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Classification of ECG and Identification of Cardiac Arrhythmias Using ANN

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Abstract: Electrocardiogram is an important tool to assess cardiac health condition. An early and accurate detection of arrhythmia is highly solicited for augmenting survivability. In this paper, using MAT LAB tools, different statistical features are extracted from both normal and abnormal ECGs. These features include arithmetic mean, variance, standard deviation, kurtosis and skewness. The values of the feature vector reveal information regarding cardiac health state. This paper focuses on using of artificial neural network as a classifier for identifying the abnormalities of ECG. Levenberg-Marquardt Back Propagation Neural Network (LMBPNN) method is used for classification tested on MIT-BIH data base. Classification results are compared in terms of classification accuracy, specificity and sensitivity. The experimental results showed classification accuracy of 90.9 to 96.6 for different classes and 12 types of arrhythmias were identified.
Keywords: Artificial Neural Network, ECG, feature extraction, classification

I. INTRODUCTION

The ECG signal is characterized by five peaks and valleys and are labeled P, Q, R, S and T. A good performance of an ECG analyzing system depends largely on the accurate and reliable detection of the QRS complex, as well as the T and P waves. The P wave indicates the activation of the upper chambers of the heart (the atria) while the QRST wave complex represent the excitation of the lower chambers of the heart (ventricles). Sino Atrial node (SA), located at the top of the right chamber or Atrium (RA) is called as the heart's "natural pacemaker". The electrical signal that stimulates the heart beat starts from SA node and branches through atria, causing them to contract and eventually pump blood to the ventricles, the lower chambers. If, for any reason, the pacemaker is disrupted, the heart may beat at an abnormal rate, impacting the circulation of blood throughout the body.

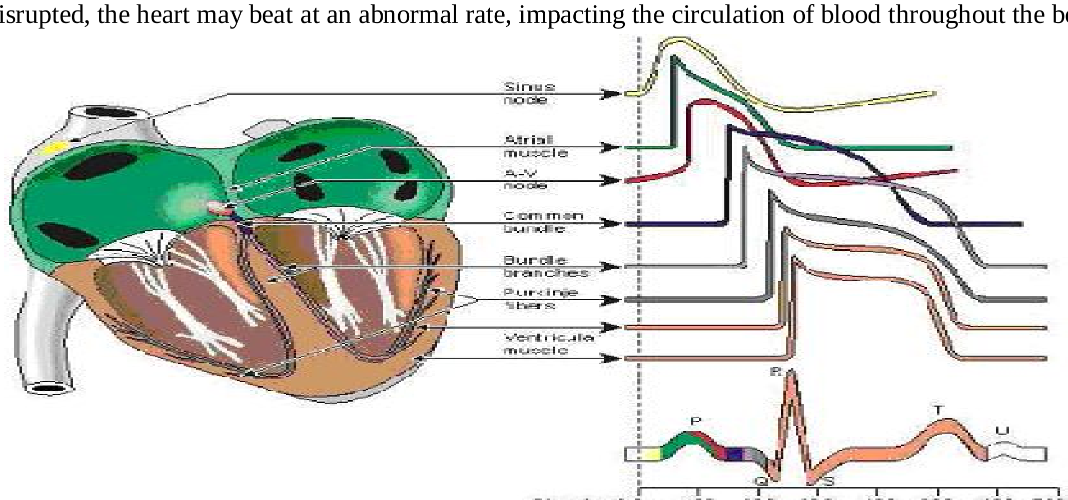

Figure1: ECG waveform characteristics and their corresponding positions in heart.

The electrical signals described above are measured by the electrocardiogram where each heart beat is displayed as a series of electrical waves characterized by peaks and valleys. An ECG gives two major kinds of information. First, by measuring time intervals on the ECG, the duration of the electrical wave crossing the heart can be determined and consequently whether the electrical activity is normal or slow, fast or irregular can be determined. Secondly, by measuring the amount of electrical activity that passes through the heart muscle, a cardiologist may be able to find out if parts of the heart are large or overworked or any other related abnormality. The frequency range of an ECG signal is 0.05 – 100 Hz and its dynamic range is [1-10] mV. Figure1 shows ECG waveform characteristics and their corresponding positions in heart and a typical normal ECG signal is as shown in figure 2 [1].

