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# Implementation of Methodology for Classification of ECG by Artificial Intelligence

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**Abstract:** Electrocardiogram (ECG), a non-invasive technique is used as a primary diagnostic tool for cardiovascular diseases. A cleaned ECG signal provides necessary information about the electrophysiology of the heart diseases and ischemic changes that may occur. It provides valuable information about the functional aspects of the heart and cardiovascular system. The objective of the thesis is to automatic detection of cardiac arrhythmias in ECG signal. Recently developed digital signal processing and pattern reorganization technique is used in this thesis for detection of cardiac arrhythmias. The detection of cardiac arrhythmias in the ECG signal consists of following stages: detection of QRS complex in ECG signal; feature extraction from detected QRS complexes; classification of beats using extracted feature set from QRS complexes. In turn automatic classification of heartbeats represents the automatic detection of cardiac arrhythmias in ECG signal. Hence, in this thesis, we developed the automatic algorithms for classification of heartbeats to detect cardiac arrhythmias in ECG signal. QRS complex detection is the first step towards automatic detection of cardiac arrhythmias in ECG signal. A novel algorithm for accurate detection of QRS complex in ECG signal peak classification approach is used in ECG signal for determining various diseases. As known the amplitudes and duration values of P-Q-R-S-T peaks determine the functioning of heart of human. Therefore, duration and amplitude of all peaks are found. R-R and P-R intervals are calculated. Finally, we have obtained the necessary information for disease detection. For detection of cardiac arrhythmias; the extracted features in the ECG signal will be input to the classifier. The extracted features contain morphological l features of each heartbeat in the ECG signal. We have detected bradycardia and tachycardia. Massachusetts Institute of Technology Beth Israel Hospital (MIT-BIH) arrhythmias database has been used for performance analysis.

**Keywords :** Electrocardiogram (ECG), MIT-BIH database, Probabilistic Neural Networks (PNN), Wavelet toolbox.

## Introduction

Electrocardiography is the study of the electrical impulses that are produced by the heartbeat. The reflection of bio-signals might happen at any arbitrary point in the time scale since bio-signals are non-stationary signals. Therefore, in order to get an accurate diagnosis of illness, the ECG signal pattern and the heart rate variability may need to be studied for a number of hours. As a result of the vast amount of data being analysed, the research is laborious and time consuming. In light of this, the computerised analysis and categorization of cardiac illnesses might be of great assistance in the diagnostic process. The electrocardiogram may be broken down into phases that approximately correspond to the repolarization and depolarization of the muscle fibres of the heart. The P-wave, also known as atrial depolarization, and the QRS wave are both related to the depolarization phases (ventricles depolarization). The T-wave may be thought of as corresponding to the re-polarization phases. An irregular heartbeat is the most common symptom of arrhythmia, which is a condition that affects the heart and is caused by a breakdown in the heart's electrical system cells. It makes the heart pump blood less efficiently and creates abnormalities in the technique that the heart employs to convey electrical impulses. Finding cardiac disease in its earliest stages is of great assistance in improving our ability to recognise arrhythmias and increasing the likelihood of leading a long and healthy life. The method of recognising patterns on an ECG includes the following steps: pre-processing of the ECG signal; detection of the QRS; feature extraction; and usage of a neural network for signal classification. In order to distinguish between QRS and non-QRS areas, an Artificial Neural Network (ANN) is used as a classifier. The vast majority of QRS detection algorithms that have been described in published works can identify the R-peak, and distinct criteria are used in order to pinpoint the onsets and offsets of the QRS complexes.

