Survey on Cardiac Arrhythmia Techniques in ECG Signal

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Abstract-- Electrocardiogram (ECG) signal is a graphical representation of the cardiac muscle activity, which is most important biomedical signal. Cardiac Arrhythmia is the abnormality in the Heart which can be diagnosed with the help of Electrocardiogram (ECG) signal. The features of ECG signal can be extracted using various techniques are present in the literature. The peak detection of the QRS Complex and test its suitability for medical diagnosis using MIT-BIH database is present in the literature, and the results are compared with the existing models by taking mean absolute relative error and Error% as performance criteria.Finally identified that there is scope of research in Cardiac Arrhythmiaand Computational Intelligence techniques are giving the better results.

Keywords-- *Electrocardiogram, Feature Extraction, QRS detection, peak detection, classification and Computational Intelligence.*

I. INTRODUCTION

Cardiac Arrhythmia is the abnormality in the Heart which can be diagnosed with the help of Electrocardiogram (ECG) signal. ECG signal is a graphical representation of the cardiac signal, which is most important biomedical signal, taken for the feature extraction. Since it is very difficult to analyse the ECG signal due to the size, noise and changes in the signal, automatic system for ECG signal processing is essential. For this, ECG signal is processed using wavelets based signal processing, feature extraction and classification is done to identify the Cardiac activity in very sensible manner. The normal ECG signal consists of P wave which indicates atrial contraction, the QRS Complex indicates ventricular contraction and the T wave indicates ventricular relaxation and atrial relaxation is obscured by the QRS complex.

II. LITERATURE REVIEW

The following sections deals with brief research reviews of various detection and classification of cardiac arrhythmias, cardiac transient rhythms for ECG using wavelet transforms, Filters, non-linear dynamics, Fuzzy Logic and Artificial Neural Network (ANN) techniques which are found in the literature and outlines the proposed approach of the present thesis work.

A. Review of Cardiac Arrhythmia using Wavelet Decomposing Techniques

[Bernard W, John R.G, John M.M, John K, Charles S, Williams, Robert H.H, James R.Z, Eugene D, and Robert C.G, 1975][1], describes the concept of adaptive noise cancelling, an alternative method of estimating signals corrupted by additive noise or interference. The method uses a “primary” input containing the corrupted Signal and a “reference” input containing noise correlated in some unknown way with the primary noise. The reference input is adaptively filtered and subtracted from the primary input to obtain the signal estimate. Adaptive filtering before subtraction allows the treatment of inputs that are deterministic or stochastic, stationary or time variable. Experimental results illustrate the usefulness oftechnique in a variety of practical applications which include the cancelling of various forms of periodic interference in electrocardiography, the cancelling of periodic interference in speech signals, and the cancelling of broad-band interference in the side lobes of an antenna array and shown that a sine wave and Gaussian noise can be separated by using a reference input that is a delayed version of the primary input.

[Donald E.G, Alan S.W, Jyh-Yun W, Malcolm C.L, and John H.T, 1978][2], describe a technique for detection and classification of cardiac arrhythmias for ECG or VCG data. The approach is based on the use of R-R interval data and the development of simple models that describe the sequential behavior of such intervals characteristic of different arrhythmias which persist over a period of about six or more heartbeats and also deals with arrhythmias that manifest themselves as abrupt changes in the observed R-R intervals. The techniques used to analyze observed R-R intervals are statistical in nature, allowing one to assign likelihoods or probabilities to various potential diagnoses.

[Donald E.G, Alan S.W, Jyh-Yun W, Malcolm C.L, and John H.T, 1978][3], describes the problem of detection and identification of cardiac transient rhythms, using the associated R-R interval sequence. A generalized likelihood ratio technique is proposed, in which the transient rhythm category is identified by means of a maximum-likelihood hypothesis test. Simultaneously, the magnitude of the change in the R-R interval pattern is estimated. The method is easily mechanized on-line using a moving window of data and presented gains. Experimental results using actual data are presented to indicate the utility of the method.

[Pan J and Tompkins W.J, 1985][4], developed a real-time algorithm for detection of the QRS complexes of ECG signals. It reliably recognizes QRS complexes based upon digital analyses of slope, amplitude, and width. A special digital band pass filter reduces false detections caused by the various types of interference present in ECG signals. This filtering permits use of low thresholds, thereby increasing detection sensitivity. The algorithm automatically adjusts thresholds and parameters periodically to adapt to such ECG changes as QRS morphology and heart rate.

[Penny D.J, Rigby M.L, and Redington A.N, 1991][5], describe to assess whether regional abnormalities of ventricular function are present in patients after the Fontan operation and to explore the implications of any such abnormalities for ventricular filling. Prospective studies with 25 patients after the Fontan operation were compared with 25 healthy controls and 12 patients with a uni-ventricular atrio-ventricular connection, before the Fontan operation. They have observed that incoordinate ventricular relaxation is common after the Fontan operation which may have important implications for ventricular diastolic filling, pulmonary blood flow, and cardiac output in these patients.

[NitishV.T, and Yi-Sheng Z, 1991][6], proposed several adaptive filter structures for noise cancellation and arrhythmia detection, which essentially minimizes the mean-squared error between a primary input, that is noisy ECG, and a reference input, which is either noise that is correlated in some way with the noise in the primary input or a signal that is correlated only with ECG in the primary input. Also to eliminate baseline wander, 60 Hz power line interference, muscle noise, and motion artifact several filters are used. An adaptive recurrent filter structure is proposed for acquiring the impulse response of the normal QRS complex and is applied to several arrhythmia detection problems.

[Senhadji L, Carrault.G, Bellanger.J.J, and Passariello.G, 1995][7]described the use of wavelet transforms to recognize isolated cardiac beats for classification rate, and the correlation coefficient between the original pattern and the reconstructed one. The energy based representation and the extrema distribution estimated at each decomposition level-and their quality has been assessed by using principal component analysis. Their capability of discrimination between normal, premature ventricular contraction, and ischemic beats has been studied by means of linear discriminant analysis. This also led to the identification of the most relevant resolution levels.

[Voss.A, Kurths.J, Kleiner.H.J, Witt.A, Wessel.N, Saparin.P, Osterziel.K.J, Schurath.R, and R.Dietz, 1996][8], introduced new methods of non-linear dynamics (NLD) which were compared with traditional methods of heart rate variability (HRV) and high resolution ECG (HRECG) analysis to improve the reliability of high risk stratification, in which simultaneous 30 min high resolution ECG's and long-term ECG's were recorded from 26 cardiac patients after myocardial infarction (MI). These are divided into two groups depending on a low risk group (group 2, n = 10) and a high risk group (group 3, n = 16). The control group consisted of 35 healthy persons (group 1). From these, electrocardiograms were extracted standard measures in time and frequency domain as well as measures from the new non-linear methods of symbolic dynamics and renormalized entropy. The methods of NLD describe complex rhythm fluctuations and separate structures of non-linear behavior in the heart rate time series more successfully than classical methods of time and frequency domains.

[Yu H.H, Surekha.P.R, and Tompkins W.J,1997][9],present a "mixture-of-experts" (MOE) approach to develop customized electrocardigram (ECG) beat classifier in an effort to further improve the performance of ECG processing and to offer individualized health care. A small customized classifier is developed based on brief, patient-specific ECG data. It is then combined with a global classifier, which is tuned to a large ECG database of many patients, to form a MOE classifier structure.

[Beniteza D, Gaydeckia P.A, Zaidib A and Fitzpatrickb A.P, 2001][13], proposed a new robust algorithm for QRS detection using the first differential of the ECG signal and its Hilbert transformed data to locate the R wave peaks in the ECG waveform. Using this method, the differentiation of R waves from large, peaked T and P waves is achieved with a high degree of accuracy. In addition, problems with baseline drift, motion artifacts and muscular noise are minimized. The performance of the algorithm was tested using standard ECG waveform records from the MIT-BITH Arrhythmia database

[Sternickel K, 2002][14], proposed a technique for the automatic detection of any recurrent pattern in ECG time series. Wavelet transform is used to obtain a multi-resolution representation and Neural Networks are trained with the wavelet transformed templates providing an efficient detector even for temporally varying patterns within the complete time series. The method is robust against offsets and stable for signal to noise ratios larger than one. Its reliability was tested on 60 Holter ECG recordings of patients.

[OwisMd.I, Abou-Zied A.H, Youssef A.B.M, and Kadah Y.M, 2002][15], presented a study of the non-linear dynamics of electrocardiogram (ECG) signals for arrhythmia characterization. The correlation dimension and largest Lyapunov exponent are used to model the chaotic nature of five different classes of ECG signals. The model parameters are evaluated for a large number of real ECG signals within each class. The presented algorithms allow automatic calculation of the features. The statistical analysis of the calculated features indicates that they differ significantly between normal heart rhythm and the different arrhythmia types and, hence, can be rather useful in ECG arrhythmia detection.

[Kohler B, Hennig C and Orglmeister R, 2002][16], described the QRS complex which reflects the electrical activity within the heart during the ventricular contraction, the time of its occurrence as well as its shape provide much information about the current state of the heart. Due to its characteristic shape, the automated determination of the heart rate, as an entry point for classification schemes of the cardiac cycle, and used in ECG data compression algorithms. So QRS detection provides the automated ECG analysis algorithms. The evolution of QRS detection algorithms reflects the great advances in computer technology. The computational load determined the complexity and performance of the algorithms, It is the intention of the authors to provide an overview of the recent developments as well as of formerly proposed algorithms that were already reviewed in. The overview is focused on the description of the principles.