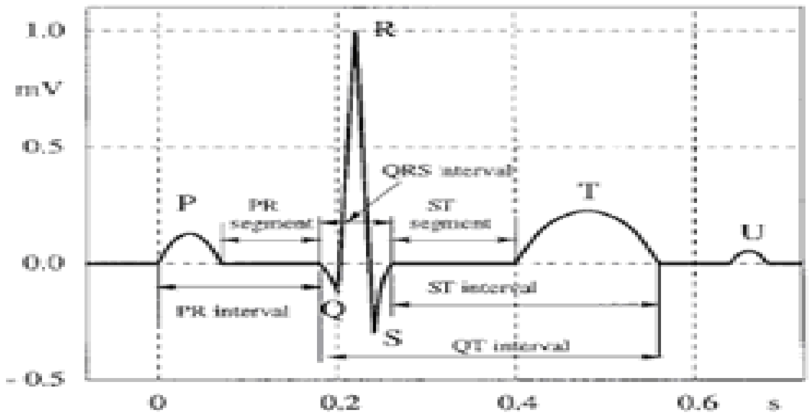

Figure 2: The ECG signal and its different components.

Table 1: Normal ECG wave amplitudes and durations.

ECG parameters	Typical amplitude [mV] and wave duration [seconds]
P wave	0. 25 mV
R wave	1. 60 mV
Q wave	25 percent of R wave
T wave	0.1 to 0.5 mV
P-R interval	0.12 to 0.20 seconds
Q-T interval	0.35 to 0.44 seconds
S-T segment	0.05 to 0.15 seconds
P wave interval	0.11 second
QRS interval	0.09 second

Various machine learning and data mining methods have been applied to improve the accuracy for the detection of ECG arrhythmia. Because of the nonlinear and non stationary nature of the ECG signal, nonlinear extraction methods are good candidates for extracting the information in the ECG signal [2]. Since artificial neural networks are basically a pattern matching technique based on non-linear input-output mapping, it can be effectively used for detecting morphological changes in non-linear signals such as the ECG signal[3]. This paper proposes to use Back propagation neural network (BPNN) and Levenberg-Marquardt (LM) methods for classification of ECG signals from MIT-BIH data base.

II. REVIEW OF LITERATURE

Several studies have presented the performance of neural network systems when used for the detection and recognition of abnormal ECGs [4]. The use of neural network systems in ECG signal analysis offers several advantages over conventional techniques. The neural network can perform the necessary transformation and clustering operations automatically and simultaneously. The neural network is also able to recognize complex and nonlinear groups in the hyperspace[5]. The latter ability is a distinct advantage over many conventional techniques. However, little work has been devoted to deriving better parameters for reducing the size of the network while maintaining good classification accuracy.

Artificial neural network (ANN) model was used by Niranjana Murthy et al,to predict coronary heart disease based on risk factors comprising of ST-segment and T-wave amplitude changes [6]. Guler et al., [7] adopted two stages of neural networks for classifying input ECG signal into four types of beats and to improve the diagnostic accuracy [8]. SVM is another class of machine learning algorithm that can perform pattern recognition based on the theory of statistical learning [9]. The KNN method is an instance based learning which is widely used data mining technique in pattern recognition and classification problems [10].

A. Feature Extraction

The statistical analysis and classification for discrimination among normal and arrhythmic conditions of ECG were performed using MATLAB on the set of spectral data obtained from MIT-BIH. The following features like arithmetic mean, variance, standard deviation, Skewness and Kurtosis were extracted. A brief description of each of these features is given below.

When performing analysis of complex data, major problems might arise from the number of variables. Generally the large number of variables require large amount of memory and computation power or a classification algorithm which over fit the training sample and generalizes poorly to new samples of extraction.

Mean, median, mode and standard deviations are first order statistical features. Variance, kurtosis and skewness are higher order statistical features[11]. Standard deviation gives the measure to quantify the amount of variation or dispersion of a set of data values. Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. Data with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly and have heavy tails[12]. Skewness indicates asymmetry and deviation in distribution analysis from a normal distribution.

1) *Mean:* When a set of values has a sufficiently strong central tendency .The set by a few numbers that are related to its moments, the sums of integer powers of the values.

