Received: October 23, 2017

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Arrhythmia Detection Based on Hybrid Features of T-wave in Electrocardiogram

Raghu Nanjundegowda[1]* **Vaibhav Aniruddha Meshram[2]**

[1]*Jain University, India*
[2]*Dayananda Sagar University, India*
* Corresponding author's Email: raghu1987n@gmail.com

Abstract: An Electrocardiogram (ECG) is used as one of the important diagnostic tools for the detection of the health of a heart. An automatic heart abnormality identification methods sense numerous abnormalities or arrhythmia and decrease the physician's pressure as well as share their work load. In ECG analysis, the main focus is to enhance degree of accuracy and include a number of heart diseases that can be classified. In this research paper, arrhythmia classification is proposed using Hybrid features of T-wave in ECG. The classification system consists of majorly three phases, windowing technique, feature extraction and classification. In feature extraction phase various features are used such as Differential Entropy (DE), Peak-Magnitude RMS ratio, Auto Regressive feature based Yule Walker, Burgs method. In classification phase Deep Neural Network (DNN) classifier is used. This classifier categorizes the normal and abnormal signals efficiently. The experimental analysis showed that, the Hybrid features Arrhythmia classification performance of accuracy approximately 98.3%, Specificity 98.0% and Sensitivity 98.6% using MIT-BIH database.

Keywords: Auto regressive method, Burgs method, Deep neural network, Differential entropy, Electrocardiogram, Peak-magnitude root mean square ratio, Yule walker.

1. Introduction

In present days, the computerized ECG acquisition system plays an important role in monitoring and recording the signal in real time and helps to recognize the normal and abnormal heart conditions [1]. It is a non-invasive technique and used for the detection of a broad range of cardiac conditions like Arrhythmia, Heart rate variability, etc. [2]. Earlier research works were based on ECG signals to improve the time complexity, decrease the high amount of information lost and reduce the cardiologist's burden. To overcome these problems computer based automated techniques are required for arrhythmia detection from large medical dataset [3, 4]. In some cases, medical specialist facing issues like, two signals have similar patterns, but show different diseases and in some other cases, two signals have different patterns but indicate the same disease. In these cases, medical specialist can't easily diagnose the diseases. Therefore, only the ECG signals appearance is not an accurate approach to detect the possible diseases. Using another feature of these signals might be helpful to detect the diseases [5]. Several techniques are used to detect and classify heart related diseases like arrhythmia and Normal Sinus Rhythm (NSR).

In the past few decades, several methods for ECG analysis and heart disease detection have been developed to improve the heart abnormality classification. The ECG signals majorly include five basic peaks such as P, Q, R and T peaks and occasionally U waves. The P peak indicates as atrial depolarization and T wave indicates the repolarization of ventricle. The position of the QRS complex waveform is the significant section in the ECG signal research [6]. The ECG signal is different for different persons similarly, different for same person dissimilar kinds of heartbeats either may fast, slow, etc. In some literature, several existing techniques have used for heart abnormality classification such as Support Vector Machine (SVM), Radial Basis Function (RBF), Linear Discriminant Analysis (LDA), Principle Component Analysis (PCA), and so on [7, 8]. The heart abnormality detection using the ECG signal have major issue such as signals are varying significantly for each person (based on gender, age, etc.). Also, some physical conditions cause ECG signals to change for the same person over the time. Therefore, the dynamic nature of the ECG signal, a fixed structure based techniques cannot be used [9]. In this paper, DWT coefficient and Time domain based features are employed for ECG signal feature extraction such as DE, peak magnitude RMS ratio, Auto regressive features like Yule-Walker Method, and Burgs method. The Hybrid features improve the ECG signal classification and also, with the help of SVM classifier two abnormal heart related diseases are identified.

This paper is organized as follows: Section 2 survey several existing techniques of Arrhythmia classification using ECG signals. In section 3, DWT based transformation, feature extraction methods are presented with DNN classification. Section 4 shows the experimental results of ECG signal based Arrhythmia classification using MIT-BIH database and Section 5 provides some concluding remarks.

2. Literature review

A. Daamouche, L. Hamami, N. Alajlan, and F. Melgani [11] presented a wavelet optimization strategy depends on the mixture of the poly phase representation of wavelets and PSO. This strategy finds the wavelets that indicate the beats of discrimination capability calculated through an empirical measure of the classifier efficiency. The SVM classifier illuminates the accuracy and stability of the proposed method and poly phase permits the wavelet filter bank from angular parameter. The wavelet method for ECG signal improves the classification accuracy but, this proposed technique not suitable for all datasets.

P. Kora and K.S.R. Krishna [12] presented Wavelet Coherence (WTC) method for ECG signal investigation. The WTC measures the similarity among two waveforms in the frequency domain. The features are extracted from ECG signal after that optimized with the help of Bat algorithm. The optimized features are classified using Levenberg Marquardt neural network classifier. These techniques select the relevant features and reduce the feature redundancy as well as improve the classification accuracy but, this architecture is a bit time consuming.

