Identification and Diagnosis of Cardiovascular Diseases Using A Backpropagation Neural Network Combined With A Weight Tuning Using Logistic Regression

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ABSTRACT:

A typical obstacle in obtaining high-accuracy arrhythmia classification models using artificial neural networks is a lack of adequate training samples of various ECG signals. To address this issue, this study proposes a unique technique based on a feed forward back propagation neural network with a weight updation coefficient based on logistic regression. The results reveal that the weight adaptation technique improves the performance of all classification networks. The suggested approach is useful in classifying various arrhythmias.

Keywords: Artificial Neural Network, ANN, ECG, Arrhythmia, Electrocardiography, Discrete Wavelet Transform

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I. INTRODUCTION:

The electrocardiogram (ECG) is a diagnostic technique that measures the electrical activity of the heart using a skin electrode. The shape and heart rate of the human heart beat represent the cardiac health. It is a noninvasive technology in which the signal is captured on the surface of the human body and utilised to identify cardiac problems. Many Cardiologists are now having problems establishing a precise diagnosis for ECG arrhythmia illnesses. Furthermore, the traditional approach of visual examination is more sophisticated and time-consuming. The data from an electrocardiogram may be used to diagnose several forms of arrhythmia. It may be beneficial for determining how well a patient is responding to therapy, thus a computerised interpretation of ECG and issues will be developed in order to examine the various arrhythmias employing Artificial Neural Networks (ANN). The shape of the ECG waveform and heart rate typically represent the status of the cardiac heart. If appropriately evaluated, an ECG may reveal information about numerous arrhythmia illnesses of the heart. The standard heartbeat and the ECG signal are shown in fig.1. Shape, P wave repetition, complicated QRS, T wave, and R-R span are the basic limits of a normal heartbeat. The differences in these borders point to a cardiac problem that may occur for a variety of reasons. Arrhythmia refers to the two periods of the erratic beat, and certain arrhythmias are dangerous to patients. Arrhythmia refers to an irregular heartbeat. Tachycardia is a condition in which the heart beats excessively quickly. Bradycardia is a condition in which the heart beats too slowly.

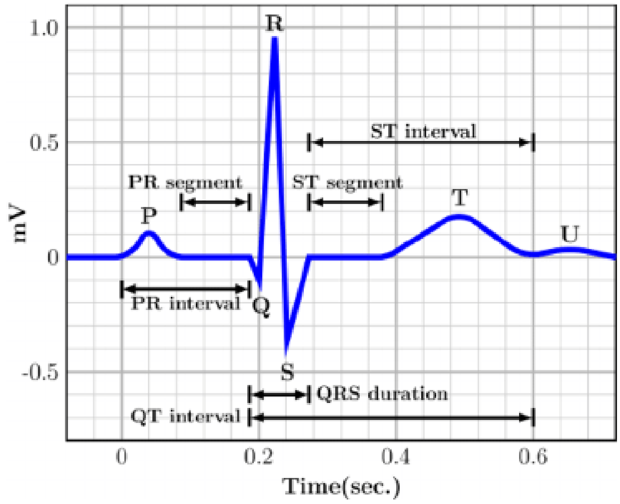


Figure 1:ECG Beats and intervals

The huge variety in the morphologies of ECG waveforms is the most challenging difficulty that today's automated ECG arrhythmia analysis faces. Thus, our primary goal is to devise a simple solution that requires minimal processing time while maintaining accuracy. The current study addresses many technical elements of developing a software programme to categorise Arrhythmia from an input ECG signal to cardiac diagnostics using signal processing and wavelet transformations. The suggested method was created with the goal of providing effective medical treatment to cardiac patients while they are being transferred to a hospital. Many Cardiologists are now having problems establishing a precise diagnosis for ECG arrhythmia illnesses. Furthermore, the traditional approach of visual examination is more sophisticated and time-consuming. The data collected from an electrocardiogram may be used to diagnose several sorts of cardiac problems. Existing techniques rely on heart rate, RR interval, and other parameters, however these variables are incapable of classifying several classes due to their strong correlation and nonlinearity. If the recorded signal includes undesired noise, such as power line interface and baseline drift, it is reduced using software filtering utilising digital filters in the next step of the operation. Following that, the RR interval and numerous ECG properties are extracted using the wavelet transform, which is useful for measuring heart rate.

