# A Review and Comparative analysis of Heart using Electrocardiogram (ECG)

Pooja Sharma<sup>1</sup>, Dr. D.V. Gupta<sup>2</sup>

<sup>1</sup>JMIT, Radaur, Yamuna Nagar

<sup>2</sup>COER, Roorkee

Abstract—ECG (Electrocardiogram) gives an electrical activity of the heart. Sinus Bradycardia with Sinus tachycardia is considered as the main ECG abnormalities. Numbers of Electrocardiogram are from the diagnosis of different patient's classes, in which Electrocardiogram shows the information for the abnormality in the concerned patient. ECGs are analyzed by the physicians and interpreted depending upon their experience. However, interpretations may vary from physician to physician. Therefore, this effort is all about the computerization and constancy in the analysis of the ECG signals for diagnosing and interpreting the measures precisely. This would support to start an initial treatment for the problems and a lot of lives might be saved. A lot of work has been executed previously; this review shows ECG (Electrocardiogram) classification to diagnose the patient's condition. For thresholding of such Difficult-to-Diagnose-Signals, P-Wave, PR-Interval, QRS-Interval, ST-Interval, T-Wave etc., examination of each method is different and contributes outcomes in several parameters. Neural network is used to train the network. The output of the neural network gives the weighting factor of each signal to create the data set. Electrocardiogram (ECG) MNPQT-waveform time interval and weight factor and the specific death infection or condition that predicts the condition of the patient preserved in the database. A software program is written in MATLAB. The resultant outputdatasets point outthe associated disease and predicts the causes. In this paper, analysis is performed on different techniques of 'Electrocardiogram (ECG) and prediction of exact disease infection or state of a patient' is done using various methods.

**Keywords** — continuous wavelet Transform; discrete wavelet transform; ECG; heart structure; wavelet transform

## I. INTRODUCTION

Electrocardiogram (ECG) [1] represents the electrical activity of the heart showing the regular contraction and relaxation of heart muscle. The heart condition is utilized for diagnosing the significant tool known as Electrocardiography. ECG waveform analysis is utilized for diagnosing the various heart abnormalities. ECG signal processing techniques has baseline correction, de-noising, arrhythmia detection and parameter extraction. The Electrocardiogram waveforms consist of five

basic waves M, N, P, Q, and T waves and sometimes U waves. The P wave represents atrial depolarization, N, Q and Q wave is commonly known as QRT complex which represents the ventricular depolarization and T wave represents the repolarization of ventricle [2].

The most necessary ECG content waveform study is the QRS complex morphology. The Electrocardiogram signal may be at variance for the same human being such that they are poles apart from each other and at the same time similar for dissimilar types of heartbeats [3]. The pacemaker cells within the sinoatrial (SA) node used to generate and regulate the rhythm of the heart, which is located at the right atrium top. The normal heart beat is usual. The depolarization of atrial is forever followed by ventricular depolarization.

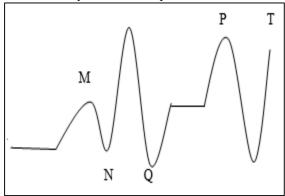


Fig.1 ECG Waveform

In Sinus Tachycardia, the production rate is faster and inSinus Bradycardia the production rate is less, but the signal will be guided by the normal route. BPNN [4] has a significant advantage to solve problems that either do not have an algorithmic explanation or explanationis very complex. These types of networks are applied efficiently in the medical domain used for clinical diagnosis, image and signal analysis and interpretation of the considered signals. The Heart Attack perdition system (conventional) is identified as Back Propagation Neural Network structure for the accurate performance of the classification tasks. Neural Network [5] is one of the most widely used methods of ECG beat classification; Multi-Layer Perception (MLP) based on the Neural Networks has been chosen to be able to classify the ECG signals. They are being trained by means of Supervision

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long proceedings. A large number of known wavelet family sum functions provide this analysis [8].