V.H.C. de Albuquerque [13] illustrated the arrhythmia identification in ECG signal using supervised machine learning methods of Optimum Path Forest (OPF) classifier. The proposed method's efficiency and effectiveness are compared with the different feature extraction methods and classifiers. The OPF discovered more skills to generalize data. This technique is more efficient in terms of computation time of testing and training. But, sometimes possibilities of miss prediction activities were occurring.

S.S. Kumar, and H.H. Inbarani [14] proposed Multi-granulation rough set based classification approaches are applied for ECG cardiac arrhythmia categorization. The classifier was verified ECG signals of 24 channels were recorded from the database. The Pan-Tomkins's and Wavelet Transform (WT) methods have been decided on to gain a compact set of features. The classifier improves the classification accuracy. In this work, only a limited number of ECG channels are taken for the experiment and all channels are not taken.

D. Ai [15] evaluated Fast feature fusion technique of Generalized-N-Dimensional (GND)-ICA for ECF heartbeat classification based on multi-linear subspace learning. In feature fusion, all extracted feature of ECG signal heartbeat was arranged as a two-way tensor, in which feature-fusion procedure was implemented using a multi-linear subspace-learning method, GND-ICA. The SVM classifier was used for classification, which classified the heartbeats. This classifier decreased the classification time and removed the redundant features. This work achieved high accuracy, but limited number of ECG channels are used.

3. Proposed methodology

ECG signals majorly provide the heart diagnosis information such as rhythm function and disease related information, etc. Yet, this concealed information can be used to detect abnormalities. Here, the input signals are taken from MIT-BIH database, the input signals are pre-processed using an IIR filter, after that time and frequency domain features are extracted from DWT. In feature extraction time domain based, statistical based and morphological features are used such as DE, peak-magnitude-RMS ratio, Auto Aggressive feature, Yule-Walker Method, Burgs method. Finally, the signals are classified as normal or abnormal signal, in case abnormal then again classify the disease. Below the Fig.1 indicates the proposed architecture diagram and description.

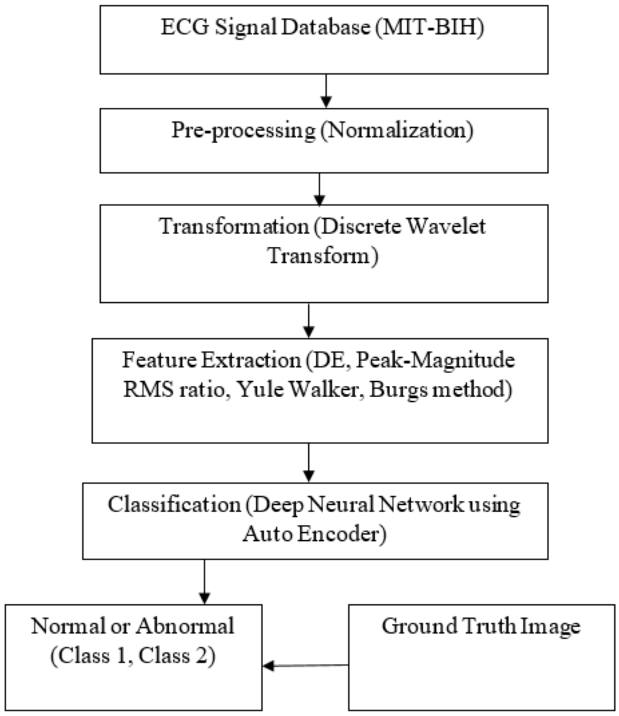

Figure.1 Proposed architecture of arrhythmia classification

3.1 Signal data acquisition

An acquisition of an ECG signal helps to detect heart rate, disease, and heart related essential information. The major ECG databases are Personal Health Record (PHR) dataset, MIT-BIH sinus arrhythmia and NSR dataset, etc. In this research work input raw data are taken from the MIT-BIH arrhythmia database for identifying the normal and arrhythmia conditions. This database includes 47 subjects and 23 channels randomly taken from a 4000 set of ECG data collected from outpatient as well as inpatient at Boston's Beth Israel Hospital. Rest of the 25 channels are selected from the same set. The sampled ECG channels are 360HZ. Each channel with 11-bit resolution over 10mV range.

3.2 Signal preprocessing

The ECG signals are extracted from the database. It consists of major noises like baseline wandering and power line interference which are the most substantial noises in the ECG signal analysis. The general pre-processing techniques are Finite Impulse Response (FIR), Median Filter, Savitzky - Golay Filtering, Polynomial Filtering, etc. Here, Infinite Impulse Response (IIR) filter is used to remove the signal noise. Baseline wandering that arises due to respiration lies between 0.15Hz and 0.3 Hz. The power-line interference is a narrow-band noise centered at 60 Hz with a bandwidth of less than 1 Hz. Amplitude and baseline potential of ECG signal from a same direction can be affected by many factors, which will greatly affect the accuracy of recognition and classification. To improve the accuracy of recognition and classification, normalization should be done to ECG signals. The method is to set the baseline to 0, and the maximum amplitude to 1 or -1. Here, extract the features of R peak location as the primary peaks. After that moving some sample of left side and some sample of right side to find PQST and R peaks to extract that particular portion using windowing technique.

