ECG Heart Disease Detection using DWT and Artificial Neural Network

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Abstract : ECG being a non-stationary signal, the irregularities won't be periodic and cannot show up all the time, but would manifest at positive irregular intervals throughout the day. So, continuous ECG monitoring permits observation of cardiac variations over an extended period of time, either at the bad side or when patients are ambulatory, providing more information to physician. The Arrhythmia detection techniques used until now are complex in nature. Reduction in complexity remains the challenge now a day. Also arrhythmias classification methods based on ECG signals were developed but were weak and inaccurate. So it is important to develop computer based system that categorizes ECG signals and make improvements in the techniques of ECG analysis. There are many types of heart arrhythmias which can be detected by analysis of the ECG signals. In ECG analysis, the most focus is to reinforce degree of accuracy and embrace a lot of range of heart diseases which will be classified. ECG signals have well defined P, T waves and QRS complexes. The present work will help in building up a PC based framework that will be capable to classify the ECG signals**.**

I. INTRODUCTION

The Heart ailments are the foremost widely known infection that has influence individuals round the world. The utilization of medical specialty instrument notably for vascular system helped heaps in reducing untimely death sue to heart condition. Cardiovascular diseases (CVD) are the foremost well-known reason for death. Of these more than seventy five percent take after coronary conduit ailment and stroke. Determination of CVD is frequently done by taking note of the heart-sounds, electrocardiogram or by ultrasound. The electrocardiogram (ECG) records the heart bioelectric potential variation as it beats. Although new techniques offer more specific diagnostic evidence in some instances, the ECG still has an important role in cardiology since it is an effective, simple, noninvasive and low-cost procedure. Cardiologists are the specialists who concentrate on sicknesses of the heart. The key components of this increasing hazards are overweight, smoking, cardiovascular disease, elevated sterol, polygenic disease etc.

Analysis of the ECG signal is vital as many arrhythmia are potentially dangerous and life threatening. An arrhythmia episode can be produced by an alteration of electrical impulses formation or conduction. Also, a combination of both is possible.

In particular, the diagnosis of atrial fibrillation (AF) is made when the electrical activity of the atria becomes completely disorganized and its component fibers are discharged irregularly and asynchronously, resulting in a general failure of the contraction mechanism of these cardiac chambers. During this process, the atrial mass may react to more than 500 impulses per minute, completing each depolarisation-repolarisation. On direct visualization, the atrial chambers are found to have a continuous shimmering action rather than intermittent forceful contractions. Atrial fibrillation in the ECG is represented by continuous, irregular waves on the baseline. In AF, the ventricles appear to respond randomly to the extremely rapid assault of f waves. In fact, irregularity of the ventricular rate is a characteristic of AF. The QRS retain their usual configuration and the most common ventricular rate response is about 150 to 180 per minute, but this is variable. Another common alteration of the heart rhythm are premature ventricular contractions (PVC). PVCs can appear in groups in which case, the term bigeminy (B) or trigeminy is applied depending on the number of PVCs on each group. Long episodes of PVCs can be a warning of incoming severe arrhythmia.

In ECG examination, the principle center is to upgrade level of precision and incorporate more number of heart maladies that can be arranged. No. of techniques have been proposed to classify ECG pulse in view of the quantity of highlights extricated from the ECG signals. The objective of the feature extraction step is to locate the littlest arrangement of highlights that empowers adequate characterization rates to be accomplished. The examiner can't gauge the execution of set highlights without preparing and testing the classifier. In this manner, a include determination is an iterative and critical process that includes preparing diverse capabilities until ideal characterization execution is accomplished. In the present work neural network based classifier is created to group five sorts of arrhythmias, in particular, left bundle branch block (LBBB), right bundle branch block (RBBB), atrial premature beat (APB), paced beats (PBs) and first degree AV block (AVB) beats together with typical (N) beats. Proposed classifier utilizes four morphological highlights i.e. R top plentifulness, QRS term, RR interim and PR interim alongside eight wavelet based component i.e. change of detail coefficients acquired after eight level wavelet disintegration of every ECG beats.