[De Chazal P and Reilly R.B, 2003][17],presents the classification performance of an automatic classifier of the electrocardiogram (ECG) for the detection of normal, premature ventricular contraction and fusion beat types. Both linear discriminants and feed forward neural networks were considered for the classifier model. Features based on the ECG waveform shape and heart beat intervals were used as inputs to the classifiers. Data was obtained from the MIT-BIH arrhythmia database. Cross validation was used to measure the classifier performance. A classification accuracy of 89% was achieved which is a significant improvement on previously published results.

[Brugada J, Brugada R and Brugada P, 2003][18], analyzed a large cohort of patients with Brugada syndrome without previous cardiac arrest to understand the determinants of prognosis. Total 547 patients with an ECG diagnostic of

Brugada syndrome and no previous cardiac arrest were studied. The mean age was 41+/-15 years, and 408 were male. The diagnostic ECG was present spontaneously in 391 patients. In the remaining 156 individuals, the abnormal ECG was noted only after the administration of an antiarrhythmic drug. Logistic regression analysis showed that a patient with a spontaneously abnormal ECG, a previous history of syncope, and inducible sustained ventricular arrhythmias had a probability of 27.2% of suffering an event during follow-up. Individuals with Brugada syndrome and no previous cardiac arrest have a high risk of sudden death. Inducibility of ventricular arrhythmias and a previous history of syncope are markers of a poor prognosis.

[Jager F, Taddei A, Moody G.B, Emdin M, Antolic G, Dorn R, Smrdel A, Marchesi C, and Mark R.G, 2003][19], goal was to develop a challenging and realistic research resource for development and evaluation of automated systems to detect transient ST segment changes in electrocardiograms and for supporting basic research into the mechanisms and dynamics of transient myocardial ischaemia. Human expert annotators used newly developed annotation protocols and a specially developed interactive graphic editor tool (SEMIA) that supported paperless editing of annotations and facilitated international co-operation via the Internet. The database contains 86 two- and three-channel 24 h annotated ambulatory records from 80 patients and is stored on DVD-ROMs. The database annotation files contain ST segment annotations of transient ischaemic (1155) and heart-rate related ST episodes and annotations of non-ischaemic ST segment events related to postural changes and conduction abnormalities. The database is intended to complement the European Society of Cardiology ST-T database and the MIT-BIH and AHA arrhythmia databases.

[Chazal P.D, O'Dwyer M, and Reilly R.B, 2004][21], proposed a method for the automatic processing of the electrocardiogram (ECG) for the classification of heartbeats. The method allocates manually detected heartbeats to one of the five beat classes normal beat, ventricular ectopic beat (VEB), supraventricular ectopic beat (SVEB), fusion of a normal and a VEB, or unknown beat type. Data was obtained from the 44 non-pacemaker recordings of the MIT-BIH arrhythmia database. The data was split into two datasets with each dataset containing approximately 50 000 beats from 22 recordings. The first dataset was used to select a classifier configuration from candidate configurations. Twelve configurations processing feature sets derived from two ECG leads were compared. Feature sets were based on ECG morphology, heartbeat intervals, and RR-intervals. All configurations adopted a statistical classifier model utilizing supervised learning. The second dataset was used to provide an independent performance assessment of the selected configuration. This assessment resulted in a sensitivity of 75.9%, a positive predictivity of 38.5%, and a false positive rate of 4.7% for the SVEB class.

[Markowska-Kaczmar U and BartoszKordas, 2005][25], focused on the QRS complex detection in electrocardiogram but, the idea of further recognition of anomalies in QRS complexes based on the immunology approach is described. In order to detect QRS complexes the neural network ensemble is proposed. It consists of three neural networks. The details referring to this solution has been described.

[Chen S.W, Chen H.C, and Chan H.L, 2006][27], proposed a simple moving average-based computing method for real-time QRS detection. The overall computational structure of the proposed algorithm allows the QRS detection to be performed and implemented in real-time with high time- and memory-efficiency. Algorithm performance was evaluated against the MIT-BIH Arrhythmia Database. Finally, it could function reliably even under the condition of poor signal quality in the measured ECG data.

[Wang Y, Plataniotis K.N, and Hatzinakos D, 2006][28], investigated identification of human subjects from electrocardiogram (ECG) signals. Two types of features, namely analytic and appearance features are extracted to represent the characteristics of heartbeat signal of different subjects. Feature selection is performed to find out significant attributes and are compared the performance of different classification algorithms. It has been proposed data fusion and classification schemes to achieve promising results with 100% correct human identification rate and 98.90% accuracy for heartbeat identification.

[Almagro S, Elena M.M, Bastiaans M.J, and Quero J.M, 2006][31],designed a real- time, denoise, and compress algorithm based on the wavelet transform (WT) for abdominal electrocardiograms (AECG) signals. It is done at the first stage before extracting the fetal electrocardiogram (FECG) from the AECG. A new mother wavelet (MW) is designed for AECG analysis. No complex low and high pass reconstruction and decomposition filters, with biorthogonal properties, are needed as is traditionally the case. The algorithm can also be used to design a MW for other purposes.

[Behbahani S, 2007][33],utilized adaptive filters for noise cancellation and then ECG signal analysis. Signals recorded from the human body provide valuable information about the biological activities which exhibit time-varying, non-stationary responses. The signals are always contaminated by a drift and interference caused by several bioelectric phenomena, or by intrinsic noise from the recorder and noise from electrode-skin contact.

[Starck Jean L, Fadili Jalal, and MurtaghFionn, 2007][35],described the undecimated wavelet transform and its reconstruction and the relation between two well-known undecimated wavelet transforms, the standard undecimated wavelet transform and the isotropic undecimated wavelet transform, then new filter banks specially are designed for undecimated wavelet decompositions.

[Mikhled A, and Khaled D, 2008][36], proposed a new approach based on the threshold value of ECG signal determination using Wavelet Transform coefficients. The ECG signal allows for the analysis of anatomic and physiologic aspects of the whole cardiac muscle. Different ECG signals are used to verify the proposed method using MATLAB software and it is compared with the Donoho's method for signal denoising.

[Rahman M.Z.U, Shaik R.A, and Reddy D.V.R.K, 2009][41], proposed several signed LMS based adaptive filters, having multiplier free weight update loops for noise cancellation in the ECG signal. The adaptive filters minimize the mean-squared error between a primary input, which is the noisy ECG, and a reference input. The different forms of noise are 60Hz power line interference, baseline wander, muscle noise and the motion artifact. The application of these algorithms on real ECG signals obtained from the MIT-BIH data base and compared their performance with the conventional LMS algorithm.

[Chang H.H and MouraJose.M.F, 2010][47],discussed the usefulness of spectral graph theory to automatically classify biomedical signals. The edges of the local graph encode the statistical correlations among the data, and the entire graph presents the intrinsic global structure of the data. The Cheeger constant studied in spectral graph theory is a measure of goodness of graph partitioning. The classifier is the optimization of a functional derived from the Cheeger constant and is obtained by exploiting the graph spectrum. The application of the classifier to contrast-enhanced MRI data sets demonstrates that the graph based automatic classification. The evaluation shows that the spectral graph classifier outperforms other methods like the commonly used thresholding, the isoperimetric algorithm, and a level set based approach.

[Gupta R, Bera J.N, and Mitra M, 2010][48],illustrated a low-cost method for online acquisition of ECG signal for storage and processing using a MATLAB-based Graphical User Interface (GUI). The single lead ECG is sampled at a rate of 1 kHz and after digitization, fed to a microcontroller-based embedded system to convert the ECG data to a RS232 formatted serial bit-stream. This serial data stream is then transmitted to a desktop Personal Computer at a rate of 19.2 kbps and a state-of-the art developed software stores it automatically in a temporary data file. The original ECG data is reconstructed from the digital data set by a conversion formula. The MATLAB-based GUI is designed to perform online analysis on the ECG data to compute the different time-plane features and display the same on the GUI along with the ECG signal plot.

[Ghasemi M, Ghaffari, A, Sadabadi H, and Golbayani H, 2010][52],proposed a method based on the continuous wavelet transform. In this method, the rescaled wavelet coefficients and dominant scales of the electrocardiogram (ECG) components are used to detect ECG characteristic points. The algorithm is applied to the PTB database of the PhysiobankThen, the results were evaluated using pertinent reference QT. The criterion used for evaluation of the method's performance is the root mean square (RMS) error.

[Sufi F, and Khalil I, 2011] [58], demonstrated an innovative technique that performs real-time classification of CVD. With the help of this real-time classification of CVD, the emergency personnel or the hospital can automatically be notified via SMS/MMS/e-mail when a life-threatening cardiac abnormality of the CVD affected patient is detected. As features extraction and expectation maximization (EM)-based clustering running on a hospital server that generate a set of constraints for representing each of the abnormalities, the patient's mobile phone receives these set of constraints and employs a rule-based system that can identify each of abnormal beats in real time. This detects cardiac abnormalities with 97% accuracy on average. This enables faster identification of cardiac abnormality directly from the compressed ECG, to build an efficient telecardiology diagnosis system.

[Ayub S, Saini J.P, 2011][59],describes the use of MATLAB based artificial neural network tools for ECG analysis for finding out whether the ECG is normal or abnormal. To classify this, various weighted neural networks were tried with different algorithms with training inputs from the standard MIT-BIH Arrhythmia database and tested by providing unknown patient data from the same database. The results obtained with different networks and different algorithms are compared, to identify whether the ECG beat is normal or abnormal, cascade forward back network algorithm has shown 99.9 % correct classification.

