Cardiac Arrhythmia Classification Using Error Back Propagation Method

Indu Saini and B. S. Saini

Abstract—**Arrhythmia classification is a very demanding task in medical domain. A great need of handling voluminous ECG data has posed necessity of using artificial intelligence techniques such as artificial neural network (ANN) for detection and classification of these heart beats. In this paper a neural network technique with error back propagation method has been used to classify four different types of arrhythmias, namely, Left bundle branch block (LBBB), Right bundle branch block (RBBB), Atrial premature beat (APB) and Paced Beat (PB) with normal ECG signal. The multilayer perceptron feedforward neural network has been used for modeling the network architecture. The arrhythmic features, on which classification methodology is based, are chosen from morphology of QRS complex.**

Index Terms—**Artificial neural network, arrhythmia, back propagation algorithm, confusion matrix, multilayer perceptron.**

I. Introduction

The ECG or electrocardiogram signal measures the electrical activity of specialized heart cells that generate repetitive self-induced action potential. Each action potential generated leads to a contraction of the heart muscle and thus the heartbeat. A normal ECG signal consists of a P, QRS, T and U wave. In case of disease affecting the heart, the ECG waveform gets distorted according to the area which is not functioning normally. Thus by inspection of the waveform, the nature of disease can be diagnosed easily.

Arrhythmia or dysrhythmia is a heart disorder representing itself as an irregular heartbeat due to malfunction in the electrical system cells in the heart. It causes the heart to pump blood less effectively and causing disorders in the heart conduction process [1]. There are many types of arrhythmias based on heart rate, mechanism or site of origin. Some of them are mostly benign but some may indicate the susceptibility of serious heart disease, stroke or sudden cardiac death thus making the correct and computationally efficient means of automatic detection of abnormal heart beats imperative. In this paper a neural network approach is adopted to classify four types of arrhythmias, namely, LBBB, RBBB, APB and paced beat together with normal beat. All these arrhythmia types have specific morphology in their ECG waveform.

The artificial neural network is an interconnected group of artificial neurons that uses a mathematical model based on a connectionist approach to computation. The principal advantage of this approach is that it is a type of non-linear processing system that is ideally suited for tasks, where there is no existing algorithm for task completion such as in arrhythmia classification [2].

The organization of this paper is as follows: Section 1 deals with the introduction of ECG, cardiac arrhythmia and artificial neural network. Section 2 discusses the various steps of the classification process. In section 3, the neural network training is explained. The section 4 forwards the classification results obtained and section 5 concludes the work done.

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II. Methodology

The block diagram in fig. 1 depicts the overall methodology for the arrhythmia classification used in this work. The complete scheme includes various steps like data acquisition, ECG pre-processing, feature extraction and finally training of the neural network. The performance evaluation of the classifier has been done using different statistical parameters.

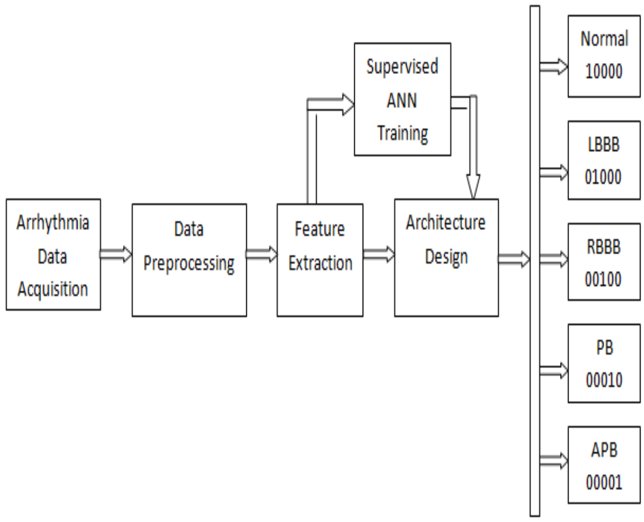

Fig. 1. Schematic representation of classification methodology.

A. ECG Data Acquisition

MIT – BIH arrhythmia database was used in this work for training, validation and testing of designed classifier model. This is a standard database containing 48 half-hour excerpts of two channel ambulatory ECG holter recording, digitized at 360 samples per second per channel with 11 bit resolution [3]. The dataset composition used in this work is summarized in Table I below.

TABLE I: COMPOSITION OF DATASET

Arrhythmia	Normal	LBBB	RBBB	PB	APB	Total beats
No. of training data beats	130	130	130	13 0	130	650
No. of validation data beats	30	30	30	30	30	150
No. of testing data beats	40	40	40	40	40	200
MIT-BIH data files	112-115-122	214	118-212	21 7	232	

B. ECG Pre-Processing

The digitized ECG signal contains many types of contaminations. Hence they require pre-processing before feature extraction. For this a low pass filter with cut-off frequency 100 Hz was used. The base line wandering was removed by subtracting the signal from a low order polynomial.

C. Feature Extraction

A feature set was made from every individual heartbeat of ECG signal which characterizes the particular type of arrhythmia. The morphological features of QRS complex were used for arrhythmia discrimination criteria [4], which are RR- interval [5], [6], R- peak amplitude and QRS duration of ECG signal.

