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A Neural Network Approach for ECG Classification

Vichitra Dubey[1], Vineet Richariya[2]
[1]*Student of Master in Technology software engineering LNCT bhopal*
[2]*Head of theDeptt. Of Computer Science & Engineering LNCT Bhopal*

***Abstract*- bioelectrical signal, which records the heart's electrical activity versus time, is an electrocardiogram (ECG). It is an important diagnostic tool for assessing heart functions. The interpretation of ECG signal is an application of pattern recognition. signal pre-processing, QRS detection, feature extraction and neural network for signal classification are those techniques which used in this pattern recognition comprise**. There are **Different ECG feature inputs were used in the experiments to compare and find a desirable features input for ECG classification. Among different structures, it was found that a three layer network structure with 25 inputs, 5 neurons in the output layer and 5 neurons in its hidden layers possessed the best performance with highest recognition rate of 91.8% for five cardiac conditions.**

***Keyword*-- ECG, QRS, Neural Network**

I. INTRODUCTION

The ECG is a bioelectric signal, which records the heart's electrical activity versus time; therefore it is an important diagnostic tool for assessing heart function. The electrical current due to the depolarization of the Sinus Atria (SA) node stimulates the surrounding myocardium and spreads into the heart tissues. A small proportion of the electrical current flow to the body surface. By applying electrodes on the skin at the selected points, the electrical potential generated by this current can be recorded as an ECG signal. The interpretation of the ECG signal is an application of pattern recognition. The purpose of pattern recognition is to automatically categories a system into one of a number of different classes. An experienced cardiologist can easily diagnose various heart diseases just by looking at the ECG waveforms printout. In some specific cases, sophisticated ECG analyzers achieve a higher degree of accuracy than that of cardiologist, but at present there remains a group of ECG waveforms that are too difficult to identify by computers. However, the use of computerized analysis of easily obtainable ECG waveforms can considerably reduce the doctor's workload. Some analyzers assist the doctor by producing a diagnosis; others provide a limited number of parameters by which the doctor can make his diagnosis.

As illustrated in Figure 1.1 there are four major steps to the ECG signal pattern recognition, namely, pre-processing of the signal, QRS detection, ECG feature extraction and ECG signal classification.

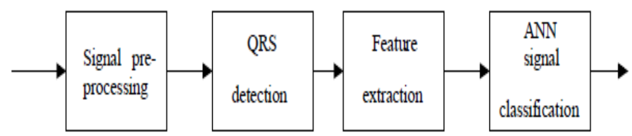

Figure 1.1 Pattern Recognition

The first step is the measurement of acquisition period, which requires a wide range of the ECG signal collection including different abnormalities. The data could be collected from real subjects in the future, but it is presently available from the database. The second step is QRS detection which to corresponds to the period of ventricular contraction or depolarization. The third step is to find the smallest set of features that maximize the classification performance of the next step. ECG feature extraction is mainly used in this step. The choice of features depends on the techniques used in the forth step. Consequently the set of features that are optimal for one technique are not necessarily optimal for another. Because of the unknown interactions of different sets of features, it is impossible to predict the optimum features for a chosen classification technique. Different techniques such as statistical classifiers, artificial neural network and artificial intelligence can be used for ECG classification. The artificial neural network will be used in this project to do the ECG classification. Neural networks are especially useful for classification function, which are tolerant of some imprecision if plenty of training data is available. If there are enough training data and sufficient computing resources for a neural network, it is possible to train a feed-forward neural network to perform almost any signal classification solution. Generally, the ECG is one of the oldest and the most popular instrument-bound measurements in medical applications. It has followed the progress of instrumentation technology. Its most recent evolutionary step, to the computer-based system, has allowed patients to wear their computer monitor or has provided an enhanced, high.