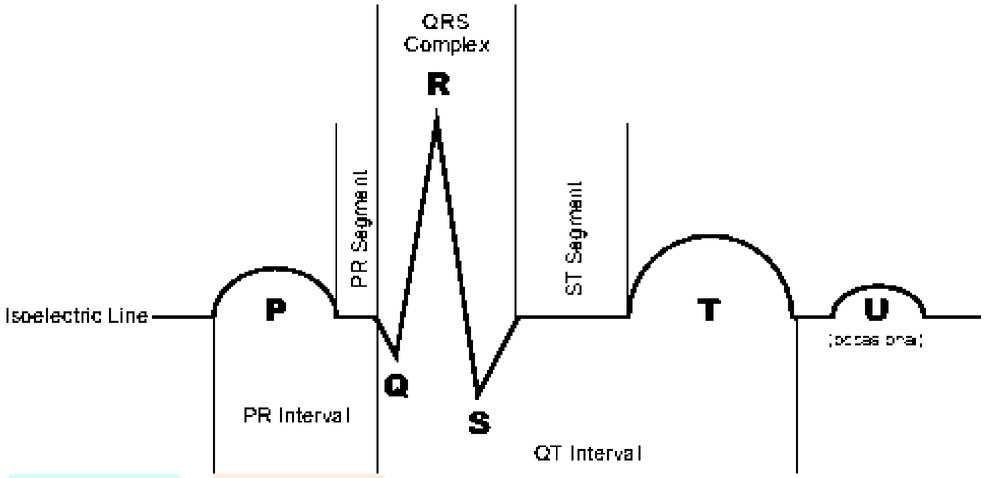


**Figure 1: Represents a typical ECG waves.**

Figure 1 presents an analysis of the curve depicting the time interval between heartbeats, often known as normal ECG waveforms. The figure has a certain degree of crispness to it. Figure 1 demonstrates the periodic sharpness that may be seen. This acuteness is due to the contraction of the ventricular muscle. The term for this phenomenon is "depolarization." During the process of depolarization, the resting potential of the muscle fibres was lost. As a general rule, the signal prepares to deviate somewhat in a negative direction before continuing with a significant positive taper. After then, there was a second income departure to the negative. "QRS complex" is the term used to describe the contraction of the ventricles. After the QRS complex, an A oscillation may be noticed. The ST range or the ST wave are two other names for this oscillation. At this point, the difference in potential may be quantified. At this point, you will draw a line that will be referred to as the isoelectric line. The T-wave then comes after this (representing the depolarization). The presence of a P wave in the atrium demonstrates that the individual is now in an enthusiastic state. Last but not least, a U wave does not always appear. It is normally of a low magnitude. Papillary muscle repolarization is hypothesised to be represented as U waves in an electroencephalogram. Figure 2 illustrates an electrocardiogram, which may be inspected to get a better understanding of the signal. This signal is far smoother than the genuine ECG signal, which is not as smooth.

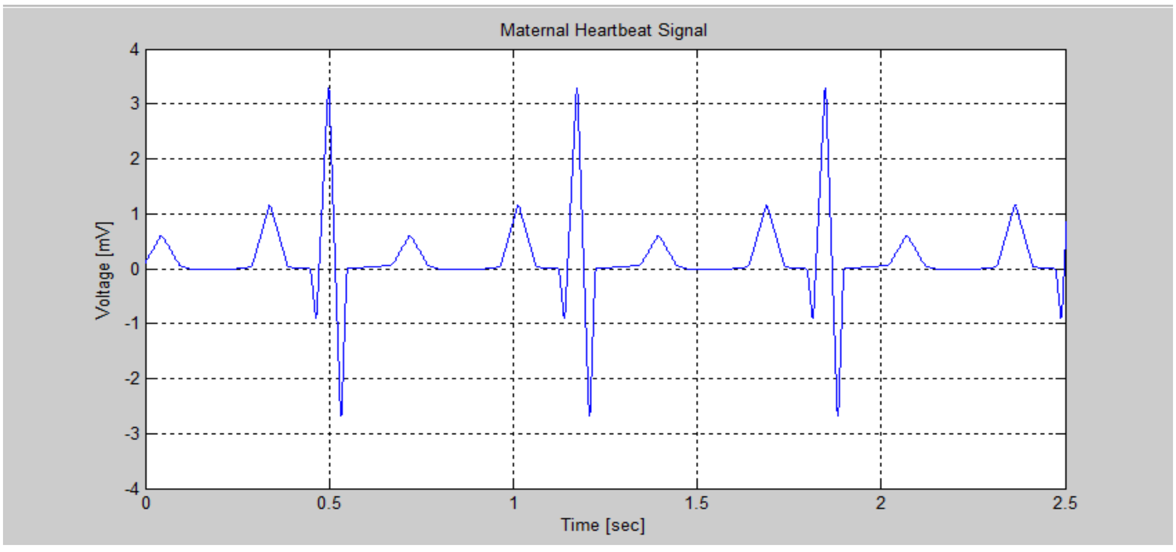


**Figure 2: Shape of the electrocardiogram**

An ECG is a measurement of the electrical activity of the heart muscle that may be taken from the surface of the skin and from various angles as in Figure 3. An electrocardiogram can be used to diagnose a variety of heart conditions. When the heart muscle contracts and pumps blood to all regions of the body, action potentials are created inside the heart muscle as a result of a mechanical process. This results in electrical activity within the heart muscle.

