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A Hybrid-Neuro Computing Approach for Cardiac Arrhythmia Classification

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Abstract: A number of techniques have been proposed in literature for classification of electrocardiography (ECG) tracing. Mainly statistical procedures and automated approaches are used. In this paper, authors present a hybrid neural computing technique that is used to diagnose and classify arrhythmias. The performance of the network over normal and abnormal ECG traces has been evaluated. The signal processing includes statistical calculations, feature extraction using Elman1-ANN and wavelet based compression approach. Performance of the presented artificial neural network is experimentally evaluated and compared with work in other studies. The simulation results based on the proposed approach illustrate recognition rate of 93.06%,91.97% and 90.83% for three hybrid artificial neural networks. A smaller time to compute the simulation results further supports the effectiveness of the approach. MatLab R2014a is used for statistical calculations.
Keywords: Arrhythmia; Pattern Recognition; Euclidean Distance; ECG (Electro-cardiograph).

1. Introduction

Electrocardiograph (ECG) is a graphical representation of cardiac function based on bioelectrical signals. This graphical record represents heart muscle activities that result from depolarization and polarization of the heart muscle cell membrane [1]. Piece wise/ segment wise examination of the ECG tracing is used to arrive at a diagnosis. Any variations from the normal ECG trace are referred to as arrhythmia [2]. Arrhythmias are classified into various types based on the bioelectrical pattern observed, which a tedious and sensitive task is. The quality of living is improved by timely detection of heart abnormalities which is highly dependent on accurate interpretation of ECG tracing [3]. Various techniques have been devised to detect and classify arrhythmias [4,5,6]. Use of various artificial neural networks types for detection and classification of arrhythmias is well-documented [7,8,9,10]. Artificial Neural Network models represent an extension of the conventional processes techniques in which the weights are updated with gain of experimental knowledge [11].

Input layer in the artificial neural network is the sensory input. Output shows the corresponding label. Hidden layer is the feature layer [12]. Input-output relationship for complex and low cost systems results in decrease of generalization behaviour capabilities of ANN [13].

Scaled input data is presented to the input nodes of an ANN, which is subsequently passed on to the hidden layer through weights. Each node at the hidden layer computes the sum of weighted inputs together with a bias [14]. ANNs perform well on nonlinear data. These networks show better predictive quality in comparison to linear and multiple regression models [15]. However, these methods have merits as well as demerits. Some techniques require larger processing time as far as training is concerned. The complexity of the ANN too grows with the increasing number of variables. This limits the capacity for detection of abnormalities. Therefore, there is a need for improvement in the methods used for detection and classification of arrhythmias. Keeping pace with the requirement, we present a hybrid neural network developed by hybridizing Elman1 with Elman to detect and classify arrhythmias. To improve the accuracy of detection and classification 274 ECG tracings were obtained from different patients in an experimental setting. Out of these, 50% tracings were used for training the neural network and 50% for testing the neural network. We achieved an accuracy rate of the order of 90.83%, 91.97% and 93.06%, respectively, achieved with the hybridized artificial neural networks. Boolean bit distribution has been used to classify the arrhythmias (Table1). Illness number is recorded from the data set chosen. The number of tracings selected from among the data set is indicated in Table 1. The table also shows type of illnesses classified in this study.

Table 1: Classification of ECG tracings

Illnesses	Boolean distribution	Type	Number of traces
1	1 0 0 0 0 0 0 0 0 0 0	Normal trace	186
15	0 0 1 0 0 0 0 0 0 0 0	A trial fibillation	6
9	0 0 0 0 1 0 0 0 0 0 0	Left bundle branch block	8
10	0 0 0 0 0 0 1 0 0 0 0	Right bundle branch block	48
5	0 0 0 0 0 0 0 0 1 0 0	Sinus tachycardia	13
3	0 0 0 0 0 0 0 0 0 0 1	Old anterior myocardial infarction	13

2. Methodology

2.1 Principle of the proposed work

In this methodology it is presented an Elman1- Elman hybrid Neuro-computing approach on vectors representing whole ECG trace. ECG data is a long-term record from the heart. Long term data makes the data to grow significantly. Compression is required to reduce the data while retaining time and frequency features of the signal. Elman1-Elman-Wavelet based artificial neural network hybrid approach is proposed in this study. Data is acquired from the UCI data base[16]which comprises of data on eleven different illnesses in addition to that for normal subjects. Only six illnesses are selected for the purpose of this study from the data base. Normal data comprises of 186 waveforms while different abnormal ECG waveforms contain 88 waveforms.

