IARJSET

ISSN (Online) 2393-8021
ISSN (Print) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology
ISO 3297:2007 Certified
Vol. 3, Issue 7, July 2016

Analysis of ECG Signals using Hybrid Classifier

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Abstract: This research paper describes a novel method in which analysis of the ElectroCardioGraphy (ECG) signals is done using the hybrid classifier. As it is an already known fact that ECG signals are used by doctors to diagnose the heart activity of the subject and on the basis of knowledge about its peaks, treatment of the disease is done. Hence, the purpose of this research work is to identify the Normal, Apnea, Ischemia and Tachycardia signals using the method of Principal Component Analysis (PCA) and Neuro-Fuzzy classifier. PCA algorithm is used to extract the relevant information from the ECG input dataset which are their P-QRS-T parameters values. Then the extracted features data is analyzed and classified using the hybrid of Artificial Neural Networks (ANN) and Fuzzy Logic classifiers i.e. Neuro-Fuzzy classifier. Then these classification results are compared and observed a good accuracy of around 96% in the classification.

Keywords: ANN, ECG, Fuzzy, Neuro-Fuzzy, PCA.

I. INTRODUCTION

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. For this, Electro Cardio Graphy (ECG) is an existing way of measuring the electrical activity of the heart. And Doctors exploits ECG to diagnose and treatment for the related problems.

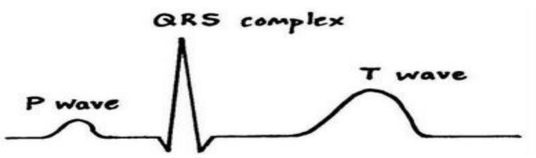

Fig.1. ECG waveform with its characteristic points

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 [3]	HB + WED + NNC	95.3%
Chan et al. [4]	CCORR + NC	90.8%
Chiu et al. [5]	DWT + NC, ED	95.71%
Yao and Wan [6]	DWTMRRS + PCA	91.5%
Boumbarov et al. [7]	PCA + RBFNN	86%
Homer et al. [8]	RARMA + NNC	85.2%
Agrafioti and Hatzinakos [9]	AC + WT + NNC	92.3%
Lourenco et al. [10]	MANRHB + NC	94.3%

Among these algorithms, real time QRS algorithm [11-13], software based algorithm [14-17], CWT [18], matched filters [19], linear predictive coding [20], ECG slope criteria [21], power spectral density [22], second order derivatives [23], DWT [24], wavelet transforms [25-27] are studied. In [1-2], 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 using the hybrid of Artificial Neural Network and Fuzzy Logic i.e. Neuro-Fuzzy Classifier.

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.

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, proposed 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. ANN, Fuzzy and Neuro-Fuzzy classifiers.

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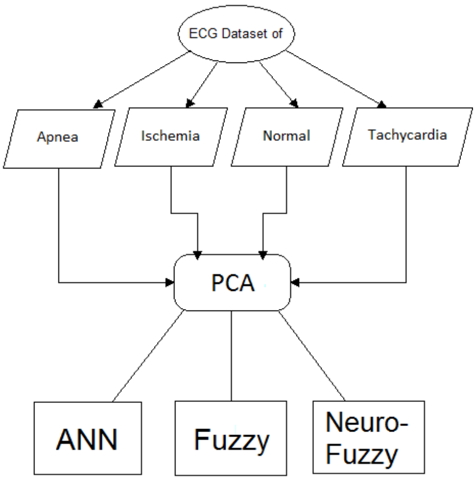

Fig.2. Block Diagram of the Proposed method

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

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

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.

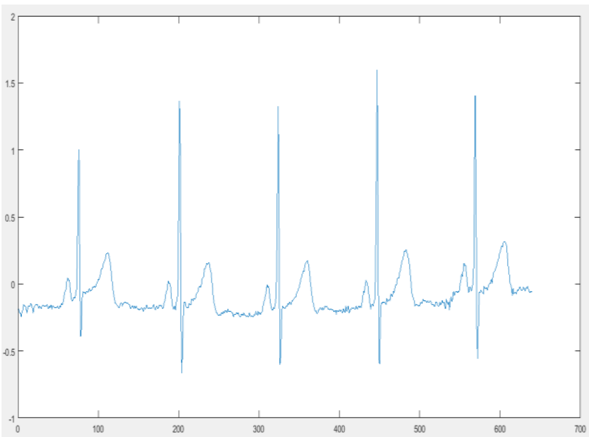

Fig.3. Normal ECG Signal Waveform

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.