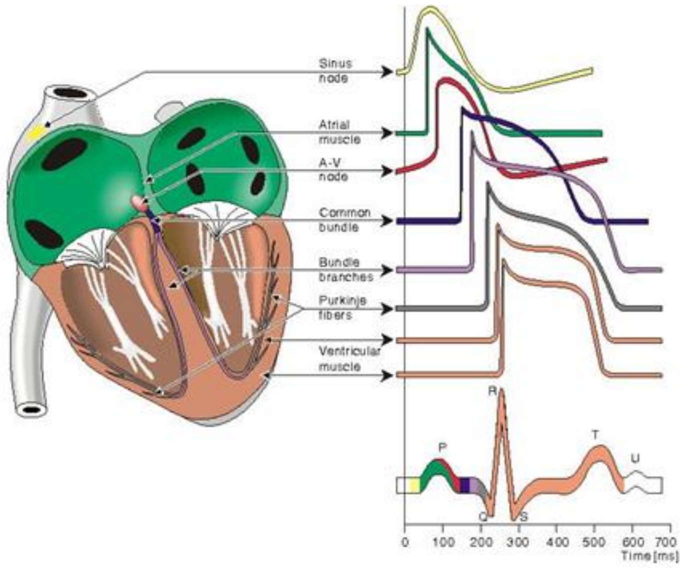


**Figure 3: The heart's anatomy with waveforms from different specific part of the heart.**

**Literature Review**

Dr. Sudhir G. Akojwar,Pravin Kshirsagar and Vijetalaxmi Pai "Feature Extraction of EEG Signals Using Wavelet and Principal Component analysis" [Feature Extraction of Electroencephalogram Signals] In this study, a comparative examination of the various kinds of EEG signals together with the findings of feature extraction utilising the two best techniques of feature extraction—the wavelet transform method and the principal component analysis—are presented. The electroencephalogram is a record of the electrical activity that occurs in the brain. In addition, in order to categorise these illnesses, we will need to extract the characteristics. Therefore, this work provides consecutive findings using wavelet and PCA for EEG data associated with illnesses such as epileptic seizure activity, slow wave activity, brain death, and brain malignancies. [1]

Sudhir G. Akojwar, Pravin R. Kshirsagar "A Novel Probabilistic-PSO Based Learning Algorithm for Optimizing Neural Networks for Benchmark Problems" [Unique Probabilistic-PSO Based Learning Algorithm] In this study, a contemporary and resolute update of the conventional particle swarm optimization (PSO) algorithm is endorsed for the purpose of optimising the initial weights and biases of multilayer feedforward neural networks (MLFFNN) via back propagation (BP). The combination of probabilistic-PSO and MLFFNN sevenfold helps in fast convergence of MLFFNN in assortment and sortilege to various benchmark problems. This is accomplished by eradicating the imperfection of back-propagation that results in the network becoming mired at either local minima or local maxima. The parameters for velocity and location are handled differently by the propane probabilistic-PSO compared to the standard PSO. In velocity parameters, just the particle best value is used to guide the particle's movement towards the pursuit in the search space, while in normal PSO, both the particle best and the global best values are utilised for determining the particle's new velocity. A new parameter known as the probability parameter (P0) was created, and its purpose was to determine whether or not the normal PSO should be modified such that, rather than utilising the same random number to fly across search space, individual particles used distinct random numbers. Once the optimal value for initial weights and biases was obtained, the MLFFNN was then employed for classification and sortilege of different neural network benchmark problems. The suggested approach was used to discover the initial weights and biases for MLFFNN with BP. The neural network benchmarking databases include a wide variety of datasets originating from a wide variety of different fields. All of the datasets include data from the actual world and all of the datasets reflect meaningful problems, which may be referred to as diagnostic tasks. The results of a comparison between the probabilistic PSO technique that was suggested and other approaches that are already in use. [2]

The adaptive neuro-fuzzy inference system (ANFIS) algorithm was developed by Nazmy et al. for the purpose of ECG wave categorization.

The RR-interval of the electrocardiogram is used to determine the input, and the feature extraction is carried out with the assistance of Independent Component Analysis (ICA) and Power spectrum. According to the findings of this study, the different types of ECG signals may be categorised as follows: normal sinus rhythm; premature ventricular contraction; atrial premature contraction; supraventricular tachycardia; ventricular tachycardia; and ventricular fibrillation. The classification accuracy is also reached by the use of the ANFIS technique. [3] Alan and Nikola published an article in which they employ chaos theory for the categorization of ECG signals and the extraction of features. The concepts of phase space and attractors, correlation dimension, spatial filling index, and approximation entropy are discussed in this article. A brand new software has been constructed for ECG classification, and it is based on the chaotic approach. Additionally, a semi-automatic programme has been developed for the feature extraction. The software is useful for classifying the electrocardiogram data and extracting features from the signal. [4]