The *mean* of the values $x_1, \ldots\ldots, x_N$

$$\overline{x} = \frac{1}{N}\sum_{j=1}^{N} x_j \quad \text{---(1)}$$

2) *Variance:* While the mean describes the location of a distribution, the variance is a way to capture its scale or degree of being spread out. The unit of variance is the square of the unit of the original variable. The positive square root of the variance, is called the standard deviation.

$$Var(x_1 \ldots\ldots x_N) = \frac{1}{N-1}\sum_{j=1}^{N}(x_j - \overline{x})^2 \quad \text{-----(2)}$$

3) *Standard Deviation :* The standard deviation of a multiple set of values is a measure of statistical dispersion of its values. The standard deviation is usually denoted with the letter σ. It is defined as the square root of the variance.

$$\sigma(x_1 \ldots\ldots x_N) = \sqrt{Var(x_1 \ldots\ldots x_N)} \quad \text{----(3)}$$

where $\sigma = \sigma(x_1 \ldots\ldots x_N)$ is the distribution's standard deviation

4) *Skewness :* It is a measure of the asymmetry of the probability distribution of a real-valued random variable. A positive value of skewness denotes a distribution with an asymmetric tail extending out towards more positive x, while a negative value signifies a distribution whose tail extends out towards more negative x[13]. Of course, any set of *N* measured values is likely to give a nonzero value, even if the underlying distribution is in fact symmetrical (has zero skewness). For this to be meaningful, we need to have some idea of *its* standard deviation as an estimator of the skewness of the underlying distribution.

$$Skew(x_1 \ldots\ldots x_N) = \frac{1}{N}\sum_{j=1}^{N}\left[\frac{x_j - \overline{x}}{\sigma}\right]^3 \quad \text{------ (4)}$$

5) *Kurtosis :* Kurtosis is more commonly defined as the fourth cumulant divided by the square of the second cumulant, which is equal to the fourth moment around the mean divided by the square of the variance of the probability distribution minus 3, which is known as "excess kurtosis". The conventional definition of the kurtosis is

$$Kurt(x_1 \ldots\ldots x_N) = \left\{\frac{1}{N}\sum_{j=1}^{N}\left[\frac{x_j - \overline{x}}{\sigma}\right]^4\right\} - 3 \quad \text{-----(5)}$$

where the -3 term makes the value zero for a normal distribution.

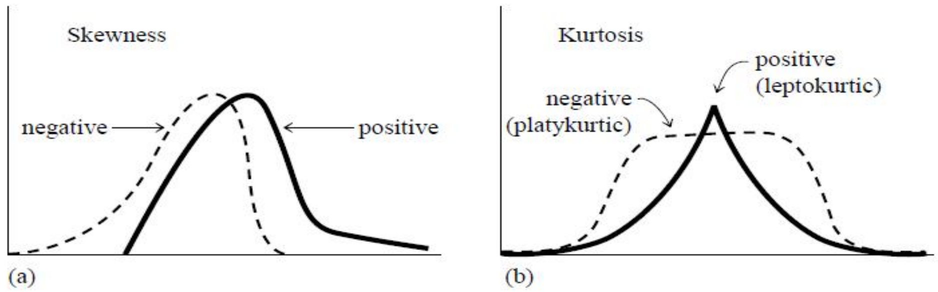

Figure3: Distributions whose 3rd and 4th moments are significantly different from a normal(Gaussian) distribution. (a) Skewness or 3rd moment. (b) Kurtosis or 4th moment.

That being the case, the skewness or third moment, and the kurtosis or fourth moment should be used with caution or, better yet, not at all. The kurtosis is also a non dimensional quantity. It measures the relative peakedness or flatness of a distribution. A distribution with positive kurtosis is termed leptokurtic. A distribution with negative kurtosis is termed Platykurtic. an in-between distribution is termed mesokurtic[14].

III. MATERIALS AND METHODS

The proposed approach for the classification of arrhythmias in ECGs involves pre-processing of the ECG signal, extraction of distinguishing features and classification using ANN technique. The outline of the whole process is shown as flow chart (Figure 4). Generally, multilayer feed forward neural networks can be trained as non-linear classifiers using the generalized back propagation algorithm (BPA)[15]. The BPA is a supervised learning algorithm, in which a mean square error function is defined and the learning process aims to reduce the overall system error to a minimum. 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[16]. The weight update is in the direction of 'negative descent', to maximize the speed of error reduction. The step size is chosen heuristically; in the present case, a learning constant q = 0.9 was chosen. For effective training, it is desirable that the training data set be uniformly spread throughout the class domains. The available data can be used iteratively, until the error function is reduced to a minimum.