[Abbas H.H, 2011][60],deals with the implementation of software system to remove 0.5 Hz baseline wander noise from the ECG signal using multistage adaptive filter and the performance of the implemented system has been checked for changing the values of noise levels, the convergence factor of the adaptive algorithm, and the length of the adaptive filter. The performance of the implemented system changes by the above factors values. Then an adaptive filter with the best values for the above factors has been used as a prototype to build multistage filter.

[Narayana K.V.L, Rao A.B, 2011][61],deals with the detection of QRS complexes of ECG signals using derivative based/Pan-Tompkins/wavelet transform based algorithms. Different ECG signals from MIT/BIH Arrhythmia data base are used to verify the various algorithms using MATLAB software. Wavelet based algorithm is compared with the AF2 algorithm/Pan-Tompkins algorithms for signal denoising and detection of QRS complexes. In the wavelet based algorithm, the ECG signal has been denoised by removing the corresponding wavelet coefficients at higher scales. Then QRS complexes are detected and each complex is used to find the peaks of the individual waves like P and T, and also their deviations.

[Dangare C.S, Apte S.S, 2012][62], developed, a Heart Disease Prediction system (HDPS) is using Neural network which predicts the likelihood of patient getting a Heart disease. For prediction, the system uses sex, blood pressure, cholesterol like 13 medical parameters. Here two more parameters are added i.e. obesity and smoking for better accuracy. It has been observed that neural network predict heart disease with nearly 100% accuracy.

[Mesbah M, Malarvili B, Colditz P.B, and Boashash B, 2012][64],proposes a new method for newborn seizure detection that uses information extracted from both multi-channel electroencephalogram (EEG) and a single channel electrocardiogram (ECG). The aim is to assess whether additional information extracted from ECG can improve the performance of seizure detectors based solely on EEG. Two different approaches were used to combine this extracted information. They are first approach is feature fusion, which involves combining features extracted from EEG and heart rate variability (HRV) into a single feature vector prior to feeding it to a classifier. The second approach is classifier or decision fusion, is achieved by combining the independent decisions of the EEG and the HRV-based classifiers. The neonatal seizure detection algorithms achieved 95.20% sensitivity and 88.60% specificity for the feature fusion case and 95.20% sensitivity and 94.30% specificity for the classifier fusion case.

[Aarathi B, and Saba Fathima S, 2012][65],presents a technique to extract QRS complex by spatial velocity method, with the reference to detected QRS complex remaining other features in the smoothed signal are extracted by windowing techniques. The extracted features can be used for analysis of heart abnormalities. So, current framework can be used as a virtual cardiologist, which can analyze the signal fast so that abnormality can be detected immediately. Finally, the decision making rules using the ECG features for the detection of RBBB and LBBB are implemented to get effective and an efficient result.

[Rehman S.A and Kumar R.R, 2012][70], proposed various adaptive filter based algorithms that can be applied to ECG signal in order to remove various artefacts and are used for the analysis with Power line Interference. Simulation studies proposed novel algorithms like NLMS and DLMS based adaptive systems present better performances compared to existing realizations LMS, SRLMS and NSRLMS based procedures in terms of signal to noise ratio.

[Patel A.M, Gakare P.K, and Cheeran A.N, 2012][71], proposed an efficient arrhythmia detection algorithm using ECG signal so that detection of arrhythmia at initial stages is possible using a smart-phone which is readily available anywhere which makes complete system mobile. Subjects for experiments included normal patients, patients with Bradycardia, Tachycardia, atrial premature contraction (APC), patients with ventricular premature contraction (PVC) and patients with Sleep Apnea. Pan-Tompkins algorithm was used to find the locations of QRS complexes and R Peaks. The system is accurate and efficient to classify arrhythmias as high overall performance (97.3%) for the classification of the different categories of arrhythmic beats was achieved.

[Gradl S, Kugler P, Lohmuller C, and Eskofier B, 2012][72], developed an application for Android TM-based mobile devices that allows real-time electrocardiogram (ECG) monitoring and automated arrhythmia detection by analyzing ECG parameters. ECG data provided by pre-recorded files or acquired live by accessing a Shimmer TM sensor node via Bluetooth TM can be processed and evaluated. The application is based on the Pan-Tompkins algorithm for QRS-detection and contains further algorithm blocks to detect abnormal heartbeats. The algorithm was validated using the MIT-BIH Arrhythmia and MIT-BIH Supraventricular Arrhythmia databases. More than 99% of all QRS complexes were detected correctly by the algorithm. Overall sensitivity for abnormal beat detection was 89.5% with a specificity of 80.6%.

[Kumar N, Ahmad I, and Rai P, 2012][73], introduces the digital filtering method to cope with the noise artifacts in the ECG signal. The ECG lead-II signal is taken. The butterworth IIR filter and FIR type1 filters are applied on the ECG signal. The basic bandwidth used for the ECG monitoring is from 0 .5 Hz to 100 Hz.

[Islam M.K, Haque A.N.M.M, Tangim G, Ahammad T, and Khondokar M.R.H, 2012][74], deals with the study and analysis of ECG signal processing by means of MATLAB tool effectively. Generation & simulation of ECG signal, acquisition of real time ECG data, ECG signal filtering & processing, feature extraction, comparison between different ECG signal analysis algorithms & techniques, detection of any abnormalities in ECG, calculating beat rate and so on using the most familiar and multipurpose MATLAB software along with LABVIEW.

[Shouman M, Turner T, and Stocker R, 2012][75], identified gaps in the research on heart disease diagnosis and proposed a model to systematically eliminate those gaps by applying data mining techniques to heart disease treatment data to provide as reliable performance.

[Mukhopadhyay S, Biswas S, Roy A.B, and Dey N, 2012][76], presents a multi-resolution wavelet transform based system for detection P,Q,R,S,T, peak complexes from original ECG signal and are stored over the entire signal and the time interval between two consecutive R-peaks and other peaks interval to detect anomalies in behavior of heart. The peaks are achieved by the composition of Daubesis sub-bands wavelet of original ECG signal. The accuracy of the P,Q,R,S,T, complex detection and interval measurement is achieved up to 100% with high exactitude by processing and thresholding the original ECG signal.

[Muthuchudar A, and Baboo S.S, 2013][78], deals with some of the recent developments in the processes such as denoising, data compression, feature extraction and classification of the ECG signals. These processes are discussed each with suitable examples.

[Salari Nader, Shohaimi S, Najafi F, Nallappan M, and Karishnarajah I, 2013][81],aimed to develop an integrated model, based on the feature selection and classification, for the automatic classification of ACS. A dataset containing medical records of 809 patients suspected to suffer from ACS was used. For each subject, 266 clinical factors were collected. At first, a feature selection was performed based on interviews with 20 cardiologists; thereby 40 seminal features for classifying ACS were selected. Next, a feature selection algorithm was also applied to detect a subset of the features with the best classification accuracy. As a result, the feature numbers considerably reduced to only seven. Lastly, based on the seven selected features, eight various common pattern recognition tools for classification of ACS were used.

[Karthikeyan V, Vijayalakshmi V.J, and Jeyakumar P, 2013][83],aimed at the determination of an effective arrhythmia classification algorithm using the Heart Rate Variability (HRV) signal. The method is based on the Generalized Discriminant Analysis (GDA) feature reduction technique and the Multi-Layer Perceptron (MLP) neural network classifier. The proposed Arrhythmia classification method is applied to input HRV signals, obtained from the MIT-BIH databases. Here, four types of the most life threatening cardiac arrhythmias including left bundle branch block, fist degree heart block, Supraventricular tachyarrhythmia and ventricular trigeminy can be discriminated by MLP and reduced features with the accuracy of 100%.

[ErgenBurhan, 2013][89],focuses on the denoising of phonocardiogram (PCG) signals by means of discrete wavelet transform (DWT) using different wavelets and noise level estimation methods. The signal obtained by denoising from PCG signal con-taminated white noise and the original PCG signal is compared to determine the appropriate parameters for denoising. The comparison is evaluated in terms of signal to noise ratio (SNR) before and after denoising.

[Lee D H, Park J W, Choi J, Rabbi A, and Fazel-rezai R, 2013][90], implemented the European database for evaluation of automatic detection of the ST segment. The method comprises several steps viz., ECG signal loading from database, signal preprocessing, detection of QRS complex and R-peak, ST segment, and other relation parameter measurement. The developed application displays the results of the analysis.

[Malviya N, Rao, and T.V.K.H, 2013][91],proposed to remove these noises with different types of adaptive and non-adaptive digital filters, where LMS, NLMS, and RLS algorithms are used for de-noising the ECG signals and the obtained simulation results are presented in MATLAB. Also, the Performances of the filters are compared based on the SNR values, complexity and mean square error.

[Tantawi M.M, Revett K, Salem A, and Tolba M.F, 2013][100],goal is to quantitatively evaluate the information content of the fiducial based feature set in terms of their effect on heart beat classification accuracy. To this end, a comprehensive set of fiducial based features was extracted from a collection of ECG records. This feature set was subsequently reduced using a variety of feature extraction/selection methods such as principle component analysis (PCA), linear discriminant analysis (LDA), information-gain ratio (IGR), and rough sets (in conjunction with the PASH algorithm). The performance of the reduced feature set was examined and evaluated with respect to the full feature set in terms of the overall classification accuracy and false (acceptance/rejection) ratios (FAR/FRR). The indicates that the PASH algorithm, deployed within the context of rough sets, reduced the dimensionality of the feature space maximally, while maintaining maximal classification accuracy.

