Scientific Journal of Impact Factor (SJIF): 4.72
e-ISSN (O): 2348-4470
p-ISSN (P): 2348-6406

International Journal of Advance Engineering and Research Development

Volume 4, Issue 10, October -2017

Comparison of Artificial Neural Networks for Cardiac Arrhythmia Classification

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Abstract— *Arrhythmia is an anomalous electrical activity of the heart, and an electrocardiogram (ECG) is a method to identify abnormalities in heart like arrhythmias. Due to some factors like presence of noise and nonstationary nature, it is difficult to analyze and interpret an ECG signal. Usually computer-aided analysis of ECG results assists medical experts to detect arrhythmias. In this work, ECG signal is denoised and features like RR-interval, average RR-interval, pre- and post RR-intervals, R-amplitude, CWT coefficients after PCA reduction are used to classify arrhythmias. Here six types of beat classes of arrhythmia as recommended by the Association for Advancement of Medical Instrumentation are analyzed for classification, they are Normal beat (N), Left bundle branch block beat (LBBB), Right bundle branch block beat (RBBB), Premature ventricular contraction (V), Atrial Premature beat (A) and Paced beat (P). Beats are classified using artificial neural networks. Five different networks are used for classification, they are Feed forward backpropagation, Elman backpropagation, Cascade forward backpropagation, Layer recurrent and NARX. The results showed that Feed forward back propagation classified the N, L, R, V, A and P arrhythmia classes with high accuracy of 94.2%.*

Keywords—*Electrocardiogram (ECG), Arrhythmia, Denoising, Continuous Wavelet Transform (CWT), Artificial Neural Networks***.**

I. INTRODUCTION

In today's world, arrhythmia is the main reason for heart-related problems. Most of the sudden cardiac deaths are due to cardiac arrhythmias. This effect is because of the deficiency of oxygen transported to the coronary artery. Some medical experts say that abnormal symptoms can occur before the sudden heart attack. If such abnormal symptoms can be identifiedand diagnose, there would be time to prevent deaths due to heart attack and start the treatment [1, 2].

An ECG waveform contains some specific areas that indicate each process occurring within the heart (PQRST wave). The P-wave is formed as a representation of atrial contraction. The QRS-complex, represents the ventricular contraction that sends blood to different parts of the body. The T-wave represents the ventricular recovery time and the refilling of the atrium. Duration and amplitude of the PQRST wave provide the required information for classifying a specific type of cardiac arrhythmia. It may be possible to decrease the severe cardiac conditions, if monitoring systems were there to detect abnormal rhythms [3]. These abnormal rhythms are called as cardiac arrhythmias [4]. Some researchers used artificial neural networks (ANNs) for the classification of ECG signals and obtained accurate results (within 99.0 % or greater) [3, 5, 6]. Usually, medical experts identify abnormalities through visual inspection of ECG signals, ANNs mimic this process with the help of training data and classify areas of abnormalities. While acquiring biological signal data like ECG, some noise may be induced because of different reasons. These induced noises may result in incorrect signal analysis. Therefore, it is essential to detect the sources of these noises and remove them to avoid misdiagnosis [1–4, 7].

Arrhythmia is deviationin the electrical activity of the heart. Arrhythmias include irregular beat frequency, ventricular ectopic beats or premature supraventricular and atrial fibrillation or flutter, etc. These arrhythmias can lead to sudden deaths, while others are prevalent in palpitations [17]. Some signals that have been classified correctly with the help of ANNs include arrhythmias, bundle branch blocks, and carditis [3, 5, 8–11, 12–14, 15, 16. There are two types of Bundle Branch Block (BBB), right and left. The left BBB carries nerve impulses that cause contraction of the left ventricle and vice versa. Left BBB is usually caused by some diseases like myocardial infarction and arteriosclerosis, while right BBB usually occurs rarely from underlying heart disease. BBB is usually diagnosed by the duration of the QRS wave, this duration is greater than 110 ms.

