Australian Journal of Basic and Applied Sciences, 9(35) November 2015, Pages: 321-330

ISSN:1991-8178

Australian Journal of Basic and Applied Sciences

Journal home page: www.ajbasweb.com

Classification of Cardiac Arrhythmia Using Wavelets and Probabalistic Neural Network

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ARTICLE INFO

Article history:
Received 1 November 2015
Accepted 28 November 2015
Available online 18 January 2016

Keywords:
Electrocardiogram (ECG), Cardiac Arrhythmia MIT-BIH database, Probabilistic Neural Network(PNN)

ABSTRACT

Electrocardiogram (ECG) is a graphical form for electrical activity of cardiac muscle. A healthy human heart beats, 72 times per minute under normal conditions. For every heartbeat the cardiac muscle undergoes specific electrical activity which identifies the pattern in the ECG signal. It consists of PQRST wave which represents heart functions. Normal healthy heart can be recognized by normal ECG signal while heart disorder or arrhythmias signals contain variations in terms of features and attributes in their corresponding ECG waveform. The patterns of the ECG signal changes due to the abnormalities in the heartbeat. The abnormality in the ECG is called Arrhythmia. There are different statistical techniques to classify normal and abnormal signals. The Cardiac arrhythmia identification using neural network gives more performance and accuracy. The features are extracted from the ECG signal by using several statistical formulas. The features are then given to the neural network in the proposed work by using, MIT-BIH Arrhythmia dataset and the classification using Probabilistic Neural Network is done. This proposed system gives the statistical analysis for identification of normal and abnormal ECG with more accuracy and sensitivity.

To Cite This Article: I.S. Siva Rao, T. Srinivasa Rao, P.H.S. TejoMurthy and P.V.G.D. Prasad Reddy., Classification of Cardiac Arrhythmia Using Wavelets and Probabalistic Neural Network. ***Aust. J. Basic & Appl. Sci.,*** *9(35): 321-330, 2015*

INTRODUCTION

The electrical activity of the human heart is depicted by a biomedical instrument in the form of an Electrocardiogram (ECG). The generation of the electrical signals is due to the relaxation and contraction of the human heart. These electrical signals are recorded in the form of electrocardiogram to the study the behavior of human heart, by which a doctor can understand the problem present in the heart[17]. The abnormal signal which is called cardiac arrhythmia is diagnosed and treated to save the patient in time[8]. A Doctortakes the ECG graph and classifies the cardiac arrhythmia and treats the patient. The ECG signal taken from the bio-medical instrument contains several types of noises which can be lead to error in the classification (Sathya, R., 2015). So this noisy ECG data is preprocessed and features are extracted for the classification. In this paper, the author has applied probabilistic neural networks for analyzing cardiac rhythms (Muthuchudar, A., 2013) TheNeural network isapplied inmany areas especially for analyzing cardiac rhythmsand classification of normal and abnormal signalsand many more.Recognition of peaks of ECG signals is essential to diagnose the abnormality (TarmiziAmaniIzzah, 2013).

1.1ECG Description:

The human heart contains four chambers viz., left atrium, right atrium, left ventricle and right ventricle which works in two phases. Depolarization is a phase which is an electrical activity corresponds contraction and repolarization is another phase which is relaxation[5]. These two phases correspondsthe ECG signal by PQRST points. P-wave for atrial depolarization, QRS for ventricles depolarization and T-wave for ventricular repolarization (Stalin Subbiah, 2015). The Normal ECG waveform is shown in Fig. 1

There are several ways to extract the features such as amplitude and frequency components.The ECG signal analysis is done be pre-processing, denoiseand then features are extracted for classification and get the output from the neural network (Asutosh Kar1, Leena Das, 2011).

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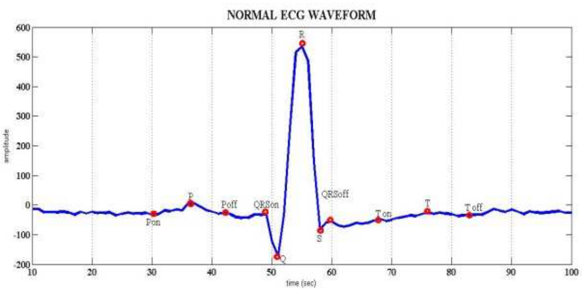

Fig. 1: Normal ECG Waveform.