3.3 Transformation

Transformation is a mathematical tool which is used to shift signals from time domain to frequency domain. Transforms change the representation of signal by projecting it into a set of basic functions but don't change the signal information. The major transformations are employed in peak detection namely Discrete Wavelength Transform (DWT), Fast Fourier Transform (FFT), Walsh-Hadamard Transform (WHT), etc.

3.3.1. Discrete wavelet transform

The DWT is providing superior time resolution and frequency resolution. The DWT have time and frequency localization capacity, so it will extract the local features from input ECG signal and helps to reduce the feature degradation. In WT the input signals are decomposed and resultant signals have both higher and lower frequencies. The ECG signal $x(t)$, is correlate with a wavelet function Ψ. The Continuous WT (CWT) is defined in Eq. (1),

$$w(a,b) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{a}}\Psi(\frac{t-b}{a})dt \tag{1}$$

Where a and b are two variables, the scale and translation parameters respectively. The function set Ψ is a wavelet family (mother wavelet). Since the parameters (a,b) are continuously valued, the transform is called a CWT. The DWT identify the input ECG signals and gives the adequate information. The DWT decompose the input signals into various channels with multi resolutions. The DWT is mathematically defined in Eq. (2),

$$\varphi_{m,n} = \frac{1}{\sqrt{a^m}}\varphi(\frac{t-nba^m}{a^m})dt \tag{2}$$

Where m and n are two integers for handling the dilation and translations respectively, φ is a wavelet function. After the DWT based transformation signal is moved to the feature extraction stage using different features.

3.4 Feature extraction

The Wavelets coefficients are used to extract the significant features from the ECG signal such as Time Domain features, Morphological features, and Statistical Features, to improve the heart related disease classification.

3.4.1. Differential entropy

A DE is used to measure the complexity of a continuous random variable, which is related to the minimum description length. DE features are more suited for drowsiness recognition tasks. Energy spectrum is the average energy of ECG signals in frequency bands. DE is originally defined in Eq. (3),

$$h(X) = \int_x f(x) \log\big(f(x)\big)\, dx \tag{3}$$

Here, X is a random variable, $f(x)$ is the probability density function of X. For the time series X obeying the Gauss distribution $N(\mu, \sigma^2)$ and the length of ECG sequence is fixed. Thus, DE is calculated by Eq. (4),

$$h(X) = -\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \log\left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}\right) dx \tag{4}$$

Although the original ECG signals do not follow a certain fixed distribution, it can be found that ECG signals are subjected to Gaussian distribution. DE is equivalent to the logarithm energy spectrum in a certain frequency band. The researcher has frequently used logarithm energy spectrum. Since, the low frequency energy is higher than the high frequency energy in ECG, so after the logarithm of energy, the ability of discriminating ECG pattern can be balanced between high and low frequency energy.

3.4.2. Peak-magnitude to root mean square ratio

Determine the positive peak and negative peak values of the single transition waveform or the single pulse waveform: the minimum peak value as the low or first state level and the maximum peak value as the highest or second state level. The mathematical equations of Peak-Magnitude to Root Mean Square Ratio (PRMS) is described in Eq. (5),

$$\mathrm{PRMS} = \frac{\|\mathrm{X}\|_\infty}{\sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{n}=1}^{\mathrm{N}} |\mathrm{X}_\mathrm{n}|^2}} \tag{5}$$

This algorithm is best suited to the analysis of waveforms with state levels of negligible or relatively short duration [16].

3.4.3. Morphological features

The heartbeat of ECG signal majorly consists of three peaks such as QRS complex, P wave, and T wave. The signals are non-stationary nature means the statistical characteristics. These signals are changed in terms of time and position. To identify the P Q R S T waves position of various ECG signal are determined by using MATLAB function to estimate its duration and amplitude of the waves. Here, R peak, Tmin and Tmax peaks are used for feature extraction to efficiently predict the normal and abnormal signals. T peaks are more effected to the abnormal signals compared to the other peaks, so Tmin and Tmax features are used.

3.4.4. Auto regressive feature

Autoregressive (AR) methods calculate the Power Spectral Density (PSD) of the signal using parametric approach. The AR method provides better frequency resolution and no spectral leakage problem. The AR model indicated the random process and time varying process in nature. Two methods used to estimate AR models are briefly described below,

3.4.4.1. Yule-Walker method

This strategy, calculate the AR parameters are evaluated by resulting of the auto correlation data function. This method helps to find the estimation of minimization of minimal squares of the forward expectation error and are described in Eq. (6),

$$\begin{bmatrix} r(0)_{xx} & \cdots & r(-p+1)_{xx} \\ \vdots & \ddots & \vdots \\ r(p-1)_{xx} & \cdots & r(0)_{xx} \end{bmatrix} \times \begin{bmatrix} a(1) \\ \vdots \\ a(p) \end{bmatrix} \tag{6}$$