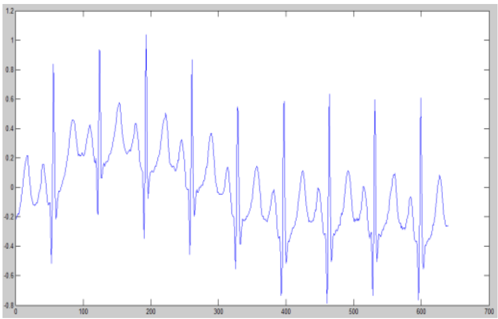

Fig.4. Apnea Signal Waveform

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.

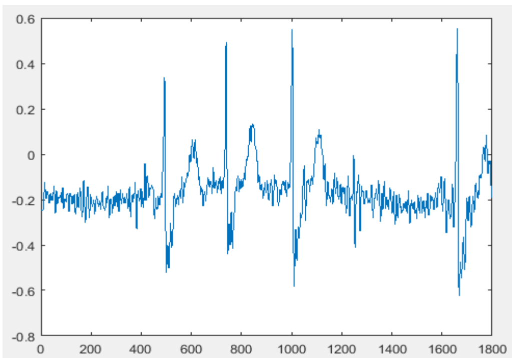

Fig.5. Ischemia Signal Waveform

DOI 10.17148/IARJSET.2016.3717

IARJSET
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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.

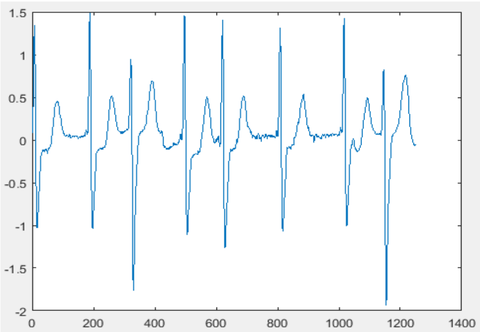

Fig.6. Tachycardia Signal Waveform

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 eigen values of the covariance matrix $V^{-1}CvV$ where V is the eigenvectors matrix. D is the diagonal matrix of eigen values 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 eigen values

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

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

$$W[m, n] = V[m, n], \qquad (6)$$

for m = 1, . . . ,P
n = 1, . . . , L where $1 \leqslant L \leqslant P$.

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

C. ANN

Firstly, 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.

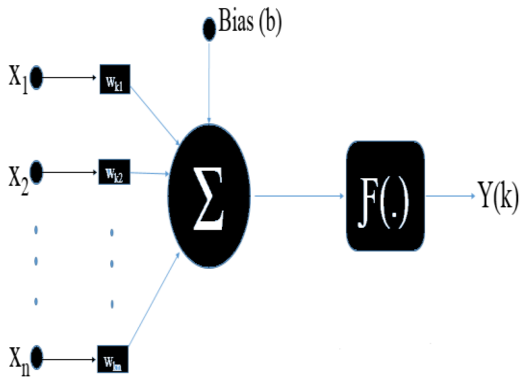

Fig.7. ANN Model

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

$$v_k = u_k + b_k \qquad (11)$$

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.

D. 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

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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.

E. NEURO-FUZZY

Neuro-Fuzzy classifier consists of five layers of nodes out of the five layers, the first and the fourth layers consist of adaptive nodes there are Fuzzification and Defuzzification, while the second, third and fifth layers consist of fixed nodes there are Rule, Normalization, and Summation neuron. The Neuro-Fuzzy classifier to implement the Fuzzy rules is shown in Fig.8, in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

