ISSN: 2278 – 909X
International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 5, Issue 7, July 2016

ECG Signals Analysis using PCA with Neural Network and Fuzzy Logic

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***Abstract*— In the paper, a method is proposed for the analysis of the ElectroCardioGraphy (ECG) signals. ECG signals are exploited to measure the heart activity of the person. So, for the proper analysis of the ECG, a knowledge of its peaks should be there. Hence, the purpose of this research is to address in identifying the Normal, Apnea, Tachycardia and Ischemia signals using the method of Principal Component Analysis (PCA) and various classifiers i.e. Support Vector Machine (SVM), Artificial Neural Networks (ANN) and Fuzzy Logic. PCA algorithm is used to extract the relevant information from the ECG input data which are their P-QRS-T parameters values. Then the extracted features data is analyzed and classified using Support Vector Machine (SVM), Artificial Neural Networks (ANN) and Fuzzy Logic classifiers. Then these classification results are compared and observed a good accuracy of around 92% in the classification.**

***Index Terms*— ANN, Apnea, ECG, Fuzzy, Ischemia, PCA, SVM, Tachycardia.**

I. INTRODUCTION

ElectroCardioGraphy (ECG) is a way exploited for measuring the electrical activity of the heart. There can be so many heart related diseases present in this world among the human beings. So, because of problems in the heart, many people die every year. And Doctors exploits ECG to diagnose and treatment for the related problems.

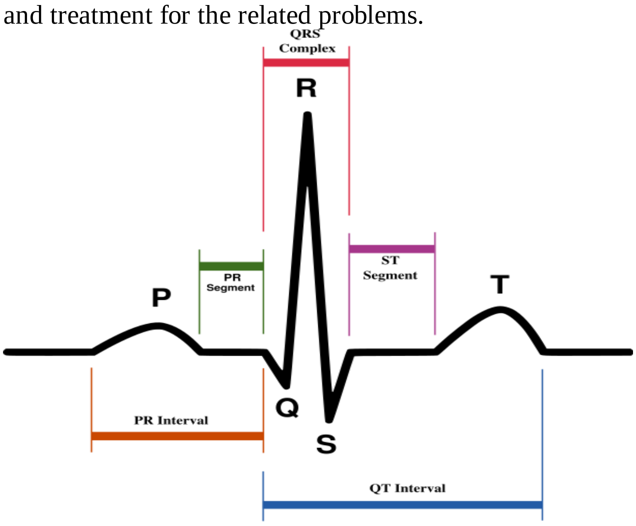

Fig.1. ECG waveform with its characteristic points

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This diagnosis can be made automatic if these ECG signals obtained for different subjects can be differentiated on the basis of some pattern. A standard ECG waveform is shown in the Fig.1. In the figure, P-QRS-T waveform is represented and these points can be used as the characteristic points for the ECG signal. For various signals in ECG, variation in the P-QRS-T waveform can be observed. There are so many algorithms already developed for the delineation of the ECG signals.

TABLE.I

SUMMARY OF THE EARLIER PROPOSED METHODS

STUDY	TECHNIQUE	ACCURACY
Shen [2]	HB + WED + NNC	95.3%
Chan et al. [3]	CCORR + NC	90.8%
Chiu et al. [4]	DWT + NC, ED	95.71%
Yao and Wan [5]	DWTMRRS + PCA	91.5%
Boumbarov et al. [6]	PCA + RBFNN	86%
Homer et al. [7]	RARMA + NNC	85.2%
Agrafioti and Hatzinakos [8]	AC + WT + NNC	92.3%
Lourenco et al. [9]	MANRHB + NC	94.3%

Among these algorithms, real time QRS algorithm [10-12], software based algorithm [13-16], CWT [17], matched filters [18], linear predictive coding [19], ECG slope criteria [20], power spectral density [21], second order derivatives [22], DWT [23], wavelet transforms [24-26] are studied. In [1], ECG beats were detected using principal component based technique. And similarly some other beats are selected in other researchers.