The r_{xx} represents the elements of the matrix in the above Eq. (6) that indicates an unbiased estimate of auto covariance function. Where r_{xx} can be defined by Eq. (7),

$$r_{xx}(m) = \frac{1}{N}\sum_{N=0}^{N-m-1} x^*(\mathrm{n})\mathrm{x}(\mathrm{n}+\mathrm{m}), \quad \mathrm{m} \geq 0 \tag{7}$$

Calculating the above set of $(p + 1)$ linear equations, the AR coefficients can be obtained in Eq. (8),

$$P_{xx}{}^{BU} = \frac{\sigma_{wp}{}^2}{\left|1+\sum_{k=1}^{P} \hat{a}_p(k) e^{-j2\pi f k}\right|^2} \tag{8}$$

While $\hat{\sigma}wp$ gives the approximated lowest mean square error of the p^{th}-order predictor given as Eq. (9),

$$\sigma^2{}_{wp} = E^f{}_p = r_{xx}(0)\prod_{k=1}^{P}[1 - |a_k(k)|^2 \quad (9)$$

3.4.4.2. Burg's method

This method calculates the AR spectral depends on the decreasing he forward and backward prediction errors. The benefit of this method is to without estimate the autocorrelation function, calculate the reflection coefficient easily. The major strength of this method is calculation of Power Spectral Density (PSD). The way of estimation of PSD is different in Berg's and Yule-Walker method. The PSD calculation using Burg's method is indicated as $P^{BU}{}_{xx}(f)$ described in Eq. (10),

$$P^{BU}{}_{xx}(f) = \frac{\widehat{E_P}}{|1+\sum_{k=1}^{P}\widehat{a_P}(k)e^{-j2\pi fk}|^2} \quad (10)$$

Where, $\widehat{E_P}$ defines the total error of least squares. These methods avoid the spectral leakage issue and generates better frequency resolution. After the feature extraction the signals have gone through the classification step, here DNN classifier is used and described in below section.

3.5 Classification

After the extraction of features from pre-processed data, the ECG data are used for predicting the abnormal and normal signal. The classification is used DNN, which produce compositional models where the object is expressed as a layered composition of primitives. The DNN, minimize the cross entropy or noise between the actual and predicted outcomes. This usually involves neural layers learning on huge dataset. An additional layer allows configurations of lower layer features constructing complex data hypothetically.

3.5.1. Deep neural network using auto encoder

The DNNs typically working like feed forward networks. Here, the data flow from the input layer to the output layer with no looping back. The major advantage of DNN classifier as, during classification, the possibilities of missing some signals in this situation the classifier automatically takes the signal and used to further process. The DNN allocates a classification score $f(x)$ during prediction time. To every input data sample $x = [x_1, \ldots\ldots x_N]$ via a forward pass. Characteristically, f is the function, which involves a sequence of layers of computation, which is represented in the Eq. (11),

$$Z_{ij=}x_i w_{ij};\ Z_j = \sum_i Z_{ij} + b_j;\ X_j = g(Z_j) \quad (11)$$

Where, input of the layer is x_i, its output is x_j w_{ij} are the model parameters and $g(.)$ realizes the mapping or pooling function.

Layer-wise Relevance Propagation decomposes the classifier output $f(x)$in terms of relevance's r_i attributing to each input component x_i its share with which it contributes to the classification decision described in Eq. (12),

$$f(x) = \sum_i r_i \quad (12)$$

Where, $r_i > 0$is indicates the positive evidence supporting the classification decision and $r_i > 0$negative evidence of the classification, otherwise neutral evidence.

The DNN is able to investigate the unknown feature coherences of input signals. The DNN provides a hierarchical feature learning approach. So, the high level features are derived from the low level feature with a greedy layer wise unsupervised pre-training data. Thus, the key objective of DNN is to handle the complicated functions that can represent high level abstraction.

3.5.2. Stacked auto encoder

The auto encoder neural network includes multiple layers of sparse auto encoders. Each layer output support to the input of the successive layers. An auto encoder attempts to learn an approximation to the identity function, shown in the Eq. (13),

$$\hat{x} = h_{w,b}(x) \approx x \quad (13)$$

The DLN exploits the unsupervised pre-training technique with greedy layer wise training. This technique executes at time one layer in unsupervised pre training, beginning from input to output layer. The first sparse auto encoder (1st hidden layer) is trained on the raw inputs(x) to learn primary features $h^{(1)}$ on the inputs.

The structure of an auto encoder is depicted in Figure 2. During the pre-training process, all of weight and bias parameters have learned to lessen the cost function. The Fig. 3 shows the Softmax classifier using auto encoder. The input data use the forward propagation to train sparse auto encoder to attain the basic features.