The detection of ECG waves and the determination of their characteristic points are completed. The process of recognition begins with the detection of the most essential events, which signify ventricular depolarization and are represented by the QRS complex. The R peak is then identified as a location where the slope changes from positive to negative. The slope threshold and search criteria are used to identify further P and T waves and calculate their start and offsets. The observed parameters are used to calculate parameters like as PR interval, RR interval, and QRS duration, among others, which are then saved for future processing. The last objective in ECG processing is to categorise the ailment. A decision logic-based illness categorization algorithm has been created. The parameters gathered in the previous step are utilised to interpret the arrhythmia in this stage. The developed algorithm checks for several criteria listed in the various categorization tables for each type of sickness. If any of the characteristics are met, a specific type of illness is determined.

Section 1 provides a quick introduction to the thesis, describing how Arrhythmia Classification is frequently utilised in biomedical industries and how it is valuable in this respect. ECG classification is a well-known approach, and there are several literatures accessible to cover it thoroughly, as summarised in section 2. Section 3 demonstrates how to employ ANN models as a framework for ECG classification. Filtering, feature extraction, and ANN approaches are discussed in length here. The performance measures are then examined one by one in section 4. Also included in this part are the values derived from each performance measure, as well as the graphs displayed for each metric. Section 5 contains the primary conclusions that can be drawn from this study.

II. Literature Survey

Deep learning methods' current state-of-the-art performance in typical ECG classification challenges has prompted academics to adapt similar algorithms to medical applications like as image and signal processing. Deep learning algorithms based on Recurrent Neural Networks (RNN), mainly Long Short Term Memory Networks (LSTM) [1], and Convolutional Neural Network (CNN) [2], have demonstrated substantial progress in the Electrocardiograph (ECG) area. The ability of a Neural Network (NN) to automatically learn complicated representative features directly from data has become a significant advantage of employing Deep Neural Networks, replacing the requirement for human feature extraction. The use of these breakthroughs enables the development of self-learning algorithms that utilise ECG data to predict input and output arrhythmia class while effectively and efficiently evaluating deep characteristics. Another advantage of using DNN is that it provides higher accuracy and better outcomes in the categorization of fine-grained ECG signals in the presence of limited data [4].