ECG based classification of cardiac arrhythmias has been investigated by many researchers in numerous papers. These methods differ in three main regions namely features, classifiers and evaluation schemes. Features include Hermit coefficients [22, 24, 26], higher order statistical features [19, 26], morphological features [18, 20, 29], principle component analysis and wavelet features [21, 23, 27, 28]. Different classifiers like self-organizing map (SOM) [24], support vector machine (SVM) [23, 26, 28], artificial neural networks (ANN) [21, 22], conditional random field (CRF) [19], linear discrimination analysis (LDA) [18, 25], and ensemble methods [29] are considered in different papers.

In this work, ECG signal is denoised and features like RR-interval, average RR-interval, pre- and post RR-intervals, R-amplitude, CWT coefficients after PCA reduction are used to classify arrhythmias. Artificial neural networks are used for classification, they are Feed forward backpropagation, Elman backpropagation, Cascade forward backpropagation, Layer recurrent and NARX.

The paper is organized as follows: Section 2 explains the methodology, Section 3 provides methods and materials Section 4 shares the simulation results and Section 5 has the conclusion.

II. METHODOLOGY

ECG signals are collected from MIT-BIH database. These signals are denoised to remove the noise and features are extracted for arrhythmia classification. This work is divided into different modules they are

1. Collecting ECG signals
2. Preprocessing (denoising)
3. Feature extraction
4. Classification of arrhythmias

The block diagram of ECG arrhythmia classification is given below in figure 1.

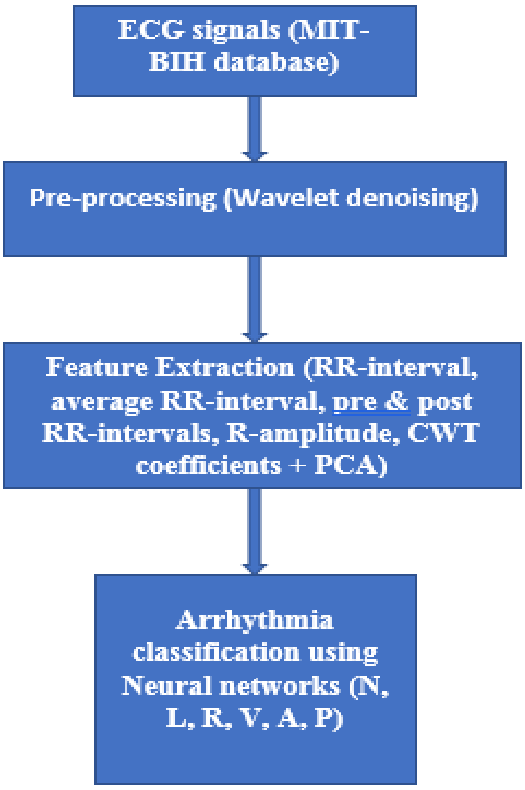


Figure 1: Block diagram for Arrhythmia classification

III. METHODS AND MATERIALS

A. Dataset

The MIT-BIH database is a very popular database for ECG signals of inpatients and outpatients that is provided by MIT and Boston's Beth Israel Hospital. It consists of ten databases for different test purposes. One among them is the Arrhythmia Database that contains 48 half-hour recordings of two-channel ambulatory ECG. The database consists of annotated ECG sampled at a rate of 360 Hz with 11-bit resolution over a 10-mV range.

B. Preprocessing

The ECG signal is preprocessed by using wavelet denoising method. ECG signal is denoised with sym4 wavelet and it is illustrated in figure 2. Wavelet denoising majorly involves two steps: Decomposition, Thresholding the wavelet coefficients. For denoising choose a wavelet, level N, threshold selection rule and apply soft thresholding for wavelet coefficients.