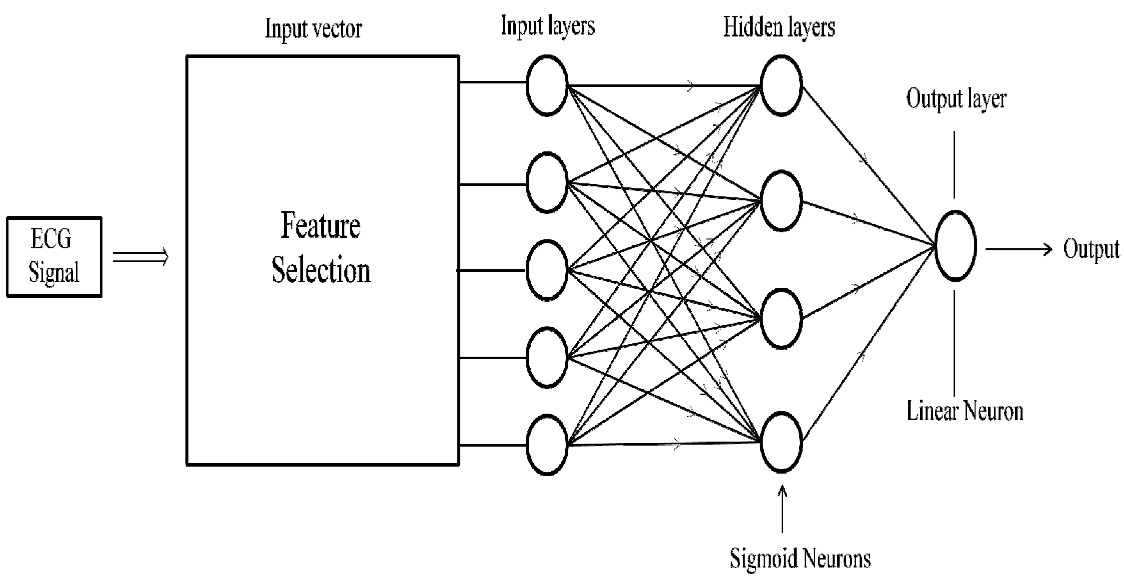

Figure 4: Outlines of overall ANN classification-flow chart.

A. Levenberg-Marquardt(LM) Algorithm

The Levenberg-Marquardt (LM) algorithm is basically an iterative method that locates the minimum of a multivariate function that is expressed as the sum of squares of non-linear real-valued functions [17] [18]. LM can be thought of as a combination of steepest

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descent and the Gauss-Newton (GN) method. This LM algorithm is more robust than GN algorithm which essentially means that it finds a solution even if it starts far off the final minimum. During the iterations, the new configuration of weights in step k+1 is calculated as follows $W(k+1) = W(k) - (J^T J + \lambda I)^{-1} J^T \varepsilon(k)$ (3) where J – the Jacobian matrix, λ - adjustable parameter, ε - error vector. The parameter λ is modified based on the development of error function E. If the step causes a reduction of E, it can be accepted. Otherwise, λ is changed; reset the original value and recalculate $W(k+1)$.

B. Data Pre-processing

Data pre-processing is the primary step for any model development. We deleted columns with all 0's and missing values and we also deleted columns of which most of the elements are 0's. We got 182 columns of which 12 are categorical and 170 are numerical. Next, we deleted 32 rows with missing values and the rest 37,500 samples were considered for analysis. We completely randomize the data sets after missing records deletion. There is no outlier in our data. The data set is partitioned into three: Training set (68%), Validation set (16%), and Test set (16%).

C. Arrhythmia Classification

Arrthymia considered for the purpose of this study were classified into twelve categories, namely

1) Left Bundle Branch Block (LBBB
2) Normal Sinus Rhythm (NSR)
3) Premeture-Ventricular Contraction (PVC)
4) Premeture- Atrial Contraction (PAC)
5) Right Bundle Branch Block (RBBB
6) 2^{nd}degree Heart Block (2^{o} HB)
7) Ischemic Dilated Cardiomyopathy (IDC)
8) Sick Sinus Syndrome (SSS) Sudden Cardiac Arrest(SCA)
9) Paced Beat(PB
10) Junctional Ectopic Beats(JEB)
11) Fusion of Ventricular and Normal Beat (FV &NB).