II. RESEARCH METHODOLOGY

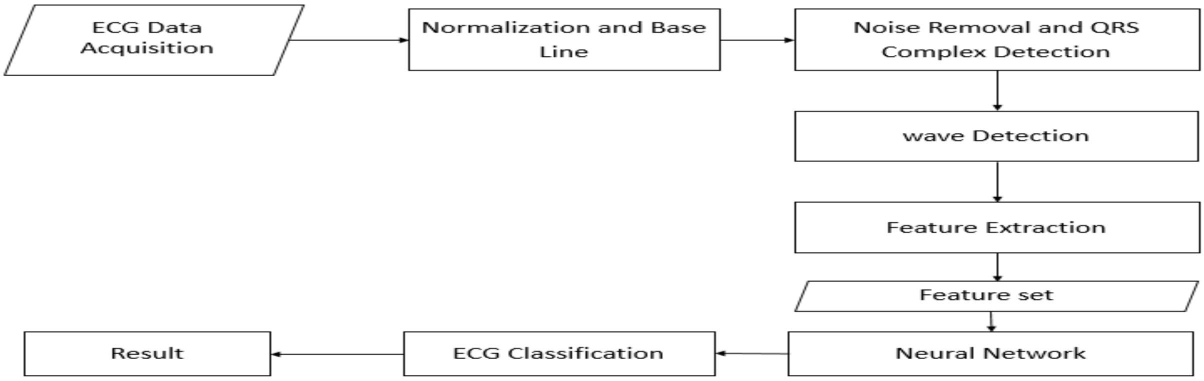


Fig. 1: Block diagram of classification methodology

A ECG Data Aquisition

The data base representing different conditions of heart for training and testing of proposed classifier was obtained from arrhythmia database.

B Normalization and Base Line Correction

The ECG signals in this work were normalized using the Eqn. 1. The ECG signal is then corrected for base line using equation Eqn. 2 because it was seen that signals are well above the reference zero base line.

$$ECGsignal = ECGsignal/|(ECGsignal)max| \quad (1)$$

$$ECGsignal = ECGsignal - mean(ECGsignal) \quad (2)$$

C Noise Removal and QRS complex Detection

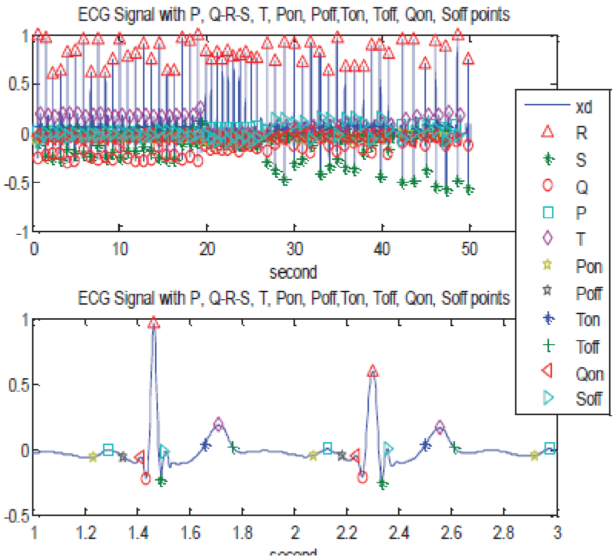
Three, five and eight level de-noising is performed using DWT on ECG signals obtained after baseline correction and Normalization. Noises such as Electromyogram (EMG), power-line interference (PLI) and base line wandering (BLW) are removed by subtracting de-noised signal at level eight from de-noised signal at level three. De-noised signal at level five is subtracted from the denoised signal at level 3 to get QRS complexes. The squaring operation is performed on ensuing signal to reinforce the relatively high frequency QRS complex. The output shows several peaks within the duration of a single QRS complex that's why smoothing of the output of the preceding operation is done using a moving-window integration filter. A window width of N=30 was taken for frequence of 360 Hertz.

Hard thresholding was then applied over the high frequency QRS to remove the unrelated noisy peaks. Proposed threshold value is given as:

$$Threshold = maximum\ (x3) \times mean(x3) \qquad (3)$$

Where x3 is output obtained once moving window integration.

A search for the maximum above threshold on de-noised signal gives the actual location of the R peak. Then minima are searched on either side of detected R peak to localize Q and S points.



D. Detection of P and T Wave

The P and T wave are detected using windowing technique. The search window starts at two hundred ms before and ends seventy ms before the situation of R peak. Then to find onset and off set of P wave, a backward and forward search is formed to find the minima from the point of maximum of P wave with suitable search window. T wave is detected in the same way as P wave only difference is that now search window starts after the location of R peak.

E. Feature Extraction

After detection of varied waves and complexes in ecg signals, four morphological features i.e. RR interval of successive two ECG beats, QRS duration, R peak amplitude and PR intervals of every signal beats were calculated. Variance of details coefficients (d1 to d8) of each ECG beats was also obtained by eight level decomposition of signal obtained after base line correction operation using DWT. A feature set consisting of twelve options were created by taking these four morphological features along with eight wavelet features from every individual heartbeat of ECG signal which characterizes the particular type of arrhythmia.