Now, in this research paper, a novel method is proposed for the classification of the different types of ECG signals i.e. Apnea, Ischemia, Normal and Tachycardia. In this, PCA algorithm is utilized to identify the ECG signals.

This research paper is organized in the following sections as: Section II tells about the overview of the complete work using a block diagram. Section III tells about the different types of ECG signals used and the proposed method. Then in section IV, results are discussed followed by conclusion in section V.

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II. BLOCK DIAGRAM

In the the Fig. 2 shown is the block diagram representing the overview of the work done during this research. In this, four different types of ECG waveforms are taken namely Apnea, Ischemia, Normal and Tachycardia. Then, as shown in the block diagram, propsed method i.e PCA is applied on these signals and their characteristic points are computed. After that, on the basis of these characteristic points, ECG signals are classified using the three different classifiers i.e. SVM, ANN and Fuzzy classifiers.

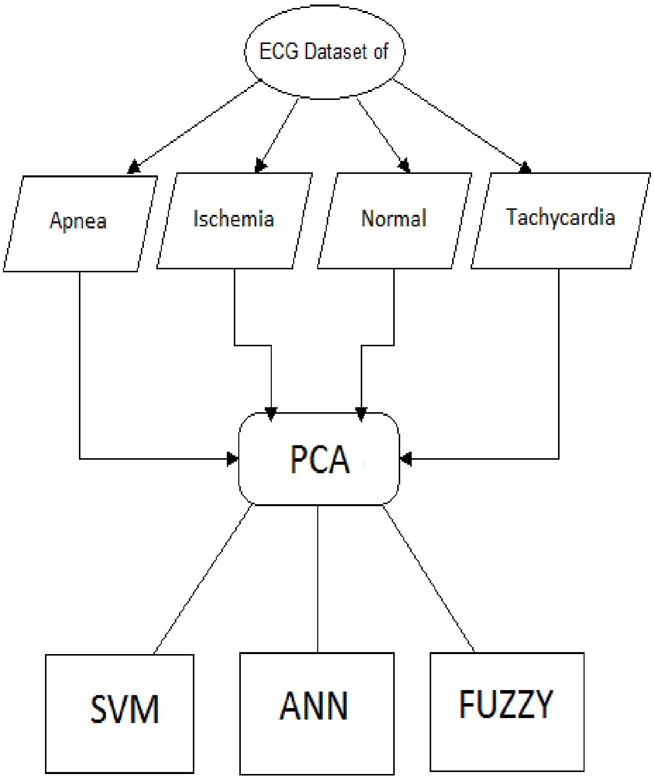

Fig.2. Block Diagram of the Proposed method

III. PROPOSED METHOD

A. Data-Set

Dataset is taken from the MIT-BIH database for the different types of ECG signals utilized during this research. Among these signals, Apnea, Ischemia and Tachycardia are the three types of situations in the subjects having heart related problems with normal signal as the fourth type. Dataset for ECG detection is loaded from the MIT-BIH database of Physiobank ATM. It is shown below in the Table II.

TABLE II

DESCRIPTION OF DATASET USED

ECG Signals	Training	Testing	Total
Apnea	18	12	30
Normal	18	12	30
Ischemia	18	12	30
Tachycardia	18	12	30

These signals are explained in brief in the sub-sections.

a. Normal ECG

Fig.3 represents an ECG waveform showing the heart condition of a normal human being. Comparing with the Fig.1, P-QRS-T points are observable in the Fig.3.