In the next hidden layer of pre training data, the auto encoder technique calculates its features using the same method from the preceding hidden layers. Eq. (14) describes auto encoder,

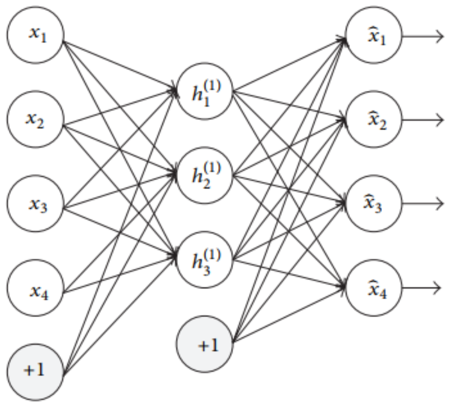

Figure.2 Structure of an auto encoder

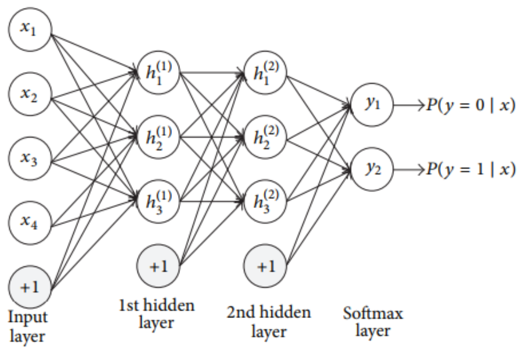

Figure.3 Stacked auto encoder with softmax classifier

$$cost = \frac{1}{2n}\sum_{i=1}^{n}(x_i - x_i)2 + \beta\sum_{j=1}^{m} KL\ \left(p|\hat{p}_j\right) + \frac{\lambda}{2}\sum_{i=1}^{n}\sum_{j=1}^{m}\theta_{ij}^{2} \qquad (14)$$

Where, hidden nodes are represented in m, inputs are n, weight of sparsity penalty as β , the probability of firing activity indicated as $\hat{p}\,j$, the sparsity parameter is denoted as ρ , weight delay is represented as λ, KL is Kullback-Leibler divergence function, and θ is weight of hidden nodes. Using DNN classifier, the ECG signal is classified successfully whether the signal is normal or abnormal. After the classification, output images are validated with ground truth images. Using ground truth image verify the output signals, whether the DNN classifier is properly classified or not. The experimental analysis of Arrhythmia classification and performance calculations of existing and Hybrid features techniques are described in the below sections.

4. Experimental result and discussion

In this section, the experimental results have been described in detailed. The experiments were implemented on PC with 1.8GHz Pentium IV processor using MATLAB (version 6.5). Here, the various combinations of features were tested and trained by using DNN of ECG signal from MIT-BIH database. This dataset consists of 48 half-hour extracts of two channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory. But in this study, two sets of signals are taken such that 18 normal signals and 18 abnormal signals, so total 36 signals are taken in same training and testing cases. The hybrid feature identifies the ECG signal using the normal signal or SNR and abnormal signal or Arrhythmia. The performance evaluation of the proposed system is described in below section.

The DNN utilizes the unsupervised pre-training technique with greedy layer wise training, starting from the input layer to the soft max layer. The first sparse auto encoder is trained on the features to learn the primary features $h^{(1)}$ on inputs. All of DNN parameter settings based on ECG signal are shown in Table 1. The performance evaluation of the proposed method is described in below section.

Table 1. DNN parameter settings

Parameter	Values
Maximum iterations: SAE learning	400
Maximum iterations: Softmax learning	1000
Hidden layer size	100, 50
L2Weight Regularization	0.004
Sparsity Regularization	4
Sparsity Proportion	0.15
Scale Data	False

Table 2. ECG features and their normal durations

Features	Descriptions	Durations
P	First short upward movement of the ECG	80ms
PR	Estimation of beginning of the P wave to the beginning of the QRS complex	120-200ms
QRS	Normally begins with a downward deflection Q, a larger upwards deflection R and ends with a downward S wave	80-120ms
PR	Connects the P wave and the QRS complex	50-120ms
ST	Connects the QRS complex and the T wave	80-120ms
T	Normally a modest upward waveform	160ms
QT	Calculation of beginning of the QRS	

The Table 2 depicts the ECG features along with their description and normal durations. The ECG features like peaks, segments and intervals are having normal amplitude and duration values. In arrhythmia classification ECG signals play a major role. The major limitation of ECG based heart disease prediction is the normal ECG signals are different for every person and similarly, same disease has different signs in different patient's ECG signal. Sometimes, two different diseases may have nearly the same effects on ECG signals. Therefore, the utilization of DNN classifier technique can improve the new patient's ECG arrhythmia diagnosis.

4.1. Performance evaluation

The ECG signals are extracted from proposed combined features of time domain, morphological and statistical features such as DE, Peak magnitude RMS, Yule walker (YM) method, and Burgs (BR) method. DNN classifier decides whether the signals are normal (SNR) or abnormal (Arrhythmia). In this experimental analysis the proposed DNN classifier performance is compared with the other existing classifiers like Neural Network (NN), Support Vector Machine (SVM), in terms of Accuracy, Specificity, and Sensitivity. The estimation has been done for these parameters using TP, FP, FN, and TN values, where TP refers to true positive, TN is true negative, FP is false positive and FN is false negative. The calculation of parameters is described below,

Accuracy: Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations. The accuracy is directly proportional to true results, consider both true positives and true negatives among the total number of cases scrutinized. The parameter of accuracy is calculated in Eq. (15),

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \times 100 \qquad (15)$$

Specificity: The measures the proportion of negatives that are correctly identified and specificity is described in Eq. (16).

$$Specificity = \frac{TN}{(TN+FP)} \qquad (16)$$

Sensitivity: The sensitivity calculates the ratio of positives that are appropriately recognized signals and mathematical equation of sensitivity is described in Eq. (17).

$$Sensitivity = \frac{TP}{(TP+FN)} \qquad (17)$$

In experimental analysis, the ECG signal based prediction of normal and abnormal signals. In below section, the Arrhythmia disease signal and Normal signals are shown below.