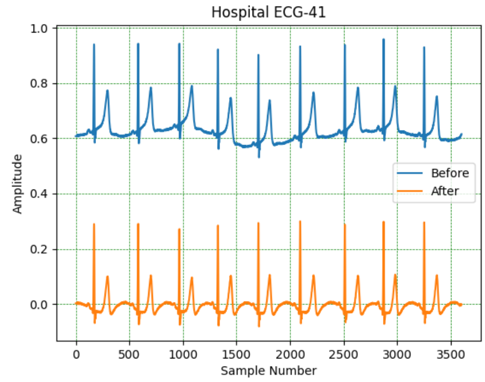
The extremely accurate patient-specific ECG categorization and monitoring system based on a 1-dimensional CNN technique was presented in [3]. This method combines extracted characteristics with classification to create a unified learner. The MIT/BIH arrhythmia dataset may be used to evaluate classification performance. The precision of the cutting-edge approach was the greatest. J.I.Williams et al. [5] carried out the measurement, which was separately assessed by a panel of cardiologists and the AHA. It is offered an analysis of a series of proposals aimed at standardising measurement in quantitative ECG. These AHA suggestions have gained worldwide acclaim. Zhao et al [6] introduced a novel feature extraction method for accurate cardiac rhythm identification. The proposed classification method consists of three components: data pre-processing, feature extraction, and ECG signal categorization. To get the feature vector of ECG data, two different feature extraction algorithms are combined. The wavelet transform is used to obtain the transform coefficients as the characteristics of each ECG segment. At the same time, autoregressive modelling (AR) is used to determine the temporal structures of ECG waveforms. Finally, a support vector machine (SVM) with a Gaussian kernel is employed to categorise various ECG heart rhythms. The total accuracy of the computer simulations used to estimate the performance of the suggested strategy was 99.68%. The method, filtering process based on moving averages published by V. S. Chouhanet.al [7], gives smooth spike-free ECG output, which is suitable for slope feature extraction. The first step is to extract the slope feature from the filtered and drift corrected ECG signal, which is then processed and transformed such that the derived feature signal is greatly amplified in the QRS area and suppressed in the non-QRS zone. The suggested technique has a detection rate of 98.56% and a positive predictive value of 99.18%. S.C.Saxena et al. developed a modified mixed wavelet transforms approach in [8]. The approach was created to evaluate multi-lead ECG data in order to diagnose heart diseases. For QRS detection, a quadratic spline wavelet (QSWT) was utilised, and for P and T detection, a Daubechies six coefficient (DU6) wavelet was used. For the identification of different heart disorders, a process based on ECG data and a point scoring system has been developed. When both diagnostic criteria produced the same findings, the consistency and dependability of the discovered and measured parameters were validated. Table 1 compares several strategies for extracting ECG signal features. Ramli and Ahmad discussed correlation analysis for aberrant ECG signal feature extraction in [9]. Their planned research looked on a method for extracting essential characteristics from ECG signals from a 12-lead system. They picked II as the typical feature for identifying prevalent cardiac disorders throughout their whole research. The cross-correlation analysis approach was employed. Cross-correlation analysis determines the similarity of two signals and extracts the information contained in the signals. Their test findings indicated that the proposed approach could efficiently extract characteristics that distinguished between the kinds of heart disorders studied as well as normal heart signal. Laurence et al. [10] describe a continuous wavelet transform-based approach for investigating the non-stationary strength and phase delay of respiratory sinus arrhythmias (RSA). The RSA is the cyclic fluctuation of instantaneous heart rate at the frequency of breathing. Paced breathing or postural alterations, low respiratory frequencies, and quick changes have all been seen in investigations of cardio-respiratory interaction during sleep. Bekir Karhket et al.[11] used an artificial neural network using ECG signals examined in the temporal domain to detect matching arrhythmias, with a 95% success rate for identifying arrhythmias. Chuang-chienet et al. [12] developed an effective arrhythmia identification method that uses the correlation coefficient in the ECG signal to identify QRS complexes. The correlation coefficient and the RR interval were used to assess the similarity of arrhythmia. Stefan Gradl et al. [13] examined the

Pan-Tompkins method for QRS detection, template construction and adaption, feature extraction, and beat categorization. The MIT-BIH Arrhythmia and MIT-BIH Supraventricular Arrhythmia databases were used to verify the method. The system properly recognised more than 98% of all QRS complexes. The overall sensitivity for detecting irregular beats was 89.5%, with a specificity of 80.6%. J. Lee, K. et al. [14] used wavelet transform and linear discriminate analysis to analyse input features. This suggested approach achieves excellent arrhythmia identification accuracy of 97.52, 96.43, 98.59, and 97.88% for NSR, SVR, PVC, and VF, respectively.

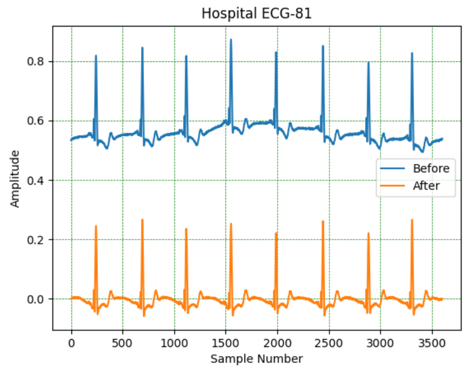
METHODOLOGY

Deep learning-based arrhythmia classification typically consists of three main phases: filtering, mapping, and identification. The whole ECG signal comprises noise. This disturbance must be removed from the ECG signal when it is filtered. The suggested technique is described below. To train and test the algorithm, MIT-BIH datasets and real-time hospital data are gathered.

a) Zero Phase Low-Pass Filtering: Base-line drift in chest-lead ECG data may be induced by coughing or breathing with substantial movements of the chest, or by moving an arm or leg in the case of limb-lead ECG capture. Variations in temperature and bias in the instrumentation amplifiers may occasionally produce baseline drift. Its frequency range is typically 0.5 Hz. A high pass filter with a cut-off frequency of 0.5 Hz is employed to reduce baseline drift. Before extracting the unique features of the ECG signals from the provided dataset, the overall ECG signal must be filtered to remove noise. Among the early studies on noise reduction in ECG, the use of zero phase low pass filters was the simplest and most widely used[15]. The graphic below shows the filtering result. The blue ECG is the original ECG, while the red ECG is the baseline removed signal.