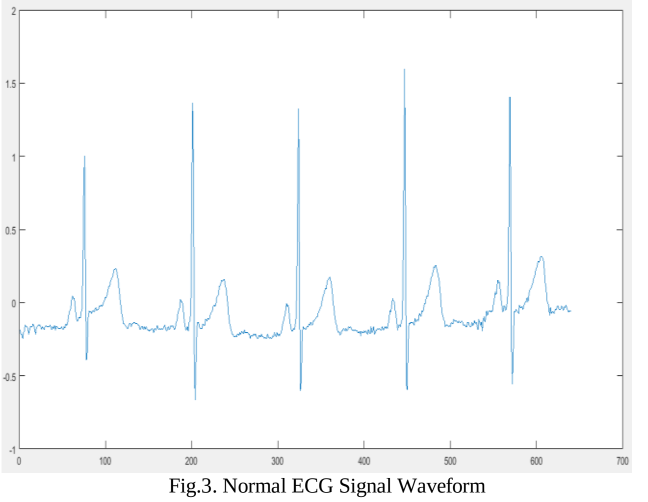

Fig.3. Normal ECG Signal Waveform

TABLE III

DIFFERENT PHASES IN NORMAL ECG

Section of ECG	Source
P-Wave	Record the electrical activity through the upper heart chambers (Atria Excitation)
QRS-Complex	Record the movement of electrical impulses through the lower heart chambers. (Atria repolarization + Ventricle depolarization)
T-Wave	Corresponds to the period when the lower heart chambers are relaxing electrically and preparing for their next muscle contraction. (Ventricle repolarization)
ST Segment	Corresponds to the time when the ventricle is contracting but no electricity is flowing through it.

In the Table III, normal ECG signal is explained that how the peaks in ECG are obtained depending on the different situations in the heart.

b. Apnea

Apnea is defined as ECG waveform obtained during the intermittent halt of breathing in the subject. It is due to the irregular sleep and related to the accrued risks of high pressure level. It is shown in the Fig.4.

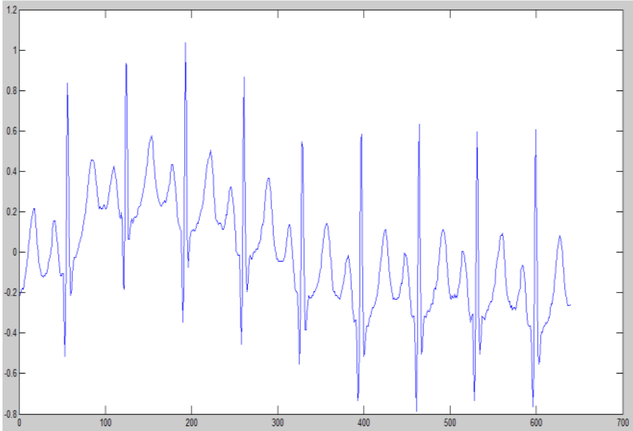

Fig.4. Apnea Signal Waveform

c. Ischemia

Ischemia is a type of ECG signal in which T wave is inverted. In this, sometimes, decrease in the amplitude and disappearance of the R wave may also occur. This type also includes a shift of the ST segment. It is shown in the Fig.5.

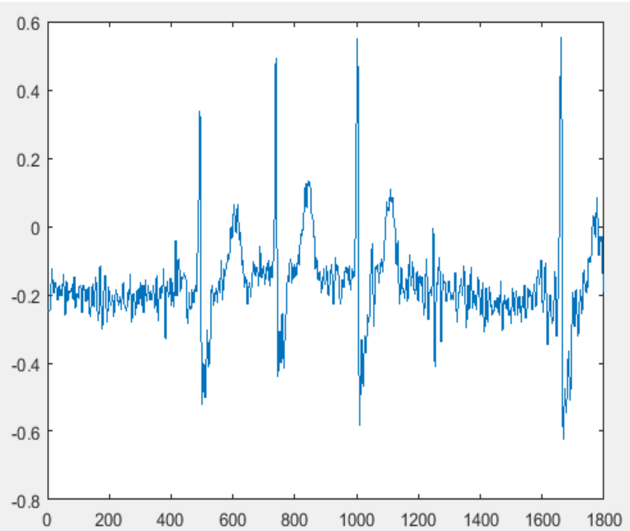

Fig.5. Ischemia Signal Waveform

d. Tachycardia

Tachycardia is a condition in the ECG in which atrial and ventricular rates are accelerated exceeding the normal ECG rate. Beats in the tachycardia are regular but comparatively faster. It is also observed by the presence or absence of the P or flutter waves in the signal.