In this study, Castro et al. discuss the process of feature extraction with the use of wavelet transform technology. They also provide an algorithm that will use wavelet transform technology in order to extract the characteristics of an ECG signal. This approach first removes noise by the application of a soft or hard threshold, and then the characteristic of the ECG wave is separated into a coefficient vector through the use of optimum wavelet transformation. This approach chooses the mother wavelet transform set of orthogonal and biorthogonal wavelet filter bank by means of the greatest possible correlation with the ECG signal. This method was created in this way that was presented. Following the completion of the ECG analysis, the signal coefficients are summarised before being categorised into QRS complex, T wave, and P wave, respectively. [5] Back-Propagation Neural Network and Fuzzy Neuro Learning Vector Quantization (FLVQ) were used as classifiers in the ECG classification study carried out by Wisnu Jatmiko and colleagues [3]. They relied only on the data provided by the MLII lead in their research. Left Bundle Branch Block beat, Normal beat, Right Bundle Branch Block beat, and Premature Ventricular Contraction are the classifications that are taken into consideration. Specifically, back propagation and FLVQ were the training classification techniques that they employed for this investigation. When Back-Propagation is used, it offers an average accuracy of 99.20 percent, and when FLVQ is used, it offers 95.50 percent. This result demonstrates that back-propagation is more effective than FLVQ, and it also demonstrates that back-propagation has drawbacks when compared to categorised unknown category beats, but not when compared to FLVQ. FLVQ shows consistent accuracy, despite the fact that it beats in categories that are unknown. [6] Maedeh Kiani Sarkaleh,, devised a method that is based on Neural Networks for the categorization of Paced Beat, Atrial Premature Beat arrhythmias, and the normal beat signal. They employed the Discrete Wavelet Transform to extract features, then combined those characteristics with temporal interval information while training the neural network. The neural network-based classifiers have been trained and tested on around ten recordings taken from the MIT/BIH arrhythmia database. The conclusion drawn from the modelling reveals that the accuracy of categorization is 96.54 percent. [7]

In this study by Karpagachelvi.S, a classification technique for ECG beats based on RVM is suggested, and it is then applied to the MIT-BIH arrhythmia database in order to categorise five different types of aberrant waveforms and normal beats. The sensitivity of the RVM classifier is examined during the feature exacting process, and the results are compared with those of ELM. The result that was achieved provides more evidence that the RVM technique is better to the more conventional classifiers. [8] Ruchita Gautam and Anil Kumar Sharma suggested a method based on the concept of dyadic wavelet transform. This approach is used for the purpose of locating the QRS complex. In this procedure, the attention is placed on the time gap between two R waves that have occurred consecutively, and the heartbeat is then calculated. This approach is performed on the ECG waveforms to identify the dieses Ventricular Late Potentials and to separate the wave P R & T, both of which are connected with characteristics of ECG waveforms. The determination of the R waves is the primary focus of this approach, and the threshold is positioned at 75% of the highest peak value. [9]

With the use of K-clustering methods, Manpreet Kaur and A.S. Arora demonstrate how the output signal may be evaluated; the parameters being looked at include wave form, duration, and amplitude. This clustered K was able to reduce the sum of the distance from each point to the centroid with the assistance of a method called K-clustering. In this method, the initial step involves giving information about the point to the nearest cluster that is centred on the centroid. In the second phase, information is provided on lines where the values have been self-resigned. MIT-BIH is the source of the data that is used for the analysis. The success rate of categorization is 99.98 percent for set 2, set 3, set 4, set 5 and set 7; however, it is only 87.5 percent for set 1, and it is only 75 percent for set 6. [10]

Maedeh Kiani Sarkaleh and Asadollah Shahbahrami. In this study, we emphasise how vital it is to be able to recognise cardiac arrhythmias in order to properly diagnose cardiac abnormalities. The classification of ECG arrhythmias has been attempted using a number of different methods; unfortunately, these algorithms are not particularly effective. In light of this, the aim of this study is to present an expert system for the categorization of arrhythmias based on electrocardiograms (ECGs). Processing ECG recordings and extracting certain characteristics is done with the help of the discrete wavelet transform, and the classification operation is carried out by a neural network. The technology that is being presented has the capability of identifying two distinct arrhythmias. Our neural network-based classifier was trained and tested using recordings from the MIT-BIH arrhythmias database. These recordings were utilised for both training and testing. The results of the simulation reveal that our method has a classification accuracy of 96.5 percent employing 10 different files, one of which is considered normal. [11] Pratiksha Sarma, S. R. Nirmala, Kandarpa Kumar Sarma. Many people succumb to heart ailments over their lifetime. As a result, there is an ongoing need to create technologies that are capable of providing prior indication concerning the condition of the heart. This is necessary as well due to the fact that different locations may have varying types of medical services. In such circumstance some new ways employing particular signal processing techniques might give great help. In the medical literature, several classification algorithms for cardiac arrhythmias have been presented; however, many of these algorithms do not function to the best of their abilities. In this paper, we offer a technique for the categorization of ECG arrhythmias that makes use of artificial neural networks (ANN). In order to pre-process the electrocardiogram data, the Fast Fourier Transform is used. Following the extraction of various characteristics via the use of Linear Prediction Coefficients (LPC) and Principal Component Analysis (PCA), the classification is carried out using Multi-Layer Perceptron Artificial Neural Networks (ANN). [12].

