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Research paper

Performance Evaluation of Neural Networks and Adaptive Neuro Fuzzy Inference System for Classification of Cardiac Arrhythmia

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Abstract

In diagnosing the heart diseases, the beat classification of Electrocardiogram (ECG) plays a vital role. This work proposes a good design of an expert system for classification of the normal beat (N), left bundle branch block beat (L), premature ventricular contraction (V), paced beat (P) , atrial premature beat (A) and right bundle branch block beat (R) using time domain, S-Transform and discrete wavelet transform (DWT). The extracted feature set is given to adaptive neuro fuzzy inference system (ANFIS) and artificial neural network (ANN) for classification. The performance analyses on various normal ECG and abnormal ECG signals from 44 subjects of the MIT-BIH arrhythmia database. In this work, the performances of three neural networks, Cascade forward back propagation, nonlinear auto-regressive exogenous model (NARX) and Elman back propagation are compared with ANFIS. Contrast to the neural networks the AN-FIS shows better performance in the experimental outcomes.

Keywords: *Electrocardiogram; discrete wavelet transform; S-Transform; ANN; ANFIS*

1. Introduction

This Arrhythmia (irregular heart beat) is the main reason for heart-related problems. Sudden cardiac deaths are due to cardiac arrhythmias. This is because of the insufficient oxygen transferred to the coronary artery. Some physicians say that abnormal symptoms arise before the sudden heart ache. If such abnormal indications are identified and diagnose in advance stage, then it is possible to stop deaths due to heart attack and give appropriate treatment [1, 2].

In ECG waveform, PQRST wave indicate each operation take place within the heart. The QRS-complex, represents the ventricular contraction which transports blood to different parts of the body. Duration and amplitude of the PQRST wave provide important details to classify a certain type of cardiac arrhythmia. It is feasible to reduce the critical cardiac disorders, if continuous monitoring systems were there to detect irregular rhythms [3]. These irregular rhythms are termed as cardiac arrhythmias [4]. Earlier for the classification of ECG signals some researchers used artificial neural networks (ANNs) and obtained accurate results (within 99.0 % or greater) [3, 5, 6]. Usually, physicians identify irregularities by visual examination of ECG signals, ANNs imitate the process with the help of training data and classify areas of abnormalities. While acquiring and collecting biological signals data like ECG, some noise may be induced, and it might corrupt important information because of different reasons. These induced noises may give wrong outcome in the signal analysis. Hence, it is prime to detect the primary sources of noises present in ECG and remove them to avoid misdiagnosis of the signal [1–4, 7].

Arrhythmia means deviation in the electrical action of heart. They include irregular beat frequency, ventricular ectopic beats and atrial fibrillation, etc. These arrhythmias can lead to immediate deaths, while others lead to palpitations [17]. Some ECG signals that are classified correctly with the help of ANNs include arrhythmias, carditis [3, 5, 8–11, 12–14, 15, 16] and bundle branch blocks. There are two different kinds of Bundle Branch Block (BBB), left BBB and right BBB. The left BBB transfer nerve impulses that originate contraction of the left ventricle and contrariwise. Left BBB is normally caused by some disorders like arteriosclerosis and myocardial infarction , while right BBB normally occurs rarely from masked heart disorder. BBB is normally detected by the duration of the QRS width, this wave width is more than 110 ms.

ECG based classification of cardiac arrhythmias are investigated by many researchers in many papers. These methods vary in three aspects namely features, classification methods and evaluation procedure. Features include Hermit coefficients [22, 24, 26], morphological features [18, 20, 29], higher order statistical features [19, 26], 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], ensemble methods [29] and linear discrimination analysis (LDA) [18, 25] are considered in various papers.

In this work, ECG signal is denoised and to classify arrhythmias, we have used wavelet transformed based features, morphological features, S-transform based features. ANFIS and Artificial neural networks are used for classification, they are Elman back propagation, Cascade forward back propagation and NARX.

2. Methodology

ECG beat classification technique block diagram is shown in Figure 1. In this work, the proposed method consist of three specific stages such as (i) ECG signal preprocessing and R-peak detection using Wavelet Transform (WT) (ii) feature extraction, and (iii) Classification. ECG signals are collected from MIT-BIH database. These signals are denoised to remove the noise and wavelet transformed based features, morphological features, S-transform based features are extracted for arrhythmia classification.