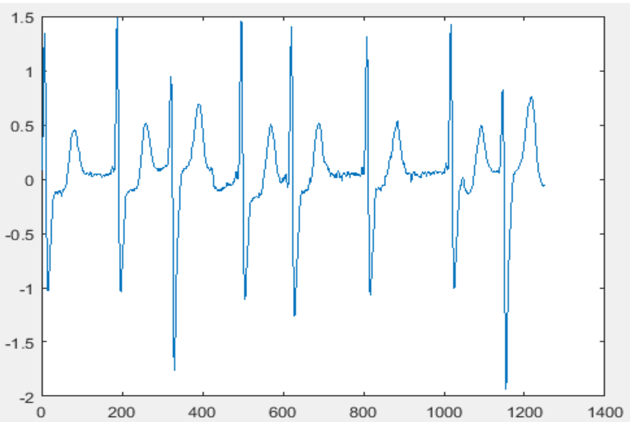

Fig.6. Tachycardia Signal Waveform

B. PCA

PCA is an orthogonal linear transformation. It transfers the data to a new frame of reference such the largest variance of any projection of the information involves lie on the first coordinate (first principal component), the second largest variance lies on the second coordinate (second principal component), and so on. Linear projection method to reduce the number of parameters. Map the data into a space of lower dimensionality.

PCA Algorithm:

Let X be an input data set.

Now, Perform the following steps:

Calculate the mean:

$$m[p] = \frac{1}{Q}\sum_{q=1}^{Q} X[p,q] \qquad (1)$$

Calculate the mean deviation and keep the data in the matrix $D_m[P \times Q]$:

$$D_m = X - m.h \qquad (2)$$

where h is a 1 × Q row vector of all 1's:

h[q] = 1 for n = 1, …….Q

Find the covariance matrix Cv:

$$Cv = D_m . D_m^{\ T} \qquad (3)$$

Find the eigenvectors and eigenvalues of the covariance matrix $V^{-1}CvV$ where V is the eigenvectors matrix. D is the diagonal matrix of eigenvalues of Cv.

$$D[m,n] = \lambda_p \qquad (4)$$

for m = n = p is the m^{th} eigen value of the covariance matrix Cv.

Rearrange the eigenvalues

$$\lambda_1 \geq \lambda_2 \geq \lambda_3 .... \geq \lambda_Q \qquad (5)$$

Choosing components and forming a feature vector: save the first L columns of V as the M × L matrix W,

W[m, n] = V [m, n], (6)

for m = 1, . . . ,P

n = 1, . . . , L

where 1 ⩽ L ⩽P.

Deriving the new data set: The eigenvectors with the maximum eigenvalues are projected into space. This projection results in a vector represented by fewer dimension (L < P) containing the essential coefficients only.

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C. SVM

SVM i.e. Support Vector Machine classifier is utilized for ECG signals classification because of its multi-classification ability in differentiating various classes. SVM is explained using the equations in which margin between the support vectors is to be maximized. For this compute the parameters f, f_0 of the hyperplane so that to:

$$\text{minimize} \quad J(f, f_0) \equiv \frac{1}{2}\|f\|^2 \tag{7}$$

subject to langrangian equations.