**Proposed System Design**

Denoising an electrocardiogram signal and locating the QRS complex within it are the two steps that yield information about a variety of cardiac abnormalities. Validation of the diagnosis of heart disorders is provided as a result of this. Due to the significance of this factor, it has garnered a significant deal of respect among the medical world. The detection is made more challenging by the presence of noise as well as time-varying morphology. The elimination of impurities from the ECG signal is made easier by preprocessing the ECG signal. The following are the several categories that ECG contaminants may be placed into: Interference from power lines, contact noise, patient electrode motion artefacts, muscle noise, and baseline wandering are some of the issues that might arise. In order to get rid of baseline wandering and the other types of wideband noise, digital filtering techniques and methods based on wavelets are used. Taking two approximation level coefficients allows for the removal of the baseline wandering as well as the sounds mentioned above.

Most of the clinically features which are useful for diagnostic the disease can be found in the time interval between components of ECG and the value of the signal amplitude. For example, the Q-T feature is used to recognition one dangerous disease, the Long Q-T Syndrome (LQTS), which is responsible of thousand deaths each year. The shape of T wave is a critical factor and it is essential to identify it correctly since inverted T waves can be caused as an effect of a serious disease named coronary ischemia.

Designing an algorithm in order to extract the ECG features automatically is very hard since ECG signal has a time-variant behavior. As a result of these signal properties, we face with multiple physiological constraints and the existence of noise.

In recent years several algorithms have been proposed for detection those features. In they introduced a method to extract wavelet features and used SVM for classification. In this thesis, we proposed a method for recognition of time interval and amplitude of various wave parts of ECG. In the First stage of our approach, the R-peak is detected accurately. For this purpose we used wavelet. In the second stage, the other ECG components are identified by using a local search around the detected R-peak. We can summarize this approach: The location of the R-wave has been identified by using wavelet transform.

Each R-R interval from ECG signal is segmented as follow:

Within an interval, finding the maximum and minimum of the wave which are corresponding to the Q and S waves. Since P-wave and T-wave is dependant to other factors; we must provide some deterministic point in order to find their location. These points are including the end point of S-wave or Soff, the start point of T-wave or Ton, and the start point of Q-wave or Qon.

### 1 R-peaks detection

The detection of R-peak is the first step of feature extraction. For this purpose, we used DWT due to its ability to recognize different locations of the waves accurately. Similarly to the preprocessing, we apply the same steps in order to compute the scale and choose the mother function. We have the QRS complex signal as an input which has the frequencies between 5Hz and 15Hz, so we select scale of order 4 and choose the Db4 mother wavelet. The Db4 wavelet is very popular for the detection and location of R peaks due to the strong similarity of its shape to the ECG signal. Our method is organized in the following steps. By performing wavelet decomposition, we down sampling the input. Therefore the amount of unnecessary information is reduced but the component of QRS is not changed.

In order to find the location of R-peak, first we choose the locations which their amplitude are greater than 60% of the max value of the whole input signal. Since we remove the noise from the signal in the previous step, it is useful for R-peak detection.

Since we decompose the signal into 4th level, the R-peak location in the modified signal is at least 0.25 of the R-peak location in the original signal. So in order to find the actual location of R-peal we must convert the founded positions by multiplying them with 4.

Another important point is that R-peak location in modified signal is not exactly on the original signal at a scale of 4. Position of the signal will change during the down sampling, so we must to do local search around the R-peaks which calculated in previous part. The interval of this search can be limited to a window of ± 20 samples.

### 2 P, Q and S detection algorithms

The accuracy of detecting R-peak completely affected on P, Q and S detection parts since their location is determined relatively to R-peak. In the other hand, detect the location of R- peaks are corresponding to recognize the heart beat interval. One of the most popular features in ECG signal processing is the R-R interval which can be computed by the following formula:

$$R\_R(i) = R(i+1) - R(i)$$

Where R (i) and R (i + 1) are the indexes of the current and next R wave peak respectively.

### 3 S wave detection

The S-wave is located on the end of the QRS complex so in order to find its location we must start from R-peak location plus 6 units because range of the shortest length of it is between 0.016 and 0.036 seconds. This range is corresponding to 6 and 13 samples. The stop point of search interval is related to the value of R-R interval. However the maximum length of the RS intervals is recorded is around 0.27 seconds where its R-R interval was 1.41 seconds.