(a)



(b)

Figure 2 : ECG denoising (a & b)

The blue tint in the accompanying figure represents the raw ECG collected from the hospital. The given ECG has baseline drift noise. When the transfer function form [b, a] is required, numerical issues may arise since the conversion between roots and polynomial coefficients is a numerically sensitive process, even when N >= 3. Create a highpass filter to remove the lower-frequency components (the baseline wander). The cut-off frequency should be chosen such that the ECG signal information is not altered while removing as much of the baseline drift as feasible; hence, the lowest-frequency component of the ECG should be saught. This is supposed to be determined by the slowest heart rate. The heart rate may decrease below 40 beats per minute, meaning that the lowest frequency is 0.67 Hz. Again, since this is not a workout, a suitably low cutoff frequency of about 0.5 Hz should be employed. A linear phase filter is used to prevent phase distortion, which might disrupt numerous temporal relationships in the cardiac cycle.

Table 1: Filter Coefficient

Parameter	Filter Coeff. Values
b	[0.97575445, -2.92726336, 2.92726336, -0.97575445]
a	[1., -2.95091385, 2.90302503, -0.95209675]

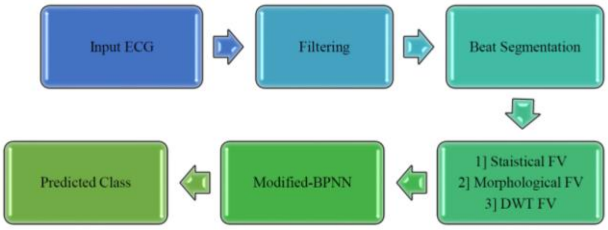


Figure:3 Architecture of Proposed Model

a) ECG beat Segmentation:

i.Smoothing and filtering of raw data:

The derivative-based method amplifies high frequency sounds, resulting in strong difference signals owing to noise. As a result, the ECG data is first smoothed and filtered to remove power frequencies and high frequency noise.

Detection of QRS Regions:

Owing to the high frequency content of the QRS region [5-15 Hz] the derivative of these regions of ECG have higher amplitudes. As the sampling instants of digital ECG data remains constant the amplitude differences are proportional to the derivatives which can be used to detect the QRS regions. Double differencing and squaring intensifies the magnitudes of the difference signal in the QRS regions which aids in the localisation of the QRS regions as in Fig. 2 (b).

The process involves the following steps, From the ECG data array e (n) the squared double differences are calculated at all points to yield the difference array d (j).

$$d1(i) = e(i+1) - e(i), i = 1,2,\ldots n-1$$

$$d1(j) = d1(j+1) - d1(j), j = 1,2,\ldots n-2$$

$$d(j) = [d2(j)]^2$$

where e(n) is the ECG data array with total n points, and d(j) is the squared double difference array.

The difference array is sorted in decreasing order of magnitude, and the difference peaks that are greater than a fixed threshold value of 3% of the maximum are chosen. Because the maximum length of the QRS regions is 150 ms, all difference peaks within an interval of 75 ms of each chosen difference peaks are deleted to prevent the potential of detecting multiple peaks in the same QRS area. As illustrated in Fig 2, the QRS areas are recognised as being within a window of 75 ms of each chosen peak on the ECG data array (c).

Detection of R peaks:

The R peaks are the QRS regions' positive peaks. These are discovered by comparing the relative magnitudes of the QRS areas. To reduce mistakes caused by baseline drift, a maximum search was performed on the relative magnitudes for each window.