Half of the data is used for training the artificial neural network and another half is used for testing the results. For consistency, even if data set contains odd samples, one sample is kept both in training and testing data. The input to the Elman comprises of four components:

First vector comprises of a 5-bit vector. ECG trace is plotted using MatLab command. The longest R peak is detected using statistical procedure annotation technique; portion of the wave containing Q wave and QRS offset are extracted which forms a 5 bit vector. ------(1)

Thirteen parameters are extracted from this trace. --------(2)

Therefore a 18 bit vector is formed, i.e.,

V_1= component(1) + component(2)

ECG trace is downloaded from the data base. The wave form is compressed using db6 wavelet. This forms 13 bit trace. --------(3)

Eleven parameters are extracted from this 13 bit trace and a24-bit vector is formed.--------(4)

V_2= component(3) + component(4)

Va $=V_1+V_2$ -------- (5)

All four components comprising vector Va, therefore constitute a set of 42 inputs which correspond to the complete tracing, as an input for the neural network.

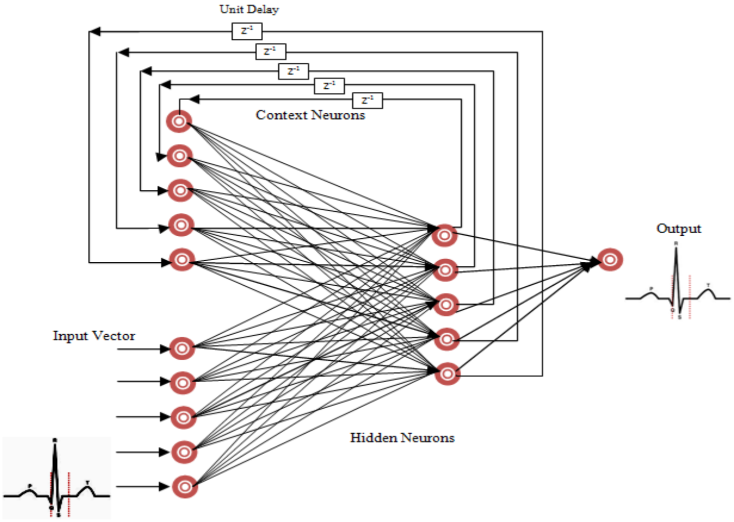

Fig. 1 Schematic illustration of the Elman1-Artificial neural network

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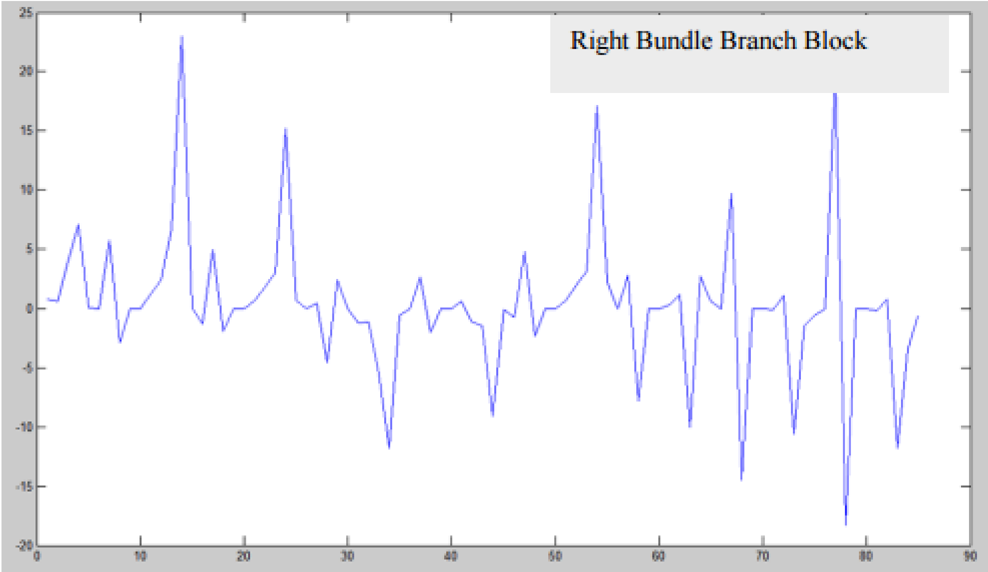