### 4 Q-wave detection

The Q-wave indicates the start point of the QRS complex section. It is reported that Q- wave peak location can be found in the range between 0.02 to 0.06 seconds from R-peak. In the other hand, this interval is equal to 8 and 22 samples. But this interval must be relevant to the value heart beat length. Therefore Q-R interval varies from one patient to another, for example a patient with a R-R equal to 235 can have a Q-R interval equal to 19 and another one can have Q-R equal to 8 while has a R-R equal to 292. As a result, the range for search will be larger for longer R-R interval.

### 5 P- wave detection

Since P-wave can be located far or near from Q-wave, it is necessary for its interval to be relative to the R-R interval value.

It is reported that duration of the P-R interval is between 0.09 and 0.19 seconds and this interval also depends on the R-R interval. This interval is equal to 19 and 38 samples. From the point of view of proportional, the limits are 14% to 22% of the respective RR range. One of the benefits of this approach is that we can detect P-waves with low amplitude, so according to the search area interval.

### 6 T-wave detection

Finding T-wave in ECG signal is the most complicated task. Designing a procedure for detecting T-wave is difficult since it has a time variant behaviors. By checking the ECG waveform someone can see that the T-wave is located as the interval which has largest amplitude between S and the middle of the R-R interval. Therefore, the search interval for T started from S-wave and finished at the middle point of the R-R interval.

### Algorithm Design

**Artificial Neural Network**

**Input = Traininput TrF[], Testfeatures TsF[], Threshold T, Feedbackcount n**

**Output= Refine weight for each object.**

**Step 1:** Read Trainfeature TrF

**Step 2:** Read Trainfeature TsF

**Step 3:** for each (tsf into TsF)

**Step 4:** for each (trf into TrF)

If (feedbackcount != n)

**Step 5:** send feed layer to tsf again

tsF ← feedLayer[]

execute for all neurons

early stop

**Step 6:** optimizedfeedLayerweight

**Step 7:**weight = FeedLayer[0];

**Step 8** : return cweight;

**Proposed hybrid machine learning algorithm**

The proposed algorithm provides the overcome of IoT prediction approach according to Machine Learning (ML) approach. I-Heart algorithm illustrates the overall body parameters values, which is calculate by different machine learning algorithms. The bellow algorithm has used for generate the patient health report according the combination sum rule prediction approach.

**Input:** Input values for all parameters HashMap <Double Value, String class> which contains the all attributes values like {Heart_Rate, QT, RR,PR} etc. Policy patterns {P1,P2,Pn}

**Output :** Generate sample report for individual patient.

**Step 1 :** *for each read Hashmap*

$$Extracted\_Attribute[i][j] \sum_{i=0,j=0}^{n} (a_{[i]}, a_{[j]} \ldots\ldots\ldots a_{[n]}, a_{[n].})$$

**Step 2:** *if Extracted_Attribute[j] similar to P[1]*

*NormalPos = +1*

*MasterLits1. Add ← (NormalPos)*

**Step 3 :** *if Extracted_Attribute[j] similar to P[2]*

*AbnPos = +1*

*MasterLits2. Add ← (AbnPos)*

**Step 4 :** *if Extracted_Attribute [j] similar to P[n]*

*DenPos = +1*

*MasterLits3. Add ← (DenPos)*

**Step 5:** *end for*

**Step 6 :** ***calculate*** *the fitness factor for all classes using below formula for all class list*

$$f = \sum_{k=0}^{n} \frac{F(x)}{SumF(x)}$$

**Step 7:** *Weight _CurrentList[w]* $= \frac{MasterLits[i]}{TotalTest}$ **100*

**Step 8 :** *Sort _CurrentList[w] using desc order*

**Step 9 :** *Recommend _CurrentList[0] for final class for patient profile.*

**Step 10 :** *end procedure*

**Results and Discussions**

In this section we present and discuss the outcome of both neural network structures, namely, the ANN. The ECG signals were given as an input to both nets after pre-processing and in the case of the CNN after applying the GASF transformation. The results enlighten how much a classification problem can be improved by means of CCN compared to the standard feed forward neural net. The performance of the nets was assessed by executing the whole training process 10 times and testing after the net was completely trained. In this sense we are able to estimate the mean value of the final performance of each neural network.