Proposed System:

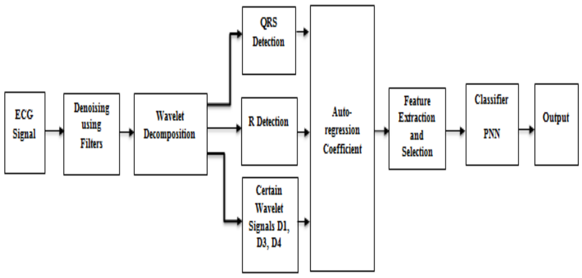

Fig. 2: Block Diagram for the Methodology of the proposed system.

First, the ECG signal is denoised by using filters for noise elimination and preprocessing. The ECG points detected by using wavelet decomposition are P-wave, QRS wave, R wave and certain wavelet signals. By using auto-regression coefficients, features are selected. These selected features are given to PNN Classifier to get the output. Once the features have beenextracted, samples are randomly selected and this new set is split into training and testing. The training samples are employed to the classifier for testing the samples (MajidMoavenian, Hamid Khorrami, 2010). Fig.2 is the flowchart illustration for the methodology of the proposed system.In the first step, the ECG signal is taken from MIT-BIHdatabases, which is publicly available. The preprocessing aims to reduce the noise from the ECG signal, obtained from the standard 12 leads. Finite impulse response (FIR) recursive digital filters are usedfor attenuating the noises (Shing-Hong Liu, 2013). The ECG consists of the heartbeatfiducial points mostly, P wave, the QRS complex, and T wave.To evaluate different representations, distinct set of featuresare extracted from the ECG signal. These sets were selected using auto-regression technique largely disseminated for representing a heartbeat to classify arrhythmia. The goal is to classify a normal and abnormal signal of the heart (Afonso, V.X., 1999).

The raw ECG signal is taken from Physio-Bank, Physio-Toolkit, and Physio-Net. For Normal ECG, MIT-BIH normal sinus rhythm database (nsrdb) is used. This database consists of 18 long-term recordings of subjects from the Arrhythmia Laboratory at Boston's Beth Israel Deaconess Medical Centre. In this database we have taken 10,000 samples per 60 seconds from nsrdb. For Abnormal ECG, MIT-BIH Arrhythmia database (mitdb) records no 101, ML11 and V1 signals with 10,000 samples per 60 seconds are used.

The peaks of ECG signal values are statistically analysed taking mean, variance, standard deviation, kurtosis and auto-regression coefficient for feature extraction and selection. Table-I shows the statistical analysis for raw normal and abnormal ECG signal without filtering. Figures 2 and 3 represent the raw and normal abnormal signals. Now these raw normal and abnormal ECG signals are decomposed by using wavelet decomposition.

2.1 Wavelet Decomposition:

Let $\Psi(t)$ be a complex valued function in $L^2(R)$, whose Fourier transform $\hat{\Psi}(\omega)$ satisfies:

$$\int_{-\infty}^{\infty} \frac{|\hat{\Psi}(\omega)|^2}{|\omega|} d\omega = C_\Psi < +\infty \quad (1)$$

Let $\Psi s(t) = 1/s\ .\Psi(t/s)$ be the dilation of $\Psi(t)$ by a scale factor of $s>0$

(Eq. (1). The WT of a function $f(t) \in L^2(R)$ at scale s and position τ is defined by:

$$W\,f(s,\tau) = 1/s \cdot \int_{-\infty}^{\infty} f(t)\Psi^*\left(\frac{t-\tau}{s}\right)dt \quad (2)$$

Where * denotes complex conjugation. In a case of WT (equation (2) is invertible.

$$f(t) = \frac{1}{C_\Psi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} Wf(s,\tau).\Psi^*\left(\frac{t-\tau}{s}\right)d\tau.\frac{ds}{s^2} \quad (3)$$

The selected wavelet is

$$\Psi(t) = \frac{1}{\sqrt{2.\pi.\sigma}}.e^{-t/2.\sigma}.\sin\alpha.t.e^{\beta t} \quad (4)$$

Where α and β is selected according to the highest frequency in ideal ECG signal and σ is the dispersion which is to modify the shape.In our experiment we used $\alpha = 200 \cdot \pi$, $\beta = -1/3$. The Wavelet Transform depends upon two parameters, scale *s* and position τ. The dyadic wavelet is determined using a scale $s = 2^j$, where $j \in Z$ and Z is the integral set.