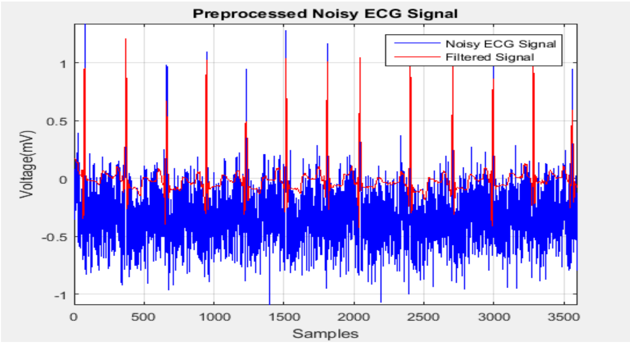


Figure 2: Denoised ECG signal (Record 100 of ten seconds duration)

The experimental results of the preprocessing method are presented in Table 1. The performance of this method is evaluated on three different metrics such as signal to noise ratio (SNR), mean square error (MSE), percentage root mean square difference (PRD %). When compared with the other wavelets like haar, db06 and bior4.4, SNRout of sym4 is larger. Hence sym4 is used for wavelet denoising.

Table1: Experimental results of the preprocessing method

RECORD No.	WAVELET	SNRi	SNRo	MSE	PRD	PSNR	COMPUTATIONAL TIME
100	haar	5	11.73068092	0.008261611	25.90991294	68.96015613	34.18956
		10	16.1711629	0.003096507	15.53967225	73.22208303	67.452031
	db06	5	12.75558517	0.006612286	23.02605908	69.92728737	8.208773
		10	25.56017772	3.64E-04	5.272196955	82.51950451	8.538706
	bior4.4	5	13.45424195	0.005658405	21.23299961	70.60386321	61.481583
		10	24.54774802	4.58E-04	5.921267229	81.51814077	7.267925
	sym4	5	13.88548429	5.16E-03	20.21738642	71.00678967	35.361908
		10	24.00264525	5.20E-04	6.307663962	80.96715002	88.107282

C. Feature Extraction

In this work, the features extracted are as follows:

1. R-wave amplitude
2. Average RR-interval
3. Pre- RR-interval
4. Post RR interval
5. 17 CWT coefficients after applying PCA reduction

In total there are 21 features. These features are extracted from all beats for classifying purpose. ComputeContinuous Wavelet Transform of the ECG signal using pattern-adapted wavelet. Thresholding concept is used to find R-peaks. The R-peaks can be detected by thresholding peaks above 0.5mV.

D. Neural networks

The design for neural network structure in classifying ECG signals consists of input layer, and output layer with one or more hidden layers. The input layer consists of a neuron for each input (i.e. features). The number of neurons in the hidden layer depends on the optimization through trial-and-error method. The output layer consisted of six output neurons that correspond to each output (arrhythmias). The networks used here are Feed forward backpropagation, Elman back propagation, Cascade forward backpropagation, Layer recurrent and NARX.

Feed forward networks consists of three layers – input layer, hidden layer and output layer. These types of networks can be used for any kind of input to output mapping. Elman networks are feedforward networks along with layer recurrent connections and tap delays.Cascade forward networks are similar tofeed forward networks with a connection from input layer and previous layer to the following layers. It has a potential to learn any finite input-output relationship.In layer recurrent networks, each layer has a connection with a tap delay, which allows it to have a powerful response to time series input data. Nonlinear autoregressive network with external inputs (NARX) is a recurrent dynamic network with feedback connections.

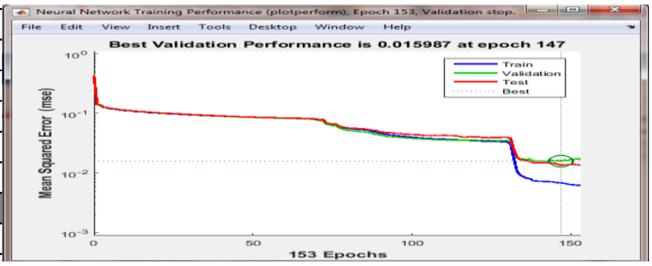
IV. RESULTS

In this paper six different arrhythmias are classified, they are Normal beat (N), Left bundle branch block beat (LBBB), Right bundle branch block beat (RBBB), Premature ventricular contraction (V), Atrial Premature beat (A) and Paced beat (P).87776 beats were obtained from 48 signals (MIT-BIH Arrhythmia database) for six arrhythmias (N, L, R, V, A, P). From these beats, half of them (43888 beats) are given to the neural network as training beats and remaining beats are considered as testing beats (43888 beats).