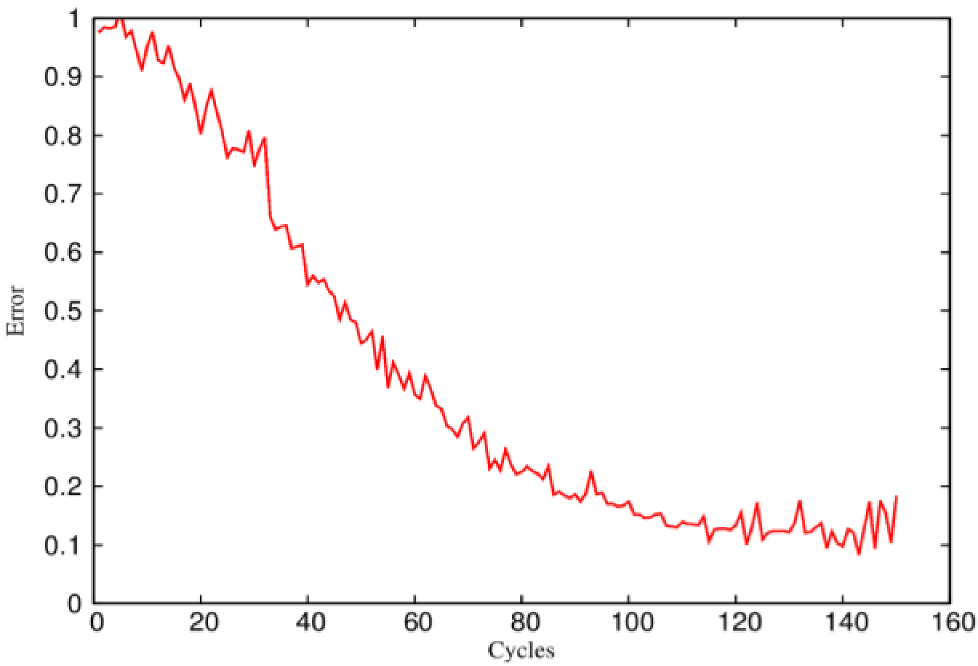


**Figure 5: The error of the training set of the artificial neural network**

After 10 runs of the complete training, the neural net got an average accuracy of 86.4% on the prediction set. Table 1 (Left Structure) shows the accuracy of both training and prediction sets in each run The best accuracy reached was 89.3% in prediction set. Figure 5 and Figure 6 show the training set MSE and accuracy, respectively, through the 220 cycles of training of the run with the best accuracy. It can be observed that the neural network had learnt with a good rate until the last cycles where it ceased to learn.

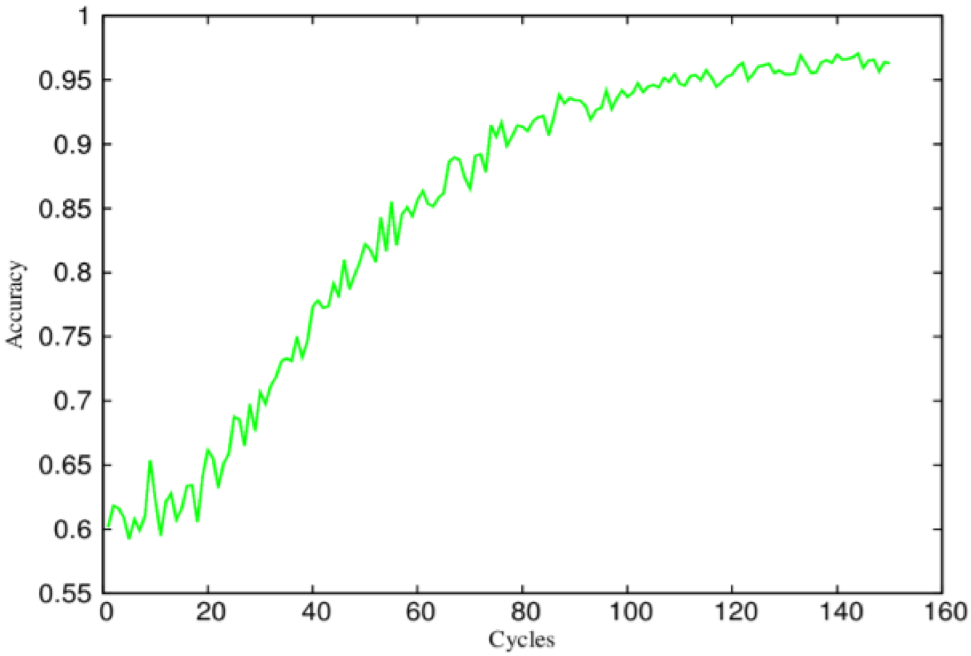


**Figure 6: Accuracy of the training set of the artificial neural network.**

We developed and assessed two artificial neural network architectures for ECG signal classification. The neural networks were fed with input signals in time series format for the ANN and in image format for the Feed Forward ANN. The image for the FFANN was obtained proposing the GASF transformation. Clearly the first method shows having problems generalizing what it learnt, in contrast, the second method generalized pretty well, getting an accuracy of 99.0% in the best run.

The comparative analysis of overall algorithms has done with some confusion metrics. The algorithm shows the Figure 7 for all algorithms including proposed algorithm.