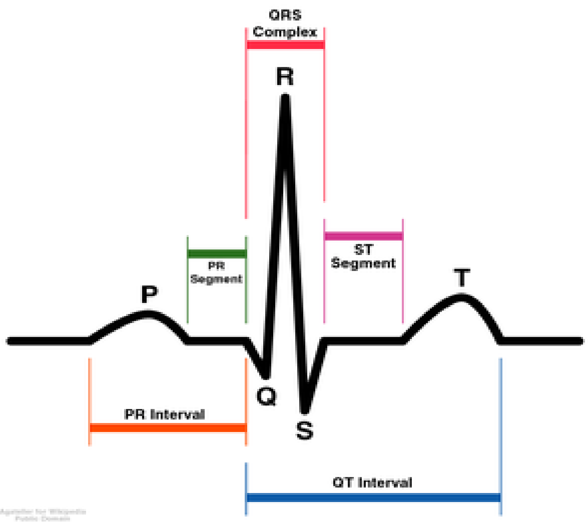


Fig. 2: waveform pf PT wave

TABLE I: COMPOSION OF DATASET
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Arrhythmia	N	LBBB	RBBB	PB	APB	AVB	TOTAL BEATS
No. of training beats	51	51	51	51	51	51	306
No. of testing beats	21	21	21	21	21	21	126
MIT-BIH data files	103, 115, 122, 123	111, 109, 214	118, 124, 212	107, 217	209, 232	207	432

F. Network Topology

Three layers; one input, one output and one hidden layer eed forward back propagation NNs are created, Net1-Net6, one for each class of ECG to be classified. The number of neurons in input layer was taken twelve in line with the twelve features being used in the classification. Output layer neuron number was fixed three with purelinear activation function. To determine variety of hidden layer neurons continual experiments were performed with totally different number with tansigmoid activation operate. To determine the optimum number of hidden layer neurons repeated experiments were performed with different numbers of neurons

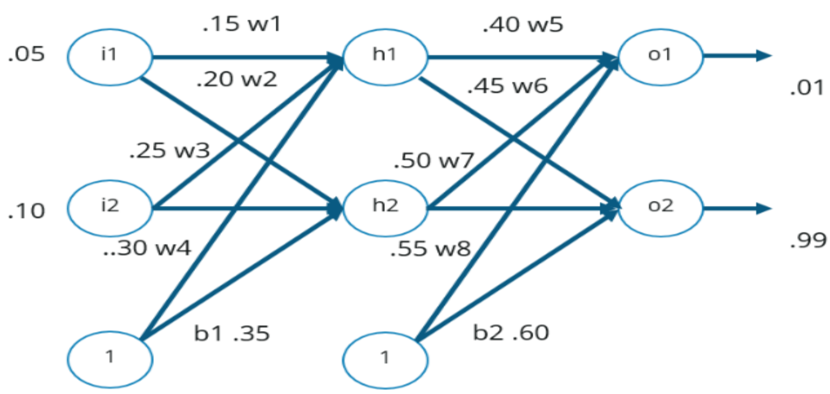
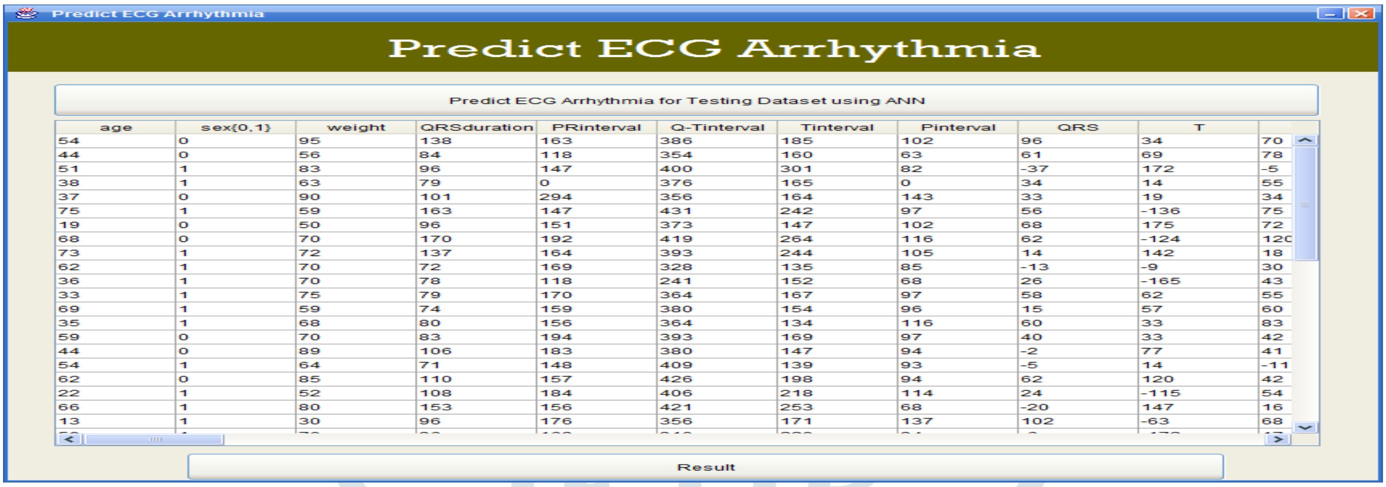