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II. Overview Of ECG System

The standard 12 ECG systems consist of four limb electrodes and six chest electrodes. Collectively, the electrodes (or leads) view the electrical activity of the heart from 12 different positions, 6 standard limb-leads and 6 pericardial chest-leads showed in Table1.1Each lead:

(1) Views the electrical activity of the heart from a different angle,
(2) has a positive and negative component, and
(3) monitors specific portions of the heart from the point of view of the positive electrode in that lead

Table 1.1 ECG lead system. Source:(Jardins T. D., 2002)

Standard Leads	Limb Leads	Chest Leads
Biopolar Leads	Unipolar Leads	Unipolar Leads
Lead I	AVR	V1
Lead II	AVL	V2
Lead III	AVF	V3
		V4
		V5
		V6

The ECG, over a single cardiac cycle, has a characteristic morphology as shown in Figure 1.3 comprising a P wave, a QRS complex and a T wave. The normal ECG configurations are composed of waves, complexes, segments, and intervals recorded as voltage (on a vertical axis) against time (on a horizontal axis). A single waveform begins and ends at the baseline. When the waveform continues past the baseline, it changes into another waveform. Two or more waveforms together are called a complex. A flat, straight, or isoelectric line is called a segment. A waveform, or complex, connected to a segment is called an interval. All ECG tracings above the baseline are

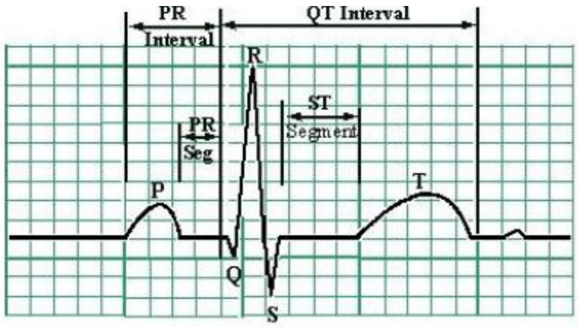

Figure 1.3 The Human ECG signal over one cardiac cycle

A: The P wave

The propagation of the SA action potential through the atria results in contraction of the atria (depolarisation), producing the P wave. The magnitude of the P wave is normally low (50-100uV) and 100 msec in duration.

B:The PR interval

The PR interval begins with the onset of the P wave (Pi) and ends at the onset of the Q wave (Qi). It represents the duration of the conduction through the atria to the ventricles. Normal measurement for PR interval is 120ms-200ms. It is shown in Figure 1.4.

Figure 1.4 PR Interval

The PR Segment begins with the endpoint of the P wave (Pt) and ends at the onset of the Q wave (Qi). It represents the duration of the conduction from the atrioventricular node, down the bundle of its end through the bundle branches to the muscle. It is shown in Figure 1.5.

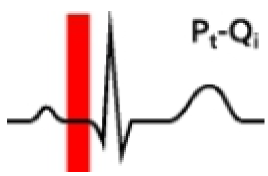

Figure 1.5 PR Segment

C: *The QRS complex*

The QRS complex corresponds to the period of ventricular contraction or depolarization. The atrial repolarisation signal is swamped by the much larger ventricular signal. It is the result of ventricular depolarization through the Bundle Branches and Parkinje fibre. The QRS complex is much larger signal than the P wave due to the volume of ventricular tissue involved, although some signal cancellation occurs as the waves of depolarization in the left and right sides of the heart move in opposite directions. If either side of the heart is not functioning properly, the size of the QRS complex may increase. As shown in Figure 1.6. QRS can be measured from the beginning of the first wave in the QRS to where the last wave in the QRS returns to the baseline. Normal measurement for QRS is 60ms-100ms.