Clearly, making the norm minimum will makes themargin maximum. This is a nonlinear (quadratic) optimization task subject to a set of linear inequality constraints. Hence, the SVM decision function is expressed as equations

$$f = \sum_{i=1}^{N} c_i . z_i . x_i \tag{8}$$

$$\sum_{i=1}^{N} c_i . z_i = 0 \tag{9}$$

D. ANN

With SVM, ECG classification is also done using Artificial Neural Network (ANN). In this also, train the network first by using some training data. A suitable training algorithm results in an ANN which is capable of generating a non-linear mapping function with the proficiency of demonstrating relationships between given ECG features and cardiac disorders.

$$u_k = \sum_{j=1}^{n} x_j . w_{kj} \tag{10}$$

$$v_k = u_k + b_k \tag{11}$$

A well designed ANN will exhibit good generalization when a correct input output mapping is obtained even when the test input is slightly different from the data used to train the network.

E. FUZZY

Zong and Jiang (1998) described the method of fuzzy logic approach single channel ECG beat and rhythm detection. The method summarized and makes use of the medical knowledge and diagnostic rules of cardiologists. Linguistic variables have being used to represent beat features and fuzzy conditional statements perform reasoning. The algorithm can identified rhythms as well as individual beats. This method also handling the beat features and reasoning process is heuristic and seems more reasonable as stated in their paper. It also presented that this method may be of great utility in clinical applications such as multi-parameter patient monitoring systems, where many physiological variables and diagnostic rules exist.

IV. Results & Discussion

Now, in the results, Eigen values computed from the PCA algorithm are utilized to detect the characteristic points in the ECG signals. These characteristic points includes Q, R,S and T peaks of the different types of ECG signals viz. Apnea, Ischemia Normal and Tachycardia signals.