For the classification of cardiac arrhythmias using ANN we have taken the analysis of mean, variance, standard deviation, kurtosis and skewness as the input variables which are derived from heart rate signals. The specific values [19][20] for the different arrhythmias chosen are as shown in Table 1.

D. Performance Evaluation Method

We have evaluated the performance of the classification algorithms using three measures; specificity, sensitivity, classification accuracy. These measures are defined using True Negative (TN), True Positive (TP), False Negative (FN) and False Positive (FP) [21][22].

1) *True Negative:* both classifier and physician suggested absence of any kind of arrhythmia
2) *True Positive:* an instance where arrhythmia detection coincides with decision of physician
3) *False Positive:* an instance where system labels a healthy case as an arrhythmia one
4) *False Negative :*system labels an arrhythmia as healthy
5) *Classification Accuracy:* Accuracy is the ratio of number of correctly classified cases, and is given by

Accuracy= (TP+TN) / N----------------------- (18)

Total number of cases are N

6) *Classification Sensitivity:* Sensitivity refers to the rate of correctly classified positive. Sensitivity may be referred as a True Positive Rate. Sensitivity should be high for a classifier

Sensitivity = TP / (TP+FN) ------------------- (19)

7) *Classification Specificity:* Specificity refers to the rate of correctly classified negative and is equal to the ratio of TN to the sum of TN and FP. False Positive Rate equals (100-specificity).

Specificity=TN(FP+TN)..................................(20)

IV. RESULTS

The neural network is trained with back propagation algorithm (variable learning rate back propagation) Levenberg-Marquardt (Figures 5& 6). The network is provided with 37,500 different samples for training and testing. Out of which 68% of the samples is used for training the network, 16% of the samples is used for testing the network and the remaining 16% of the samples are used for validating the network. The results are compared over repeated iterations by shuffling the training sample values. The error histogram is a plot between error value and the number of instances the error has occurred. The error histogram of 20 bins is plotted as shown in figure-7. The center of the histogram has minimum error and the error increases as we move away from the center.

As shown in figure-8, the dashed line indicates the outputs in regression plot while the best possible fit between network outputs and desired targets is indicated by a solid dash line. The relation between outputs and targets is indicated by the regression value. The regression plot gives information about how close the output of our model is to the actual target values. The network outputs have a strong linear relation to desired targets if the value of Regression coefficient approaches unity. If the value of regression coefficient approaches zero, the relation between output and targets cannot be predicted.

The performance plot is a plot between Mean Square Error (MSE) and the number of epochs. MSE is the average squared difference between outputs and targets. MSE of Zero implies no error. As the training process progresses, the MSE value reduces. When the MSE value is reduced to a minimum value, the training stops and the network is validated with the samples. In the validation phase, if the network behaves properly, then the training stops at 917^{th} iterations and it is ready for testing. The LM shows better performance compared to other methods based on MSE. Table-2 gives classification of 12 types of arrhythmias(class 1 to class 12) and the percentage of accuracy, sensitivity and specificity.