Fig. 2 Right Bundle Branch Block

Va is applied at the input nodes of the Elman to classify the beats, Therefore instead of the whole ECG trace, the authors use 42 elements vector,5. This is a method to recognize and classify the pattern with lesser number of elements representing the whole trace. At the same time the complexity of the circuit is also reduced.

2.2 Network Architecture

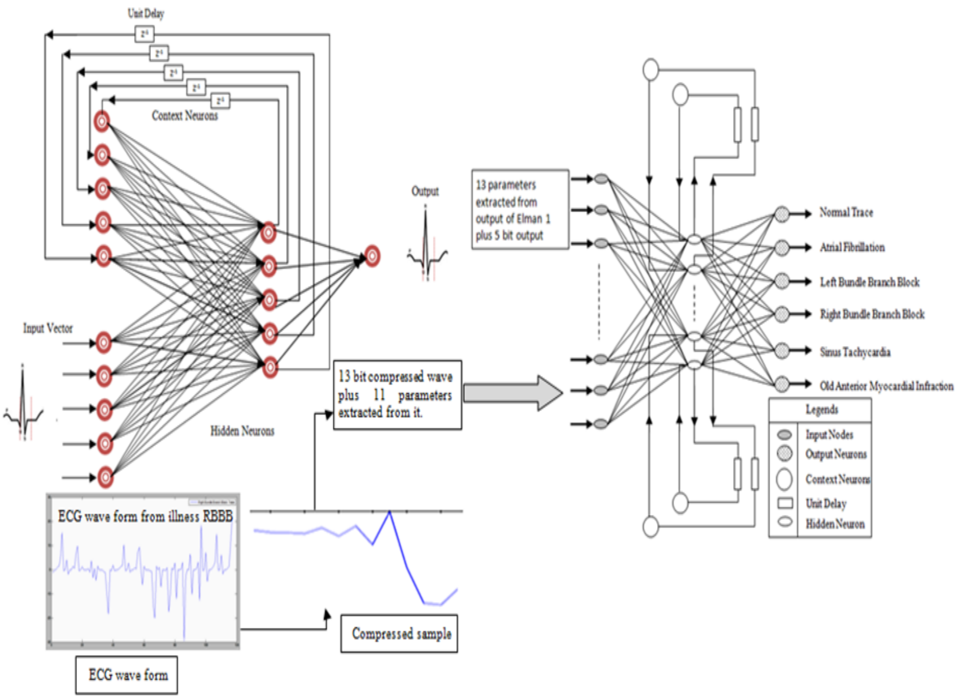

Fig. 3 Elman1-Elman Hybrid artificial neural network with 42 inputs and 6-output nodes

2.2.1 Elman1-Artificial neural network

Elman1 artificial neural network design has been used for feature extraction. From the ECG trace QRS complex parameters are extracted by making use of statistical technique and also by adopting manual annotation. The procedure adopted allocates tallest peak as the R peak. Manual annotation allocates Q point and QRS offset. This forms a 5 bit vector. This vector serves as input to the Elman1-ANN. Elman1 ANN is a unity network. The input applied at the input nodes is reproduced at the output. At the output the first normal pattern is compared