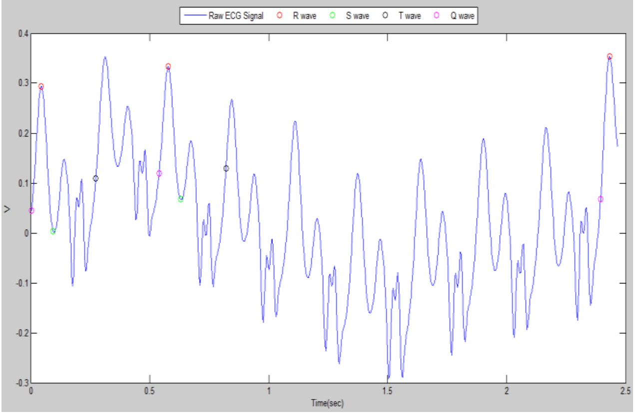

Fig.7. Apnea ECG Peaks Detection

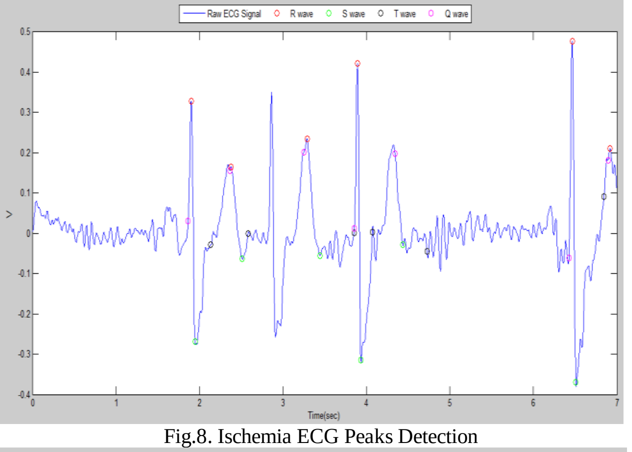

Fig.8. Ischemia ECG Peaks Detection

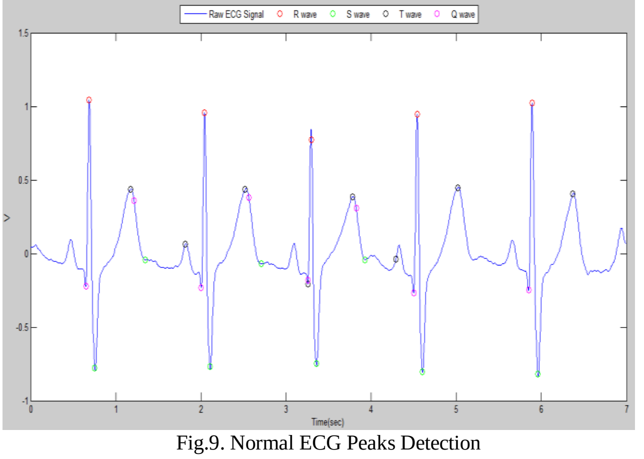

Fig.9. Normal ECG Peaks Detection

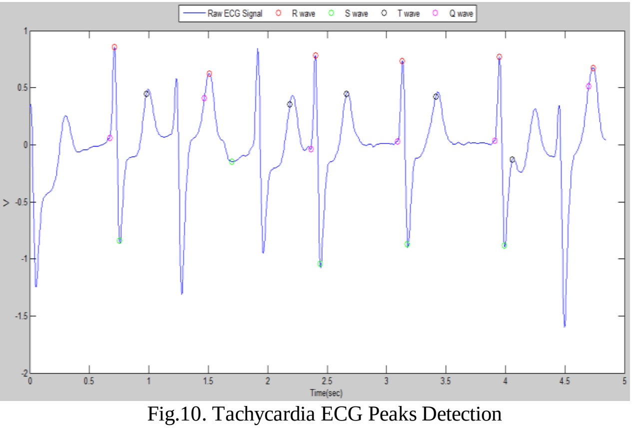

Fig.10. Tachycardia ECG Peaks Detection

In the Fig.7-10 shows the parameter detection in the ECG signals selected as sample from the datasets. It can be observed from the signals figures that variation among the signals can be observed.

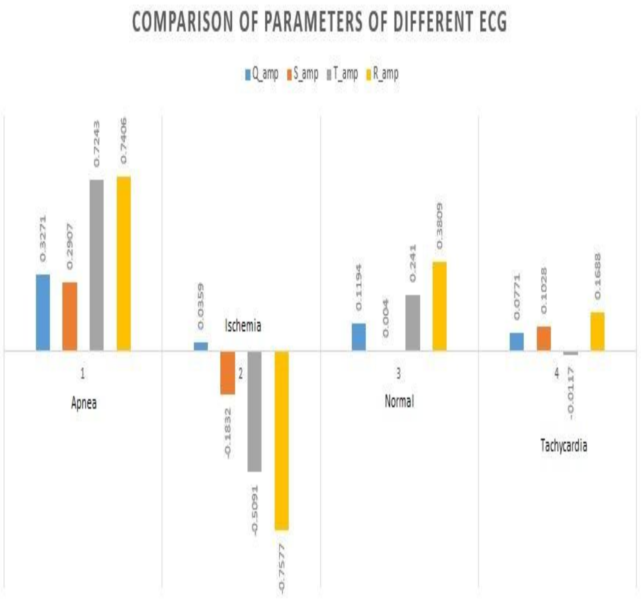

Fig.11. Comparison of characteristic points of different ECGs

Next in the Fig.11 shows is the graph representing the comparison among the feature values extracted using the Principal Component Analysis (PCA) algorithm. And it can be observed from the figure that there is difference among the characteristic points i.e. Q, R, S and T peaks.

TABLE IV

CONFUSION MATRIX FROM SVM

Targets / Output	AP	IS	NR	TC	Accuracy
AP	10/12	1/12	1/12	0/12	83.33%
IS	1/12	10/12	1/12	0/12	83.33%
NR	0/12	0/12	12/12	0/12	100%
TC	0/12	1/12	2/12	9/12	75%

Now, these parameters obtained, are used in the classifiers for the classification of these ECG signals. For the classification, firstly SVM is used. In this classifier, 120 subjects dataset is used in total. Among these, 72 subjects are used to train the SVM and remaining are tested on this trained classifier. The results from the SVM classifier are shown in the Table IV which shows a confusion matrix of the tested dataset. In this table, AP, IS, NR and TC represents Apnea, Ischemia, Normal and Tachycardia respectively.