[Stojanovic R, Knezevic S, Karadaglic D, and Devedzic G, 2013][104],Existing biomedical wavelet based applications exceed the computational memory and consumption resources of low-complexity embedded systems. In order to make such systems capable to use wavelet transforms, optimization techniques are proposed. The Real Time QRS Detector and "De-noising" Filter are developed and implemented in 16-bit fixed point microcontroller achieving 800 Hz sampling rate, occupation of less than 500 bytes of data memory, 99.06% detection accuracy, and 1 mW power consumption.

[Sabherwal P, 2013][105], reviewed the emerging role of the wavelet transform in the interrogation of the ECG is discussed in detail. An algorithm has been proposed to determine the r-peaks and the number of beats in sampled signal. In the first step an attempt was made to generate ECG waveforms by developing a suitable MATLAB simulator and in the second step, using wavelet transform, the ECG signal was denoised by removing the corresponding wavelet coefficients at higher scales. Then R-Peak in QRS complexes were detected and the last step is to calculate the beat. Db4 taken as mother wavelet.

[Liang W, Zhang Y, Tan J, and Li Y, 2014][107], presents a novel approach to ECG signal filtering and classification and proposed algorithm designed for monitoring and classifying the patient's ECG signals in the free-living environment. The patients are equipped with wearable ambulatory devices the whole day, which facilitates the real-time heart attack detection. In ECG preprocessing, an integral-coefficient-band-stop (ICBS) filter is applied, which omits time-consuming floating-point computations. In addition, two-layered Hidden Markov Models (HMMs) are applied to achieve ECG feature extraction and classification. The periodic ECG waveforms are segmented into ISO intervals, P subwave, QRS complex and T subwave respectively in the first HMM layer where expert-annotation assisted Baum-Welch algorithm is utilized in HMM modeling. Then the corresponding interval features are selected and applied to categorize the ECG into normal type or abnormal type (PVC, APC) in the second HMM layer. For verifying the effectiveness of our algorithm on abnormal signal detection, it has been developed an ECG body sensor network (BSN) platform, whereby real-time ECG signals are collected, transmitted, displayed and the corresponding classification outcomes are deduced and shown on the BSN screen.

[Kavitha R, and Christopher T, 2014][108],presents a technique to examine electrocardiogram (ECG) signal, by taking the features form the heart beats classification. ECG Signals are collected from MIT-BIH database. The heart rate is used as the base signal from which certain parameters are extracted and presented to the network for classification.

[Parvinnia E, Sabeti M, Jahromi M Z, and Boostani R, 2014,][110], presented a general adaptive method named weighted distance nearest neighbor (WDNN) is applied for EEG signal classification to tackle the problem of artifacts at the time of recording EEG signals. This classification algorithm assigns a weight to each training sample to control its influence in classifying test samples. The weights of training samples are used to find the nearest neighbor of an input query pattern. To assess the performance of this scheme, EEG signals of thirteen schizophrenic patients and eighteen normal subjects are analyzed for the classification of these two groups. Several features including, fractal dimension, band power and autoregressive (AR) model are extracted from EEG signals. The classification results are evaluated using Leave one (subject) out cross validation for reliable estimation. The results indicate that combination of WDNN and selected features can significantly outperform the basic nearest-neighbor and the other methods proposed in the past for the classification of these two groups. Therefore, this method can be a complementary tool for specialists to distinguish schizophrenia disorder.

[Borg J.J,(2015)][122], describes a rapid, cost-effective pre-clinical method to screen for pro- or antiarrhythmic effects of substances in an isolated heart preparation in line with the regulatory requirements of ICHS7B. The computational method "MFC method" quantifies arrhythmic episodes from isolated perfused hearts based on measuring the variation in the maximum force of contraction. Experiments were performed on hearts isolated from male Wistar rats. Arrhythmias were induced by the addition of tefluthrin or by ligation of the left coronary artery. The "MFC method" accurately measures the maximum force of every myocardial contraction and correlates it with the magnitude of the preceding beat. Arrhythmias were quantified by determining the coefficient of variation in the maximum force of contraction. This method is a useful approach to quickly identify the pro- or antiarrhythmic effects of drugs prior to more detailed analysis; particularly where the effects are varied and not easily classified under the Lambeth Conventions.

[Kanwar G, Dewangan N.K, and Dewangan K, 2015][124], discussed about ECG signal which is a periodic, that gives information about the heart activity. A lot of information about normal and abnormality about the heart can be obtained from the ECG signal. Premature ventricular contractions (PVCs) are the ectopic beats that occur from the ventricular area of the heart. It is a most common heart arrhythmia that found on a human being. Detection of Premature Ventricular Contraction (PVCs) beat from the Electrocardiogram (ECG) is the most important thing in the field of biomedical.

[DewanganN.K, and Shukla S.P, 2015][125], described about Electrocardiogram (ECG) to measure the rate and regularity of heartbeats. Comparison of overall ECG waveform pattern and shape enables doctors to diagnose possible diseases. Also discusses various techniques and transformations for feature extraction and analysis of ECG signals and makes comparison among them.

[Kishore N, and Singh S, 2015,][126], presents Electrocardiogram (ECG) classification to diagnose patient's condition. For classification of such Diagnose Signals, P-Wave, PR-Interval, QRS Interval, ST Interval, T- Wave etc, analysis of each Input pulse used to train the neural network and features are obtained using Genetic Algorithm. Output of the neural network gives weight factors of each signal to create a data set. Electrocardiogram (ECG), PQRSTU-waveforms time intervals and weight factors and prediction of particular decease infection or state of a patient condition saved in database and corresponding output-datasets indicates related disease and predict the causes.

[Jeba J, 2015][127], proposed SVM detection used and combined three various FS filter-type methods into a single ranking score, allowing us to define the relevance of each ECG restriction. The progress of automated external defibrillators that analyze the surface electrocardiogram (ECG) signal if either rapid VT or VF is spotted.

[Gradl S, Leutheuser H, Elgendi M, Lang N, and Eskofier B.M, 2015][134],implemented three different state-of-the-art algorithms and evaluated the precision of the R-peak localization and suggested a method to estimate the overall R-peak temporal inaccuracy—dubbed beat slackness of QRS detectors with respect to normal and abnormal beats. Also proposed a simple algorithm that can complement existing detectors to reduce this slackness. Furthermore improved to one of the three detectors allowing it to be used in real-time on mobile devices or embedded hardware. Across the entire MIT-BIH Arrhythmia Database, the average slackness of all the tested algorithms was 9ms for normal beats and 13ms for abnormal beats. Using our complementing algorithm this could be reduced to 4ms for normal beats and to 7ms for abnormal beats to improve the precision of R-peak detection and provide an additional measurement for QRS detector performance.

[Huang G, Huang G.B, Song S, and You K, 2015][135],aimed to report the overview of Extreme Learning Machines (ELM) from the theoretical perspective, including the interpolation theory, universal approximation capability, and generalization ability. Then focused on the various improvements in ELM to improve its stability, sparsity and accuracy under general or specific conditions. Apart from classification and regression, ELM has recently been extended for clustering, feature selection, representational learning and many other learning tasks. These newly emerging algorithms greatly expand the applications of ELM. From implementation aspect, hardware implementation and parallel computation techniques have substantially sped up the training of ELM, making it feasible for big data processing and real-time reasoning. Due to its remarkable efficiency, simplicity, and impressive generalization performance, ELM have been applied in a variety of domains, such as biomedical engineering, computer vision, system identification, and control and robotics..

[Afkhami R.G, Azarnia G, and TinatiMd.A, 2016][136], proposed a novel method for accurate classification of cardiac arrhythmias. Morphological and statistical features of individual heart beats are used to train a classifier. Two RR interval features as the exemplars of time-domain information are utilized. Gaussian mixture modeling (GMM) with an enhanced expectation maximization (EM) solution is used to fit the probability density function of heart beats. Parameters of GMM together with shape parameters such as skewness, kurtosis and 5th moment are also included in feature vector. These features are then used to train an ensemble of decision trees. MIT-BIH arrhythmia database containing various types of common arrhythmias is employed to test the algorithm. The overall accuracy of 99.70% in "class-oriented" scheme and 96.15% in "subject-oriented" scheme is achieved. Both cases express a significant improvement of accuracy compared to other methods.

B. Review of Cardiac Arrhythmia using Computational Intelligence Techniques

[Silipo R and Marchesi C, 1998][10],presents some results achieved by carrying out the classification tasks of a possible equipment integrating the most common features of the ECG analysis: arrhythmia, myocardial ischemia, chronic alterations. Several ANN architectures are implemented, tested, and compared with competing alternatives. Approach, structure, and learning algorithm of ANN were designed according to the features of each particular classification task. The trade-off between the time consuming training of ANN's and their performances is also explored. Data pre- and post-processing efforts on the system performance were critically tested. These efforts' crucial role on the reduction of the input space dimensions, on a more significant description of the input features, and on improving new or ambiguous event processing has been also documented

[Maglaveras N, Stamkopoulos T, Diamantaras K, Pappas C, and Strintzis M, 1998][12], Conveys ECG information regarding the electrical function of the heart, by altering the shape of its constituent waves, namely the P, QRS, and T waves. Thus, the required tasks of ECG processing are the reliable recognition of these waves, and the accurate measurement of clinically important parameters measured from the temporal distribution of the ECG constituent waves. The problems with existing models deals with the QRS:PVC recognition and classification, the recognition of ischemic beats and episodes, and the detection of atrial fibrillation. Finally, presented a generalised approach to the classification problems in *n*-dimensional spaces using among others NN, radial basis function networks (RBFN) and non-linear principal component analysis (NLPCA) techniques. The performance measures of the sensitivity and specificity of these algorithms will also be presented using as training and testing data sets from the MIT-BIH and the European ST-T databases.