The chosen feature set efficiently describes each type of arrhythmia; for example, bundle branch block arrhythmias have characteristic feature of prolonged QRS duration. Also R-peak amplitude in LBBB arrhythmia is greater than that in RBBB. The APB is characterized by shorter RR interval whereas in paced beats, the RR interval becomes larger than the normal ECG signal [7]. Taking these features, a vector set was created containing three values per beat.

D. Network Topology

For designing classifier model, multi-layer Perceptron network was chosen with three layers; one input, one output and one hidden layer. The number of neurons in input layer was taken three according to the three features being used in classification. Output layer neuron number was fixed same as the number of classes to be discriminated i.e. five to distinguish five types of heart conditions. To determine the number of hidden layer neurons repeated experiments were performed which resulted in an optimum number of 20 hidden nodes with sigmoid activation function.

E. Input avd Target Pattern Formation

For making input patterns, the whole feature vector set was divided into three groups, namely, training, validation and testing with 65 %, 15 % and 20 % of total number of beats respectively. These patterns were formed by mixing the different arrhythmic beats according to the order shown in Table. I. The target patterns of input vector set were made using one-hot encoding method.

III. NEURAL NETWORK TRAINING

The training to the network was given using a supervised learning algorithm; back-propagation [8]. This algorithm looks for the minimum of the error function in weight space using the method of gradient descent. The connection weights are randomly assigned at the beginning and progressively modified to reduce the overall system error. The weight updating starts with the output layer and progresses backward, thus errors propagate backwards from the output nodes to the inner nodes. The combination of weights which minimizes the error function is considered to be a solution of the learning problem. Several training cycles were given to the network to alter the weights enough to generate correct outputs. Training error continued to decrease as the number of epochs increased. Actual output was compared with desired output to check classifier's accuracy.

IV. RESULTS

The performance of the designed classifier was evaluated with the help of confusion matrix and different statistical parameters. The confusion matrix as shown in Table II, gives the summary of beat-by-beat classification results for the five classes of testing beats. In this table, the diagonal elements give the number of correctly classified beats.

TABLE II: TESTING CONFUSION MATRIX

Arrhythmia Classes	Normal (beat)	LBBB (beat)	RBBB (beat)	PB (beat)	APB (beat)	No. of beats in each class	% Accuracy
Normal Beat	40	0	0	0	0	40	100
LBBB	0	39	1	0	0	40	97.5
RBBB	0	0	40	0	0	40	100
PB	1	0	1	38	0	40	95
APB	1	0	0	0	39	40	97.5
Overall Testing Accuracy = 98.00							

Other performance parameters such as overall classification accuracy, sensitivity (Se), specificity (Sp), Positive Predictive Value (PPV) and Negative Predictive Value (NPV) were also calculated for the classifier, which are listed in Table III. These terms are defined below using the values of True Positive (TP), False Negative (FN), False

Positive (FP), and True Negative (TN), which stand for the number of truly detected events, erroneously rejected events, erroneously detected events, and correctly rejected events, respectively.

Sensitivity (*Se*)

Sensitivity of an arrhythmia is the fraction of the arrhythmia samples correctly classified as that specific arrhythmia class. It is defined as in equation (1).

$$Se = \frac{TP}{TP + FN} \tag{1}$$

Specificity (*Sp*)

The specificity is the fraction of normal beats correctly classified as normal class. It is also called selectivity. It is calculated using (2).

$$Sp = \frac{TN}{TN + FP} \tag{2}$$

Positive Predictive Value (*PPV*)

It measures the ratio of correctly grouped positives. It is defined as given in (3).

$$PPV = \frac{TP}{TP + FP} \tag{3}$$

Negative Predictive Value (*NPV*)

It calculates the proportion of negative cases that were correctly identified and given as defined in (4).

$$NPV = \frac{TN}{TN + FN} \tag{4}$$

TABLE III: STATISTICAL PARAMETERS

Arrhythmia Class	Sensitivity %	Specificity %	PPV %	NPV %
Normal	100.00	98.76	95.23	100
LBBB	97.50	100	98..50	99.37
RBBB	100.00	98.76	95.23	100
PB	97.50	100	100	99.37
APB	95.00	100	100	98.76

I. CONCLUSION

The task of arrhythmia recognition was carried out for distinguishing four different types of arrhythmias together with normal ECG using artificial neural network. The classifier used is multilayer perceptron feedforward network; a universal approximator. The classification results obtained in this work show that the neural classifier has achieved very good accuracy level in distinguishing various arrhythmias. The neural classifier was designed using MATLAB software package version R2010a [9]. The Table IV shows the comparison of the present work with other published works in this area.

TABLE IV: COMPARISON OF DIFFERENT ECG CLASSIFIER

Method	Accuracy %	No. of Arrhythmia classes
R Acharya U et al [10]	88.58	8
Elif Derya Ubeyli et al [11]	96.39	4
T. M. Nazmy et al [12]	97.1	6
Ahmad Khoureich Ka[13]	97.52	6
Present work	98.0	5

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