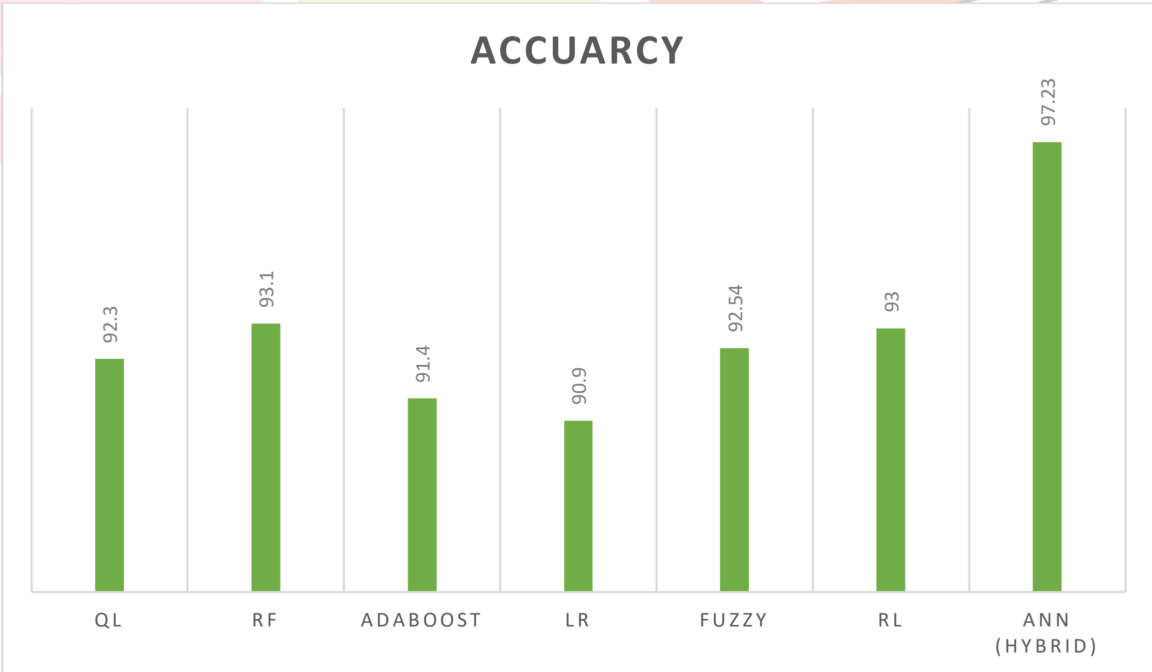


**Figure 7 : Accuracy of proposed system with multiple experiment**

The figure 7 illustrates the overall accuracy of all algorithms, including proposed I-Heart. It provides around 97.23% accuracy. The algorithm Linear Regression (LR) provides the minimum accuracy than other algorithms as 90.90%. Measurements and calculations can be characterized with regard to their accuracy and precision. Accuracy refers to how closely a value agrees with the true value. Precision refers to how closely values agree with each other.

## Conclusion

The detection and categorization of arrhythmia beats are the focus of this research. The rhythm of a person's heartbeat may vary greatly from person to person, and each individual's heartbeat has its own unique variations and a nonlinear quality. Therefore, the suggested computerised system will be useful for early detection of heart state and will assist to lower the proportion of deaths in humans that are caused by heart illness. In the recent past, awareness of the significance of cardiac disease to human existence has increased. The electrocardiogram is the primary tool used in the process of diagnosing cardiac disease. ECG signals are going to be analysed as part of this study with the intention of diagnosing heart illness. This project is carried out with the assistance of the python programming language. The wave structure that is obtained is then utilised to categorise the peaks, which are then put to use in the diagnosis of the condition. With the help of the position of the R peaks, we were able to identify the location of the other peaks. In the last step, we computed the RR and PR intervals. These time periods are particularly significant in terms of the diagnosis of illnesses. These time periods are essential for figuring out what kind of ailment a person has. In the case of tachycardia, for instance, the electrical signal is quicker than it typically is. Because of this, the length of the RR peak need to be shorter than that of a regular sinus. The PR interval is also something that is very essential to us. In the process of detecting tachycardia and bradycardia, this particular interval remained constant.

For future work automatic categorization of cardiac abnormalities is required for applications that take place in real time. It is possible to get a higher level of accuracy in the classification process by isolating more useful elements from the ECG signal. The following are some potential directions that the future may take:

• The development of a more effective approach for feature extraction, which has the potential to enhance the classification result of cardiac arrhythmias in ECG data.

• To determine the accuracy of classification using a variety of classifiers in such a way that it is able to categorise beat arrhythmias in a manner that is acceptable.

• To modify the network structure in accordance with the cost function of the multilayer neural network in order to achieve better classification accuracy when compared to the currently available ECG beat Classifier. • Real time operation for recognising cardiac arrhythmias is also possible thanks to the methodology's use of automatic detection of R-peaks and feature extraction techniques.

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