

Bradycardia & Tachycardia Disease Classification Using ECG Signal Based On GA & ANN Classification

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Abstract: Electrocardiogram illustrates the electrical activity of the heart. Tachycardia and Bradycardia are the largest part of universal ECG abnormalities. The learning of ECG signal is typically used for recognize the heart diseases. Mostly, ECG signals are recognized by the medical consultant according to their knowledge. Consequently, analysis may diverge from consultant to consultant. So, this effort is all related to study a variety of ECG signals, so that it becomes uncomplicated to detect heart diseases and several lives could be secure. In this manuscript, the recognition of cardiac arrhythmias in the ECG signal with feature extraction and classification and pre-processing, are discussed. Due to inadequate storage capacity and broadcast bandwidth there is necessitate to compact the ECG signal. In this paper numerous experiments perform on the test dataset and it is experiential that artificial neural network categorize ECG beats superior as compared to formerly used (ANFIS) Adaptive Neuron Fuzzy Inference System classifier. The constraint Precision, Recall, F-measure and accuracy are uses for identifying the ECG disease. All the simulation progression will be deliberate in MATLAB environment.

Keyword: ANN (Artificial Neuron Network), ECG, GA (Genetic Algorithm), PCA (Principle Component Analysis).

I. Introduction

Tachycardia-Bradycardia syndrome is a alternative of sick sinus syndrome (because of a functional flaw of the sinus node, the pacemaker of the heart) in which fast and slow arrhythmias rotate. This can make sinus node exit block, sinus Bradycardia sinus arrest, and sinus tachycardia is also allied with atrial fibrillation and paroxysmal supraventricular tachycardia (PSVT). During tachycardia- Bradycardia syndrome, tachycardia is accompanied by extended sinus pauses. There syndrome can be generated by atrial fibrillation or PSVT. The symptoms are analogous to those of atrial fibrillation: fatigue, chest pain, angina, dizziness, shortness of breath and fainting. Electrocardiogram (ECG) is an analysis tool that account the electrical activity of heart confirmation by skin electrode. It is a noninvasive method that means these signal are measured on the exterior part of human body, which is used in recognition of the heart diseases. Any anarchy of rhythm or heart rate, or change in the morphological model, is a suggestion of cardiac arrhythmia, which could be sensed by examination of the recorded ECG waveform. The peak and duration of the P-QRS-T wave have useful information about the characters of disease afflicting the heart. The standard ECG has 12 leads: which contain 3 - augmented unipolar leads, 3 - bipolar leads, and 3 - chest (precordial) leads. A lead is a brace of electrodes (+ve & -ve) placed on the body parts in designated anatomical locations & linked to an ECG record [3].

Unipolar leads: trace the electrical potential at a point by means of a single discovering Electrode.

Bipolar leads: trace the potential difference between two peaks (+ve & -ve poles).

Lead 1: trace potentials between the left and right arm,

Lead 2I: trace between the right arm and left leg, and

Lead 3: those between the left leg and left arm

Table 1: Types of leads used in ECG monitoring

Limb Leads	Chest Leads	Standard Leads
Unipolar	Unipolar	Bipolar
AVR	V1	Lead1
AVL	V2	Lead2
AVF	V3	Lead3
	V4	
	V5	

Unipolar Limb leads: (when the +ve terminal is on the right arm: left arm aVL, or left leg ,aVR, , aVF)One lead linked to +ve terminal acts as the assorted electrode, while the other two limbs are linked to the –ve terminal serve as the unconcerned (reference) electrode [5]. Leads (V1–V6) are unipolar chest leads situated on the left side of the thorax in a just about horizontal plane.