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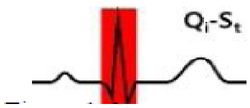

Figure 1.6 QRS Duration

D: The ST segment

The ST segment represents the time between the ventricular depolarisation and the repolarisation. The ST segment begins at the end of the QRS complex (called J point) and ends at the beginning of the T wave. Normally, the ST segment measures 0.12 second or less.The precise end of depolarisation (S) is difficult to determine as some of the ventricular cellsare beginning to repolarise. It is shown in Figure 1.7

Figure1.7 ST Segment

E: The T wave

The T wave results from the repolarisation of the ventricles and is of a longer durationthan the QRS complex because the ventricular repolarisation happens more slowly than depolarisation. Normally, the T wave has a positive deflection of about 0.5mv, although it may have a negative deflection. It may, however, be of such low amplitude that it is difficult to read. The duration of the T wave normally measures 0.20 second or less.

F: The QT interval

The QT interval begins at the onset of the Q wave (Qi) and ends at the endpoint of the T wave (Tt), representing the duration of the ventricular depolarisation/repolarisation.

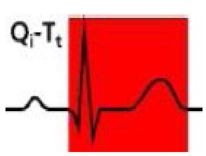

Figure 1.8 QT Interval

The normal QT interval measures about 0.38 second, and varies in males and females and with age. As a general rule, the QT interval should be about 40 percent of the measuredR-R INTERVAL. THE QT INTERVAL IS SHOWN IN FIGURE 1.8.

III. QRS DETECTION ALGORITHM

The QRS complex is the most striking waveform within the electrocardiogram (ECG).Since it reflects the electrical activity within the heart during the ventricular contraction, the time of its occurrence as well as its shape provide much information about the current state of the heart. Due to its characteristic shape, it serves as the basis for the automated determination of the heart rate, as an entry point for classification scheme of the cardiac cycle, and it is often used in ECG data compression algorithms. In that sense, QRS detection provides the fundamentals for almost all automated ECG analysis algorithms (Kohler B.U. et al., 2002). The QT interval is one parameter that is needed to receive the maximum attention Normal QTc length is 420ms, but it maybe potential concern if QTc> 450 ms and it may increase the risk of tachyarrhythmia if QTc> 500 ms. The shape of ST segment in the ECG is another important indication in the diagnosis of heart problem. So, the measurements taken on the ST segment forms another predominant factor in the interpretation phase of the ECG. So, four basic types of algorithms were included in this research. The first three types are named by a two letters prefix "AF" for algorithms based on both amplitude and first derivative, "FD" for algorithms based on first derivate only, "FS" algorithm utilises both first and second derivate. The last one is "median" algorithm.

1) Algorithms based on both amplitude and first derivative (AF1, AF2, and AF3) AF1 concept for this QRS detector was derived form the algorithm developed by Moriet-Mahoudeaux. If X(n) represents a one-dimensional array of n sample points of the synthesized digitized ECG, an amplitude threshold is calculated as a fraction of the largest positive valued element of that array.

A QRS candidate occurs when three consecutive points in the first derivative array exceed a positive slope threshold and followed within the next 100 ms by two consecutive points which exceed the negative threshold. AF2 algorithm is an adaptation of the analog QRS detection scheme developed by

Fraden and Neuman AF3 concept was taken from Gustafson The first derivative is calculated at each point of the ECG. The first derivative array is then searched for points which exceed a constant threshold, then the next three derivative values must also exceed the threshold. If these conditions are meet, point i can be classified as a QRS candidate if the next two sample points have positive slope amplitude products.

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2) Algorithms based on first derivate only (FD1 and FD2) FD1 algorithm was adapted from the one developed by Menard .FD2 algorithm is a modification of an early digital QRS detection scheme developed by Holsinger. The derivative is calculated for the ECG.This array is searched until a point is found that exceeds the slope threshold. A QRS candidate occurs if another point in the next three sample points exceeds the threshold.