## A. Heart Structure

The heart [9] is cone shapedorgan which is composed of cardiac muscle entitled as myocardium tissue. The abovementioned is the dimensions of a clasped fist and also accountable for pumping blood everywhere in the body. It weighs up about 250 up to 350grams. The pericardium is a defensive connective tissue encompassing the heart. It consists of two types of layers. The external loosely fitting sac is the actual fibrous pericardium. It also guards as well as anchors the heart to the adjoining organs. The internal layer is the serous pericardium and besides it diligently follows to the actual surface of the heart. In the middle of the external as well as internal layer is the pericardial fluid that acts as a lubricant and also condenses friction. The heart pumps nearby 2000 gallons of blood almost every day as well as beats nearly around 100, 000 times per day. The heart is a muscular pump which usually drives blood everywhere in the body that is found amongst the breastbone as well as the ribs. It is a specific cardiac muscle and also it works spontaneous. The heart [10] has four different types of chambers; the atria are the upper side of chambers that ought to obtain blood, and then the ventricles discharge blood into the arteries [11].

It has four valves splitting the chambers, Pulmonary valve, Tricuspid, also splits up the right-side of the atrium commencing the right ventricle, also divides the right-side of ventricle as of the pulmonary artery, Bicuspid valve as well separates the left-side of atrium as of the left-side ventricle in addition to the Aortic valve divides the right-side of ventricle from the aorta [12]. The heart has specifically three types of layers, epicedium, which provides it an even texture, myocardium, and also responsible for the pumping action, prepared of some muscle fibers that is utilized to associate to electrical synapses, in addition to endocardium, inner layer which can easily connect to enormous blood vessels.

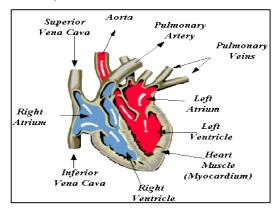


Fig.3 Structure of the heart

with the help of BP (Back-Propagation) for minimizing the squared error among the actual outputs of the network and the desired outputs. Neural network structure consists of four layers i.e. an input layer, two hidden layers, and output layer. Using the Feed-Forward Back-propagation, the input is mapped onto each node like M,NPQ,QT,T Intervals in the weight factors of hidden layer of Sinus Bradycardia and Sinus tachycardia with the output layer which is a linear combination of hidden layer outputs multiplied by their weights. The electrocardiogram is a demonstration of body surface potentials generated by the electrical actions of the heart. The recording and analysis of the ECG has a very long impact in the past and is a significant portion of the clinical valuation of an individual's cardiac status and general health [6]. ECG can also be used to conclude heart rate by scheming the time between consecutive QRT complexes. It is significant to be able to compute the heart rate between every beat, as it makes it to look at the beat-to-beat inconsistency in heart rate. Decrease heart rate unevenness is therefore used as a quantifiable indication of reduced vagal activity. The additional, reduced heart rate inconsistency has been shown to expect sudden death in patients with myocardial infarction. The ECG trace is essentially a periodic waveform as shown in Figure (1). One cycle of the ECG waveform represents one cycle of the blood transformation process from the arterial heart. One cardiac cycle in the ECG is composed of M-NPQ-T waves. The M wave is a low voltage deflection away from the baseline caused by depolarization of the atrium. The ORS complex is the largest amplitude component of the ECG caused by the vertical. The second component of the ECG is the amplitude of the vertical component of the ECG [7]. The second component of the ICS is the ICS, Depolarization, thereby preparing the myocardium for the next cycle of the ECG. Most of the clinically useful information of an electrocardiogram (ECG) is found in the interval and amplitude defined by its characteristics.

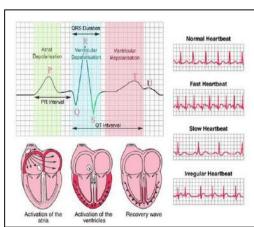


Fig. 2 ECG Signal Representation

The left-side of the heart obtains oxygenated blood in addition to the right-side be given de-oxygenated blood.

## B. ECG Signal Processing

Usually, the charted ECG signal gets contaminated by noise and artifacts that might be contained by the frequency bands point towards characteristics, similar to the ECG signal itself. To extract beneficial information from the noisy ECG signal, the raw ECG signal must be processed [13].

ECG signal processing can be divided into two phases by function.