The Wavelet Transform (Eqs. (3 and 4), at scale $s = 2^j$is obtained by

$$W f(2^j, \tau) = 1/2^j \cdot \int_{-\infty}^{\infty} f(t)\Psi^* \left(\frac{t-\tau}{2^j}\right)dt \quad (5)$$

TheDiscrete Wavelet Transformation(DWT) is done for these signals. The wavelet transform explains about a multi-resolution decomposition analysis in terms of expansion of a signal on set of wavelet basis function. The multi-resolution analysis technique is used to analyze the different frequencies using different resolutions (Vanitha*et*, S., 2015). The inputDaubechies mother wavelet is divided into 8 multi-resolution sub-bands by filters, viz, db1,db2,upto db8, where db means Daubechies wavelet (GuhanSeshadri, N.P., 2015). Figure 4 represents the output of Daubechies wavelet

Table 1: Statistical Analysis for raw Normal and Abnormal ECG Signal without filter.

Statistical Analysis	KURTOSIS	Normal ECG1 without filter	Abnormal ECG1 without filter
Mean	k1	1.206535819	2.019468923
	k2	1.182244279	2.188475426
	k3	1.226621893	2.597791679
	k4	1.297399192	1.256882348
Variance	k5	1.417954494	1.240075571
	k6	1.281877227	1.172723794
	k7	1.168734573	1.169332426
	k8	1.326548936	1.16816487
Standard Deviation	k9	1.251937754	1.192022423
	k10	1.265181477	1.171905788
	k11	1.172795734	1.174437979
	k12	1.231859785	1.178619962

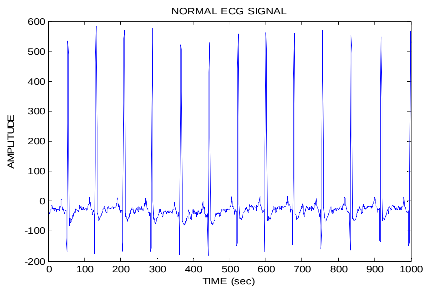

Fig. 2: The raw Normal ECG Signals.

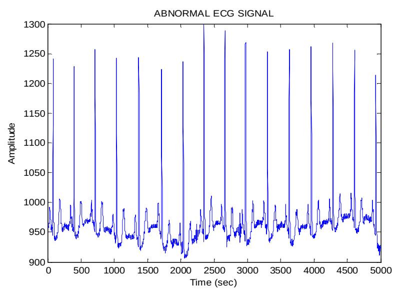

Fig. 3: The raw Abnormal ECG Signals.

2.2. Feature extraction:

After Denoising the signalsusing filters and the wavelet decomposition for 10,000 samples, auto-regression coefficients (AR) is applied for reducing upto 1000 samples by using statistical formulas mean,variance, standard deviation, kurtosis (Siva Rao*et*, I.S., 2015) to obtain patterns. From these, the features R-Peak and QRS Detection are detected.

Table:2Shows the Statistical Analysis for Denoised Normal and Abnormal ECG Signal. The corresponding Pictorial representation is shown in figure 5 and figure 6 for normal and abnormal ECG after Denoise. Table:3 Shows the Statistical Analysis for R-Peak and QRS Detection for Denoised Normal ECG Signal and thecorresponding baseline elimination, QRS Detection and R Peak for Normal Signal are shown in figure 7, figure8 and figure 9.

Table:4Shows the Statistical Analysis for R-Peak and QRS Detection for Denoised Abnormal ECG Signal and the corresponding figures are shown in figure 10 and figure 11. All these features are combined and autoregression coefficient is used statistically. These samples are given to Probabilistic Neural Network (PNN) classifier to get accurate and sensitive output with minimum error.