The Fig. 4 depicts the Arrhythmia disease ECG signal. Here, the black star are the P and T peak. Blue star is the R peak, pink star is the S peak and green peak is the Q peak. The T peak represents the high voltage, which effects the disease signal. The T peak is more effected on the abnormal signals.

The Fig. 5 depicts the normal and abnormal ECG signals. In signals of X axis is the samples in (ms) and Y axis is the Amplitude in mV. The first row is the input of normal signal and abnormal signals. The second row depicts the applied normalization techniques and detected R peaks. All R peaks are detected and based on R peak P, Q and T peaks are detected. The third row indicated as applied windowing technique. The windowing techniques for both normal and abnormal signal.

The Table 3 depicts the signal based performance of the existing classifiers and proposed classifiers with different features. Here, the various features such as DE, PRMS, BR, YM, Max, Min and proposed combined features are used. The existing NN classifier achieved 77.085 of accuracy in combined feature. The SVM classifier achieved 86.11% of accuracy for proposed feature. The proposed DNN classifier achieved 98.33% of accuracy. The training and testing performance of the window based method of Arrhythmia disease and Supraventricular Arrhythmia prediction is described in Table.3.

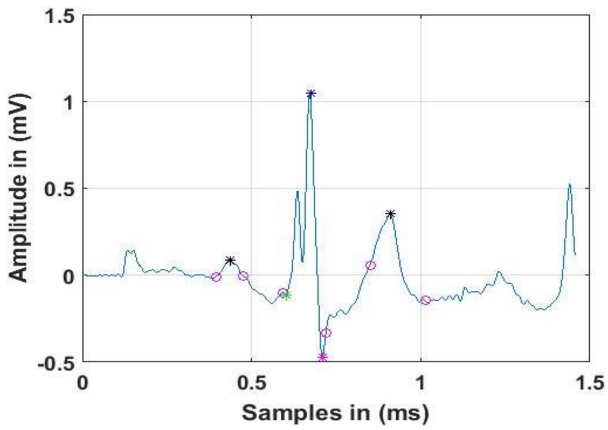

Figure.4 ECG signal of arrhythmia disease

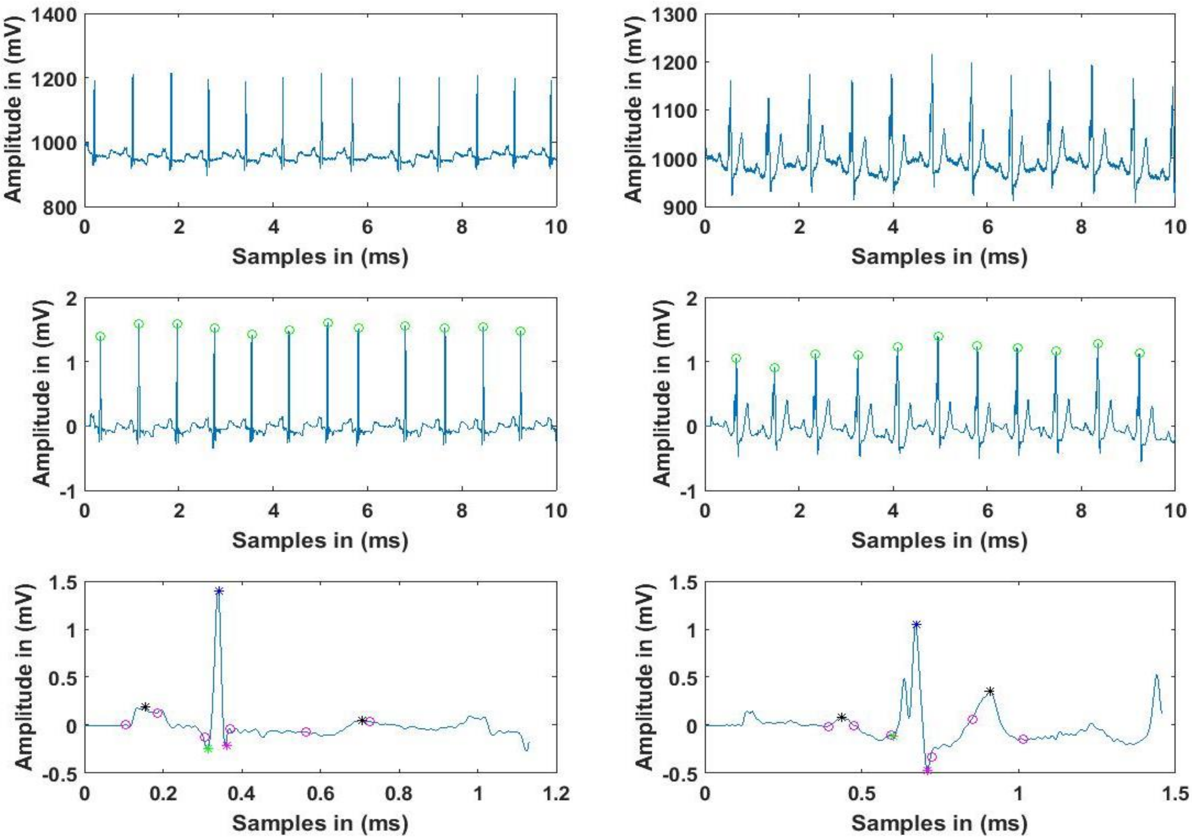

Figure.5 Normal ECG signals

Table 3. Signal based performance evaluation of different classifiers and features.

Classifiers	Features	Sensitivity	Specificity	Accuracy (%)
NN	DE	67.50	58.61	63.06
	PRMS	55.56	57.78	56.67
	BR	69.70	63.61	66.67
	YM	60.83	64.17	62.50
	Max	65.00	60.00	62.50
	Min	65.83	63.33	64.58
	Proposed	75.83	78.33	77.08
SVM	DE	77.78	55.56	66.67
	PRMS	55.56	94.44	75.00
	BR	38.89	83.33	61.11
	YM	66.67	66.67	66.67
	Max	88.89	72.22	80.56
	Min	66.67	72.22	69.44
	Proposed	88.89	83.33	86.11
DNN	DE	75.28	65.83	70.56
	PRMS	68.06	96.39	82.22
	BR	89.17	87.78	88.47
	YM	94.72	11.67	53.19
	Max	85.56	76.67	81.11
	Min	74.17	65.56	69.86
	Proposed	98.61	98.06	98.33

Table 4. Training and testing performance of arrhythmia disease and supraventricular arrhythmia disease

Arrhythmia Diseases			
Classifiers	Training and Testing		
	20-80	40-60	80-20
NN	62.8	66.67	76.5
SVM	60	71.90	74.67
DNN	63.9	72.85	77.33
Supraventricular Arrhythmia Disease			
Classifiers	Training and Testing		
	20-80	40-60	80-20
NN	20-80	40-60	80-20
SVM	53.8	62.4	71.9
DNN	59	68.4	72.8

Table 5. Comparative study of prosed and existing work

Existing Work	Accuracy
Artificial Neural Network techniques of arrhythmia classification using ECG signals [17]	96.21%
An arrhythmia classification algorithm using a dedicated wavelet adapted to different subjects [18]	97.94%
Arrhythmia disease detection of wavelet coherence and bat technique using ECG signals [19]	94.07%
Modular NN based arrhythmia classification [20]	93.95%
