN – False Negative: Wrongly identifying the Abnormal subject

The obtained performance metrics from the network are listed in the table 2.

Table 2. Performance Metrics

S. No	**Performance Metrics**	**Obtained Results (in %)**
1.	Sensitivity	100
2.	Specificity	75
3.	False positive rate	25
4.	Precision	81.8
5.	True positive rate	100
6.	Classification error	11.8

From the obtained results of performance metrics, it is inferred that EBP learning algorithm performs better so that the classification error falls as 11.8%. The rate of identifying the subjects correctly is achieved 100% and that of not identification is lesser as 25%

4. CONCLUSION

The network is trained using EBP training algorithm for better convergence of error correction. The trained network outperforms better with the error rate as 11.8 %. Since the applications of this work are focused towards identification of tachycardia, the error rate has to be still further decreased as the focus towards identification is much sensitive for patients. From the signal it is also observed that there is a significant change in the peak amplitude of the signal between the normal and abnormal subjects. Hence, for further analysis, peak resonance frequency can be considered for identifying abnormalities. In addition, the network can be optimized with deep learning algorithms so that the error converges towards zero in future.

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