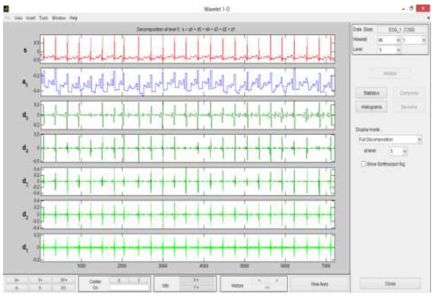

Fig. 4: Daubechies wavelet.

Table 2: Statistical Analysis for Denoised Normal and Abnormal ECG Signal.

Statistical Analysis	KURTOSIS	Normal ECG1 with filter (ecgsmooth)	Abnormal ECG1 with filter (ecgsmooth)
Mean	k1	1.525910483	1.852818037
	k2	1.20710369	1.92200894
	k3	1.27721548	2.420407061
	k4	1.319927025	1.414634205
Variance	k5	1.427424044	1.238666013
	k6	1.298270989	1.171885415
	k7	1.16968934	1.168927602
	k8	1.308651624	1.168300446
Standard Deviation	k9	1.256513476	1.191763384
	k10	1.270426239	1.171689894
	k11	1.172457784	1.173155976
	k12	1.225305064	1.178572479

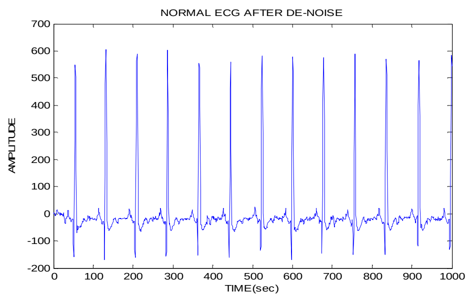

Fig. 5: Normal ECG After Denoise.

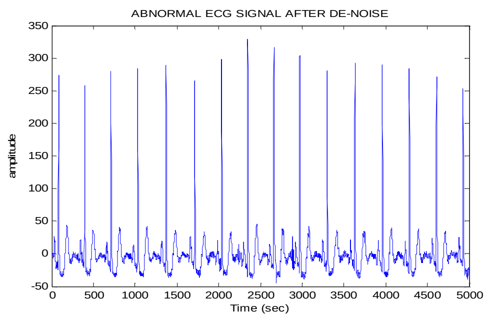

Fig. 6: Abnormal ECG After Denoise.

Table 3: Statistical Analysis for R-Peak and QRS Detection for Denoised Normal ECG Signal.

Statistical Analysis	KURTOSIS	Normal ECG1 with filter (qrs detection)	Normal ECG1 with filter(r peak)
Mean	k1	1.225882196	1.633556573
	k2	1.171546483	1.563085595
	k3	1.18154791	2.253588095
	k4	1.177480923	1.476295575
Variance	k5	1.263070574	1.259595338
	k6	1.276962934	1.562994555
	k7	1.344523286	2.132839191
	k8	1.264601424	1.180863558
Standard Deviation	k9	1.312049854	1.264149424
	k10	1.295180393	1.396953911
	k11	1.516357122	2.277432233
	k12	1.331956874	1.181696582

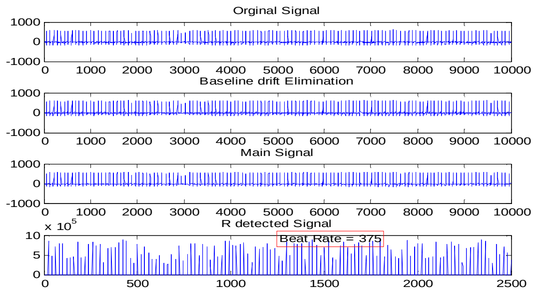

Fig. 7: Baseline elimination of ECG AfterDenoise.

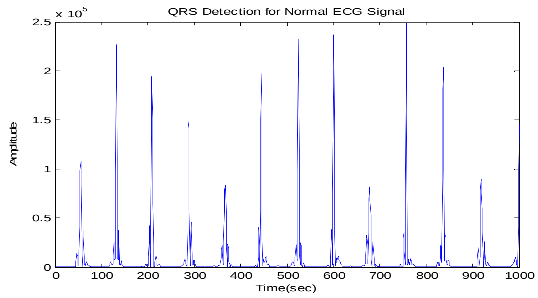

Fig. 8: QRS Detection for Normal ECG Signal.