- Pre-Processing
- Feature Extraction

## 1) Pre-Processing

The preprocessing step removes or suppresses noise from the raw ECG signal. Pre-processing the ECG signal can remove contaminants from the ECG signal. In general, ECG pollutants can be classified into the following categories:

- Power line interference
- Contact noise/ Electrode pop
- Artifacts of patient–electrode motion
- EMG (Electromyographic) noise
- Baseline wandering

Among these noises, power line interference and baseline prevention are the most important and can have a great influence on the electrocardiogram signal analysis. Except for these two noises, other noise can be broadband and can be a complex process of stochastic distortion of the ECG signal in general. Power line interference is narrowband noise centered on a bandwidth of less than 1 Hz at 60 Hz (or 50 Hz). Usually ECG signal acquisition hardware can eliminate power line interference. However, baseline drift and other wideband noise are not easily suppressed by hardware equipment. Instead, software schemes are more powerful and feasible for offline ECG signal processing [14].

## 1) ECG Feature Extractions

Electrocardiogram (ECG) is a realistic record of the direction and magnitude of electrical disturbances generated by depolarization and repolarization of the atria and ventricles. Electrocardiography was widely used to diagnose many heart diseases. One heart cycle of the ECG signal consists of P-QRS-T waves. Much of the clinically useful information in ECGs comes from the spacing and amplitude defined by the characteristics (wave peak and Time duration). Improved accuracy and speed for automatic ECG feature extraction is especially important for long recordings [15].

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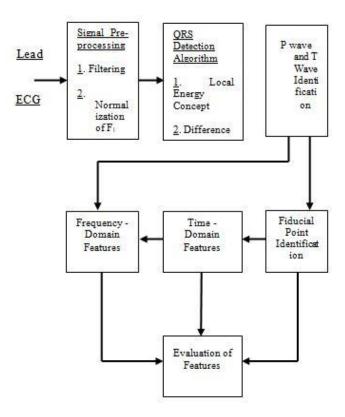


Fig.4 QRS Detection

The ECG feature extraction system provides the basic functions (amplitude and spacing) to be used for subsequent automatic analysis. In recent years, many techniques have been proposed to detect these features. The previously proposed ECG signal analysis method is based on the time domain method. However, it is not always appropriate to study all the features of the ECG signal. Therefore, the frequency representation of the signal is required. Deviations in normal electrical patterns represent a variety of heart diseases. Normal heart cells undergo electrical stimulation [16].

In recent years, several studies and algorithms have been developed to try and analyze ECG signals. The classification methods evaluated over the past decade reveal their own strengths and weaknesses, including Digital signal analysis, Fuzzy logic techniques, Artificial neural networks, Hidden Markov models, genetic algorithms, Support vector machines, Self-organizing maps, Bayesian and other approaches.

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## 2) QRS Complex Detection

Detection of R-peaks and consequently QRS complexes in ECG signals provides information on heart rate, conduction velocity, tissue status and various abnormalities of the heart. It provides evidence for the diagnosis of heart disease. For this reason, we have received considerable attention in the field of ECG signal processing. However, over time, the presence of noise and changing shapes make it difficult to detect. After performing QRS complex detection for feature extraction, you can analyze the function in several ways. For example, heart rate variability (HRV) analysis can be performed on the R-R interval signal to demonstrate the status of the heart and nervous system [17].

## 3) ECG Compression Techniques

real-time

Data compression methods is the classification as those that has the compressed data being reconstructed for the original signal and techniques in which higher compression ratios can be achieved by introducing some error in the reconstructed signal. Considering that the number of electrocardiogram records annually numbers in the millions and the use of sending electrocardiogram records over telephone lines used for remote analysis are rising, the requirement for efficient ECG compression method is better. Effective ECG compression technique should improve the compression ratios and also lessen the error rate in the reconstructed data [18]. (ECG) data compression reduced the storage requirements to develop a more efficient tele-cardiology system for cardiac

diminishing the

2. It is used to

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analysis and diagnosis. Real-time data compression methods are required to effectively use communication channels such as wired channels, wireless environments, and cloud computing during 24-hour ECG observations or multi-channel bio-signal acquisition. ECG data compression is also required for ECG signal transmission through ICU, emergency telemedicine, telemedicine, home care, sports, space programs, military, cellular networks, and public telephone networks with the wireless communication systems. In general, ECG compression can be classified into lossy and lossless techniques [19]. In a lossless scheme, the compressed signal is reconstructed to the correct form of the original signal, and in the lossy scheme, there is high CR with varying level of reconstruction error. Another type is based on techniques applied for compression and can be categorized as [20].