The maximum and lowest amplitude values of the ECG data array are determined for each detected QRS window. To get the relative magnitudes, subtract the mean of the highest and lowest values from all data points in that frame. The R point positions of the related QRS window are determined by the position of the maximum of the relative magnitudes. To prevent the potential of detecting the S point, the absolute maximum value of the QRS window is not chosen as the R-point position.

ii.Segmentation of beat:

The R peaks obtained as a result may be inaccurate. Missed peaks or erroneous detections are possible. The RR intervals are analysed using certain criteria to assure detection accuracy. The smallest difference between two subsequent R peaks is thought to be 200 ms. Any peaks observed within 200 ms of the first are deemed noise and are removed. The average RR interval for five consecutive R peaks is determined and used as a reference for the RR interval processing.

b) Feature Extraction:

The Fourier Transform (FT) solely gives frequency information; time information is not provided. STFT - offers both time and frequency information, but resolves all frequencies equally. Wavelet transform - at high frequencies, it gives excellent time resolution but poor frequency resolution, while at low frequencies, it provides good frequency resolution but poor time resolution. WT signals have several similarities to ECG signals.

i.DWT Theory:

A signal is divided into two portions, often high and low frequencies.

The low frequency portion is divided into two parts: high and low frequency. This procedure is repeated until the signal has been completely deconstructed.

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$$y_{HIGH}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n+1-k]$$

$$y_{Low}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k]$$

Where,

x[k]= Input signal.

g[n] & h[n] = Impulse response of high pass and low pass filter [3].

This technique begins by decomposing the original ECG signal by using the Discrete Wavelet Transform on it, with the Daubechies Wavelet (db4) serving as the mother wavelet. When you get rid of the components with low frequency, you get rid of the baseline, and when you get rid of the components with high frequency, you get rid of the noise in the original signal. After that, an automated R-R interval calculation should be performed using the pre-processed data from the ECG. The elimination of the baseline is the very first step in the digital processing of the electrocardiogram data. In order to accomplish this, the signal is smoothed by using the Matlab function Smooth, which implements the Moving Average method [18]. For this, the signal 100 from the MIT-BIH database was used. The signal period is 0.8 seconds, and the sampling time is 1/360 seconds; consequently, the factor that is applied is 1/300.

The filter bank that will be used to accomplish the discrete wavelet decomposition may be seen in Figure 3.

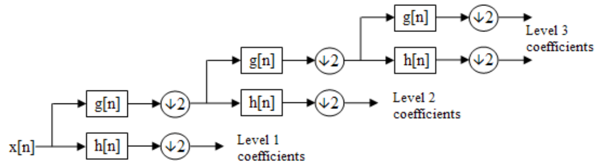

Figure.4. Filter for discrete wavelet decomposition.

The high pass and low pass characteristics of the FIR filter are denoted by the notations h[n] and g[n], respectively. Since every filtered signal is sub-sampled, the total length of the signal components is cut in half as a result. In this approach, the noise and other unwelcome components of the signal are filtered out with the use of the wavelet transform, which enables the R-R interval to be isolated. The original ECG signal vectors were constructed using 256 discrete data at the intervals of R–R for all arrhythmias. Because of this, each feature vector only comprises a single ECG beat. When just the magnitudes of the ECG signals are used to create the feature vectors, the computational cost is significantly reduced. On the other hand, the determination of the R-peak location has an effect on the feature vectors. The vectors will be scattered across the feature space if the location of the R-peak is not accurately identified. Mathematical transformations are used to the signals in order to extract additional information from the signal that is not easily accessible in its raw form. The information that is extracted is not immediately apparent in the signal. The high cost of computing may be attributed to the fact that feature vectors are generated via the application of transformations. The techniques of transformation stop the dispersion of vectors in the feature space. The measurement of ECG characteristics begins with the assessment of wave amplitude and position as the foundation. The correct selection of the reference level is essential to achieving accurate measurements. We extract a total of eight characteristics from the time domain, including wavelet features, RR intervals, QRS index, and QRS amplitude, among other things.