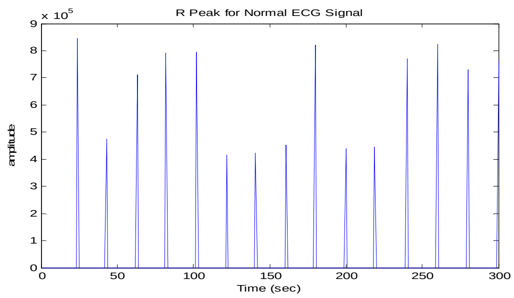

Fig. 9: R Peak for Normal ECG Signal.

III. Classification Using Probabilistic Neural Network (PNN):

After the above statistical analysis, which is applied to several ECG subjects classification is done to obtain accurate and sensible output. Total 96 ECG subjects are taken, from which 24 Normal databases and 72 abnormaldatabases are used for classification. In these 20 normaland abnormal signals are used for training and 4 normal and 52 abnormal signals are used for testing. The Classification of data is done by using PNN after decomposition and statistical analysis. There are different classification algorithms in which neural network gives accurate and best performance.

3.1Neural Network:

A Neural Network is an interconnection of input nodes and output nodes with associated weights in each connection which is inspired by biological neuron of brain (Gupta, K.O., 2012). A neural network connects from the output of one neuron to the input of another.Neural network plays an important role in machine learning, pattern recognition, cognitive science and also it is the family of statistical learning algorithms inspired by biological neural networks (Ajeet Sharma and KushagraBhardwaj, 2015). The architecture of neural network is shown in the figure 12. The network is trained by using back propagation algorithm so as to get the sum square error reaching minimum values. For effective training, the data is spread throughout the class. The training is done on the data repetitively to get the error to its minimum. After training is completed the test data is applied on the basis of proposed network.

Table 4: Statistical Analysis for R-Peak and QRS Detection for Denoised Abnormal ECG Signal.

Statistical Analysis	KURTOSIS	Abnormal ECG1 with filter(qrs detection)	Abnormal ECG1 with filter(r peak)
Mean	k1	1.181220008	1.647985018
	k2	1.673796884	1.288211638
	k3	1.702793534	1.599294662
	k4	2.45459721	1.429242418
Variance	k5	1.31899799	2.09696477
	k6	1.731965172	1.233916441
	k7	1.297900244	1.326956021
	k8	1.240173557	1.98495943
Standard Deviation	k9	1.203009234	1.975272791
	k10	1.335504889	1.239701382
	k11	1.196477173	1.327003384
	k12	1.186823847	2.044728525

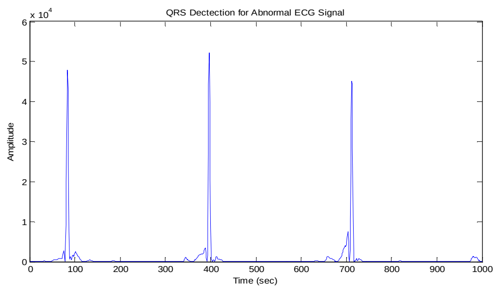

Fig. 10: QRS Detection for Abnormal ECG Signal.

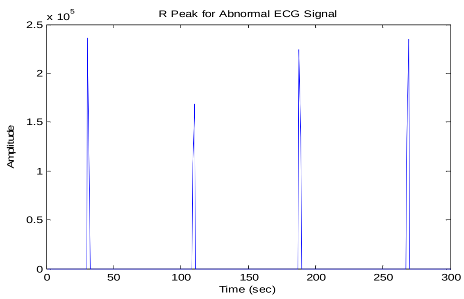

Fig. 11: R Peak for Abnormal ECG Signal.

IV. Results:

The Probabilistic Neural network (PNN) Classifier is applied on this MIT-BIHArrhythmia dataset in MATLAB. Todetermine the accuracy, specificity and sensitivity of the classifier their results are analyzed for various evaluation metrics. In Neural network the data is selected and trained to the network to evaluate its performance using entropy and confusion matrix.Figure 13 shows the two layered feed forward network with sigmoid hidden layer and softmax output layer(pattern net)[20]. The network is trained with scaled conjugate gradient backpropagation (trainscg).