ECG waveform and Interval:

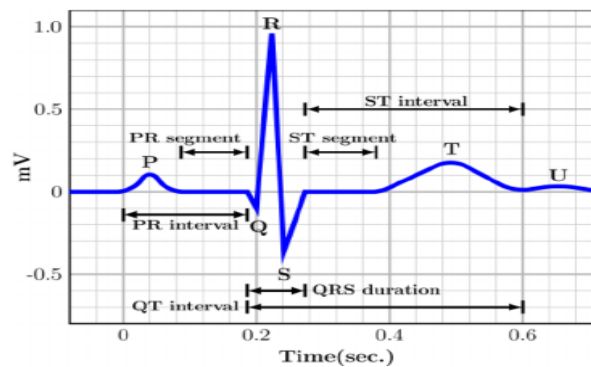


Figure 1: Schematic representation of normal ECG waveform

P wave: The peak level of this voltage signal is low (just about 1mV) and symbolizes depolarization and reduction of the right and left atria. Absence of P waves might suggest junction rhythm, atrial fibrillation, or ventricular rhythm.

QRS complex: The QRS complex is the chief voltage deflection of roughly 10–20 mV but might vary in size based on age, and gender. The voltage peak of QRS complex may also provide record about the cardiac disease of ECG signal.

T wave: Symbolize ventricular repolarization and Large T waves might signify ischemia, and Hyperkalaemia

Table 2: Amplitude and duration of waves, intervals and segments

S.No	ECG waves	Peaks voltage Values(mV)	Time duration(mS)
1	P-wave	0.1-0.2	60-80
2	PR-segment	-	50-120
3	PR-interval	-	120-200
4	QRS complex	1	80-120
5	T-wave	.1-.3	100-120
6	ST segment	-	120-160
7	ST-interval	-	320
8	RR-interval	-	(0.4-1.2)

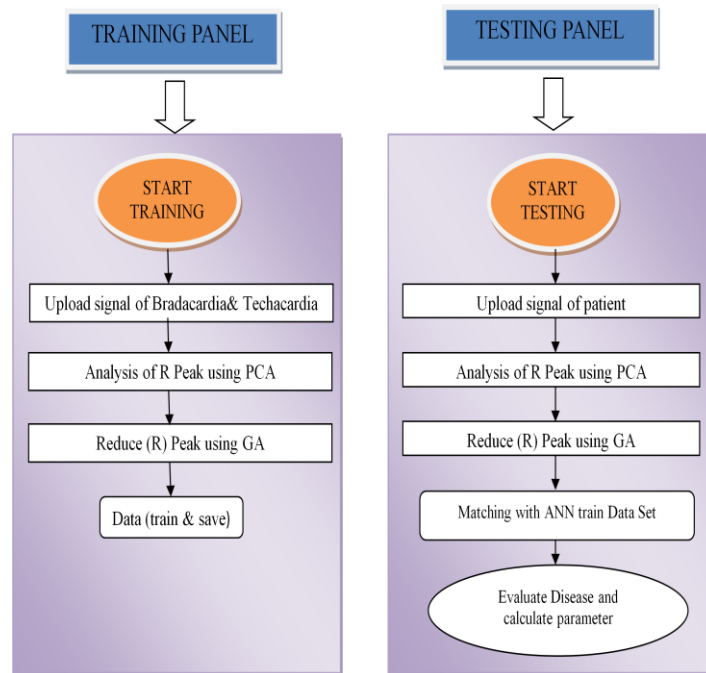
Methodology used for Classification:

The procedure of the methodology can be understood with the subsequent flow diagram which noticeably explains the job in steps.

To recognize Bradycardia and tachycardia heart problem, the whole course is divided into two steps named as:

Training phase

Testing Phase



Uploaded signals of Bradycardia& Techycardia:

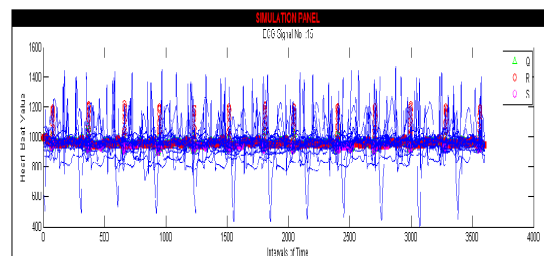


Figure 2: Uploaded signals of Bradycardia& Techycardia

For the training function Database from physionet.org has been uses for performance examination. I have used 180 ECG signal in the training upload.