3) Algorithm utilizes both first and second derivate (FS1 and FS2) FS1 algorithm is a simplification of the QRS detection scheme presented by Balda. The absolute values of the first and second derivate are calculated from the ECG. Two arrays are scaled and then summed. One of the array is scanned until a threshold is met or exceeded. Once this occurs, the next eight points are compared to the threshold. If six or more of these eight points meet or exceed the threshold, the criteria for identification of a QRS are met.FS2 algorithm was adapted from the QRS detection scheme developed by Ahlstrom and Tompkins. The rectified first derivative is calculated from the ECG. Then this first rectified derivative is smoothed. The rectified second derivative is calculated. The first smoothed derivative is added to the rectified second derivative. The maximum value of this array is determined and scaled to serve as the primary and secondary thresholds. The array of summed derivative is scanned until a point exceeds the primary threshold. In order to find a QRS candidate, the next six consecutive points must all meet or exceed the secondary threshold.

4) Algorithm based on median filter A median filter is a non-linear filter for processing digital signal. It is also a good selection for QRS detection (Chazal D. P., 1998).

IV. ECG Feature Extraction

After pre-processing, the second stage towards classification is to extract features from the signals. The features, which represent the classification information contained in the signals, are used as inputs to the classifier used in the classification stage.

The goal of the feature extraction stage is to find the smallest set of features that enables acceptable classification rates to be achieved. In general, the developer cannot estimate the performance of a set of features without training and testing the classification system. Therefore, a feature selection is an iterative process that involves trailing different feature sets until acceptable classification performance is achieved.

Feature extraction is a key step in most pattern analysis tasks; the procedure is often carried out intuitively and heuristically. The general guidelines are:

- Discrimination: features of pattern in different classes should have significantly different values.
- Reliability: features should have similar values for pattern of the same class.
- Independence: features should not be strongly corrected to each other.
- Optimality: some redundant features should be deleted. A small number of features are preferred for reducing the complexity of the classifier. Among a number of approaches for the task, the principal component analysis has, by far, been the most widely used approach.

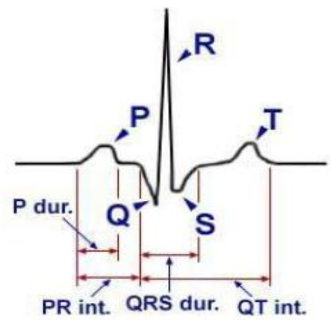

Figure 2.2 ECG feature extraction

In one work by Chazal, 178 features were abstracted from a QRS complex for a representative ECG beat. After applying the transforms to the features there were a total of 229 transformed features. Methods for calculating these features were determined from many existing ECG literatures. In another work 30 features were extracted for a neural network using a back propagation training algorithm (Pretorius L.C. et al., 1992). These features will be the input of the next stage. With the above-mentioned features, the more the input the more complex will be the network structure of the classification. The classification speed will become so slow in the normal personal computer that it cannot be accepted in research. To solve this problem, important and basic features from ECG waveform will be introduced from the introduced literature. Moreover, the compressed form of the signal is added to the extracted features to check the improvement of the classification performance in classification stage. The selected features in this research are based on the existing feature extraction algorithm The ECG features can be divided into two main categories: morphological and statistical features. Figure2.2 illustrates a general indication of the P wave, QRS complex, T wave, and U wave as well as the ST segment, P-R and Q-T intervals in a normal ECG cycle.

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A group of important morphological parameters such as: the QRS complex duration, R-R interval, P-R interval, Q-T interval, ST segment, and R wave amplitude can be detected by applying different signal processing techniques such as QRS detection, QT interval and ST segment analysis. The ECG features can be extracted from the QRS complex, the ST segment, the statistical, and power spectral density (PSD) of the signal.

V. NEURAL NETWORK CLASSIFICATION

Artificial neural networks (ANN) have been trained to perform complex function in various fields of application including pattern recognition, identification, classification, speech, vision and control system. A neural network is a massively parallel-distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects.

1) Knowledge is acquired by the network through a learning process,
2) Inter-neuron connection strengths known as synaptic weights are used to store the knowledge.

In theory, neural networks can do anything a normal digital computer can do. We can train a neural network to perform a particular input leads to a specific target output. Such a situation is shown in Figure 2.3 (Demuth H. and Beale M., 2001). There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning, to train a network.