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Pravin B Desai , Dr Yuvraj K Kanse , Dr Chandrashekhar, Mahesh B Neelagar/ Identification and Diagnosis of Cardiovascular Diseases Using A Backpropagation Neural Network Combined With A Weight Tuning Using Logistic Regression

ii. Higher Order Statistical Features:

It was shown that higher order statistics, or HOS, are less sensitive to the morphological changes of an electrocardiogram (ECG), and the nonlinear and dynamic character of these features helped to extract the subtle changes that were present in the ECG data. For each pulse, the skewness, kurtosis, and 5th moment statistics are computed. Skewness refers to the degree to which the mean deviates from the median.

c) Proposed Classification:

The modified backpropogation neural network belongs to the category of feed forward neural networks and is a subtype of the supervised neural forward feed network. Advised the use of a generalised neural regression network (MBNN), which is a method that incorporates one-pass learning and makes use of neural networks as a tool for defining and controlling nonlinear systems. The main benefit of using MBNN is that the network "learns" from the examples as soon as they are stored and may do so in only one pass over the data. This allows for faster generalisation. It indicates that the use of MBNN is beneficial owing to its capability of converging on the underlying function of the data with just a few available training samples due to the fact that it has a smaller sample size requirement. The MBNN is composed of four different levels. As can be seen in figure 1, these layers are labelled as follows: input layer, pattern layer, summation layer, and output layer. All of the measurement variables x are passed on to all of the neurons that are present in the second layer, which is known as the pattern layer, by the input neurons of the input layer, which are simply distribution neurons. The MBNN's Pattern layer is the first hidden layer under its surface. The number of training samples that are currently accessible in the training data set is proportional to the number of neurons that are currently available in this layer. Each neuron acts as a training pattern, and the output of the pattern layer provides the distance between the input patterns and the ones that have been stored. The third layer is a summation layer, and it consists of two neurons: one neuron is for denominator summation, which adds up the weight values coming from each of the hidden neurons, and the other neuron is a numerator summation unit, which adds up the weight values multiplied by the actual target value for each hidden neuron. The output layer is the fourth layer, and it is the one that divides the two outputs that it gets from the hidden layer in order to produce the anticipated output.

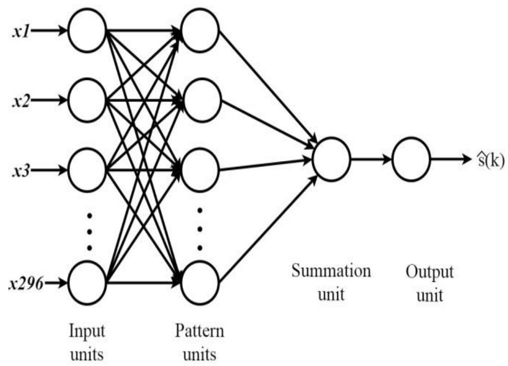

Figure:5 MBNN Architecture

ALGORITHM OF MODIFIED BPNN

Step 1: Initialize the weights to small random Values.

Step 2: Choose the pattern X^{d}_{k} and apply it the input layer $V^{o}_{k} = X^{d}_{k}$ for all k

Step 3: Propagate the signal through the network

$V^{m}_{i} = f(net^{m}_{i}) = f(\sum_j w^{m}_{ij} V^{m-1}_{j})$

Step 4: Compute the deltas for the output layer

$\delta^{M}_{i} = f(net^{M}_{i})\,(t^{d}_{i} - V^{M}_{i})$

Step 5: Compute the deltas for the preceding layer for m =M, M-1,..2

$\delta^{M-1}_{i} = f(net^{m-1}_{i}) \sum_j w^{m}_{ij} \delta^{m}_{j})$

Step 6: Update all the connections

$\Delta w^{m}_{u} = \eta \delta^{m}_{i} V^{m-1}_{j}$ $\quad w^{new}_{ij} = w^{old}_{ij} + \Delta w_{ij}$

Modified BPN : $w^{new}_{ij} = w^{old}_{ij} + \Delta w_{ij} * \alpha * L(w)$

Step 7: Goto 2 and repeat for the next pattern.

III. EXPERIMENTS AND RESULTS:

The MIT/BIH arrhythmia database is employed in this Experiment in order to verify the suggested Method. Comment for both planning data and beat class data that has been validated by independent professionals is included in the database.