Principal Component Analysis (PCA): Principal component analysis (PCA) is a statistical practice whose purpose is to compact the information of a large set of associated variable into a hardly any variables.

Performance steps are:

- i. Mean vector of data: $z' = \frac{1}{B} \sum_j^B z'$
- ii. Covariance C=
 $\frac{1}{B} \sum_j^B (z_j - z)^T (z_j - z)$
- iii. Calculate Eigen- value and vector: To select the Eigen value and vector a threshold value is set i.e. Threshold =max.value *75/100;
- iv. Select the Principle Component: Highest value of Eigen vector is P.C.

Genetic algorithms: GAs is an optimization practice and heuristic examination inspired by acknowledged evolution. They have been effectively applied to a widespread series of real-world troubles of major complication.

The foremost components of GA are: crossover, mutation, and a fitness function.

Crossover: The crossover is completed to discover novel solution space and crossover machinist corresponds to swap the parts of strings between choose parents.

Mutation: When individuals are symbolized as bit strings, mutations consist of nullify a randomly selected bit.

Fitness values: The fitness rate of every individual replicate how good it is, according to its accomplishment of objectives. In invented story, there are dissimilar techniques to describe fitness function .One of them, also simplest move towards, is weight-sum method.

Artificial Neural networks: ANN is fabricated of simple components performance in parallel. These mechanisms are stimulated during biological nervous systems.

Usually, neural networks are skilled, or accustomed, so in a meticulous input directs to a particular target output. The succeeding figure reveals such a circumstance.

At this point, the network is approved, reliant on a comparison of the output in addition to the object, unless the network Output resembles the actual object.

The training criterion of NN can be recapitulated below:

- i. Input is transmitted to input neurons.
- ii. Acquired output response is evaluated to input data.
- iii. Error data is utilised to supervise the weights linked to neurons.
- iv. Hidden units locate outs its blunder during back signal.
- v. Afterwards weights get updated in the end.