[Stamkopoulos T, Diamantaras K, Maglaveras N, and Strintzis M,1998][11], developed an algorithm for feature extraction based on nonlinear principal component analysis (NLPCA). NLPCA is a relatively recently proposed method for nonlinear feature extraction that is usually implemented by a multilayer neural network. It has been observed to have better performance, compared with linear principal component analysis (PCA), in complex problems where the relationships between the variables are not linear. The NLPCA techniques are used to classify each segment into one of two classes: normal and abnormal. During the algorithm training phase, only normal patterns are used, and for classification purposes, they use only two nonlinear features for each ST segment. The distribution of these features is modeled using a radial basis function network (RBFN). Test results using the European STT database show that using only two nonlinear components.

[Gao D, Madden M, Schukat M, Chambers D, and Lyons G, 2004][20], presented a diagnostic system for cardiac arrhythmias from ECG data, using an Artificial Neural Network (ANN) classifier based on a Bayesian framework. The Bayesian ANN Classifier is built by the use of a logistic regression model and the back propagation algorithm. A dual threshold method is applied to determine the diagnosis strategy and suppress false alarm signals. The experimental result shows more than 90% prediction accuracy.

[AcharyaR.U, Kumar A, Bhat P.S, Lim C.M, Iyengar S.S, Kannathal N, and Krishnan S.M, 2004][22], aims with the classification of cardiac rhythms using an artificial neural network and fuzzy relationships and the results indicated a high level of efficacy of the tools used, with 80-85% of accuracy.

[Engin M, 2004][23], studied the application on the fuzzy-hybrid neural network for electrocardiogram (ECG) beat classification. Instead of original ECG beat, an autoregressive model coefficients, higher-order cumulant and wavelet transform variances as features are used. Tested with MIT/BIH arrhytmia database, to observe significant performance.

[Gao D, Madden M, Chambers D, and Lyons G, 2005][24], proposed a system for detection of cardiac arrhythmias within ECG signals, based on a Bayesian artificial neural network (ANN) classifier. Its performance for this task is evaluated by comparison with other classifiers including Naive Bayes, decision trees, logistic regression, and RBF networks. A paired t-test is employed in comparing classifiers to select the optimum model. The system is evaluated using noisy ECG data, to simulate a real-world environment.

[Ozbay Y, Ceylan R and Bekir K, 2006][26],presents a comparative study of the classification accuracy of ECG signals using a well-known neural network architecture named multi-layered perceptron (MLP) with back propagation training algorithm, and a new fuzzy clustering NN architecture (FCNN) for early diagnosis. The ECG signals are taken from MIT-BIH ECG database, which are used to classify 10 different arrhythmias for training. The test results suggest that a new proposed FCNN architecture can generalize better than ordinary MLP architecture and also learn better and faster.

[Meau Y.P, Ibrahim F, Narainasamy S.A.L, and Omar R, 2006][29],presents the development of a hybrid system consisting of an ensemble of Extended Kalman Filter (EKF) based Multi-Layer Perceptron Network (MLPN) and one-pass learning Fuzzy Inference System using Look-up Table Scheme for the recognition of electrocardiogram (ECG) signals to distinguish various types of abnormal ECG signals.

[Babak M and Setarehdan S.K, 2006][30],have implemented a neural network classifier to automatic classification of cardiac arrhythmias into five classes. HRV signal is used as the basic signal and linear and non-linear parameters extracted from it to train a neural network classifier and obtained better accuracy.

[Exarchos T.P, Tsipouras M.G, Exarchos C.P, Papaloukas C, Fotiadis D.I, and Michalis L.K, 2007][32],proposed a methodology for the automated creation of fuzzy expert systems from an initial training dataset, applied in ischaemic and arrhythmic beat classification in three stages: (a) extraction of a crisp set of rules from a decision tree induced from the training dataset, (b) transformation of the crisp set of rules into a fuzzy model and (c) optimization of the fuzzy model's parameters using global optimization. The arrhythmic beat classification fuzzy expert system is evaluated using the MIT-BIH arrhythmia database.

[Castells F, Laguna P, Sornmo L, Bollmann A, and Roig J.M, 2007][34], aims with the current status of principal component analysis in the area of ECG signal processin and the relationship between PCA and Karhunen-Loève transform. Aspects on PCA related to data with temporal and spatial correlations are considered as adaptive estimation of principal components. Several ECG applications are reviewed where PCA techniques are successfully employed, including data compression, ST-T segment analysis for the detection of myocardial ischemia and abnormalities in ventricular repolarization, extraction of atrial fibrillatory waves for detailed characterization of atrial fibrillation, and analysis of body surface potential maps.

[Bellazzi R, and Zupan B, 2008][37], reviewed the role of the predictive data mining to propose a framework to cope with the problems of constructing, assessing and exploiting data mining models in clinical medicine. The availability of new computational methods and tools for data analysis and predictive modeling requires medical informatics to select systematically the most appropriate strategy with clinical prediction problems. The main issues in these agreed standardized procedures for the deployment and the dissemination of the results.

[Ubeyli, E.D, 2009][38], described the application of adaptive neuro-fuzzy inference system (ANFIS) model for classification of electrocardiogram (ECG) signals. Decision making was performed in two stages: feature extraction by computation of Lyapunov exponents and classification by the ANFIS trained with the back-propagation gradient descent method in combination with the least squares method. Four types of ECG beats viz., normal beat, congestive heart failure beat, ventricular tachyarrhythmia beat, and atrial fibrillation beat, obtained from the Physio-Bank database was classified by four ANFIS classifiers. To improve diagnostic accuracy, the fifth ANFIS classifier (combining ANFIS) was trained using the outputs of the four ANFIS classifiers as input data. The proposed ANFIS model combined the neural network adaptive capabilities and the fuzzy logic qualitative approach.

[Pham H.N.A, and Triantaphyllou E, 2009][39], applied a new meta-heuristic approach, called the Homogeneity-Based Algorithm (HBA), for optimizing the classification accuracy when analyzing some medical datasets. The HBA optimizes the problem in terms of the error rates and the associated penalty costs which are different in medical applications as the implications of having a false-positive and a false-negative. The prediction accuracy enhanced when HBA is combined with traditional classification algorithms by using homogenous sets.

[Kraiem A and Charfi F, 2009][40], The objective of this paper is to develop a model for ECG (electrocardiogram) classification based on Data Mining techniques. The MIT-BIH Arrhythmia database was used for ECG classical features analysis. This work is divided into two important parts. The first parts deals with extraction and automatic analysis for different waves of electrocardiogram by time domain analysis and the second one concerns the extraction decision making support by the technique of Data Mining for detection of EGC pathologies. Two pathologies are considered: atrial fibrillation and right bundle branch block. Some decision tree classification algorithms currently in use, including C4.5, Improved C4.5, CHAID and Improved CHAID are performed for performance analysis. The bootstrapping and the cross-validation methods are used for accuracy estimation of these classifiers designed for discrimination. The Bootstrap with pruning by 5 attributes achieves the best performance managing to classify correctly.

[Ebrahimzadeh A and Khazaee A, 2009][42], describes a Radial Basis Function (RBF) neural network method used to analyze ECG signals for diagnosing cardiac arrhythmias effectively. The proposed method can accurately classifies and differentiate normal (Normal) and abnormal heartbeats. ECG beats is normalized to a mean of zero and standard deviation of unity. Feature extraction module extracts wavelet approximate coefficients of ECG signals in conjunction with three timing interval features. Then a number of radial basis function (RBF) neural networks with different value of spread parameter are designed.

[Nasiri J.A, Naghibzadeh M, Yazdi H.S, and Naghibzadeh B, 2009] [43], presented a new approach for cardiac arrhythmia disease classification. The proposed method combines both Support Vector Machine (SVM) and Genetic Algorithm approaches. Twenty two features from ECG signal are extracted semi automatically from time-voltage of R, S, T, P, Q features of an Electrocardiogram signals. Genetic algorithm is used to improve the generalization performance of the SVM classifier. For this, the design of the SVM classifier is optimized by searching for the best value of the parameters that tune its discriminate function, and looking for the best subset of features that optimizes the classification fitness function.

[Salem A.B.M, Revett K, and Ei-Dahshan E.S.A, 2009] [44], summarized some of the principle machine learning approaches to ECG classification, evaluating them in terms of the features they employ, the types of CVDs to which they are applied, and their classification accuracy.

[Ubeyli E D, 2009][45],presented the usage of statistics over the set of the features representing the electrocardiogram (ECG) signals. Multilayer perceptron neural network (MLPNN) architectures were formulated and used as basis for detection of variabilities of the ECG signals. Four types of ECG beats viz., normal beat, congestive heart failure beat, ventricular tachyarrhythmia beat, atrial fibrillation beat obtained from the Physiobank database were classified. The selected Lyapunov exponents, wavelet coefficients and the power levels of power spectral density (PSD) values obtained by eigenvector methods of the ECG signals were used as inputs of the MLPNN trained with Levenberg–Marquardt algorithm.