The Proposed work	98.33%

The Table 4 indicates the training and testing performance of the Arrhythmia diseases and Supraventricular Arrhythmia disease. The proposed DNN classifier performance is compared with the existing classifiers such as NN and SVM. The training and testing performance are divided in three sections such as 20 training samples, 80 testing samples, 40 training samples, 60 testing samples and 80 training samples, 20 testing samples. Here, Supraventricular Arrhythmia disease training and testing performance is lower than the arrhythmia classification. The Table.5 presents the comparative study of existing work performance and proposed work performance.

The existing work of arrhythmia classification using machine learning techniques are achieved 96.21% of accuracy [17]. Here, the critical role of data preprocessing and post processing steps are to reduce the input space dimension or appropriately describe the input features. In arrhythmia classification of CWT technique is used for different subjects. Here, the performance of Supraventricular ectopic beat class (S) and Ventricular ectopic beat class (V) of some subjects gives low performance and high computational load. So, the overall accuracy of the CWT technique of arrhythmia classification achieved 97.94% [18]. The bat technique based arrhythmia detection technique selects more relevant features and ignore the noise as well as redundant features. They achieved 94.07% of accuracy but, sampling signals are less in experiment [19]. The modular NN based arrhythmia classification technique achieved 93.95% of accuracy, but they take less number of sampling data in experiment.

In proposed work hybrid feature extraction methods are used for arrhythmia detection. In experimental side two sets of normal and abnormal both samples are taken and efficiently classified with 98.33% of accuracy.

5. Conclusion

An ECG signal based Arrhythmia classification is one of the most significant research areas in computer-aided diagnosis. There are many types of heart arrhythmias which can be detected by analysis of the ECG signals. ECG signals have well defined P, T waves and QRS complexes. In this research windowing technique, various feature extraction methods and classification methods are used. A DNN classifier, categorize the signal as normal or abnormal after classification output data are verified with ground truth images. The experimental result demonstrated that existing classifiers as NN and SVM shows the lower result than proposed classifier and MIT-BIH database is taken for experiment. In 100th iteration the proposed DNN classifier has achieved approximately 98.33% accuracy. Here, performance is measured in various evaluation metrics such as Accuracy, Sensitivity, and Specificity. In the future work, for further improving the classification accuracy, a multi-objective classification method is used along with appropriate features.