## 4) Direct Time-Domain Techniques

The direct method is based on extracting a subset of important samples. Direct time-domain ECG compression provides efficient performance in terms of throughput and CR. This method finds duplicates that are directly present in the ECG sample.

## 5) Transform frequency Domain Techniques

Conversion-based ECG compression methods are performed using linear orthogonal transforms on the ECG samples. This technique has a higher CR than the direct technique and is insensitive to noise in ECG signals.

	Direct Tin	Transform Frequency Domain Technique			
AZTEC	TP Algorithm	CORTES	Improved Modified AZTEC	FT Domain	DCT Domain
1. Well-liked	1. Diminishes	1. Hybrid	1. Adaptive Statically	1. Frequency	1. Represents the
data reduction	the ECG	approach of	parameters of the	amplitude	signal as a summation
algorithm.	sampling	AZTEC and TP	signal to be	representation of the	of varying magnitude
Used for pre-	frequency	algorithm.	compressed are	signal is obtained.	as well as frequency.
processing of	without		evaluated.		

TABLE 1 VARIOUS TIME-DOMAIN & FREQUENCY-DOMAIN TECHNIQUES

ECG's for	large amplitude	attain high CR	2. Optimizes the	the signal inverse	boundary conditions
Rhythm	QRS	(Compression	tradeoff between CR	FFT is applied.	and frequently used in
Analysis.	complexes.	rate) of the	and PRD (Percent	11	signal in image
		AZTEC method	Mean Square	3. Fails to provide	processing.
2. Converts raw	2. Unsuitable	and low	Difference)	the information	
ECG samples	for equally	reconstruction	·	about the correct	3. Provides high de-
points into	spaced time	inaccuracy of the		location of	correlation.
plateaus.	interval.	TP technique.		frequency	
-		•		component in time.	
				1	
	Rhythm Analysis.  2. Converts raw ECG samples points into	Rhythm Analysis.  2. Converts raw ECG samples points into CRS complexes.  2. Unsuitable for equally spaced time	Rhythm QRS (Compression rate) of the AZTEC method  2. Converts raw ECG samples points into spaced time (Compression rate) of the AZTEC method and low reconstruction inaccuracy of the	Rhythm Analysis.  Complexes.  Complexes.  Complexes.  Complexes.  Complexes.  Compression rate) of the AZTEC method and low reconstruction points into spaced time  Compression radeoff between CR and PRD (Percent Mean Square Difference)	Rhythm Analysis.  QRS complexes.  (Compression rate) of the AZTEC method  2. Converts raw ECG samples points into plateaus.  Rhythm QRS complexes.  (Compression rate) of the AZTEC method and low reconstruction inaccuracy of the plateaus.  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square Difference)  The plateaus complexes and PRD (Percent Mean Square

2. Implies dissimilar

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## II. EXISTING TECHNIQUES IN ECG

This section describes the techniques that are previously used by number of authors for simulating the Electrocardiogram.

#### A. Wavelet transform

Wavelet [21] is a wavelet-like oscillation whose amplitude starts from zero, increases and then decreases towards zero. By means of mathematical tool, the wavelet could be utilized for extracting thedata from varied data types. Recently, wavelet transform has been widely used in signal and image processing due to its time-frequency localization property. The wavelet transform is based on a set of analytical wavelets that allow decomposition of the ECG signal in the set coefficients. Each analysis wavelet has its own duration, time position and frequency band. The wavelet coefficients generated by the wavelet transform correspond to the time requirement and the measurement of the ECG components in the frequency band.Based on the theory of signal processing wavelet transform, from the Fourier transform based on the development. Wavelet transform [22] of a function is an authentic space known as alinear combination on the function of wavelet basis. It performs the linear operation of the signal and the basis function (mother wavelet). A set of integral