[Moavenian M, and Khorrami H, 2010][46],used Kernel–Adatron (K–A) learning algorithm to aid SVM (Support Vector Machine) for ECG arrhythmias classification. The proposed pattern classifier is compared with MLP (multi-layered perceptron) using back propagation (BP) learning algorithm. The ECG signals taken from MIT-BIH arrhythmia database are used in training to classify 6 different arrhythmia, plus normal ECG. The MLP and SVM training and testing stages were carried out twice. They were first trained only with one ECG lead signal and then a second ECG lead signal was added to the training and testing datasets. The aim was to investigate its influence on training and testing performance (generalization ability) plus time of training for both classifiers. Implementation of these three criteria for evaluation of ECG signals classification will ease the problem of structural comparisons.

[Korurek M, and Dogan B, 2010][49],presented a method for electrocardiogram (ECG) beat classification based on particle swarm optimization (PSO) and radial basis function neural network (RBFNN). Six types of beats including Normal Beat, Premature Ventricular Contraction (PVC), Fusion of Ventricular and Normal Beat (F), Atrial Premature Beat (A), Right Bundle Branch Block Beat (R) and Fusion of Paced and Normal Beat (f) are obtained from the MIT-BIH arrhythmia database. Four morphological features are extracted from each beat after the preprocessing of the selected records. For classification stage of the extracted features, a RBFNN structure is evolved by particle swarm optimization.

[Yang S, and Yang G, 2010][50], introduced the Electrocardiogram (ECG) pattern recognition method based on wavelet transform and standard back-propagation (BP) neural network classifier. Firstly wavelet transform of ECG to extract the maximum wavelet coefficients of multi-scale and then input to BP classify for different kinds ECG. The experimental result shows that the standard BP neural network classifier's overall pattern recognition rate is well. The ECG in this paper was from MIT-BIH. Experimental result shows that feature vector extracted by the wavelet transform can characterize ECG patterns, and BP neural network classifier has a stronger ECG recognition effect.

[Yaghouby F, Ayatollahi A, Bahramali R, Yaghouby M, and Alavi A.H, 2010][51],In this study, new methods coupling genetic programming with orthogonal least squares (GP/OLS) and simulated annealing (GP/SA) were applied to the detection of atrial fibrillation (AF) episodes. Empirical equations were obtained to classify the samples of AF and Normal episodes based on the analysis of RR interval signals. Another important contribution is to identify the effective time domain features of heart rate variability (HRV) signals via an improved forward floating selection analysis. The models developed using the MIT-BIH arrhythmia database. A radial basis function (RBF) neural networks-based model is further developed using the same features and data sets to benchmark the GP/OLS and GP/SA models. The diagnostic performance of the GP/OLS and GP/SA classifiers was evaluated using receiver operating characteristics analysis. The results indicate a high level of efficacy of the GP/OLS model with sensitivity, specificity, positive predictivity, and accuracy rates of 99.11%, 98.91%, 98.23%, and 99.02%, respectively.

[Kar A, and Das L, 2011][53],aims for the analysis of statistical feature extraction of ECG signal by several classification methods and evaluate by digital signal analysis, Fuzzy Logic methods, Artificial Neural Network, Hidden Markov Model, Genetic Algorithm, Support Vector Machines, Self-Organizing Map, Bayesian and other method with each approach exhibiting its own advantages and disadvantages. It is desired to automate the entire process of heart beat classification and preferably diagnose it accurately.

[HarikumarR, and Shivappriya S.N, 2011][54], investigated and compared a set of efficient techniques to extract and select striking features from the ECG data applicable in automatic cardiac beat classification. Each method was applied to a pre-selected data segment from the MIT-BIH database. The classification and optimization of different heart beat methods were performed based upon the extracted features. The feature extraction, feature selection, classification and optimization techniques, SVM based PSO gave higher classification accuracy with curse of dimensionality.

[Gothwal H, Kedawat S, and Kumar R, 2011][55], presents a method to analyze electrocardiogram (ECG) signal, extract the features, for the classification of heart beats according to different arrhythmias. Data were obtained from 40 records of the MIT-BIH arrhythmia database. A learning dataset for the neural network was obtained from a twenty records set which were manually classified. Fast Fourier transforms are used to identify the peaks in the ECG signal and then Neural Networks are applied to identify the diseases. Levenberg Marquardt Back-Propagation algorithm is used to train the network.

[Vishwa A, Lal M.K, Dixit S, and Vardwaj P, 2011][56], proposed an automated Artificial Neural Network (ANN) based classification system for cardiac arrhythmia using multi-channel ECG recordings. Neural network model with back propagation algorithm is used to classify arrhythmia into normal and abnormal classes. Networks models are trained and tested for MIT-BIH arrhythmia. The different structures of ANN have been trained by mixture of arrhythmic and non-arrhythmic data patient. The classification performance is evaluated using measures; sensitivity, specificity, classification accuracy, mean squared error (MSE), receiver operating characteristics (ROC) and area under curve (AUC) and 96.77% accuracy on MIT-BIH database and 96.21% on database prepared by including NSR database also.

[Karpagachelvi S, 2011][57], Extreme Learning Machines (ELM) classifier is used for searching the best value of the parameters that tune its discriminant function, and upstream by looking for the best subset of features that feed the classifier. Physionet arrhythmia database is used to classify five kinds of abnormal waveforms and normal beats. The Extreme Learning Machine (ELM) is presented and compared with support vector machine (SVM) approach in the automatic classification of ECG beats. The sensitivity of the ELM classifier is tested and that is compared with SVM combined with k-nearest neighbor classifier (kNN) and the radial basis function neural network classifier (RBF) in order to show the superiority.

[Bhardwaj P, Choudhary R R, and Dayama R, 2012][63], studied about automatic detection of cardiac arrhythmia disorders by the data analysis techniques using specific computer software to interpret complex ECG signals, and predict presence or absence of cardiac arrhythmia. This provides real time analysis and further facilitates for timely diagnosis. Support Vector Machine (SVM) technique, using LibSVM3.1 has been applied to ECG dataset for arrhythmia classification in five categories for the study. Out of these five categories, one is normal and four are arrhythmic beat categories. The dataset used in this study is 3003 arrhythmic beats out of which 2101 beats (70%) are used for training and remaining 902 beats (30%) have been used for testing purpose. Total performance accuracy is found to be around 95.21 % in this case.

[Sun Li, Lu Yanping, Yang K, and Li Shaozi, 2012][66], presents a useful technique for totally automatic detection of myocardial infarction from patients ECG. Due to the large number of heartbeats constituting an ECG and the high cost of having all the heartbeats manually labeled, supervised learning techniques have achieved limited success in ECG classification. So, discussions for applying multiple instance learning (MIL) to automated ECG classification and then a new MIL strategy called latent topic MIL, by which ECGs are mapped into a topic space defined by a number of topics identified over all the unlabeled training heartbeats and support vector machine is directly applied to the ECG-level topic vectors.

[Gupta K O, and Chatur P.N, 2012][67], focuses on some of the techniques proposed earlier for the arrhythmia classification and extraction of parameters from the ECG signal which is used for data acquisition and classification system and implementation of Artificial Neural Networks (ANN) and data mining techniques using intelligent data miner software.

[Kutlu Y, and Kuntalp D, 2012,][68],describes feature extraction methods using higher order statistics (HOS) of wavelet packet decomposition (WPD) coefficients for the purpose of automatic heartbeat recognition. First, the wavelet package coefficients (WPC) are calculated for each different type of ECG beat. Then, higher order statistics of WPC are derived. Finally, the obtained feature set is used as input to a classifier, which is based on *k*-NN algorithm. The MIT-BIH arrhythmia database is used to obtain the ECG records used in this study. All heartbeats in the arrhythmia database are grouped into five main heartbeat classes. The classification accuracy of the proposed system is measured by average sensitivity of 90%, average selectivity of 92% and average specificity of 98%.

[Castillo O, Melin P, Ramirez E, and Soria J, 2012][69],described a hybrid intelligent system for classification of cardiac arrhythmias. The hybrid approach was tested with the ECG records of the MIT-BIH Arrhythmia Database. The samples considered for classification contained arrhythmias of the following types: LBBB, RBBB, PVC and Fusion Paced and Normal, as well as the normal heartbeats.

The signals of the arrhythmias were segmented and transformed for improving the classification results. Fuzzy K-Nearest Neighbors, Multi Layer Perceptron with Gradient Descent and momentum Backpropagation, and Multi Layer Perceptron with Scaled Conjugate Gradient Backpropagation are used. Finally, a Mamdani type fuzzy inference system was used to combine the outputs of the individual classifiers, and a very high classification rate of 98% was achieved.

[Izzah T.A, Alhady S.S.N, Ngah U.K, and Ibrahim W.P, 2013][77],describes about the analysis of electrocardiogram (ECG) signals using neural network approach. Some major important features extracted from ECG signals will be fed as an input to neural network system. The target output represented real peaks of the signals is being defined using a binary number. Obtained results show the neural network pattern recognition to classify and recognize the real peaks accordingly with overall accuracy of 81.6% although there might be limitations and misclassification.