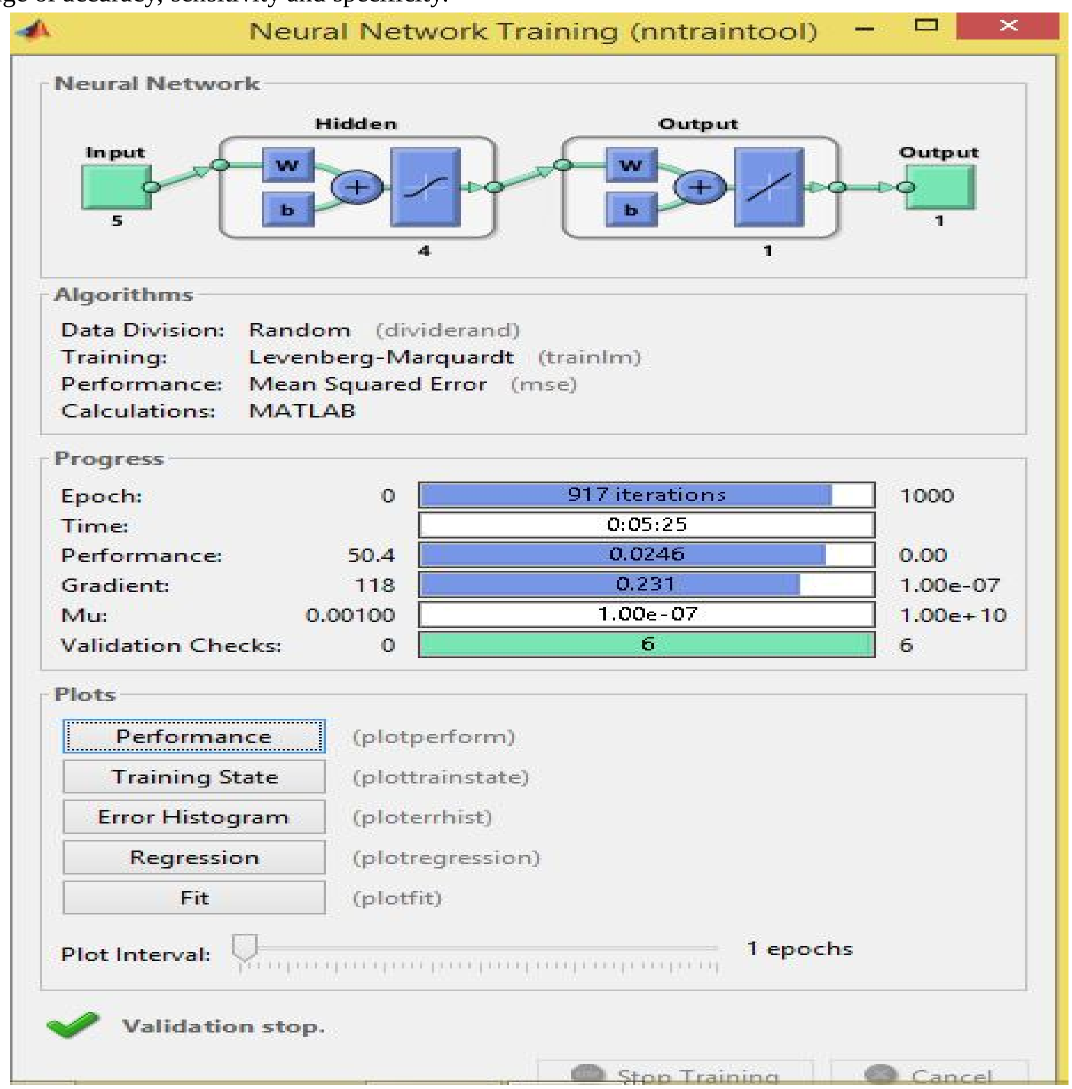

Figure 5: Neural Network Training showing performance plot between Mean Square

Error and Number of Epochs.

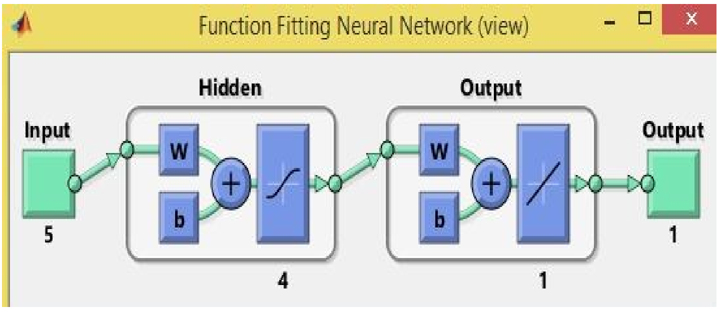

Figure 6: Neural Network Fitting Function.