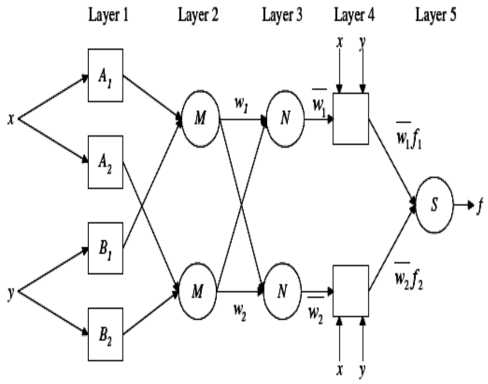

Fig.8. Neuro-Fuzzy architecture

Layer 1: Fuzzification layer Every node I in the layer 1 is an adaptive node. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by:

$$O_i^1 = \mu_{A_i}(x), \forall i = 1,2 \quad (12)$$

$$O_i^1 = \mu_{B_{i-2}}(y), \forall i = 3,4 \quad (13)$$

where x and y is the inputs to node i, where A is a linguistic label (small, large) and where $\mu_{Ai}(x)$, $\mu_{Bi-2}(y)$ can adopt any fuzzy membership function.

Usually we choose $\mu_{Ai}(x)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as:

$$\mu_{A_i}(x) = \frac{1}{1+\{((x-c_i)/a_i)^2\}^{b_i}} \quad (14)$$

where (a_i, b_i and c_i) are the parameters of the membership function. Parameters are referred to as premise parameters.

Layer 2: Rule layer a fixed node whose output is the product of all the incoming signals, The outputs of this layer can be represented as:

$$O_i^2 = w_i = \mu_{A_i}(x).\mu_{B_i}(y), i = 1,2 \quad (15)$$

Layer 3: Normalization layer are also fixed node is a circle node.

$$O_i^3 = w_i = \frac{w_i}{w_1 + w_2}, i = 1,2 \quad (16)$$

Layer 4: Defuzzification layer an adaptive node with a node the output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial.

$$O_i^4 = w_i.f_i = w_i(p_i x + q_i y + r_i), i = 1,2 \quad (17)$$

Layer 5: Summation neuron a fixed node which computes the overall output as the summation of all incoming signals.

$$O_i^5 = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \quad (18)$$

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.

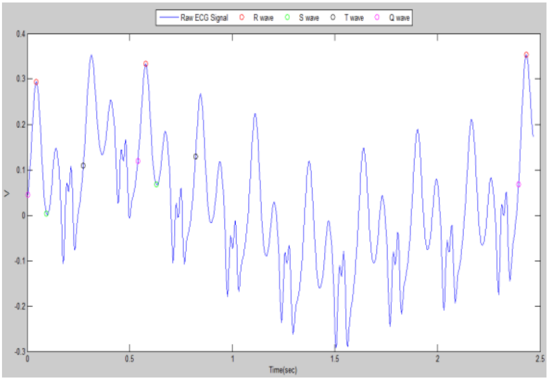

Fig.9. Apnea ECG Peaks Detection

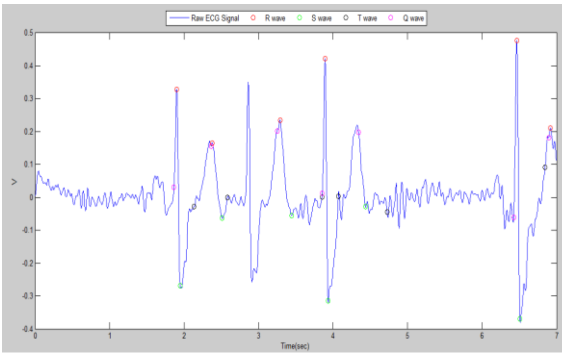

Fig.10. Ischemia ECG Peaks Detection

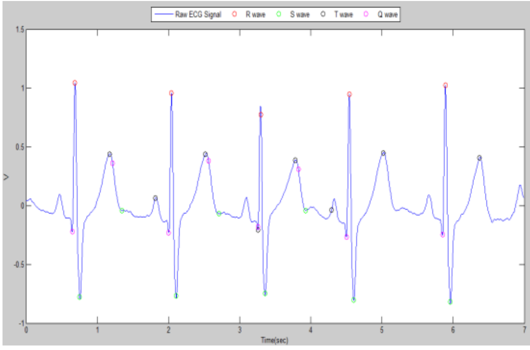

Fig.11. Normal ECG Peaks Detection

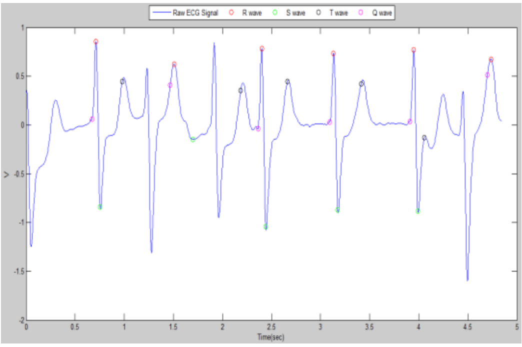

Fig.12. Tachycardia ECG Peaks Detection

In the Fig.9-12 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.