The Trained Patterns of Normal and Abnormal data shown in Table 5 is applied to the Levenberg-Marquardt (trainlm) algorithm. The Levenberg-Marquardt (trainlm) algorithmis designed toapproach second-order training speed.

Figure 15 is the pictorial representation for the Regression Chart for the training, validation,and test on the Feed forward Network. The regression for all training, validation and testing is R=0.95735.

Australian Journal of Basic and Applied Sciences, 9(35) November 2015, Pages: 321-330

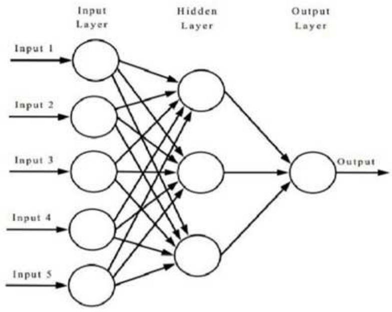

Fig. 12: Architecture of Neural Network.

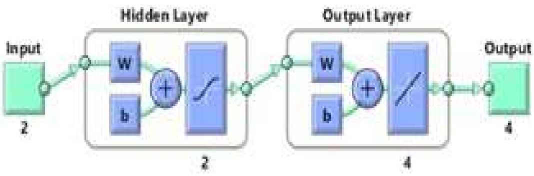

Fig. 13: Two layered feed forward network with hidden layer and output layer.

Table 5: Trained Patterns of Normal and Abnormal data.

Train	1	2	3	4	5	6	7	8	
Pattern No	WOF (1)	WF S(1)	WF RP(1)	WF QRS (1)	WOF (2)	WF S(2)	WF RP(2)	WF QRS (2)	
T1	1.207	1.526	1.634	1.226	1.869	2.208	1.632	1.398	Normal
T2	1.182	1.207	1.563	1.172	1.270	1.938	1.529	2.327	Normal
T3	1.227	1.277	2.254	1.182	1.332	1.295	1.862	1.329	Normal
T4	1.297	1.320	1.476	1.177	2.419	2.149	1.389	1.225	Normal
T5	2.019	1.853	1.648	1.181	1.433	1.474	1.234	2.149	Abnormal
T6	2.188	1.922	1.288	1.674	1.844	1.323	2.333	1.646	Abnormal
T7	2.598	2.420	1.599	1.703	1.912	1.689	1.284	2.332	Abnormal
T8	1.257	1.415	1.429	2.455	2.191	2.007	1.344	1.253	Abnormal

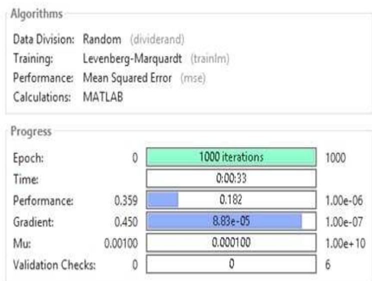

Fig. 14: Lavenberg-Marquardt algorithm.

Precision = TP/(TP+FP)
Recall= TP/(TP+FP)
F-Measure = (2.Precision.Recall)/(Precision+Recall)
Accuracy= (TP+TN)/(TP+TN+FP+FN)
where,

- TP – true positive, represents that the positive tuplesare correctly classified.
- TN – true negative, represents that the negative tuplesare correctly classified.
- FP – false positive, represents that the negative tuplesare incorrectly classified.
- FN – false negative, represents that the positive tuplesare incorrectly classified.
- Precision – represents how many selected tuples areclassified correctly.

Australian Journal of Basic and Applied Sciences, 9(35) November 2015, Pages: 321-330

- Recall – represents how many relevant tuples areselected.
- F-Measure – represents a measure that combinesprecision and recall is the harmonic mean of precisionand recall[16],[9].