[Wang J.S, Lin C.W, and Yang Y.T.C, 2013][79], presents k-nearest neighbor classifiers with HRV feature-based transformation algorithm for driving stress recognition. It has been proposed feature-based transformation algorithm which consists of feature generation, feature selection, and feature dimension reduction. In order to generate significant features from ECG signals, two feature generation approaches, trend-based and parameter-based methods are proposed. The trend-based method computes statistical features from long-term HRV variations, while the parameter-based method calculates features from five-minute HRV analysis. The kernel-based class separability (KBCS) is employed as the selection criterion for feature selection. To reduce computational load of the algorithm, principal component analysis (PCA) and linear discriminant analysis (LDA) are adopted for feature dimension reduction. The combination of KBCS, LDA, and PCA achieved satisfactory recognition rates for the features generated by both trend-based and parameter-based methods.

[MuthuchudarA, and Baboo S.S, 2013][80],used wavelet transform combining its own Neural Network boiling down to some advantage or other. After detecting the features, they try to help the cardiologists to classify the various heart diseases with more accuracy and avoidance of delay.

[Liu S.H, Cheng D.C, and Lin C.M, 2013][82], proposed an automatic configuration that can detect the position of R-waves, classify the normal sinus rhythm (NSR) and other four arrhythmic types from the continuous ECG signals obtained from the MIT-BIH arrhythmia database. In this support vector machine (SVM) was used to detect and mark the ECG heartbeats with raw signals and differential signals. An algorithm based on the extracted markers segments waveforms of Lead II and V1 of the ECG as the pattern classification features. A self-constructing neural fuzzy inference network (SoNFIN) was used to classify NSR and four arrhythmia types, including premature ventricular contraction (PVC), premature atrium contraction (PAC), left bundle branch block (LBBB), and right bundle branch block (RBBB). In a real scenario, the classification results show the accuracy achieved is 96.4%.

[MitraM, and Samanta R.K, 2013][84], presented a new approach for cardiac arrhythmia disease classification. An early and accurate detection of arrhythmia is highly solicited for augmenting survivability. Intelligent automated decision support systems have been attempted with varying accuracies tested on UCI arrhythmia data base. One of the attempted tools in this context is neural network for classification. For better classification accuracy, various feature selection techniques have been deployed as prerequisite. Correlation-based feature selection (CFS) with linear forward selection search. For classification, incremental back propagation neural network (IBPLN), and Levenberg-Marquardt (LM) classification tested on UCI data base.

[Chitupe A.R and Joshi S.A (2013)[85],performed analytical processing and related mining to classify normal and abnormalities of the ECG. It has been investigated that the results of KNN (K-Nearest Neighbour) algorithm finds relation between geometric parameters like area and behavioral parameters of ECG especially in pregnancy cases.

[Jabbar M.A, Deekshatulu B.L, and Chandra P, 2013][86],introduced a classification approach which uses ANN and feature subset selection for the classification of heart disease. PCA is used for preprocessing and to reduce number of attributes which indirectly reduces the number of diagnosis tests which are needed to be taken by a patient. An approach on Andhra Pradesh heart disease data base has been applied and it has been shown that accuracy was improved over traditional classification techniques.

[El-KhafifS.H, and El-Brawany M.A, 2013][87],aimed on the utilization of the ECG signal which have nonlinear component and its dynamical changes significantly between normal and abnormal conditions. Use of one-dimensional slices from the higher-order spectral domain of normal and ischemic subjects. A feedforward multilayer neural network (NN) with error back propagation (BP) learning algorithm was used as an automated ECG classifier recognize ischemic heart disease from normal ECG signals. Different NN structures are tested using two data sets extracted from polyspectrum slices and polycoherence indices of the ECG signals. ECG signals from the MIT/BIH CD-ROM, the Normal Sinus Rhythm Database (NSR-DB), and European ST-T database have been used. The best classification rates obtained are 93% and 91.9% using EDBD learning rule with two hidden layers for the first structure and one hidden layer for the second structure, respectively.

[Khazaee Ali, 2013][88], proposed a method for premature ventricular contraction detection. The method consists of three modules. Feature extraction module which extracts ten electrocardiogram (ECG) morphological features and two timing interval features. Then a number of support vector machine (SVM) classifiers with different values are designed and compared their ability for classification of three different classes of ECG signals. An overall classification accuracy of detection of 98.38% were achieved over nine files from the MIT/BIH arrhythmia database. The classification accuracy increased to 99.90% when particle swarm optimization (PSO) is employed.

[Chaurasia V, and Pal S, 2013][92],developed prediction models for heart disease survivability by implementing data mining algorithms CART (Classification and Regression Tree), ID3 (Iterative Dichotomized 3) and decision table (DT) extracted from a decision tree or rule-based classifier to develop the prediction models using a large dataset.

[Suma'inna, 2013][93], proposed the detection of the cardiac abnormalities based on recognition of the ECG signal patterns by using Daubechies wavelet and Artificial Neural Network (ANN). The Daubechies wavelet method is used to reduce the capacity of data without losing the actual information, while ANN is used to recognize ECG patterns and to classify the ECG into normal and abnormal.

[Wang J.S, Chiang W.C,Hsu Y.L, and Yang Y.T.C, 2013][94], presented an effective electrocardiogram (ECG) arrhythmia classification scheme consisting of a feature reduction method combining principal component analysis (PCA) with linear discriminant analysis (LDA), and a probabilistic neural network (PNN) classifier to discriminate eight different types of arrhythmia from ECG beats. Each ECG beat sample composed of 200 sampling points at a 360 Hz sampling rate around an R peak is extracted from ECG signals. The feature reduction method is employed to find important features from ECG beats, and to improve the classification accuracy of the classifier. With the selected features, the PNN is then trained to serve as a classifier for discriminating eight different types of ECG beats. The average classification accuracy of the proposed scheme is 99.71%.

[Zidelmala Z, Amirou A, Abdeslam D.O, and Merckle J, 2013][95],introduced a new system for ECG beat classification using Support Vector Machines (SVMs) classifier with rejection. After ECG preprocessing, the QRS complexes are detected and segmented. A set of features including frequency information, RR intervals, QRS morphology and AC power of QRS detail coefficients is exploited to characterize each beat. An SVM follows to classify the feature vectors. Decision rule used dynamic reject thresholds following the cost of misclassifying a sample and the cost of rejecting a sample. The proposed approach is tested with the MIT-BIH arrhythmia database. The achieved results are represented by the average accuracy of 97.2% with no rejection and 98.8% for the minimal classification cost.

[Srinivas N, VinayBabu A, and Rajak M.D, 2013][96],used Fuzzy logic and Artificial Neural Network (FANN), Precise Electrocardiogram (ECG) classification to diagnose patient's condition is essential. For classification of such Difficult-to-Diagnose-Signals, i.e. ECG signal, classification is performed using various pulses, like v1, v2, v3, v4, v5, v6 etc corresponding hidden layer in ANN i.e., P-Wave, PR-Interval, QRS-Interval, ST-Interval, T-Wave etc analysis of each Input pulse used to train the neural network. Output of the neural network gives weight factors of each signal to create a data set. Data sets are organized with clusters. These cluster data sets are analysed by Adaptive Resonance theory.

[Luz E.J.D.S, Nunes T.M, Albuquerque V.H.C.D, Papa J.P, and Menotti D, 2013][97], aimed to a fast and accurate cardiac arrhythmia signal classification process, by applying the optimum path forest (OPF) classifier. OPF classifier is used to the ECG heartbeat signal classification task and then compared the performance in terms of training and testing time, accuracy, specificity, and sensitivity of the OPF classifier to the ones of other three well-known expert system classifiers, i.e., support vector machine (SVM), Bayesian and multilayer artificial neural network (MLP), using features extracted from six main approaches considered in literature for ECG arrhythmia analysis. MIT-BIH Arrhythmia Database and the evaluation protocol recommended by The Association for the Advancement of Medical Instrumentation. A discussion on the obtained results shows that OPF classifier presents a robust performance,

[Sansone M, Fusco R, Pepino A and andSansone C, 2013][98],reviewed methods of ECG processing from a pattern recognition perspective. In particular, it has been focused on features commonly used for heartbeat classification by using few classifiers Artificial Neural Networks and Support Vector Machines because of their popularity; however, other techniques such as Hidden Markov Models and Kalman Filtering can also be mentioned.

[Martis R.J, Acharya U.R, and Min L.C, 2013][99], studied five types of beat classes of arrhythmia as recommended by Association for Advancement of Medical Instrumentation (AAMI) were analyzed viz., non-ectopic beats, supra-ventricular ectopic beats, ventricular ectopic beats, fusion betas and unclassifiable and paced beats. Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) were independently applied on DWT sub-bands for dimensionality reduction. These dimensionality reduced features were fed to the Support Vector Machine (SVM), neural network (NN) and probabilistic neural network (PNN) classifiers for automated diagnosis.

[Khazaee Ali, 2013][101],proposed a novel system to classify three types of electrocardiogram beats, namely normal beats and two manifestations of heart arrhythmia. It includes a feature extraction module, a classifier module, and an optimization module. In the feature extraction module, a proper set combining the shape features and timing features is proposed as the efficient characteristic of the patterns. In the classifier module, a multi-class support vector machine (SVM)-based classifier is proposed. For the optimization module, a particle swarm optimization algorithm is proposed to search for the best value of the SVM parameters and upstream by looking for the best subset of features that feed the classifier.

[Kim Y.H, Choi C.M.Y, Shin K.S.S, Lee M.H.S, and Kim S, 2013,][102], A method of classifying an input pattern and a pattern classification apparatus are provided. This method includes enabling artificial neural network to learn based on learning inout data received by an input layer of the artificial neural network, determining classification of an input pattern received by the input layer of the enabled artificial neural network according to an output value obtained from an output layer of the artificial neural network, the obtained output value being based on the input pattern, updating connection intensities of a plurality of connection lines of the enabled artificial neural network to output a result value indication the determined classification from the output layer when the input pattern and determining updated classification of the input pattern according to an updated output value obtained from an output layer of the updated artificial neural network., the obtained updated output value being based on the input pattern.