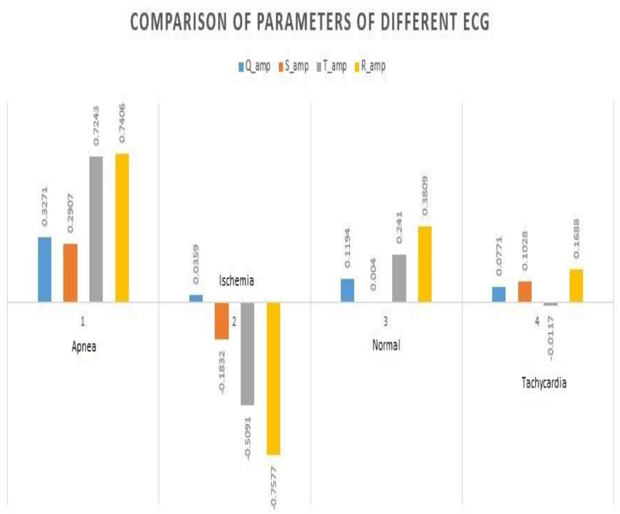

Fig.13. Comparison of characteristic points of different ECGs

Next in the Fig.13 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. Now, these parameters obtained, are used in the classifiers for the classification of these ECG signals. For the classification, firstly ANN is used. In this classifier, 120 subjects dataset is used in total. Among these, 72 subjects are used to train the ANN and 48 are tested on this trained classifier as shown in the Fig.14. The results from the ANN 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.

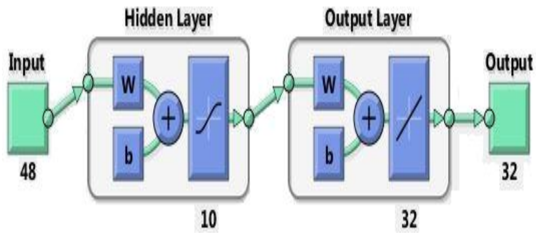

Fig.14. Neural Network

TABLE IV
CONFUSION MATRIX FROM ANN

Targets	AP	IS	NR	TC	Accuracy
Outputs					
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%

According to this table, an accuracy of 87.5% is observed which is very good and gives only satisfactory results. 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.15 shows the modelling of Fuzzy Logic which helps in the classification of the ECG signal classes. Then the Fig.16-17 shows the membership functions for the inputs (Gaussian) and outputs (Triangular) respectively. In the Table V 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.

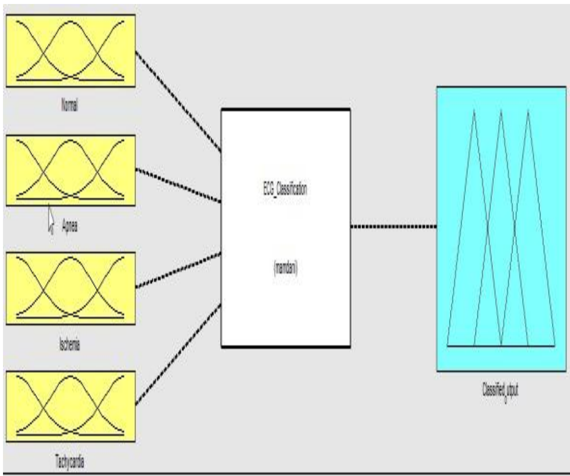

Fig.15. Fuzzy Rule Based Model

IARJSET
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ISSN (Print) 2394-1588
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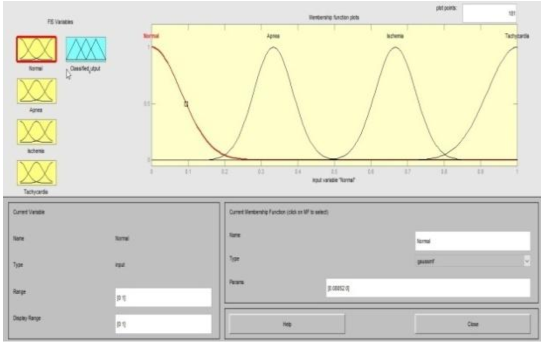