References

[1] R. Kumar, A. Kumar, and G. K. Singh, “Electrocardiogram signal compression based on singular value decomposition (SVD) and adaptive scanning wavelet difference reduction (ASWDR) technique”, *AEU-International Journal of Electronics and Communications*, Vol.69, No.12, pp.1810-1822, 2015.

[2] M.K. Senapati, M. Senapati, and S. Maka, “Cardiac Arrhythmia Classification of ECG Signal Using Morphology and Heart Beat Rate”, In: *Proc. of Fourth International Conf. on*

Advances in Computing and Communications (ICACC), pp.60-63, 2014.

[3] X. Dong, C. Wang, and W. Si, "ECG beat classification via deterministic learning", *Neurocomputing*, Vol.240, pp.1-12, 2017.

[4] S. Jadhav, S. Nalbalwar, and A. Ghatol, "Feature elimination based random subspace ensembles learning for ECG arrhythmia diagnosis", *Soft Computing*, Vol.18, No.3, pp. 579-587, 2014.

[5] W. Hassan, S. Saleem, and A. Habib, "Classification of normal and arrhythmic ECG using wavelet transform based template-matching technique", *JPMA. The Journal of the Pakistan Medical Association*, Vol.67, No.6, pp.843, 2017.

[6] E. Alickovic and A. Subasi, "Medical decision support system for diagnosis of heart arrhythmia using DWT and random forests classifier", *Journal of medical systems*, Vol.40, No.4, pp.108, 2016.

[7] F.A. Elhaj, N. Salim, A.R. Harris, T.T. Swee, and T. Ahmed, "Arrhythmia recognition and classification using combined linear and nonlinear features of ECG signals", *Computer Methods and Programs in Biomedicine*, Vol.127, pp.52-63, 2016.

[8] J.S. Wang, W.C. Chiang, Y.T.C. Yang, and Y.L. Hsu, "An effective ECG arrhythmia classification algorithm", In: *Proc. of International Conf. on Intelligent Computing*, pp.545-550, 2011.

[9] S. Shadmand and B. Mashoufi, "A new personalized ECG signal classification algorithm using block-based neural network and particle swarm optimization", *Biomedical Signal Processing and Control*, Vol.25, pp. 12-23, 2016.

[10] S.U. Kumar and H.H. Inbarani, "Neighborhood rough set based ECG signal classification for diagnosis of cardiac diseases", *Soft Computing*, Vol.21, No.16, pp.4721-4733, 2017.

[11] A. Daamouche, L. Hamami, N. Alajlan, and F. Melgani, "A wavelet optimization approach for ECG signal classification", *Biomedical Signal Processing and Control*, Vol.7, No.4, pp.342-349, 2012.

[12] P. Kora and K.S.R. Krishna, "ECG based heart arrhythmia detection using wavelet coherence and bat algorithm", *Sensing and Imaging*, Vol.17, No.1, pp.1-16, 2016.

[13] V.H.C. de Albuquerque, T.M. Nunes, D.R. Pereira, E.J.D.S. Luz, D. Menotti, J.P. Papa, and J.M.R. Tavares, "Robust automated cardiac arrhythmia detection in ECG beat signals", *Neural Computing and Applications*, pp.1-15. 2016.

[14] S.S. Kumar and H.H. Inbarani, "Cardiac arrhythmia classification using multi-granulation rough set approaches", *International Journal of Machine Learning and Cybernetics*, pp.1-16, 2016.

[15] D. Ai, J. Yang, Z. Wang, J. Fan, C. Ai, and Y. Wang, "Fast multi-scale feature fusion for ECG heartbeat classification", *EURASIP Journal on Advances in Signal Processing*, Vol.1, pp.46, 2015.

[16] N.G. Paulter, D.R. Larson, and J.J. Blair, "The IEEE standard on transitions, pulses, and related waveforms, Std-181-2003", *IEEE Transactions on Instrumentation and Measurement*, Vol.53, No.4, pp.1209-1217, 2004.

[17] M.K. Abhinav-Vishwa, S.D. Lal, and P. Vardwaj, "Clasification of arrhythmic ECG data using machine learning techniques", *International Journal of Interactive Multimedia and Artificial Intelligence*, Vol.1, No.4, pp.67-70, 2011.

[18] J. Kim, S.D. Min, and M. Lee, "An arrhythmia classification algorithm using a dedicated wavelet adapted to different subjects", *Biomedical engineering online*, Vol.10, No.1, pp.56, 2011.

[19] P. Kora and K.S.R. Krishna, "ECG based heart arrhythmia detection using wavelet coherence and bat algorithm", *Sensing and Imaging*, Vol.17, No.1, pp.1-16, 2016.

[20] S.M. Jadhav, S.L. Nalbalwar, and A.A. Ghatol, "Modular neural network based arrhythmia classification system using ECG signal data", *International Journal of Information Technology and Knowledge Management*, Vol.4, No.1, pp.205-209, 2011.