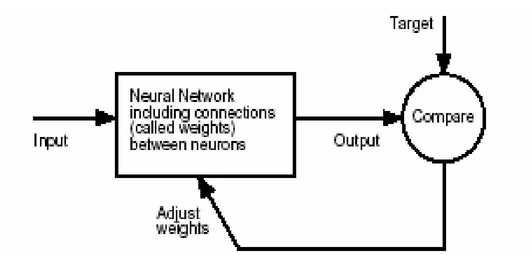

Figure 2.3 Neural Network adjust system

Pattern recognition is a research area whose goal is the classification of objects into a number of categories or classes [1].Depending on the application, these objects, or patterns, can be any group of measurements or observations that need to be classified (e.g. images or signals) [2]. The progress of classification might be supervised (when a desired output is known and used to compute an error signal) or unsupervised (when no such error signal is used) [3].

From the perspective of pattern recognition (PR), artificial neural networks (ANNs) can be regarded as an extension of many conventional or not, techniques (e.g. statistical PR, data clustering, application of fuzzy sets, structural PR, syntactic PR etc. [5]) which have been developed over several decades [4]. Neural networks are adaptive machines which have 'a natural propensity for storing experiential knowledge and making it available for use' [6]. In other words, an artificial neural network is an adaptive mathematical model or a computational structure that is designed to simulate a system of biological neurons to transfer information from its input to output in a desired way [7]. They are called adaptive because they can be trained in order to learn to estimate the parameters of some pattern using a small number of exemplars at a time [3]. Neural network consists of simple discrete interconnected units called neurons. These neuronal nodes are linked by a set of weighted connections or synapses (Fig.1). Learning is accomplished by adjustment of these weights so that an association between an input and an output pattern is discovered or analyzed. The architecture of these networks is organized into layers of neuronal units and is strictly bounded to the training method adopted. The dataset to be analyzed is fed to the so-called *input* layer and the information, after being distributed to all of the input neurons, flows towards the *output* layer, passing through some intermediate or *hidden* layers.

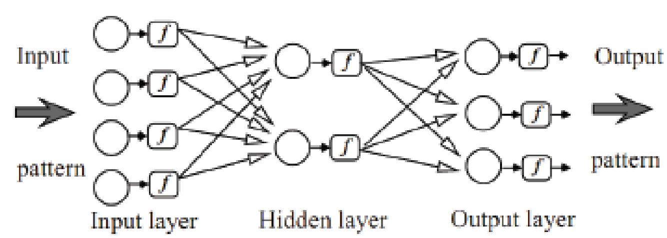

Fig.1 A multi-layer neural network.

Each neuron is a simple mathematical model which transforms its input to an output response. This transformation involves two steps: First, the activation of the neuron is computed as the weighted sum of its inputs, and second this activation is transformed into a response by using a transfer function (Fig.2) [3]. The most popular transfer functions are: the linear function, the step function, the logistic function and the Gaussian function. In this paper, we use the sigmoid transfer function (a special case of the logistic function) for the output and the hidden neurons and the linear function for the input ones (Fig.2).

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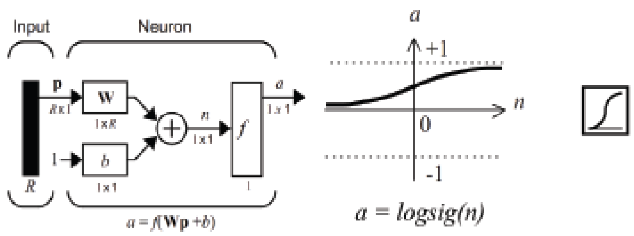

Fig.2 A typical neuron and the sigmoid transfer function.