Fig. 3: ANN diagram

III. Testing

For testing the results 126 beats of different class of ECG beats are used. Table I shows the sample data of ECG signal, which is used to test networks output to recognize beat class. Each network created and trained is tested with 21 beats of same category and twenty one beats every of alternative category and testing confusion matrix is made. If during the test, result is within any range as shown in block diagram in Fig.1 then this shows that the involved beat is of that category (either N or L or R or APB or PB or AVB) and if simulated output isn't matched with target it shows unclassified beat.



age	sex{0,1}	weight	QRSduration	PRinterval	Q-Tinterval	Tinterval	Pinterval	QRS	T	
54	0	95	138	163	386	185	102	96	34	70
44	0	56	84	118	354	160	63	61	69	78
51	1	83	96	147	400	301	82	-37	172	-5
38	1	63	79	0	376	165	0	34	14	55
37	0	90	101	294	356	164	143	33	19	34
75	1	59	163	147	431	242	97	56	-136	75
19	0	50	96	151	373	147	102	68	175	72
68	0	70	170	192	419	264	116	62	-124	120
73	1	72	137	164	393	244	105	14	142	18
62	1	70	72	169	328	135	85	-13	-9	30
36	1	70	78	118	241	152	68	26	-165	43
33	1	75	79	170	364	167	97	58	62	55
69	1	59	74	159	380	154	96	15	57	60
35	1	68	80	156	364	134	116	60	33	83
59	0	70	83	194	393	169	97	40	33	42
44	0	89	106	183	380	147	94	-2	77	41
54	1	64	71	148	409	139	93	-5	14	-11
62	0	85	110	157	426	198	94	62	120	42
22	1	52	108	184	406	218	114	24	-115	54
66	1	80	153	156	421	253	68	-20	147	16
13	1	30	96	176	356	171	137	102	-63	68

Specificity (Sp): The specificity is the fraction of normal beats correctly classified as normal class. It is also called selectivity. It is calculated using “(5)”.

$$Sp = TN/ (TN+FP). \qquad (5)$$

Positive Predictive Value (PPV): It measures the ratio of correctly grouped positives. It is defined as given in “(6)”.