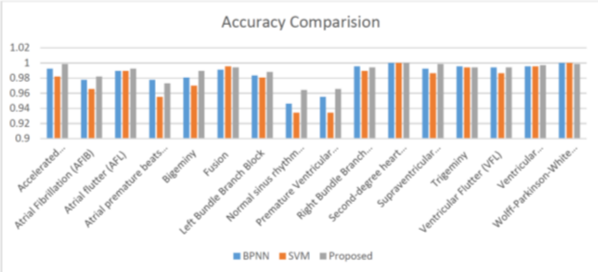

Figure 6: Comparison of accuracy

Proposed method have better accuracy than the Traditional BPNN and SVM. Minimum accuracy obtained is 93% for premature ventricular and maximum accuracy is 99% for Wolf Parkinson white.

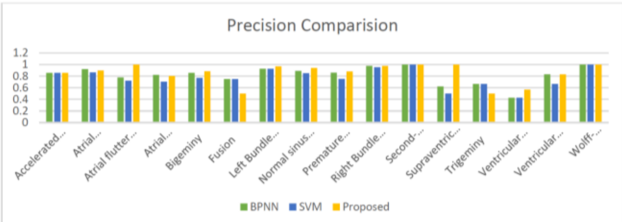

Figure 7: Comparison of Precision

Proposed method have better precision than the Traditional BPNN and SVM. Minimum precision obtained is 50% for fusion and maximum accuracy is 99% for supraventricular tachycardia.

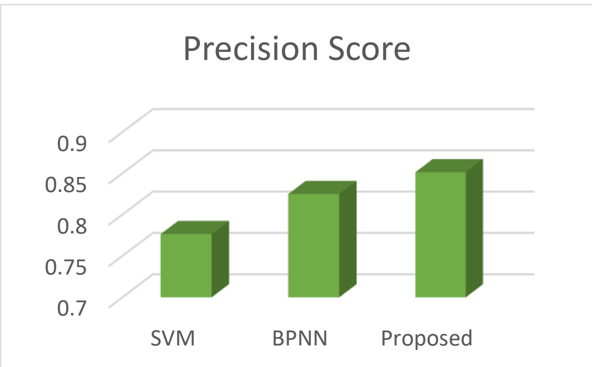

Figure 8: Average Precision Score

Proposed method have better precision than the Traditional BPNN and SVM. SVM precision obtained is 78% and BPNN achives 82% whereas Proposed achieves 84%.

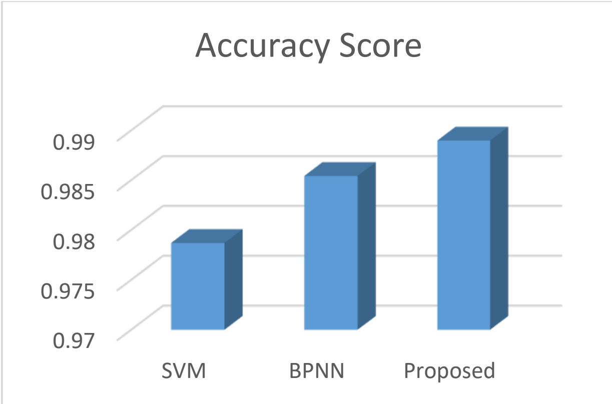

Figure 9: Average Accuracy Score

Proposed method have better accuracy than the Traditional BPNN and SVM. SVM accuarcy obtained is 97% and BPNN achieves 98% whereas Proposed achieves 99%.

IV. Conclusion:

Based on the performance parameters described above, it is evident that the results of BPNN-LRC classification for 10 hidden layers are superior to those of SVM and BPNN classification; nevertheless, it takes more time than SVM does. SVMs with linear kernels perform much worse when applied to real-time ECG data, despite the fact that they operate better than other algorithms overall. The performance of our suggested BPNN-LRC was much better. The study was carried out to the point where an algorithm was developed in order to identify and extract the Time domain characteristics, wavelet domain features, and Morphological features of ECG signals by using wavelet transform and BPNN-LRC. The study was able to estimate sixteen different types of arrhythmias effectively.

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