with the first normal pattern and a Euclidean distance of the order of e-012 is achieved. Likewise, other normal patterns are compared with first normal patterns. Similar procedure is adopted for other abnormal patterns. The features extracted at the signal appearing at the output of Elman1 are Euclidean distance, mean of the trace, threshhold1, threshhold2, mean value of spectral density estimate (PSD) represented by f1, auto covariance, autocorrelation, percent root- mean square difference (PRD), signal to noise ratio, SNR1, SNRdB, root mean square error, RMSE, Peak signal to noise ratio, PSNR and are capable of expressing the degree of variations in the ECG trace and help to classify the variations as label 1, label 2 and label 3, thus; classifying the beat type. Threshold 1 & 2 used are 18% on the left and 69% on the right side of the mean value of the captured signal.
2.2.2 Daubechies wavelet. A number of wavelets have been used in ECG data classification. The type of wavelet and the level of decomposition required to achieve the classification results depends on the data used and the application developed. Discrete wavelet transform, Daubechies wavelet (db6) further compresses the downloaded ECG trace in the proposed study. Selection of a suitable wavelet and the number of levels to which a signal is decomposed is important in the study of arrhythmic conditions of heart. In this study Daubechies wavelet is used and decomposition level used is of the order of 6. Db6 identifies the changes in ECG signal [7].The 6th level decomposition maintains the signal properties. In this study, compressed wave vector comprises of 13 element vector, n1 is the Euclidean length, a parameter derived from the decomposed vector, n2 is also a measure of magnitude, x is filtering of matrix, x11 is maximum value of the filtered signal, w is the eigen roots of the decomposed vector, c is ceptal analysis, Hest component derived from ceptal analysis, e1 is Shannon entropy e2 is the norm, e3 is the log energy and e4 is the threshold in wentropy. All these parameters are eleven in number and are extracted from compressed wave. Vector, Va from equation 5 is input to the Elman for classification of the heart data.

Table 2 Number of neurons in the output and hidden layer of Elman-ANN

Stages	Network	Input layer	Output layer	Hidden Layer
Single	NET1	42	6	6
Single	NET2	42	6	6
Single	NET3	42	6	8
Single	NET4	42	6	3
Single	NET5	42	6	7
Single	NET6	42	6	4
Single	NET7	42	6	5
Single	NET8	42	6	4
Single	NET9	42	6	4
Single	NET10	42	6	15

2.2.3 Elman-Artificial neural network
The vector, Va is applied as inputs at the input nodes of the Elman-ANN architecture presented in Figure3. The network contains H hidden neurons through random generation of weights that are updated at every iteration. Hidden neurons are connected through randomly generated weights to six outputs.

2.2.4 Data Acquisition and Description
ECG traces are downloaded from [16]. Data comprises of 274 ECG traces. These data are a mix of normal tracings and tracings of five different types of arrhythmias. The selected ECG waveforms belong to six classes including, normal trace(NT), a trial fibrillation(AF), left bundle branch block(LBBB), right bundle branch block(RBBB), sinus tachycardia(ST) and old anterior myocardial infarction (OAMI). A total of 274 traces were downloaded. Out of every class, 50% waveforms are selected for training and 50% waveforms for testing purpose. A limitation in the study is that in some of the traces, peak value appears at the farthest end of the trace. In this situation, instead of peak value point, somewhat left to the peak value is selected and other points are selected accordingly. Secondly, the number of hidden neurons chosen is not fixed. The number of hidden neurons tried are H (3, 4,5,6,7,8and 15). Number of hidden neurons for a particular network NET N(N=1:10) are indicated in Table 2. Also the training function is also not fixed. Different training functions are tried to optimize the solution. Number of epochs used, time taken to calculate the classification is also indicated in the Table3.

The hybrid artificial neural network was run on a system having 1.8GHz processor, RAM 2GB. The stopping criterion is kept as 1000 epochs during training Elman1-Elman network. To show the simplicity of the approach a low configuration system is considered and neural network is run on the same system.

3.1 Training and Testing Performance:

3.1.1 Elman 1: This network is trained with 1000 epochs. As the network shows the results of a unity network, it is stabilized and is used for testing. The network is trained with data from normal and abnormal tracings. As the network correctly reproduces the signal at the output, itis subjected to tests.