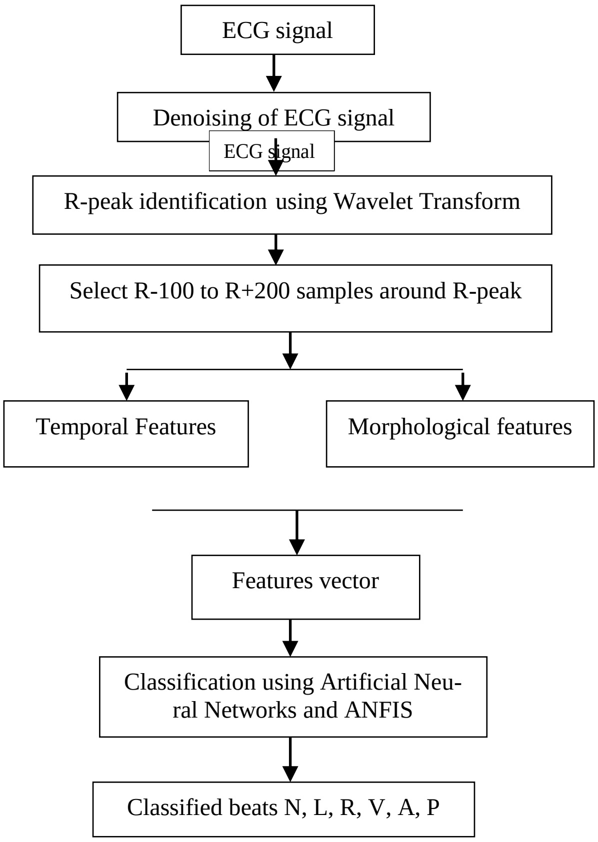

Fig. 1: Block diagram for classification of cardiac Arrhythmias

3. Methods and Materials

3.1. Dataset

The MIT-BIH database is a database which is available for ECG signals of inpatients and outpatients that is given by MIT and Boston's Beth Israel Hospital. It has databases for various test purposes. One among them is the Arrhythmia Database that holds 48 half-hour duration two-channel ECG signal recordings. The database made up of annotated ECG signal sampled at 360 Hz frequency with 11-bit resolution over a 10-mV range**.**

3.2. Preprocessing

The ECG signal is preprocessed by using wavelet denoising method. ECG signal is denoised with sym4 wavelet and it is illustrated in figure 3 and raw signal is shown 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.

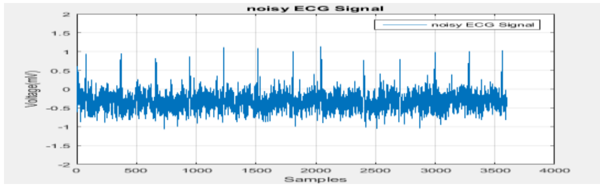

Fig. 2: ECG signal (Record 100 of ten seconds duration)

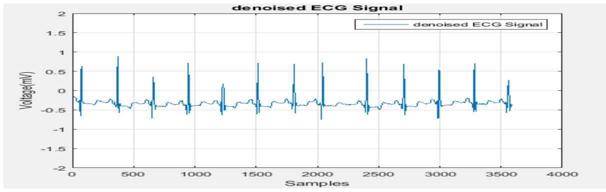

Fig. 3: Preprocessed ECG signal (Record 100 of ten seconds duration)

3.3. Feature Extraction

Generally, two different kind of features are take out from an ECG signal (a) morphological features and (b) temporal features. In this work, the features extracted are as follows:

Temporal Features: The following are the temporal features

1. RR-interval: The duration between two R-Peaks

2. R peak Amplitude – maximum energy of the signal is present in the R peak as this is that part of the signal that has maximum amplitude, is also a temporal feature.

Morphological Features: In this paper, two types of morphological features are used to categorize the ECG beats.

(a) ST based morphological features and (b) WT based morphological features. These features are taken from one interval of ECG signal. For morphological feature extraction, samples are taken from one interval of ECG signal by selecting a window of 300 samples around the R-peak.

S-Transform based Features: The ST is used to get the time-frequency representation [30] of a time domain representation of signal. The continuous Stockwell-Transform (S-Transform) of ECG signal y(t)

$$S(p,f) = \int_{-\infty}^{\infty} y(t) \frac{|f|}{\sqrt{2\pi}} e^{-(p-t)^2 f^2} e^{-j2\pi f t} dt$$

Where t and p are the time variables. f is the frequency.