The performance function is sum of squares form as in training feedforward networks, then Hessian matrix can beapproximated as$H = J^TJ$. And the gradient can be computed as$g = J^Te$. Where J is the Jacobian and e is a vector of network errors. TheLevenberg-Marquardt algorithm uses this approximation to theHessian matrix. theperformance function will always be reduced at each iterationof the algorithm.[15].The Levenberg-Marquardt function is used for training neural network. Figure 16 shows the graph for the best validation performance. The best validation performance is 0.18588 at epoch 83(iteration) of the proposed neural network.

The Receiver Operating Characteristics (ROC) for the training ROC, Validation ROC, and test ROC are shown in the figure17 for the false positive rate is between 0.8 to1.

All Confusion Matrix for training, validation, test are shown for all the target class.

Figure 19 is the pictorial representation for the Error Histogram of the PNN Classifier.

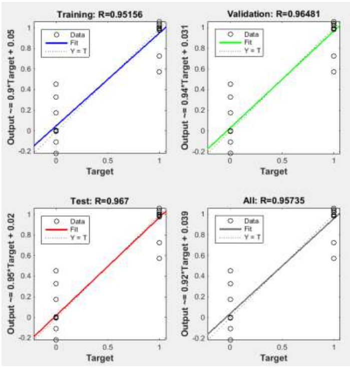

Fig. 15: Regression Chart.

Table 6: Predicted Class and Actual Class.

	PREDICTED CLASS		
ACTUAL CLASS		C1	C2
	C1	TP	TN
	C2	FP	FN

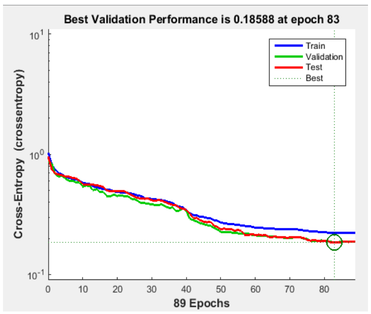

Fig. 16: Performance.

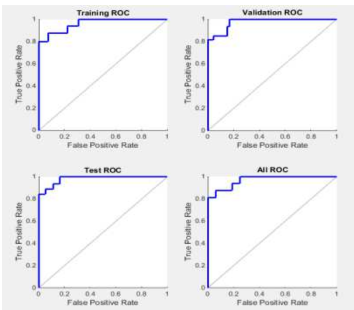

Fig. 17: ROC (Receiver Operating Characteristic).

Fig. 18: Confusion Matrix.

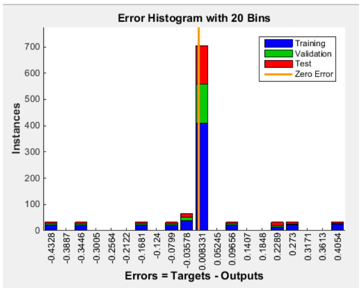

Fig: 19. Error Histogram.

Table 7: Comparison of Error Identification of Error when Wavelets and autoregressionare used.

S No	Wavelet group	Error
1	Daubechies, Haar	8%
2	Daubechies coefficient	7%
3	Haar coefficient	15%
4	Combined Auto regression coefficient	2.9%
5	Probabilistic Neural Network	0.96%

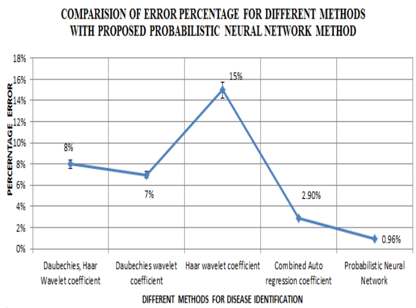

Fig. 20: Chart showing comparison of error percentage for different methods with PNN.

In the Comparison Chart shown in the figure 20.for Error Identification, it is clear that when different approaches are applied like Daubechies, Haar, combined Daubechies, Haar coefficient and combined auto-regression the error percentage is little more than that when data applied to PNN. Therefore the Classifier used gives very less error percentage. So this proposed classifier is more efficient than any other.

Conclusion:

In this paper, the authors have presented a novel feature selection method for classification of cardiac arrhythmias. The results of our proposed method are shown in figures. The performance of the proposed model for classifying the data is more accurate classification than any other. The learning methods and statistical analysis of the classifiers helped in the classification of unevenly distributed arrhythmia groups. It is evident that the statistical model analysis is more efficient to classify the bio-medical signals which are more uneven.

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