Fig.16. Membership functions for Inputs

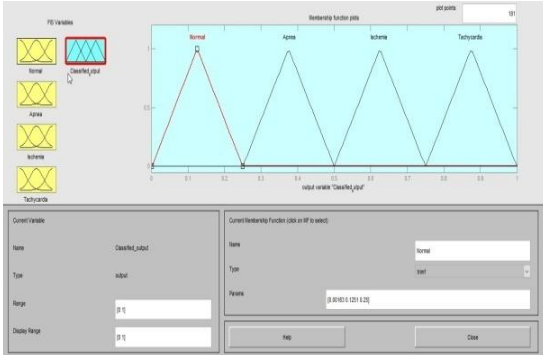

Fig.17. Membership Function for Output

TABLE V

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%

Even now, some signals are mis-classified using this classifiers which is corrected using the hybrid of Neural network and the fuzzy classifiers. Neuro-Fuzzy Classifier. Therefore, next classifier used is the Neuro-Fuzzy classifier for the classification of different types of ECG signals.

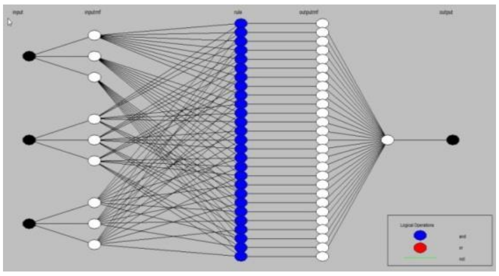

Fig.18. Neuro-Fuzzy Structure

Neuro-Fuzzy Logic is applied on the ECG signals according to the structure shown in the Fig.18. This is a Neuro-Fuzzy structure. It is a multi-layer neural network with fuzzy rules inbuilt in it. In this, Fuzzy rules are used in the hidden layer of the Neural Network and hence, named as Neuro-Fuzzy Classifier.

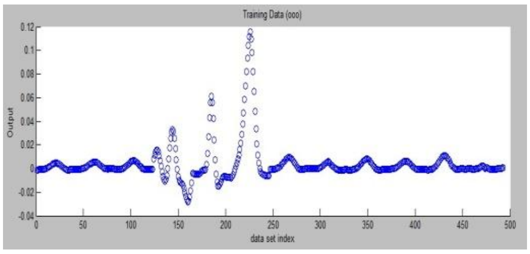

Fig.19. Training data

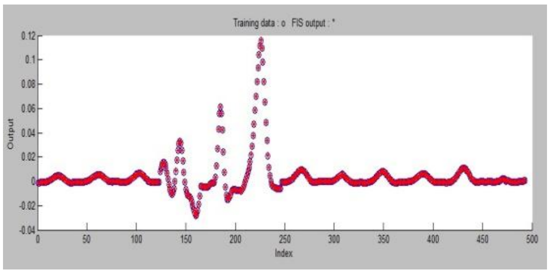

Fig.20. Trained data

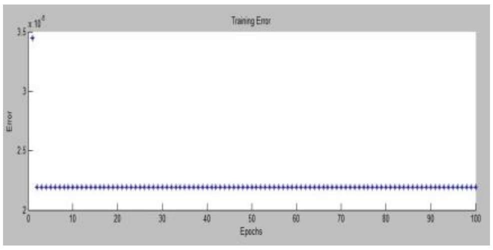

Fig.21. Training error

Now, in Fig.19-21, shows about the training data that how it will look during training (Fig.19), after training (Fig.20) and the error comes during training (Fig.21).