Using S-Transform seven features are extracted. These features are useful for classification of cardiac arrhythmias. The seven S-Transform features which were extracted are

1. Magnitude of maximum value of the Stockwell -Transform coefficients
2. Phase of maximum value of the Stockwell -Transform coefficients
3. Magnitude of minimum value of the Stockwell -Transform coefficients
4. Phase of Minimum value of the Stockwell -Transform coefficients
5. Magnitude of mean of the S-Transform coefficients
6. Phase of mean of the S-Transform coefficients
7. Standard Deviation of the Stockwell-Transform coefficients

Wavelet Transform based features: The selection of correct wavelet and the decomposition levels play an important role in the ECG signal analysis using wavelet transform (WT). The decomposition level is chosen based on the highest frequency components present in the signal. In this paper, the decomposition level taken is 4, i.e., the given signal is decomposed into the detailed coefficients D1,D2,D3,D4 and A4 approximation coefficient. The Daubechies wavelet of order 4 (db4) is selected for decomposition .For each ECG beat, mean, minimum ,maximum and standard deviation of the approximation coefficients of A4 and detailed coefficients of D1,D2,D3,D4 are considered. Total 20 statistical features are calculated from the ECG signal using Wavelet Transform.

There are

1. Maximum value of the WT coefficients of each level sub band
2. Minimum value of the WT coefficients of each level sub band
3. Mean value of the WT coefficients of each level sub band
4. Standard deviation of the WT coefficients of each level sub band

On the whole 29 temporal and morphological features have been extracted for classification.

3.4. Neural networks

In this work, six beats are classified using neural networks, they are the normal beat (N), atrial premature beat (A), left bundle branch block beat (L), premature ventricular contraction (V), right bundle branch block beat (R), and paced beat (P).The neural network structure for classifying ECG signal contains some layers called input layer, output layer with more than one hidden layers. The input layer contains a neuron for each input (i.e. features). The output layer contains six neurons that correspond to each output (arrhythmias). The networks used here are Elman back propagation, Cascade forward back propagation and NARX.

Elman networks are feed forward networks along with layer recurrent connections and tap delays [31]. Cascade forward networks are close to feed forward networks with a connection from input layer to the following layers. It has a potential to learn any finite input-output relationship. Nonlinear autoregressive network with external inputs (NARX) is a dynamic recurrent network with feedback connections.

3.5. Adaptive Neuro Fuzzy Inference System

The structure of the ANFIS is shown in figure 4.ANFIS structure consists of 5 layers of nodes, out of the 5 layers, the 1st and 4th layers contain adaptive nodes, those are Fuzzification and Defuzzification. The 2nd , 3rd and 5th layers contain fixed nodes those are Rule, Normalization, and Summation neuron. The adaptive nodes are linked with their corresponding parameters, get duly upgraded with each subsequent iteration while the fixed nodes are lacking of any parameters.

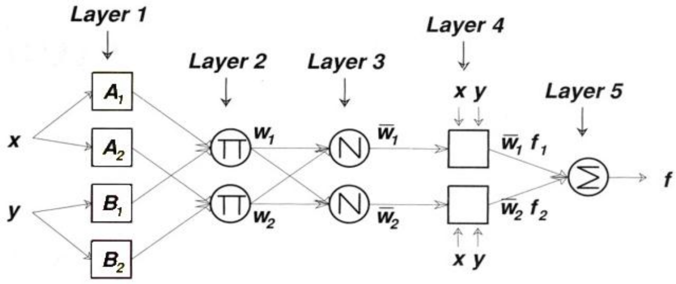

Fig. 4: Structure of ANFIS

4. Results

87829 beats were obtained from 44 signals (MIT-BIH Arrhythmia database) for six arrhythmias (N, L, R, V, A, P). From these beats, half of them (43941 beats) are given to the neural network as training beats and remaining beats are considered as testing beats (43888 beats) as shown in table 1.