Among both training and testing beats, 31734 are Normal beats, 4021 are Left bundle branch block beats, 3035 are Right bundle branch block beats, 2623 are Premature ventricular contraction beats, 670 are Atrial Premature beats and 1805 are Paced beats.Here, we took five networks and observed their performance. Feed forward back propagation network after training and testing obtained an accuracy of 94.2% and best performance at epoch 147 as shown in figure 3.

	N	L	R	V	A	P
N	30975	192	233	434	276	6
L	98	3466	7	59	9	3
R	247	15	2745	35	31	0
V	294	299	10	2067	55	21
A	97	9	39	8	296	0
P	23	40	1	20	1	1775

Feed forward back propagation with 94.2% accuracy



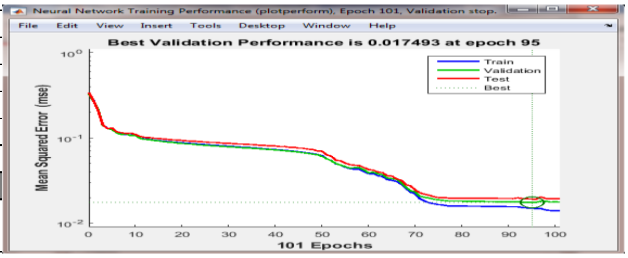
3(a) 3(b)

Figure 3: 3(a) and 3(b) are confusion matrix and performance plots of Feed forward back propagation network respectively.

Cascade forward back propagation network after training and testing obtained an accuracy of 93.5% and best performance at epoch 95 as shown in figure 4.

	N	L	R	V	A	P
N	31057	194	345	537	342	14
L	146	3459	7	88	13	0
R	199	19	2612	32	55	0
V	241	338	37	1936	45	18
A	77	1	34	4	215	0
P	14	10	0	26	0	1773

Cascade forward back propagation with 93.5% accuracy



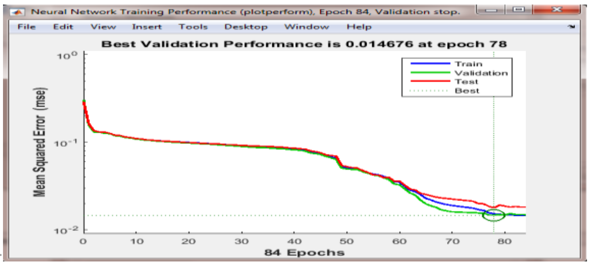
4(a) 4(b)

Figure 4: 4(a) and 4(b) are confusion matrix and performance plots of Cascade forward back propagation network respectively.

Elman back propagation network after training and testing obtained an accuracy of 93.2% and best performance at epoch 78 as shown in figure 5.

	N	L	R	V	A	P
N	31074	234	411	560	336	12
L	139	3402	14	115	8	1
R	133	16	2565	25	95	0
V	241	350	17	1881	24	23
A	123	10	28	16	206	3
P	24	9	0	26	1	1766

Elman back propagation with 93.2% accuracy

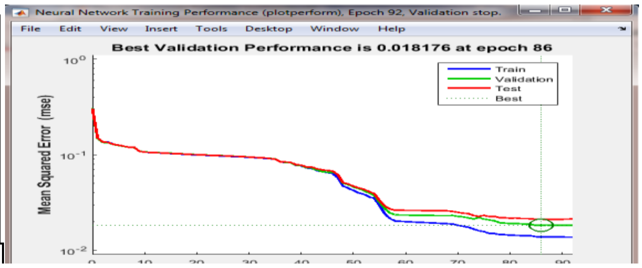


5(a) 5(b)

Figure 5: 5(a) and 5(b) are confusion matrix and performance plots of Elman back propagation network respectively.