α

$$Xw(a,b)=\int x(t)\psi(t-b/a) dt$$

- α

Function is constructed by scaling and shifted the mother-wavelet and is scaled by a factor 'a' and translated by a factor 'b' to gives (M.Aqil et al., 2015):

$$\psi a,b(t)=1/\sqrt{a\psi(t-b/a)}dt$$

#### B. Continuous wavelet transform

Continuous Wavelet Transform (CWT) [23] the signals are analyzed using a set of basis function, which are related to each other by simple scaling and translation. CWT is a wavelet transform with a permanent mother- wavelet, incessant dilation metric with a parameter of discrete translation. A wavelet transform is a convolution of the wavelet function  $\Psi(t)$  with the signal x(t). Continuous wavelet transform (CWT) [25] of a continuous square integrable function x(t) at a scale a>o and b belongs to R is expressed by the following integral

$$\alpha$$
  
  $Xw(a,b)=1 \frac{1}{\sqrt{a}} \int x(t)\psi(t-b/a) dt$ 

-α

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#### C. Discrete wavelet transform

Discrete wavelet transform (DWT) [26] is used as the discrete wavelet transform with discrete time mappings, integer expansion parameters and discrete translation parameters. We find that the discrete wavelet transform based on sub-band coding can produce the fast calculation of wavelet transform. It is easy to implement and reduces the computation time. In the case of DWT, time scale representation of the digital signal is obtained using digital filtering techniques. The signals to be analyzed pass through the filters with different cut-off frequencies at different scales. In the DWT [27], the low and high frequency components x (n), pass through a series of low pass and high pass filters having different cut-off frequencies. This results in a set of approximate and detailed DWT coefficients which in turn help

$$Xw(a,b) = \sum naax(n) \varphi a,b(n)$$

## D. Mean series signal

Base ECG trace having a thickness greater than a single pixel [28]. Oneenvelopes the detector to obtain a time series.In the envelope detector, the image is scanned column by column,the highest and lowest non-zero at each column value. Draw all upper and lower limits value, we obtain the upper and lower envelopes of the ECG

#### X=Xub+Xlb/2

In this, X is the average ECG signal, Xub and Xlb are upper and lowerenvelope of the ECG signal. Axis recognition plays an important role in further diagnosis as well as anautomatic report generation for ECG records. Initial the test square wave pulse is present at the start of any ECG trace used as a reference for the axis [29]. However, in the most practical Scan program and data capture square wave pulse.

## III. A GLANCE OF EXISTING TECHNIQUES

Numerous works in literature related with heart disease diagnosis using different techniques are demonstrated below:

AddanusDjohan etal, presented a new ECG signal compression algorithm using a symmetric wavelet transform. The proposed protocol can be used in the ECG tachycardia, ECG signal archiving and ECG data transmission through the CCUNMMICATM channel to find applications. Using the new method, PRD = 3. 946 can be used to achieve 8 to 1 compression ratio, on the contrary, the use of PRD = 10.0% and fan algorithm compression ratio of 7. 4 to 1, AzTEx3 composite ratio of 6. 8 to 1, PWD = 8.7%.

Emna Rabhi etal, concluded an ECG based on the morphological descriptor and the Hermite polynomial expansion coefficient (HPEc) for the personal identification of the new algorithm. After pre-processing, we extracted ten

morphological descriptors, divided into uniform groups (amplitude, surface interval and slope), and extracted sixty Hermite polynomial expansion coefficients (HPEc) from each heartbeat. We use a binary SVM with Gaussian kernel for classification, and we adopt a special strategy: we first group the morphological descriptors and then combine them into a single system. On the opposite hand, we isolated the Hermite polynomial expansion coefficients and associate them using the morphological descriptors of all groups in a single system to increase overall performance. We tested our algorithm against the MIT\_BIH database for 18 different health signals. The analysis of different groups showed that the best recognition performance of all morphological descriptors was 96.45%. The experimental results showed that the proposed hybrid method resulted in an overall maximum of 98.97%.