Table 1: Summary of the Training and testing beats

Heart beat type	Annotation	Total	Train	Test
Normal beat	N	63482	31748	31734
Left bundle branch block beat	L	8044	4023	4021
Right bundle branch block beat	R	6075	3040	3035
Premature ventricular contraction	V	5264	2641	2623
Atrial premature beat	A	1353	683	670
Paced beat	P	2475	670	1805
Total	6	87829	43941	43888

Here, we took three networks and observed their performance. Cascade forward back propagation network after training and testing obtained an accuracy of 94.8% as shown in Table 2. Elman back propagation network after training and testing obtained an accuracy of 92.7% as shown in Table 3. NARX network after training and testing obtained an accuracy of 92.4% as shown in Table 4.

Table 2: Confusion matrix of Cascade forward back propagation network

	N	L	R	V	A	P
N	30983	196	264	317	263	7
L	179	343	1	50	9	1
R	222	6	2713	40	71	1
V	217	347	13	2196	44	27
A	113	4	44	6	279	0
P	20	1	0	14	4	1796
Cascade forward back propagation network accuracy = 94.8						

Table 3: Confusion matrix of Elman back propagation network

	N	L	R	V	A	P
N	30981	256	452	583	367	1
L	138	3418	1	92	2	0
R	269	4	2520	37	34	1
V	246	255	16	1842	44	82
A	70	0	46	0	213	0
P	30	88	0	69	10	1721
Elman back propagation network accuracy = 92.7						

Table 4: Confusion matrix of NARX network

	N	L	R	V	A	P
N	31012	481	460	544	392	12
L	171	3210	1	111	5	7
R	175	3	2528	30	49	3
V	320	321	8	1903	35	87
A	38	0	30	0	189	0
P	18	6	8	35	0	1696
NARX network accuracy = 92.4						

In this work, 50% of the data is givens as training data and another 50% is given as testing data to the ANFIS. Train ANFIS by implementing Subtractive clustering on the data. Choose optimization method to train membership function parameters and to imitate To stop the training, enter the error tolerance and training epochs number.

Simulation of ANFIS is illustrated in the below figures from figure 4 and figure 5.

Figure 4: ANFIS with training data and testing data

The training of ANFIS is completed at epoch 2.

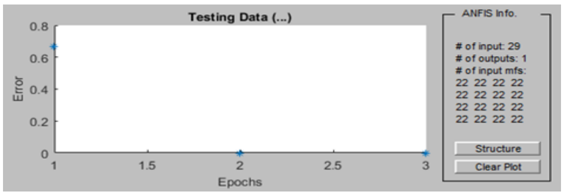

Figure 5: ANFIS with 3 epochs

In the below Table 5 classified beats of ANFIS are listed, which resulted in 98.9% accuracy. Table 3 compares the accuracies of the neural networks used with the ANFIS.

Table 5: Classified beats of ANFIS

Correctly classified beats	43461
Misclassified beats	480
Total tested beats	43941

Table 6: Comparison of neural networks with ANFIS

Networks	Accuracies
Cascade forward back propagation	94.8
Elman back propagation	92.7
NARX	92.4
ANFIS	98.9

Figure 6 shows Comparison of accuracies of the three NN's and ANFIS. When compared with neural networks, ANFIS is outperformed with 98.9% accuracy.

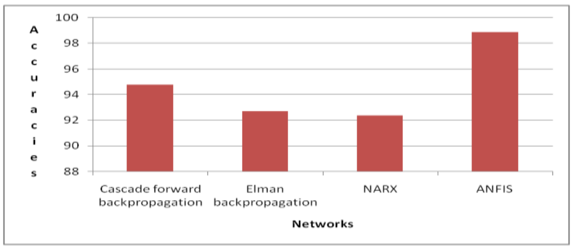

Figure 6: Comparison of accuracies of different networks

5. Conclusion

In this paper, the classifier used is an aim to recommend a solution that deploys the hybrid algorithms, to find the best ECG classification method developed for the medical environment. Here the system is composed of three major stages: ECG denoising, feature extraction and classification. The evaluation of the proposed method was performed on MIT-BIH Arrhythmia Database. Initially the records of the database are denoised using a wavelet and few temporal and morphological features are extracted forming a feature vector of 29 features. These features are given as inputs for Neural Networks and ANFIS for classification. The performance of the classifiers was compared to identify a best classifier. ANFIS presented in this work was trained with the back propagation gradient descent method along with the least squares method. ANFIS classifier gives total classification accuracy of 98.9% resulting in low rate of misclassification. The ANFIS model implemented in this work prove that it achieved the highest classification accuracy. Hence this method can be used in real time, especially for clinical practice.

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