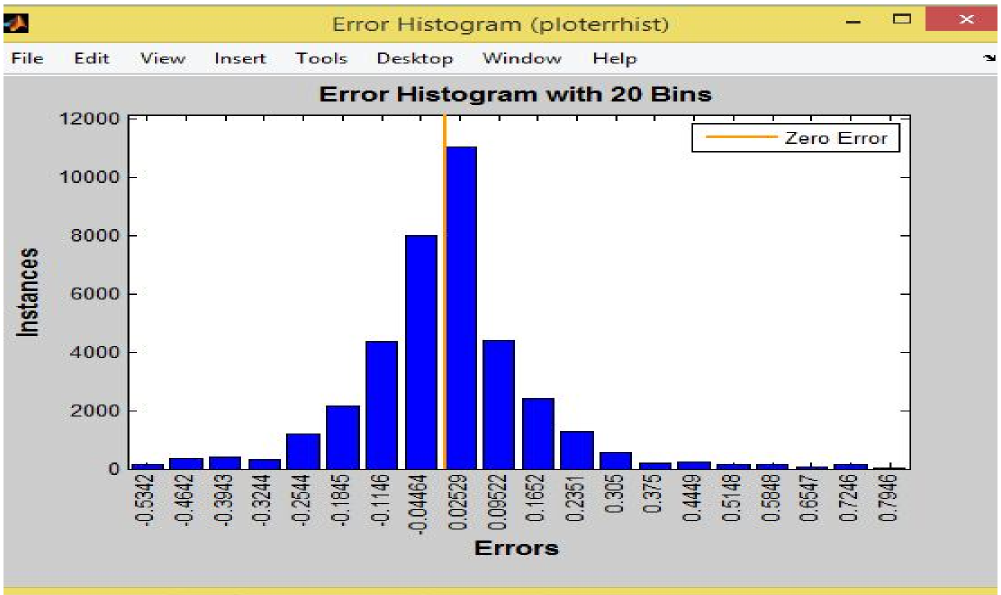

Figure7: Error Histogram Plot with 20 Bins

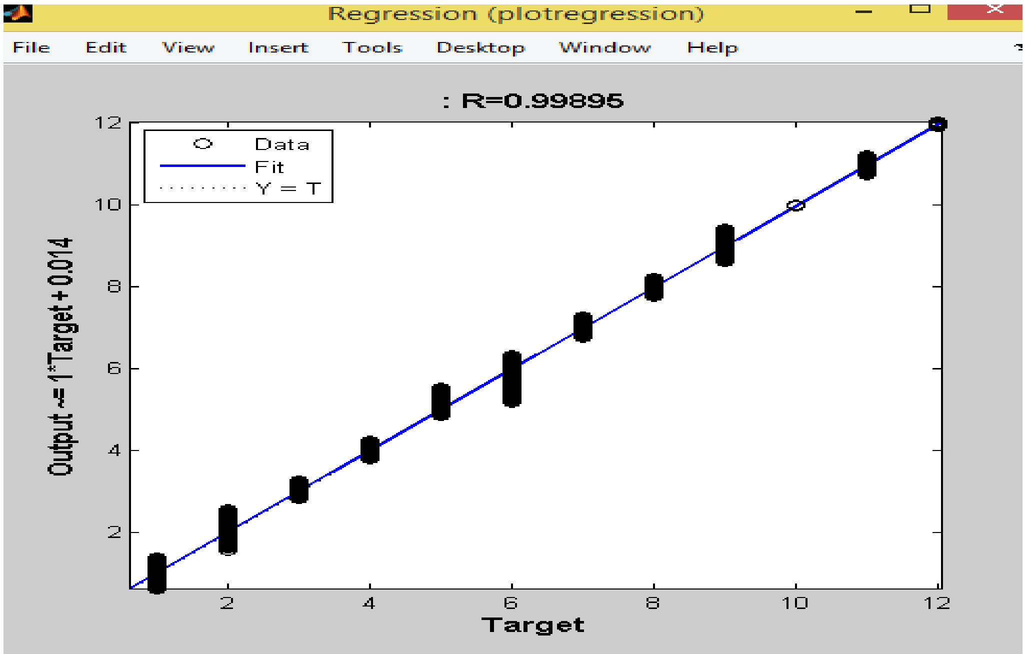

Figure8: Regression Plot showing the relation between out puts and targets.

Table 2: Statistical Results of the ECG Classification by LVQ NN showing percentage of accuracy, sensitivity and specificity.

Normal/AbNormal	Accuracy	Sensitivity	Specificity
Class 1	95.4	96.3	44.6
Class 2	90.9	93.3	93.9
Class 3	92.6	90.8	96.2
Class 4	91.2	90.9	87.4
Class 5	95.9	91.6	91.2
Class 6	90.9	91.4	95.2
Class 7	90.9	90.9	95.3
Class 8	94.2	91.1	85.5
Class 9	96.0	91.7	99.7
Class10	93.2	91.6	83.7
Class11	90.9	90.9	83.5
Class12	95.3	98.0	39.1

V. CONCLUSION

The performance of the classification algorithm (LVQ NN) was evaluated on MIT-BIH data using specificity, sensitivity and classification accuracy. These measures are defined using True Negative (TN), True Positive (TP), False Negative (FN) and False Positive (FP). The experimental results presented in this work showed a classification accuracy of 90.9 to 96.6 for different classes and 12 types of arrhythmi as were identified which were designated as class 1 to class 12 (LBBB, NSR, PVC, PAC RBB, 2^0HB, IDC, SSS,SCA,PB,JEB, FV&NB).