In the Table IV, it can be seen that this classifier doesn't give us a satisfactory results with just 85.4% of accuracy. Hence, for an improvement in the results next classifier is used i.e. ANN.

ANN applied on the dataset gives the neural network as shown in the Fig. 12 in which 72 subject parameter values are used for the training and 48 for the testing.

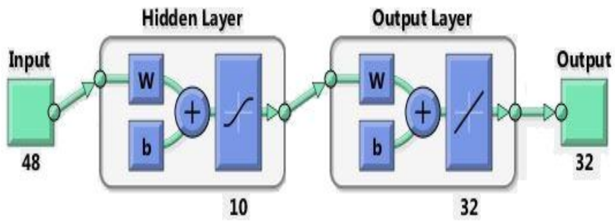

Fig.12. Neural Network

TABLE V

CONFUSION MATRIX FROM ANN

Targets / Outputs	AP	IS	NR	TC	Accuracy
AP	9/12	1/12	0/12	2/12	75%
IS	0/12	11/12	0/12	1/12	91.67%
NR	0/12	0/12	12/12	0/12	100%
TC	0/12	1/12	1/12	10/12	83.33%

Then next shown is the Table V showing the confusion matrix of these ECG signals obtained by classification using this classifier.

According to this table, an accuracy of 87.5% is observed which is very good and gives a much better results compared to SVM in which only 85.4% accuracy was observed. Next, Fuzzy is applied on these feature values obtained using these ECG datasets.

Now, the dataset is applied on the Fuzzy logic for the classification purpose. Fig.13 shows the modelling of Fuzzy Logic which helps in the classification of the ECG signal classes.

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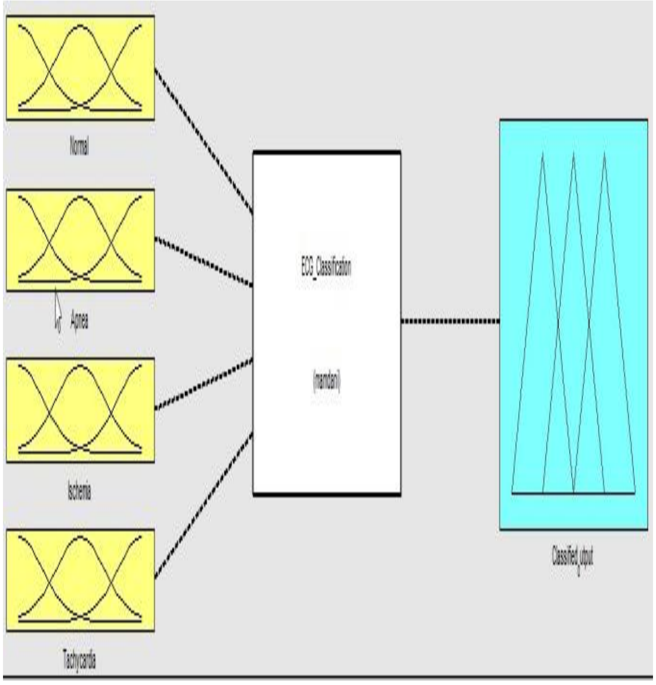