3.1.2 Elman: Elman-ANN comprises of 42 inputs, H(3,4,5,6,7,8,15) hidden neurons and six outputs to classify six different illnesses. Data compiled is copied to ten different files, randomized and each file divided into training and testing data. The network is trained by repeatedly presenting inputs to the network. Once the network shows performance, it is subjected to tests with the data not seen earlier.

Table 3. Test results of the Classifier

Data set	FP	FN	TP	TN	Se%	Sp%	RR%	Hidden neurons	Epochs	Time
NET1	24	12	119	667	90.83	96.52	**90.83**	6	6	0:00:02
NET2	28	27	109	658	80.14	97.08	80.14	6	6	0:00:04
NET3	50	25	113	634	81.88	92.69	82.48	8	6	0:0008
NET 4	152	13	126	531	90.64	91	**91.97**	3	6	0.00:03
NET5	30	14	121	657	89.62	95.63	89.62	7	6	0:00:02
NET 6	30	21	93	541	81.57	94.74	81.57	4	6	0:00:02
NET 7	29	38	105	649	78.35	94.46	78.35	5	6	0:00:02
NET 8	24	24	113	661	82.48	96.49	82.48	4	6	0:00:02
NET9	23	13	102	547	88.69	95.96	88.69	4	6	0:00:02
NET 10	32	14	94	687	87.03	95.54	**93.069**	15	6	0:00:03
					85.123	95.01	85.91			0.02208

Table 4. The test result of 3 artificial neural networks with highest recognition rates

	NT%	**AF%**	LBBB%	**RBBB%**	ST%	OAMI%	Agg. Illnesses(%)
NET10	98.46	80	66	79.16	33	80	85.87
NET1	97.82	75	66.66	94.44	55.55	40	89.08
NET4	97.64	100	66.66	92.00	81.81	44.44	96.54
Aggregate%	97.97	85	66.44	88.53	56.78	54.81	

In the process tan sigmoid is used as the activation function in the hidden layer and output layer and the network converges. The hybrid neural networks classify the ECG data. 50% of the data has been loaded for training and repeatedly training the network. The test results show a recognition rate of 93.069%. The parameters used in the study are: Goal=0.0001, Learning Rate=0.04 and Momentum=0.005,mu_dec=0.5, mu_inc=1.07,max_fail=6.The gradient, momentum and learning rate are varied slightly in all cases in order to achieve a suitable performance of the network. Network is trained by presenting repeated inputs until the network learns the behaviour. Then randomized test data is presented which the network has not seen before. Data sets for training and testing of the network are randomized to ascertain the correctness of the adopted approach. The performance of different networks is not comparable in all the networks as the number of neurons in hidden layer tried is H(3, 4, 5, 6, 7, 8 and 15) and is not fixed. Also training parameters are varied gradually in all the cases. Training parameters used in the study are learning rate and momentum. The authors have not achieved these results on fixed parameters; the study employs variations in the momentum, learning rate, gradient and other parameters. A lack of clear comparison with fixed parameters is thus a limitation of this work.

Table 5

Comparison of the composed Hybrid neuro computing technique with other classification methods using UCI data base

Structure	Features	Reference	Recognition Rate
Proposed hybrid-ANN Approach (three different structures with highest recognition rates from Table 3)	43	-	93.069%,91.97&90.83%
Two stage feed forward	12	[5]	89%
Two Stage feed forward	12	[5]	90%
Bayesian network	12	[12]	86.25%
Naïve Bayesian network	12	[12]	84.75%
LSSVM	6	[18]	100%
NNAAF	-	[19]	98.19%
FFNN	12	[20]	99.28%
Nearest neighbor method	16	[21]	>95%
FFNN&LS-SVM	12	[22]	98.11%

4 Results and discussion

Classification performance over normal and abnormal ECG traces is presented in this work. Six illnesses are considered for the purpose of this work. These have been classified using the Hybrid Neuro-computing technique. The data set for the training and testing of the network is a randomized data set. The recognition thresholds for various patterns for all illnesses are defined by the number of correctly achieved targets. The targets that are not correctly detected are misclassified ones. The recognition rate achieved, hidden neurons and epochs used to achieve the results are shown in Table 3.The best results achieved are bolded in Table 3.