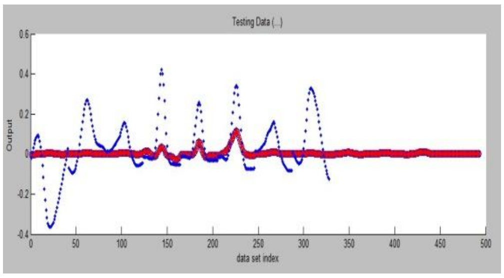

Fig.22. Testing data

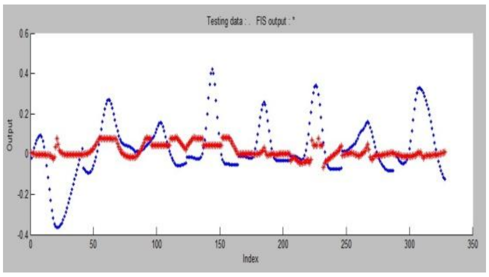

Fig.23. Testing results

Then next figures shows about testing using the Neuro-Fuzzy classifier. Among these figures, Fig.22-23 shows the testing data and testing results. And, Fig.24 represents the rule viewer which are made using the Fuzzy logic in this classifier.

IARJSET

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ISSN (Print) 2394-1588

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ISO 3297:2007 Certified

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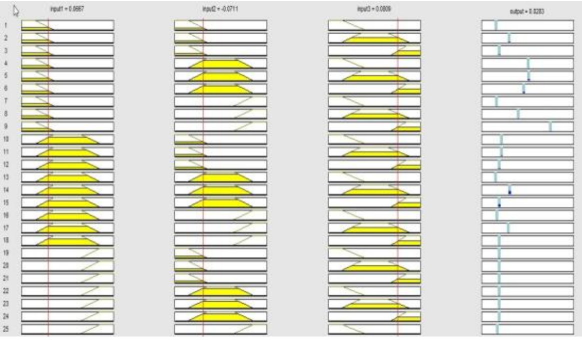

Fig.24. Neuro-Fuzzy rules

Then next, in Table VI, confusion matrix is shown showing the classification using Neuro-Fuzzy classifier. And it can be seen from the table that only 1-1 signals (AP and IS) are misclassified in the other classes but all other signals are accurately classified using this classifier.

TABLE VI
CONFUSION MATRIX FROM NEURO-FUZZY

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

Then in Table VII shown is the comparison of all these classifiers used during this research and it is perceived from the table that Neuro-Fuzzy classifier used gives the best results.

TABLE VII
COMPARISON OF THREE CLASSIFIERS

Classifier Name	Accuracy(%)
ANN	87.5
Fuzzy	91.70
Neuro-Fuzzy	95.83

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 the Neuro-Fuzzy classifier is upto 96% (approx.) which is more than the previous methods used and hence, this method can also be utilized by the doctors to classify various ECG signals.

REFERENCES

[1] Sahil Dalal, Rajesh Birok, “ECG Peaks Detection using Principal Component Analysis”, International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering, Volume 4, Issue 7, pp. 66-70, 2016.

[2] Sahil Dalal, Rajesh Birok, “ECG Signals Analysis using PCA with Neural Network and Fuzzy Logic”, International Journal of Advanced Research in Electronics & Communication Engineering (under publication).

[3] T.-W. D. Shen, W. J. Tompkins, and Y. H. Hu, “Implementation of a one-lead ECG human identification system on a normal population,” J. Eng. Comput. Innovations, vol. 2, no. 1, pp. 12–21, Jan. 2011.

[4] A. D. C. Chan, M. M. Hamdy, A. Badre, and V. Badee, “Wavelet distance measure for person identification using electrocardiograms,” IEEE Trans. Instrum. Meas., vol. 57, no. 2, pp. 248–253, Feb. 2008.

[5] C.-C. Chiu, C.-M. Chuang, and C.-Y. Hsu, “A novel personal identity verification approach using a discrete wavelet transform of the ECG signal,” in Proc. 2nd Int. Conf. Multimedia and Ubiquitous Engineering, Busan, Korea, 2008.

[6] J. Yao and Y. Wan, “A wavelet method for biometric identification using wearable ECG sensors,” in Proc. 5th Int. Summer School and Symp. Medical Devices and Biosensors, 2008 (ISSS-MDBS 2008), pp. 297–300.