Hadeer El-Saadawy et al, proposed that the electrocardiogram (ECG) has been introduced for decades as a powerful tool for diagnosing heart disease. Most publications in the field of automated ECG-based diagnostics have adopted a fixed segmentation of the heartbeat, irrespective of changes in the heart rate that may occur over the time. In this paper, an automatic and a reliable method for diagnosing the heartbeat using a new heart rate-invariant segmentation procedure is proposed. Discrete wavelet transform (DWT) is used to decompose the segmented heartbeat. The resulting wavelet coefficients are reduced using Principle Component Analysis (PCA) and then classified into five main categories using Support Vector Machine (SVM) classifiers, representing 15 classes. In order to improve the reliability of the proposed method, not only the overall accuracy, but also the average accuracy of each class is considered. The average accuracy and overall accuracy of the MIT-BIH database were 96. 35% and 99.5%, respectively.

Mohammed Al-Mahamdya et al, proposed ECG is an important tool for measuring health and disease detection. Because of many noise sources, the signal must be de-noised and presented in clear waveforms. Noise sources may include power line interference, external electromagnetic fields, random body movements, or breathing. In this project, five common and important methods of de-noising are proposed and applied to the actual ECG signals with different levels of noise pollution. These algorithms are: discrete wavelet transform (general and local threshold), adaptive filter (LMS and RLS) and Savitzky-Golay filtering. Their de-noising performance is implemented, compared and analyzed in the Matlab environment.

Sarang L. Joshi etal.,proposed that noise always reduces the quality of the ECG signal. Due to the time-varying nature of the ECG signal, . Because ECG signals are used for the primary diagnosis and analysis of heart disease, high quality

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ECG signals are required. In this paper, a variety of noise destruction ECG signals based on wavelet transform, fuzzy logic, FIR filtering, empirical mode decomposition and various methods are investigated. Including a table of results comparing the performance of various de-noising techniques based on the relevant parameters.

Seena et al, explained the comparison of different Feature Extraction and De-noising techniques using Wavelet Transform. In an ECG with a P-QRS-T wave, the QRS complex has the most significant portion for analysis. The first part of this paper deals with the comparison of three different feature extraction techniques using wavelet transform. The second part deals with de-noising ECG signals using three different wavelet transforms. The most troublesome noise source contains the frequency components within the ECG spectrum, i.e. the electrical activity of the muscle and the instabilities of the electrode skin contact. This noise is difficult to remove using a typical filter process. In this case, signal noise reduction is only possible using wavelet de-noising techniques. A comparison of different wavelet transform techniques for feature extraction and de-noising of ECG signals is proposed, which is suitable for selecting the most suitable technique. Wavelet transform is a powerful tool for analyzing ECG signals.

Shweta H. Jambukia et al., explained that the classification of electrocardiographic (ECG) signals, plays an important role in the diagnosis of heart disease. Accurate ECG classification is a challenging problem. This paper presents an investigation of ECG classifications for arrhythmia types. Early and accurate detection of arrhythmia types is important for detecting heart disease and selecting the appropriate treatment for the patient. Different classifiers can be used for ECG classification. Among all classifiers, artificial neural networks (ANNs) have become very popular and are most widely used for ECG classification. In this paper, the problems involved in ECG classification are discussed, and a detailed investigation of preprocessing technology, ECG database, feature extraction technique, ANN based classifier and performance measurement are proposed to solve the above problems. In addition, for each paper we examine, our paper provides a detailed analysis of the input beat selection and the output of the classifier.