Fig.13. Fuzzy Rule Based Model

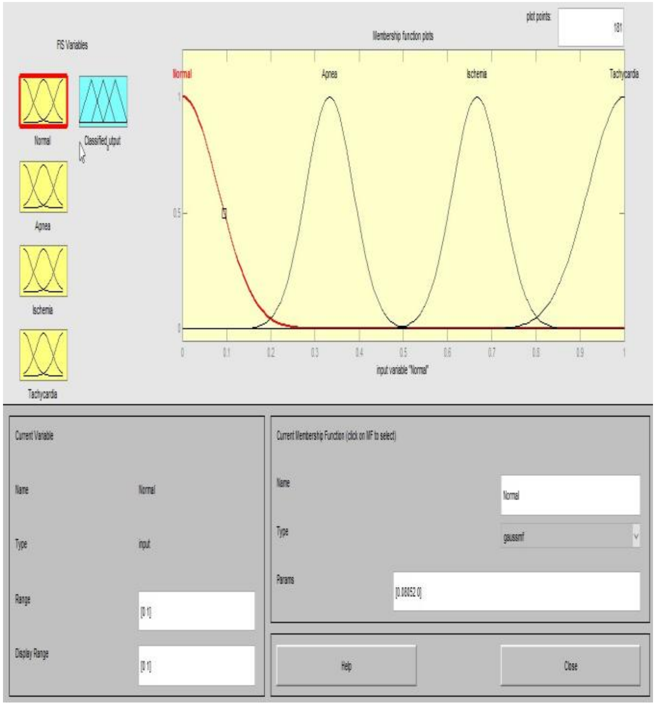

Fig.14. Membership_functions for Inputs

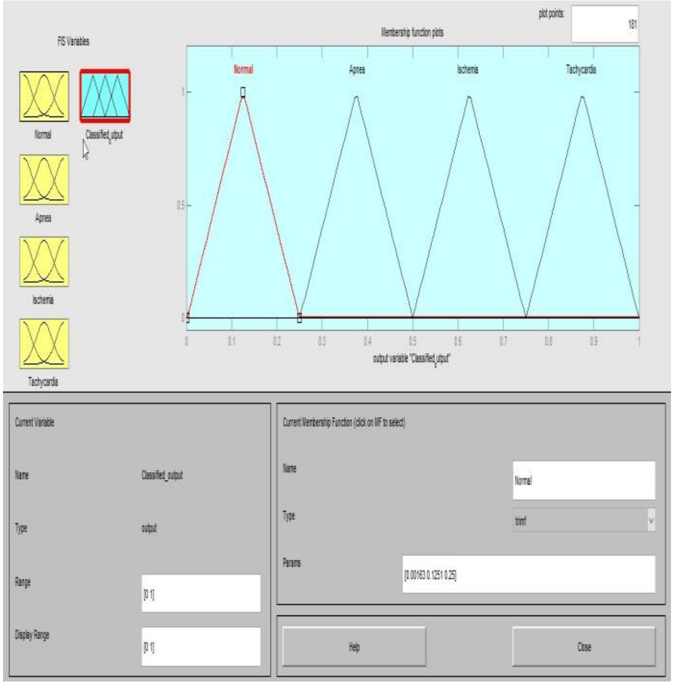

Fig.15. Membership Function for Output

TABLE VI

CONFUSION MATRIX FROM FUZZY

Targets Outputs	AP	IS	NR	TC	Accuracy
AP	10/12	0/12	0/12	2/12	83.33%
IS	0/12	11/12	0/12	1/12	91.67%
NR	0/12	0/12	12/12	0/12	100%
TC	0/12	0/12	1/12	11/12	91.67%

Then the Fig.14-15 shows the membership functions for the inputs (Gaussian) and outputs (Triangular) respectively. In the Table VI shown is the confusion matrix for the Fuzzy classifier. The table shows good accuracy in classifying the different types of ECG signals used during this project. An accuracy of 91.70% is achieved using this classifier.

V. CONCLUSION

The proposed method in this research paper utilizes Principal Component Analysis (PCA) algorithm to classify the different types of ECG signals viz. Apnea, Ischemia, Normal and Tachycardia signals, used during this research which have different characteristic points obtained using the principal component analysis algorithm. Accuracy obtained with these classifiers is upto 92% (approx..) and hence, this method can also be utilized by the doctors to classify various ECG signals.

This accuracy in classifying these ECG signals can be improved by using the hybrid of the different classifiers as the future work in this.

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