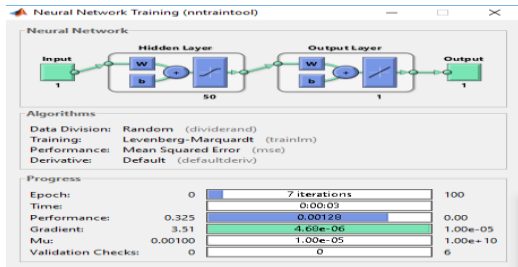


Figure 3: Neuron Network Training

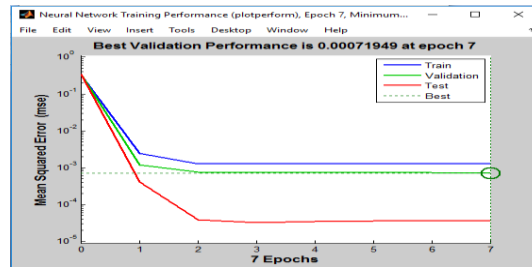
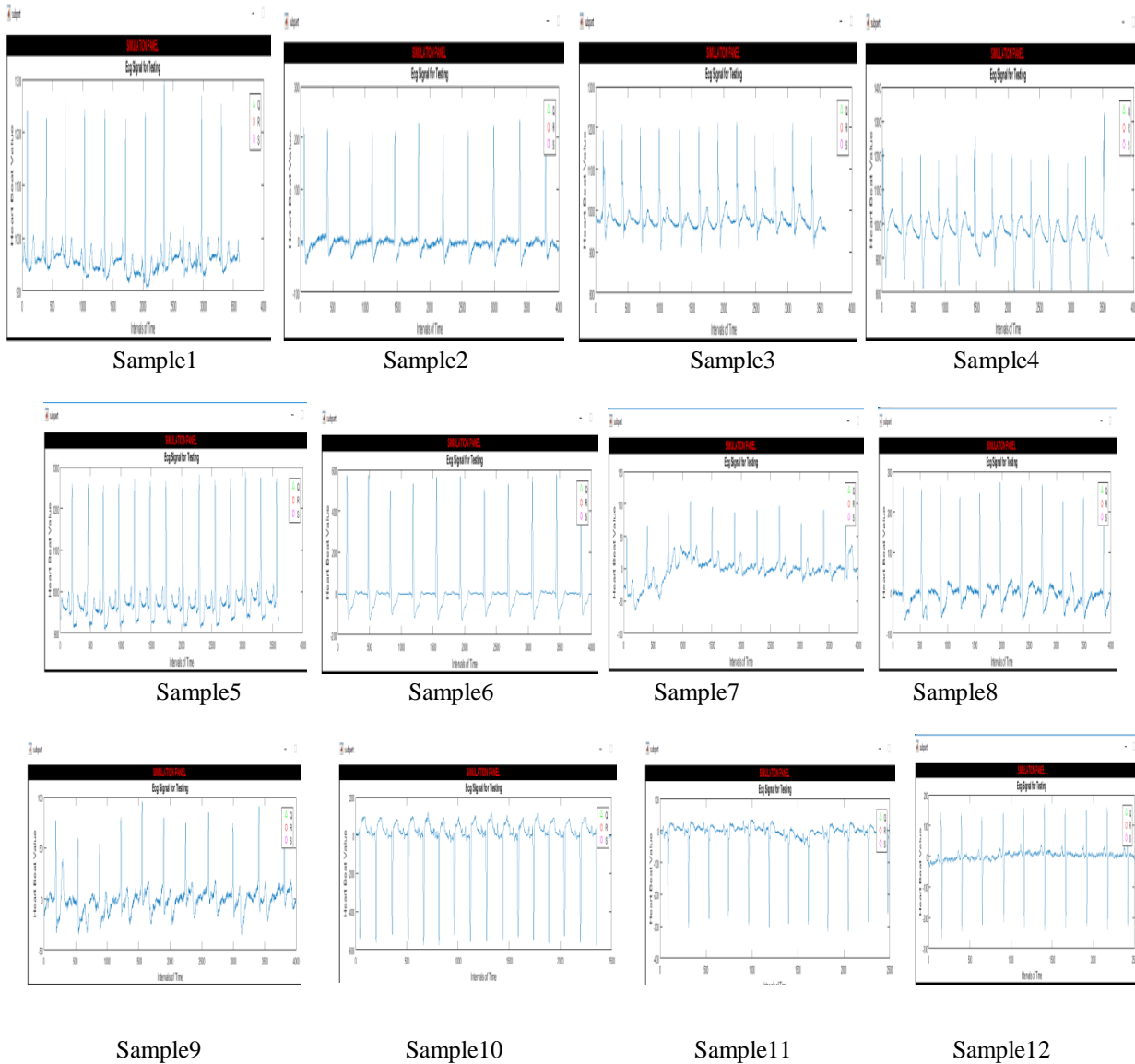


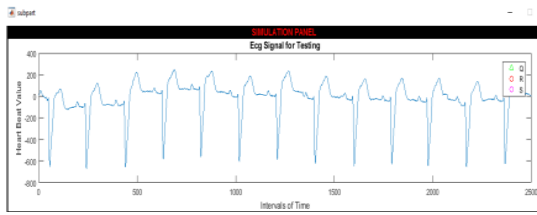
Figure 4: Neuron Network performance signal

II. Purposed Work Result Analysis:

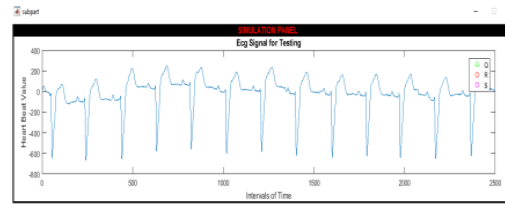
In testing development related to training process first testing samples are upload. I have taken 15 samples which are shown below:

Different patient ECG samples



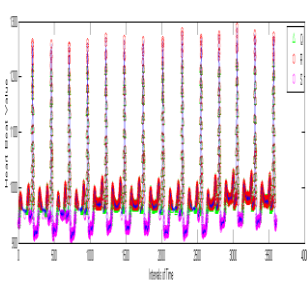


Sample13

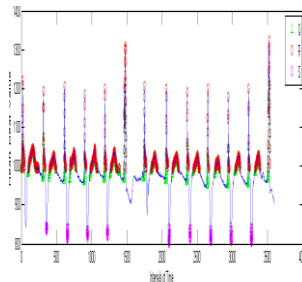


Sample14

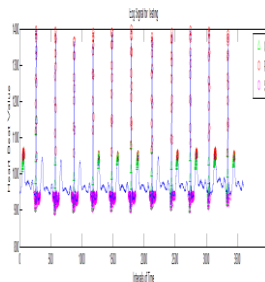
Extracted QRS signals



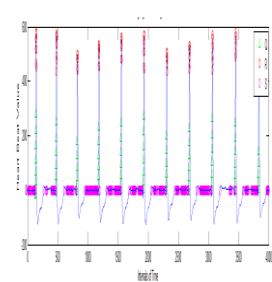
Sample1



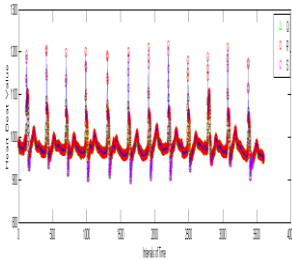
Sample2



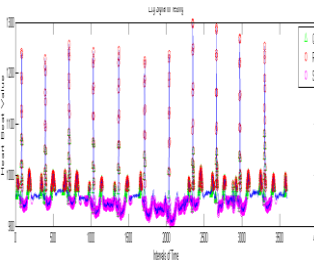
Sample3



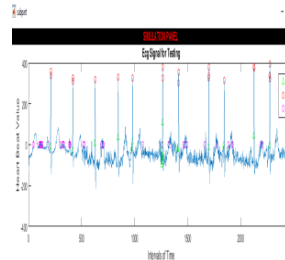
Sample4



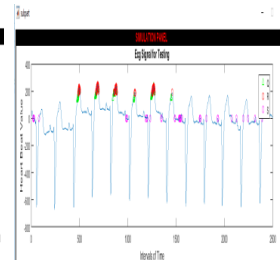
Sample5



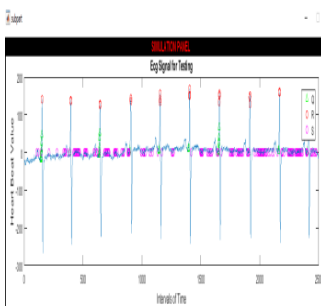
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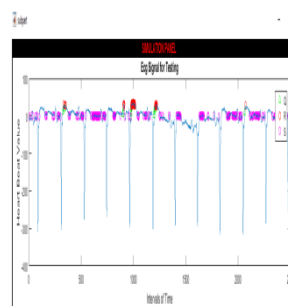
Sample7