Classification is one of the most frequently encountered decision making tasks of human activity [9]. Thus, neural networks have emerged as a significant classification tool. Their statistical non-linear character gives them clear precedence over traditional classifiers (TC) in many biomedical applications [8] [9]. The embedded non-linearity of complex real world, nature and biosignals, renders neural network classifiers suitable for such applications. Such an application is also the effective classification on multiple ECG signals. Moreover, ECG is the most widely used signal in clinical practice and one of the first signals where biomedical signal processing techniques where applied upon, [10] due to its diagnostic significance. An electrocardiogram (ECG) is an electrical recording of the heart and is used in the investigation of heart disease [11]. In this work we investigated the ability of a simple neural network to classify multiple discrete pathologic ECGs into four different classes. We affiliated the 'holistic' approach in order to process the ECGs, considering each signal as an integrated entity and not as a collection of discrete waves (P, T, QRS etc.). Thus, we fed the NN with several sample vectors that represent signals and as a result the NN created its response.

VI. LITERATURE REVIEW

The filtering techniques are primarily used for preprocessing of the signal and have been implemented in a wide variety of systems for ECG analysis. Filtering of the ECG is contextual and should be performed only when the desired information remains ambiguous. Many researchers have worked towards reduction of noise in ECG signal.

Most types of interference that affect ECG signals may be removed by band pass filters; but the limitation with band pass filter is discouraging, as they do not give best result. At the same time, the filtering method depends on the type of noises in ECG signal. In some signals the noise level is very high and it is not possible to recognize it by single recording, it is important to gain a good understanding of the noise processes involved before one attempt to filter or preprocess a signal.

The ECG signal is very sensitive in nature, and even if small noise mixed with original signal the characteristics of the signal changes. Data corrupted with noise must either filtered or discarded, filtering is important issue for design consideration of real time heart monitoring systems.[Himanshu, S. et al (2010)], designed amplifier using instrumentation amplifier AD620 (Analog Devices) to bring the peak value into a range of 1v; having gain of 1000. For collection of ECG signal he has used band pass filter with cutoff frequency 0.5Hz-150 Hz on NI ELVIS (National Instruments Educational Laboratory Virtual Instrumentation Suite) board. as shown in fig-2.1.

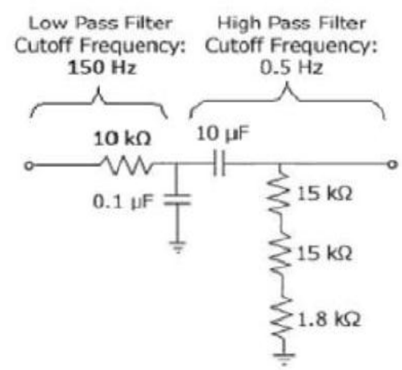

Figure 2.1: Band Pass Filter

After the filtration the output of the analog filter is fed to the NI ELVIS. It has inbuilt data acquisition card. DAQ assistant is used to collect the signal after passing through the band pass filter. The data sampled at a rate of 1 KHz. After acquiring the signal it is processed by Butterworth (IIR) 3rd order digital filter. The first digital filter is band stop filter between 49.5 to 51.4Hz to eliminate power line interference. Butterworth filter having various orders, the lowest order being the best in time domain, and higher order being better in frequency domain. It is having monotonic amplitude frequency response, which is maximally flat at zero frequency response, and amplitude frequency decreases logarithmically by increasing frequency.

The main source of baseline wandering is respiration. It is having the frequency range between 0.15 to 3Hz. They used the wavelet transform to eliminate the Baseline wandering which is an effective way to remove the signal in specified sub-bands. After the removal of baseline wandering, the resulting ECG signal is more stationary and explicit than the original signal.

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For removing the wideband noises, using Wavelet Denoise Express VI, which is one of the tools of ASPT Power line interference, is due to improper grounding of ECG equipment and interference from nearby equipment. It is removed by using notch filter. The power line interference is more influential on the signal compared to the other types of artifact. The major source of such noise is electrical activity of the muscles that should be removed i.e. the noise present due to power line interface (50HZ) is also to be removed as shown in fig-2.2 . Even though the analog amplifier having high Common Mode Rejection Ratio (CMRR), the ECG signals is contaminated by power line interference (50 HZ in India). In order to discard the sources of noise, proper filtration is required. The suppression of Baseline Wander and Power Interference can be done using digital IIR filter.