The performance of the proposed classifier is analyzed by sensitivity and specificity measurements, which are defined as:

Sensitivity (Se%) = TP/(TP+FN)*100% -----(6)

Specificity(Sp%)= TN/(TN+FP)*100% -----(7)

TP(True positive) and FN(False negative) of (6) stands for accurate detection of the real event and failure of algorithm to detect a correct output respectively. TN(True negative) and FP(false positive) of (7) stands detection of the events where events are not present and wrong detection respectively.

4.1 Test results

The authors performed ten-fold cross validation by adopting Elman-ANN approach. The results expressed in terms of specificity, sensitivity and recognition rate (Table 3). The results show that the number of hidden neurons in the hidden layer did not affect the recognition rate in the ANNs. The highest recognition rate is achieved with 15 hidden neurons. The training of the network is done by repeatedly presenting the inputs to the network. By repeating the training steps the performance of the network can be improved and better results can be achieved. The misclassification of the traces is treated as an error. Average of the three classifiers performing better and showing an average recognition rate of more than 85% are presented in Table 4. An aggregate of the hybrid classifiers(NET1,NET4 and NET10 has been 97.97%, 88.53% and 85% where as the aggregate of the results of different illnesses (NT,AF&RBBB) with more than 85% performance reported are 85.87%, 89.08%&96.54% The highest recognition rate of 93.069% with 15 neurons in the hidden layer is achieved with NET10 where as NET4 shows 91.97% with only 3 hidden neurons. NET4 uses Trainscg training function. All other NETs use Trainlm. The learning function used is Learngd. Classification results from different studies are presented in Table 5 which are comparable to our results. MatLab R2014a is used in this work.

5. Discussion

Topology of the network and data extracted from the downloaded ECG trace play an important role in deciding the performance of the classifier. Selecting different parameters might help in improving the performance of the classifier. Each feature extracted influenced the working of the classifier. Features selection can be used in this which will cover the future scope. Using various strategies for feature selection, varying performances can be achieved and an optimum solution can be obtained.

6. Conclusion

In order to classify arrhythmias effectively, the authors present a Hybrid-Neuro Computing approach towards recognizing normal and abnormal patterns. Elman1 and Elman for ECG signal classification. Elman1 does the job of feature extraction by comparing a standard signal with the signals from the same category of the illnesses. Likewise features from other illnesses in the study are extracted.

Wavelets have the ability to compress the ECG trace. This helps in approximating the signal under study by using fewer coefficients(13 element vector).The compressed signal from the ECG trace further helps to add knowledge to the database that helps to classify the data used in this work.

Sensitivity and Specificity and Time taken to simulate the results are the parameters that analyze the results. Sensitivity and specificity are the two parameters that are derived when simulated outputs are generated at the output. These parameters denote the success or failure of algorithm to correctly classify the presented output. Average Sensitivity and Specificity of 85.123% and 95.01% has been achieved in this work. Sensitivity and Specificity compute the cumulative performance index with respect to the classifier's output. The average time to simulate the results is 0.02208 seconds. Therefore Sensitivity, Specificity and Recognition rate are the performances indices used that demonstrate the effectiveness of the used methodology.

In all the networks training parameters are varied gradually to achieve the results. The goal is fixed to 0.0001, mu_max=10000000000. The proposed hybrid neural network will go a long way in automated detection and classification of arrhythmias as applied to a neural network based ECG classifier.

References

[1] Banerjee S, Gupta R, Mitra M. Delineation of ECG characteristic feature using multi resolution wavelet analysis method. Measurement 2012; 45:474-487.

[2] KMishra Amit, Raghav Shantanu. Local fractal dimension based ECG arrhythmia classification. Biomedical signal processing and Control 2010; 5: 114-123.

[3] Ubeyli Derya Elif. Adaptive neuro-fuzzy inference system for classification of ECG signals using Lyapunov exponents. Computer Methods and programmes in Biomedical 2009; 93:.313-32.