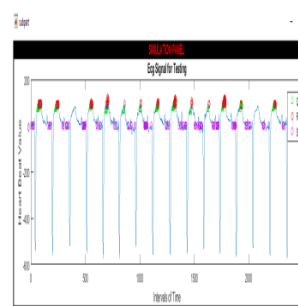
Sample8



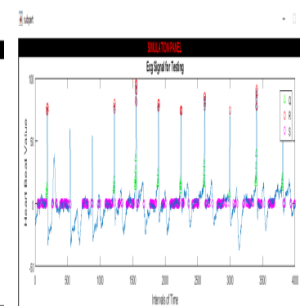
Sample9



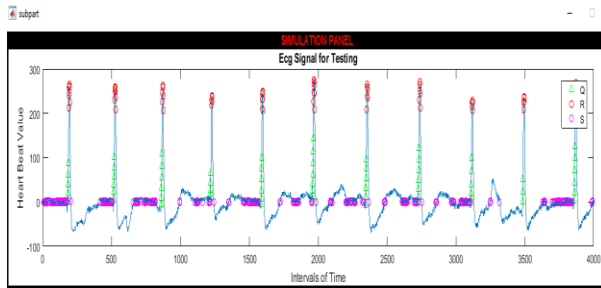
Sample10



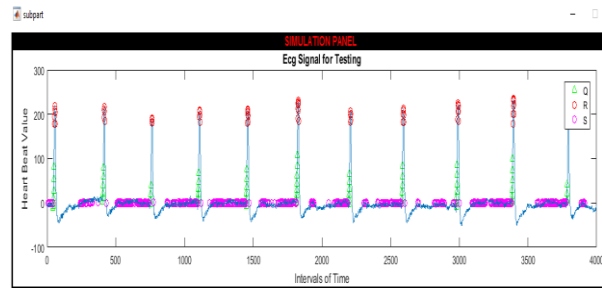
Sample11



Sample12



Sample13



Sample14

Table 3: Parameter and disease classification

S.No.	Precision	Recall	F-Measure	Accuracy	Disease classification
1	.812	.843	.827	99.34	Bradycardia
2	.823	.845	.834	99.42	Bradycardia
3	.801	.842	.821	99.28	Bradycardia
4	.810	.843	.826	96.68	Bradycardia
5	.814	.844	.828	98.67	Bradycardia
6	.848	.863	.856	99.40	Tachycardia
7	.901	.891	.896	96.81	Tachycardia
8	.882	.881	.881	96.77	Tachycardia
9	.881	.878	.880	98.35	Tachycardia
10	.899	.891	.895	98.82	Tachycardia
11	.852	.863	.858	97.72	Normal
12	.851	.862	.857	97.06	Normal
13	.874	.876	.875	98.20	Normal
14	.879	.879	.879	99.34	Normal
15	.845	.860	.852	98.96	Normal
Avg.	.851	.864	.857	98.32	

Comparison between Accuracy of Previous & Proposed work: The accuracy of previous and proposed work after disease classification is 97.67 and 98.32. The proposed work shows the 65% better result than previous work.

Table 4: Comparison of Accuracy

S No.	Accuracy of Proposed work	Accuracy of Previous work
1	98.32	97.67

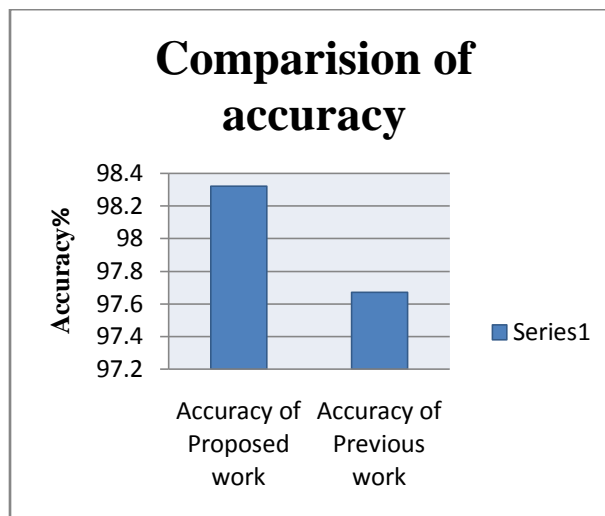


Figure 5: graphically comparison between accuracy of previous and proposed work

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Conclusion

This research was based on studying the implemented approaches in the ECG diseases and then to propose a novel technique /algorithm for classification of two cardiac disorders named as Bradycardia, and Tachycardia dependent on Artificial neural network and the Genetic algorithm. Clinical databases have accumulated large quantities of information regarding patients and their medical situation. This dissertation presents the ECG Disease Detection System based on GA, and ANN, in which detection is based on performance parameters like precision, Recall, F-measure and Accuracy. Simulation results have shown that the obtained value of precision, recall, f-measure and accuracy in favor of proposed tested waveform are 0.851, 0.864, 0.857 and 98.32 % for accuracy.

Future Scope

Future scope lies in the use of former classifiers like SVM with the aim of having multidimensional data and making use of feature reduction algorithms, so that accuracy rate can be enhanced. SVMs bring a unique solution, since the optimality problem is rounded. This is an advantage to Artificial neural network (ANN) which has several solutions related with local minima and for this reason may not be tough over different samples. For optimization algorithms similar to artificial bee colony (ABC) and (PSO) Particle swarm optimization would be used.

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