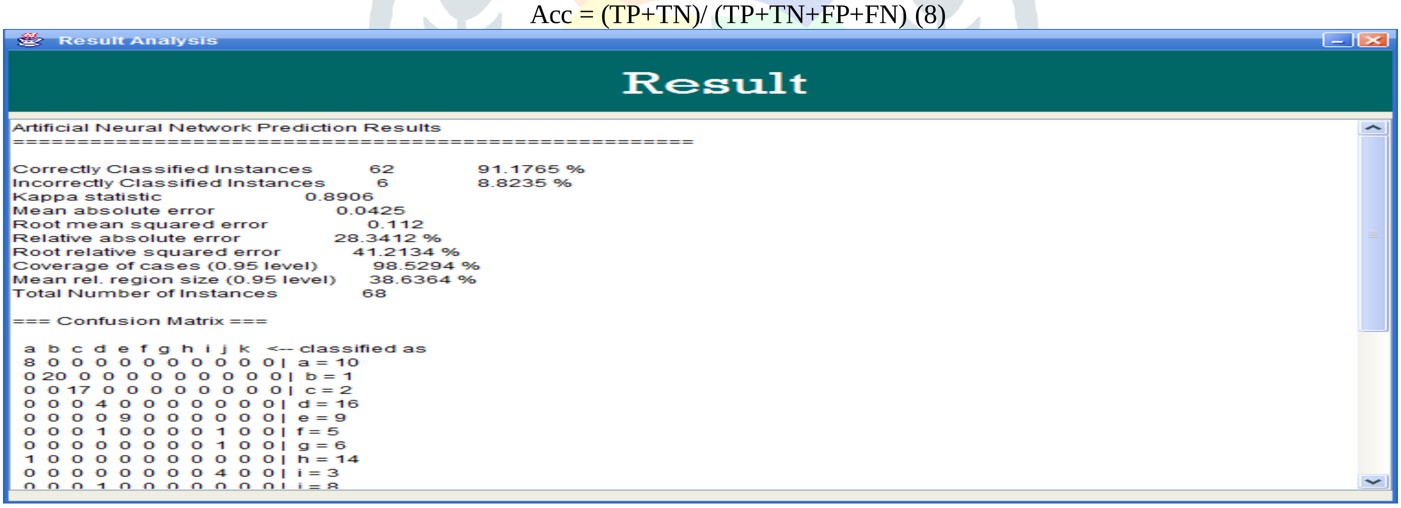
$$PPV = TP/ (TP+FP). \qquad (6)$$

Negative Predictive Value (NPV): It calculates the proportion of negative cases that were correctly identified and is defined as given in “(7)”.

$$NPV= TN/ (TN+FN). \qquad (7)$$

Accuracy (Acc): Defined by as

$$Acc = (TP+TN)/ (TP+TN+FP+FN) \quad (8)$$

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Artificial Neural Network Prediction Results
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Correctly Classified Instances        62         91.1765 %
Incorrectly Classified Instances       6          8.8235 %
Kappa statistic                    0.8906
Mean absolute error                  0.0425
Root mean squared error                0.112
Relative absolute error             28.3412 %
Root relative squared error           41.2134 %
Coverage of cases (0.95 level)         98.5294 %
Mean rel. region size (0.95 level)     38.6364 %
Total Number of Instances             68

=== Confusion Matrix ===

 a  b  c  d  e  f  g  h  i  j  k   <-- classified as
 8  0  0  0  0  0  0  0  0  0  0 |  a = 10
 0 20  0  0  0  0  0  0  0  0  0 |  b = 1
 0  0 17  0  0  0  0  0  0  0  0 |  c = 2
 0  0  0  4  0  0  0  0  0  0  0 |  d = 16
 0  0  0  0  9  0  0  0  0  0  0 |  e = 9
 0  0  0  1  0  0  0  0  1  0  0 |  f = 5
 0  0  0  0  0  0  0  0  1  0  0 |  g = 6
 1  0  0  0  0  0  0  0  0  0  0 |  h = 14
 0  0  0  0  0  0  0  0  4  0  0 |  i = 3
 0  0  0  1  0  0  0  0  0  0  0 |  j = 8
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IV.CONCLUSION

This system is designed using artificial neural network to help the physicians in the recognition of ECG patterns. ECG wave and different interval features were performed as the characteristic representation of the original ECG signals to be fed into the neural network models. Back propagation neural networks will be separately trained and tested for ECG Arrhythmias recognition. Different arrhythmias are detected with this method. For this process training and testing of back propagation neural network have been done.Thus we can conclude that the project aims at developing a quality focused software. Neural Network (NN) classifier plays an important role in dealing with uncertainly when making decisions in medical application. The ability to learn how to determine results from the training data is biggest asset. NN model was used to detect ECG changes while morphological features and wavelet coefficients are defined as inputs. The NN classifier model presented in this study was trained using Backpropagation algorithm.

REFERENCES

[1]Naveen Kumar Dewangan and S.P. Shukla, A survey on ECG signal feature extraction and analysis techniques, International journal of innovative research in electrical, electronics, instrumentation and control engineering, 3(6), June 2015. DOI 10.17148/IJIREEICE.2015.3603.

[2]C.Li, C. Zheng, C. Tai, Detection of ECG characteristic points using wavelet transform, IEEE Trans. Biomed. Eng. 42, 21-28, 1995

[3]B. Castro, D. Kogan and A. B. Geva, ECG feature extraction using optimal mother wavelet, The 21st IEEE convention of the Electrical and electronic engineers, Tel Aviv, Israel, 346350, 2000. doi:10.1109/EEEI.2000.924422

[4]Robust algorithm for arrhythmia classification in ECG using extreme learning machine. Jinkwon Kim, Hang Sik Shin, Kwangsoo Shin, and Myoungho Lee

[5]Indu Saini and B. S. Saini, Cardiac arrhythmia classification using error back propagation method, International Journal of Computer Theory and Engineering
W. T. Cheng, and K. L. Chan, Classification of electrocardiogram using HMMs

[6]Engineering in Medicine and Biology Society, Proceedings of the 20th Annual International Conference of the IEEE, vol.1: 143-146, 1998