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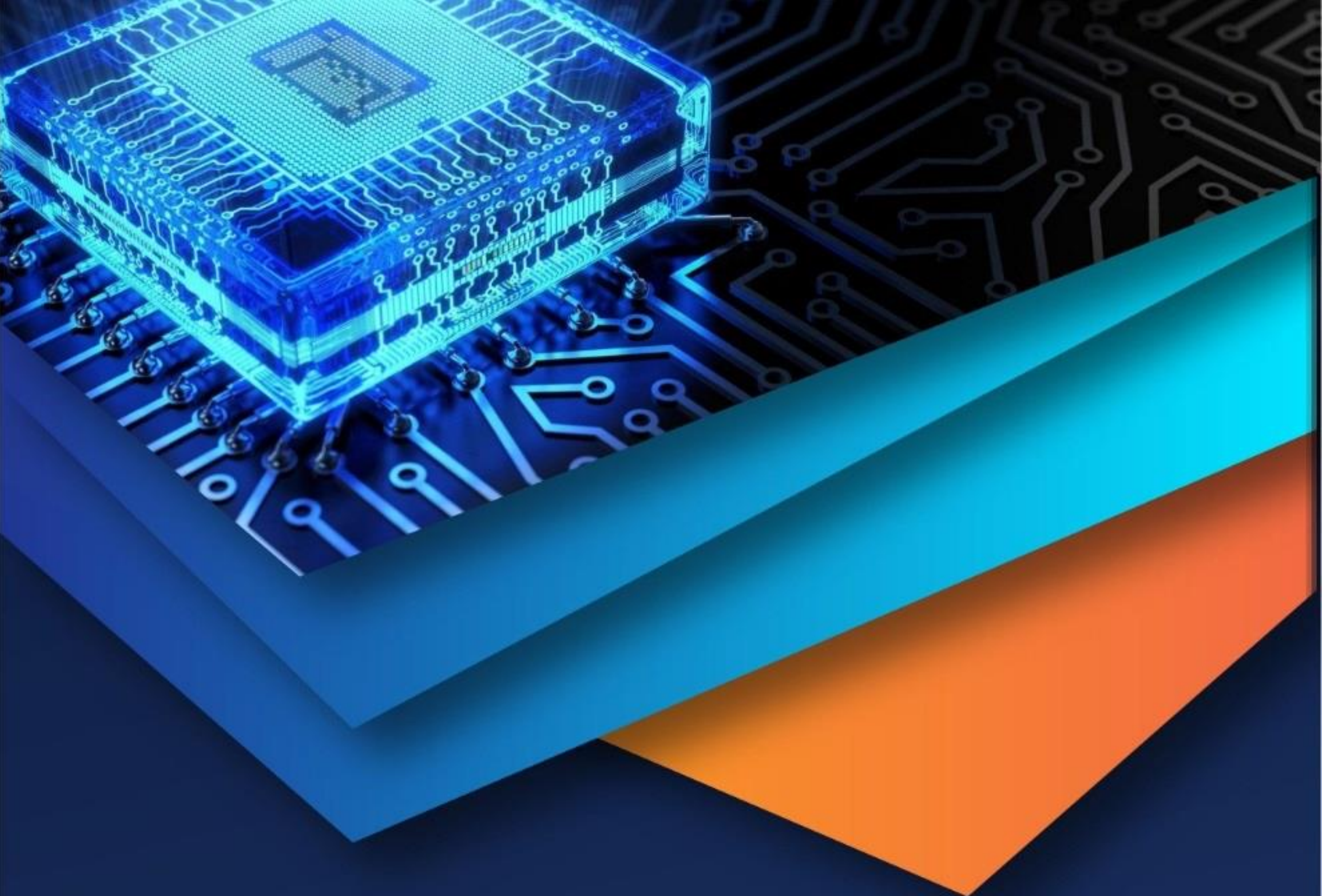

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