Layer recurrent network after training and testing obtained an accuracy of 93.4% and best performance at epoch 86 as shown in figure 6.

	N	L	R	V	A	P
N	31005	199	312	554	301	8
L	181	3395	12	113	7	2
R	154	12	2651	22	52	0
V	235	405	18	1886	41	25
A	118	1	40	9	269	0
P	41	9	2	39	0	1770
Recurrent layer with 93.2% accuracy						

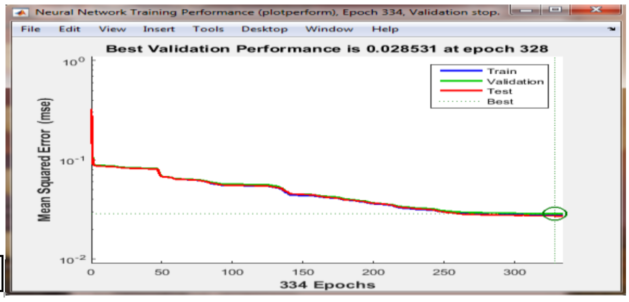


6(a) 6(b)

Figure 6: 6(a) and 6(b) are confusion matrix and performance plots of Later recurrent network respectively.

NARX network after training and testing obtained an accuracy of 92% and best performance at epoch 328 as shown in figure 7.

	N	L	R	V	A	P
N	30842	318	363	644	416	20
L	210	3215	22	93	2	1
R	411	35	2597	34	72	0
V	216	444	17	1808	28	26
A	19	1	34	1	152	2
P	36	8	2	43	0	1756
NARX with 92.0% accuracy						



7(a) 7(b)

Figure 7: 7(a) and 7(b) are confusion matrix and performance plots of NARX network respectively.

The belowfigure 8 illustrates the comparison of accuracies ofdifferent networks. In x-axis 1, 2, 3, 4, 5, represents are Feed forward backpropagation, Cascade forward backpropagation, Elman backpropagation, Layer recurrent and NARX respectively. Out of five networks Feed forward back propagation obtained highest accuracy of 94.2%.

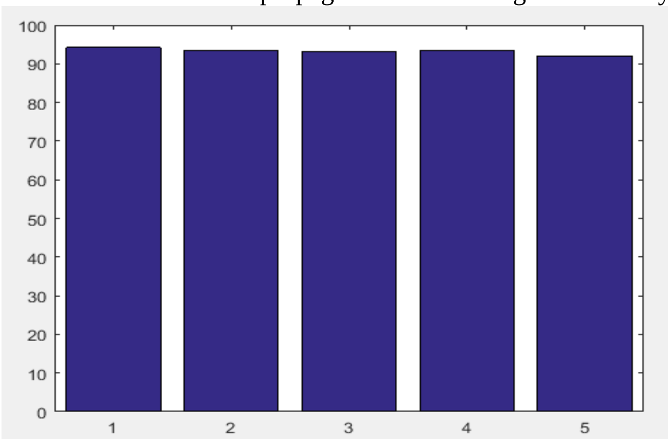


Figure 8: Comparison of accuracies of Neural networks; x-axis represent networks; y-axis represent accuracies.

V. CONCLUSION

Artificial neural network is a potent tool to diagnose patients with certain cardiac disorders like arrhythmias. Signals that have different types of deviations in the ECG waveform, are simple for an Artificial Neural Network to classify different types of arrhythmias correctly. Signals that have same characteristics, or that do not display differences in characteristics, are more difficult for the network to classify types of arrhythmias. In this work, the proposed artificial neural network has somemisclassification becausethese arrhythmias have different symptoms and require different treatments, but have signals which are similar in the ECG waveform.

The experiments have demonstrated that among five artificial neural networks Feed forward backpropagation outperforms Cascade forward backpropagation, Elman backpropagation, Layer recurrent and NARX with an accuracy of 94.2%. In future, this work can be extended for classification ofarrhythmias using Adaptive Neuro Fuzzy Inference systems to increase system performance and get high accuracies.

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