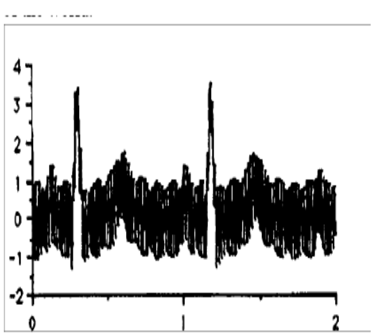

Figure 2.2 ECG Corrupted due to Power Line Interference

[Padma T. et al (2009)] , used adaptive noise filtering for removal of 50 Hz that is the power line interference because, the ECG signal also contains 50 Hz signal and if normal band reject filter is used, then the 50 Hz signal which is very important in the ECG signal will be lost. Therefore by opting adaptive noise filtering, the power line frequency can be eliminated at the same time retaining the 50 Hz signal in the original waveform.

VII. DESCRIPTIONS AND TRAINING OF THE NEURAL NETWORKS

A set of least object-sensitive ECG features was selected to form the neural network input vector. This strategy aimed to reduce the complexity of the network and facilitate the training phases of the network by employing smaller training data size. A multi-layer perceptron (MLP) classifier was designed to separate two most common ECG waveforms in the MIT/BIH database. The selected categories were N and PVC beats.

The second neural network, with a similar output to the first, was designed to perform a supervised waveforms based on Linear Vector Quantization (LVQ). The number of hidden layer neurons was chosen as ten for the first and 30 for the second, which is small enough for fast training and avoidance of overtraining, yet sufficiently large to give adequate network accuracy. The number of network outputs was selected equal to two in each of the first and the second network. The proposed with a single hidden layer is shown in figure 4.1.A target vector was arranged as the desired output for each class. Accompanying each record in the MIT/BIH database in an annotation file in which each heart beat has been identified by expert cardiologist annotators. This annotated information can be employed for designing the target vector and evaluating the classifier performance.

As indicated in figure 4.2, after 09 training epochs, a lower mean square error (MSE) and a smaller gradient were achieved using the training set. Width a smaller size of training set, the network performed better in training but had poor performances when applied to the evaluation or test sets. The two networks were trained with different waveforms extracted from the signal 106, so 1500 and 520 exemplars of normal and PVC beats respectively.

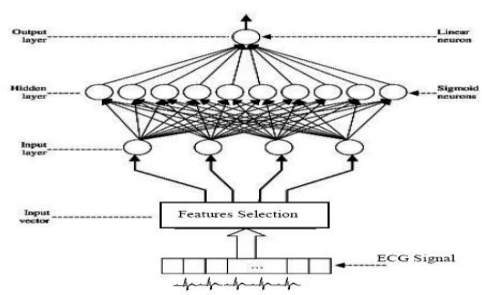

Figure 4.1: Architecture of Neural network

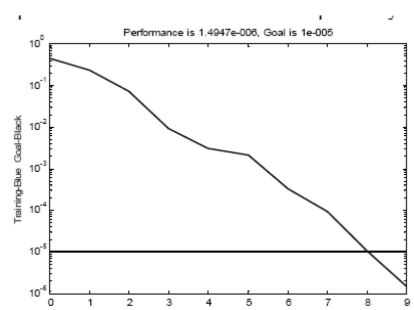

Figure 4.2: Training Epoch of Network

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VIII. CONCLUSION

To identification of human artificial neural networks can efficiently be used for the identification and classification of ECG signals. Several retraining trials indicated that achieving optimum performance, during data processing, requires the non-linear neural network model to consist of two hidden layers of 20 neurons each. A more complex model does lead to a dramatic increase of response time.

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