[4] Homaeinezhad R M, Atyabi A S, Tacakkoli E, Toosi N HJ, Ghaffari A, Ebrahimpour R. ECG arrhythmia recognition via Neuro –SVM-KNN, hybrid classifier. Expert systems with Applications 2012; 39: 2047-2058.

[5] Hosseini Gholam H, Luo D, Reynolds JK. The comparison of different feed forward neural network architectures for ECG signal diagnosis. Medical Engineering and Physics 2006; 28:372-378.

[6] Abo-Zahhad Mohanned, Al-Ajlouni.F. Ahmed, Ahmed M Sabah, Schilling JR. A new algorithm for compression of ECG signals based on mother wavelet parameterization and best-threshold levels selection. Digital signal processing; 2013; 23:1002-1011

[7] Rai Mohan Hari, Trivedi Anurag, Shukla Shailja. ECG signal processing for abnormalities detection using multi-resolution wavelet transform and artificial neural network classifier. Measurement 2013; 46: 3238-3246.

[8] Poungponsri, Suranai, Yu Xiao-Hua. An adaptive filtering approach for electro cardiogram (ECG) Signal noise reduction using neural networks. Neurocomputing 2013; 117: 206-213.

[9] Ozbay Yuksel, Ceylan Rahime, Karlik Bekir. Integration of type-2 fuzzy clustering and wavelet transform in a neural network based ECG classifier. Experts system with Applications 2011;38 1004-1010.

[10] Moavenian Majid, Khorrami Hamid. "A qualitative comparison of artificial neural networks and support vector machines in ECG arrhythmia classification. Expert systems with Applications 2010;37:3088-3093.

[11] Patnaik Amalendu, Dimitrios E Anagnostou, Rabindera K. Mishra Christos G. Christodouiou and J.C. Lyke, " Applications of Neural Networks in wireless communications".IEEE Antennas and Propagation Magazine 2004,46,pp.130-137

[12] Zheng Yuhua Meng Yan, Jin Yaochu, "Object recognition using a bio-inspired neuron model with bottom-up and top down pathways" Neurocomputing 74,2011,pp.3158-3169

[13] Adusumilli Sriyana, Bhatt Deepak,Wang Hong, Devabhaktuni, Bhattacharya Prabir. A novle hybrid approach utilizing principal component regression and random forest regression to bridge the period of GPS outages. Neurocomputing 2015,166, pp.185-192

[14] DasS,BhattacharyaA, HaldarS, GangulyA, Gu Sai, TingYP, ChatterjeeKP. Optimization of enzymatic saccharification of water hyacinth biomass for bio-ethanol:Comparison between artificial neural network and response surface methodology. Sustainable Materials and Technologies 2015; 3:17-28

[15] Laha Dipak, Ren Ye, Suganthan NP. Modeling of steel making process with effective machine learning techniques. Expert systems with Applications42, 2015, pp.4687-4696.

[16] Archive.ics.uci.edu/ml/machine-learning-databases/arrhythmia/arrhythmia.data.

[17] Wiggins M, Saad A, Litt B, Vachtsevanos G. Evolving a bayesian classifier for ECG-based age classification in medical applications. Applied soft computing 2008; 8:599-608.
[18] Polat Kemal, Akdemir Bayram, Gunes Salih, Computer aided diagnosis of ECG data on the least square support vector machine. Digital signal processing 2008; 18: 25-32.
[19] Ozbay Yuksel, Tezel Gulay. A new method for classification of ECG arrhythmias using neural network with adaptive activation function. Digital Signal Processing 2010; 20:1040-1049.
[20] Martis Joy Roshan, Acharya U Rajendra, Min Choo Lim. ECG beat classification using PCA, LDA, ICA and discrete wavelet transform. Biomedical Signal Processing and Control 2013; 8: 437-448
[21] Pal Saurabh, Mitra Madhuchhanda. Increasing the accuracy of ECG based biometric analysis by data modeling. Measurement 2012;45:1927-1932.
[22] Martis Joy Roshan, Rajendra Acharya U, Mandana KM, Ray KA, Chakraborty Chandan. Application of principal component analysis to ECG signals for automated diagnosis of cardiac health. Expert Systems with Applications 2012;39: 11792-11800.