[7] O. Boumbarov, Y. Velchev, and S. Sokolov, “ECG personal identification in subspaces using radial basis neural networks,” in Proc. IEEE Int. Workshop on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, 2009 (IDAACS 2009), Sept. 2009, pp. 446–451.

[8] M. Homer, J. M. Irvine, and S. Wendelken, “A model-based approach to human identification using ECG,” in Proc. SPIE, Orlando, FL, 2009, vol. 7306.

[9] F. Agrafioti and D. Hatzinakos, “Signal validation for cardiac biometrics,” in Proc. 2010 IEEE Int. Conf. Acoustics Speech and Signal Processing (ICASSP), Mar. 2010, pp. 1734–1737.

[10] A. Lourenço, H. Silva, and A. Fred, “Unveiling the biometric potential of finger-based ECG signals,” Computat. Intell. Neurosci., vol. 2011, no. 720971, 2011.

[11] B.U. Kohler, C. Hennig, R. Orglmeister, The principles of software QRS detection, IEEE Eng. Med. Biol. Mag. 21 (1) (2002) 42–57.

[12] C. Saritha, V. Sukanya, Y. Narasimha Murthy, ECG analysis using wavelets, Bulg. J. Phys. 35 (2008) 68–77.

[13] P. Ranjith, ECG analysis using wavelet transform: application to myocardial ischemia detection, ITBM-RBM 24 (January) (2003) 44– 47.

[14] J. Pan, W.J. Tomkins, A real time QRS detection algorithm, IEEE Trans. Biomed. Eng. 32 (3) (1985).

[15] O. Pahlm, L. Sörnmo, Software QRS detection in ambulatory monitoring – a review, Med. Biol. Eng. Comput. 22 (July) (1984) 289–297.

[16] F. Gritzali, Toward a generalized scheme for QRS detection in ECG waveforms, Signal Process. 15 (September) (1988) 183–192.

[17] G.M. Friesen, T.C. Jannett, M.A. Jadallah, S.L. Yates, S.R. Quint, H.T. Nagle, A comparison of the noise sensitivity of nine QRS detection algorithms, IEEE Trans. Biomed. Eng. 37 (January) (1990) 85–98.

[18] A. Ghaffari, H. Golbayani, M. Ghasemi, A new mathematical based QRS detector using continuous wavelet transform, Comput. Electr. Eng. 34 (2) (2008) 81–91.

[19] A.S.M. Koeleman, H.H. Ros, T.J. van den Akker, Beat-to-beat interval measurement in the electrocardiogram, Med. Biol. Eng. Comput. 23 (August) (1985) 213–219.

[20] Kang-Ping Lin, Walter H. Chang, QRS feature extraction using linear prediction, IEEE Trans. Biomed. Eng. 36 (10) (1989).

[21] I.K. Daskalov, I.A. Dotsinsky, I.I. Christov, Developments in ECG acquisition, preprocessing, parameter measurement and recording, IEEE Eng. Med. Biol. Mag. 17 (September) (1998) 50–58.

[22] Abdulnasir Hossen, Bader Al-Ghunaimi, A wavelet-based soft decision technique for screening of patients with congestive heart failure, Biomed. Signal process. Control 2 (May) (2007) 135–143.

[23] J.G.C. Kemmelings, A.C. Linnenbank, S.L.C. Muilwijk, A. Sippens-Groenewegen, A. Peper, C.A. Grimbergen, Automatic QRS onsetand offset detection for body surface QRS integral mapping of ventricular tachycardia, IEEE Trans. Biomed. Eng. 41 (September) (1994) 830–836.

[24] E.S. Jayachandran, K. Paul Joseph, R. Acharya U, Analysis of myocardial infarction using discrete wavelet transform, J. Med. Syst. 34 (October) (2010) 985–992.

[25] C. Li, C. Zheng, C. Tai, Detection of ECG characteristic points using wavelet transforms, IEEE Trans. Biomed. Eng. 42 (January) (1995) 21–28.

[26] J.S. Sahambi, S. Tandon, R.K.P. Bhatt, Using wavelet transform for ECG characterization, IEEE Eng. Med. Biol. 16 (1) (1997) 77–83.

[27] Themis P. Exarchos et al., Association rule-mining based methodology for automated detection of ischemic ECG beats, IEEE Trans. Biomed. Eng. 53 (8) (2006).