Author **Findings** Limitation A new ECG signal compression algorithm using a discrete symmetric wavelet transform is proposed that may AddanusDjohan Not give a valid compression find applications in digitalHolter recording, in ECG signal archiving and in ECG data transmission through channels EmnaRabhi New algorithm for personal identification from their Electrocardiograms (ECG) The analysis of different Cannot used for the larger groups separately showed that the best recognition performance is 96.45% for all morphological descriptors work and the results of experiments depicts that the work proposed with hybrid approach has 98.97% overall accuracy. Hadeer The resulting wavelet coefficients are reduced using Principle Component Analysis (PCA) and then classified Less efficient in work. Saadawy into five main categories using Support Vector Machine (SVM) classifiers, representing 15 classes. In addition, in order to improve the reliability of the proposed method, not only the overall accuracy but also the average accuracy of each class is considered. The average accuracy and overall accuracy of the MIT-BIH database were 96. 35% and 99.5%, respectively. Mohammed Al-Actual ECG signals at noise levels from 5dB SNR to 45dB SNR. Filters do not on different Mahamdva ranges. Sarang L. Joshi Equiripple notch filter is the best choice to remove power line interference while to remove motion artifact and Not good for decomposition

EMG noise we should select discrete Meyer wavelet and apply the improved thresholding function which

Family selection for ECG signals de-noising applications. Since the application for wavelet transform in

Neural networks are good candidates for ECG classification in terms of classification accuracy on training and

electro-cardiology is relatively a new field of research, many modern aspects of the wavelet

#### TABLE II COMPARATIVE ANALYSIS OF PREVIOUS STUDIES

## IV. PERFORMANCE EVALUATION PARAMETERS

combines features of hard and soft thresholding

The following parameters measure the ability of compression technique to reconstruct the signal and to maintain the relevant information.

## A. Compression Ratio (CR)

test datasets

Seena

Shweta

Jambukia

It is defined as the ratio between the range of the original signal and the range of the compressed signal. The compression ratio provides information on the extent to which the compression method eliminates redundant data. A high compression ratio means that there is less number of bits required to store or transmits the data that can be defined using equation as follows:

$$CR = \frac{BO}{BC}$$

Where, BO is the total number of bits required representing the original data and BC is the number of bits required to represent the compressed data.

## B. Signals to Noise Ratio (SNR)

It predicts as the ratio of the signal power (significant information) and the power of background noise (unwanted signal). It is given by using the following equation:

$$SNR = \frac{P_{Signal}}{P_{Noise}}$$

## C. Root Mean Square Error (RMS)

This is a frequently used measure of the variation among values predicted by a model and the values actually observed from the environment that is being exhibited. It delivers measure of inaccuracy in restored signal with respect to original signal, and is given by using equation as follows:

approach.

Less efficient

Not improved for clinical use

and did not work on novel processing technique.

Consider a et of n values,  $x_1, x_2, x_3, \dots, x_n$ 

$$x_{rms} = \sqrt{\frac{1}{n}(x_1^2 + x_2^2 + \dots + x_n^2)}$$

## D. Percent Mean Square Difference (PRD)

It measures the error between original with reconstructed signal, and is given by using equation as follows:

PRD (%) = 
$$100 * \frac{\sqrt{\sum_{N=1}^{N} X_s(n) - X_r(n))^2}}{\sum_{N=1}^{N} X_s(n))^2}$$

Where, N is the number of data samples,  $X_{S}$  (n) is the original and  $X_{T}$  (n) is the re-constructed signal.

# E. Quality Score (QS)

It is the ratio of CR and PRD which quantifies the complete performance of the compression methods, and is given by using the following equation: IJRECE VOL. 5 ISSUE 3 JULY.-SEPT. 2017

$$QS = \frac{CR}{PDR}$$

#### V. CONCLUSION

By using the different techniques such as wavelet transform, neural network, we can detect various features from ECG signals. The evaluation presented in this paper, provide a basic reference for home selection of ECG signal de-noising applications. Since, the application of wavelet transform in electrocardiography is a relatively new field of study, many modern aspects of wavelet technology will require further research to improve the clinical use of new signal processing techniques. These methods focus on removing power line interference, while other approaches are designed to remove the baseline drift and other types of the noise. Each method has a number of shortcomings associated with it. Studies should target to eradicate all types of noise from the ECG signal using a single hybrid method (which may be a combination of the existing methods). There are different types of algorithms for non-rigid alignment of ECG shapes extracted from ECG recordings, both digital and scanned paper recordings. Beginning from the basic idea that the patients having similar disease tagshasresemblances in their ECGs, it is clarifiedthat different algorithm for disease similarity detection, where the recall –precision values for unlike disease groups point out the efficacy.

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