[Dima S.M, Panagiotou C, Mazomenos E.B, Rosengarten J.A, Maharatna K, Gialelis J.V, Curzen N, and Morgan J, 2013,][103], addressed the problem of detecting the presence of a myocardial scar from the standard electrocardiogram (ECG)/vectorcardiogram (VCG) recordings, giving effort to develop a screening system for the early detection of the scar in the point-of-care. Based on the pathophysiological implications of scarred myocardium, which results in disordered electrical conduction. It has been implemented four distinct ECG signal processing methodologies in order to obtain a set of features that can capture the presence of the myocardial scar. Two of these methodologies are: 1) the use of a template ECG heartbeat, from records with scar absence coupled with wavelet coherence analysis and 2) the utilization of the VCG are novel approaches for detecting scar presence. Extracted features are utilized to formulate a support vector machine classification model through supervised learning.

[Bahadorinia A, Dolatabadi A, and Hajipour A, 2014,][106], used two intelligent methods for detecting cardiac arrhythmias based on combination structure of artificial neural networks, Particle Swarm Optimization Algorithm and Genetic Algorithm for optimization of weight coefficients and bias to minimize error.

[Varshney M, Chandrakar C, and Sharma M, 2014,][109],discusses various techniques earlier proposed in literature for extracting feature from an ECG signal. In addition to that, the comparative study of method which is used to check the accuracy of overall system. The proposed schemes were mostly based on Artificial Neural Networks (ANN), Support Vector Machines (SVM), Multi-layer perceptron (MLP) and Morphological descriptor time-frequency distribution (MD-TFD) and other Signal Analysis techniques. All these techniques and algorithms have their advantages and limitations.

[Ingole M.D, Alaspure S.V, and Ingole D.T, 2014][111],presents the method to analyze ECG signal extract features and classification according to different arrhythmias. A dataset was obtained from a records set which were manually classified using MIT-BIH Arrhythmia Database Directory then features are extracted using DWT (Discrete wavelet transform) and classification is done according using various methods ANN (Artificial neural network), ANFIS (adaptive neuro-fuzzy inference system), SVM (State vector machine), & Statistical classifier.

[Banupriya C.V, and Karpagavalli.S, 2014][112],employed discrete wavelet transform (DWT) in feature extraction on ECG signals obtained from MIT-BIH Arrhythmia Database. The Machine Learning Technique, Probabilistic Neural Network (PNN) has been used to classify four types of heart beats that consist of PVC, LBBB, RBBB and Normal.

[Luz E.J.D.S, .Menotti D, and Schwartz W.R, 2014][113],goal is to evaluate the use of ECG signal in low frequencies. The ECG signal is sampled in low frequencies (30 Hz and 60 Hz) and represented by four feature extraction methods, which are then feed to a Support Vector Machines (SVM) classifier to perform the identification. In addition, a classification approach based on majority voting using multiple samples per subject is employed and compared to the traditional classification based on the presentation of single samples per subject each time. Considering a database composed of 193 subjects, results show identification accuracies higher than 95% and near to optimality (i.e., 100%) when the ECG signal is sampled in 30 Hz and 60 Hz, respectively, being the last one very close to the ones obtained when the signal is sampled in 360 Hz (the maximum frequency existing in our database).

[Soorma N, Singh J, and Tiwari M, 2014][114], describes the features extraction algorithm for electrocardiogram (ECG) signal using Huang Hilbert Transform and Wavelet Transform. The purpose of feature extraction of ECG signal would allow successful abnormality detection and efficient prognosis due to heart disorder. Some major important features will be extracted from ECG signals such as amplitude, duration, pre-gradient, post-gradient and so on. Therefore, a strong mathematical model is Hilbert-Huang transform (HHT). The Hilbert-Huang transform, is implemented to analyze the non-linear and non-stationary data.

[Sanchez D, and Melin P, 2014][115], proposed a new model of a modular neural network (MNN) using a granular approach and its optimization with hierarchical genetic. This model can be used in different areas of application, such as human recognition and time series prediction. It is tested for human recognition based on the ear biometric measure. The optimization of the design parameters of a modular neural network, such as number of modules, percentage of data for the training phase, goal error, learning algorithm, number of hidden layers and their respective number of neurons. This method also finds out the amount of and the specific data that can be used for the training phase based on the complexity of the problem.

[Kumar R.G and Kumaraswamy Y.S, 2014][116], deals with an automated system for detecting arrhythmia in ECG signals gains importance. Features are extracted from time series ECG data with Discrete Cosine Transform (DCT) computing the distance between RR waves. The feature is the beat's extracted RR interval. Frequency domain extracted features are classified using Classification and Regression Tree (CART), Radial Basis Function (RBF), Support Vector Machine (SVM) and Multilayer Perceptron Neural Network (MLP-NN). Experiments were conducted on the MIT-BIH arrhythmia database.

[Florence S, AmmaN.G.B,Annapoorani G, and Malathi K, 2014][117],proposes the system which uses neural network and Decision tree (ID3) to predict the heart attacks. Here the dataset with 6 attributes is used to diagnose the heart attacks. The dataset used is a cath heart attack dataset provided by UCI machine learning repository. The results of the prediction give more accurate output than the other techniques.

[Masethe H.D and Masethe M.A, 2014][118], presented a Datamining algorithms such as J48, Naïve Bayes, REPTREE, CART, and Bayes Net are applied for predicting heart attacks. The result shows prediction accuracy of 99%. Data mining enable the health sector to predict patterns in the dataset.

[Sudhakar K, and Manimekalai M, 2014][119], aims on heart disease which is largest cause of death in developed countries. In the health care industry the data mining is mainly used for predicting the diseases from the datasets. The Data Mining techniques, namely Decision Trees, Naive Bayes, Neural Networks, Associative classification, Genetic Algorithm are analyzed on Heart disease database.

[Li Qiao, Rajagopalan C, Clifford G.D, 2014][120], proposed a VF/VT classification algorithm using a machine learning method, a support vector machine. A total of 14 metrics were extracted from a specific window length of the electrocardiogram (ECG). A genetic algorithm was then used to select the optimal variable combinations. Three annotated public domain ECG databases (the American Heart Association Database, the Creighton University Ventricular Tachyarrhythmia Database, and the MIT-BIH Malignant Ventricular Arrhythmia Database) were used as training, test, and validation datasets.

[Martis R.J, Chakraborty C and Ray A.K, 2014][121],introduced a machine-learning approach to screen arrhythmia from normal sinus rhythm from the ECG. It consists of R-point detection using the Pan-Tompkins algorithm, discrete wavelet transform (DWT) decomposition, sub-band principal component analysis (PCA), statistical validation of features, and subsequent pattern classification. The k-fold cross validation is used in order to reduce the bias in choosing training and testing sets for classification. The average accuracy of classification is used as a benchmark for comparison. Different classifiers used are Gaussian mixture model (GMM), error back propagation neural network (EBPNN), and support vector machine (SVM). The DWT basis functions used are Daubechies-4, Daubechies-6, Daubechies-8, Symlet-2, Symlet-4, Symlet-6, Symlet-8, Coiflet-2, and Coiflet-5. An attempt is made to exploit the energy compaction in the wavelet sub-bands to yield higher classification accuracy. The developed machine-learning approach can be used in a web-based telemedicine system, which can be used in remote monitoring of patients in many healthcare informatics systems.

[Sathya R, and Akilandeswari K, 2015][123], aimed on Classification performed using all the extracted features leads to misclassification of abnormalities. So feature selection is an important concept in classifying the normal and abnormal behavior of heart. MIT-BIH Arrhythmia dataset is where the classification is done in MATLAB using Fitting Neural Network.

[Ebrahimi A, Addeh J,2015][128], presents a hybrid method for automated diagnostic systems of electrocardiography arrhythmias. It includes three main modules including the denoising module, the classifier module and the optimization module. In the denoising module, the stationary wavelet transform is proposed for noise reduction of the electrocardiogram signals. In the classifier module, the adaptive neuro-fuzzy inference system is investigated. In adaptive neuro-fuzzy inference system (ANFIS) training, the vector of radius has an important role for its recognition accuracy. Furthermore, in the optimization module, the cuckoo optimization algorithm is proposed for finding optimum vector of radius.

[Padmavathi K, Ramakrishna K.S, 2015][129],deals with Atrial fibrillation (AF) which is a common type of arrhythmia that causes death in the adults .The Auto-regressive (AR) coefficients characterize the features of AF. The AR coefficients are measured for every 15 second duration of the ECG and the features are extracted using Burg’s method. These features are classified using the different statistical classifiers such as kernel Support Vector Machine (KSVM) and K- Nearest Neighbor (KNN). The performance of these classifiers is evaluated on signals obtained from MIT-BIH Atrial Fibrillation Database.

[Sharma A, and Bhardwaj K, 2015][130], proposed a Neural Pattern recognition tool to identify normal and abnormal ECG. Classification of ECG involves various methods and techniques, which have given better performance and accuracy for the analysis of heart related diseases. Artificial Neural Network is implemented for identification of normal and abnormal ECG with 100% accuracy for normal ECG detection.

[Subbiah S, Patro R. K, and Subbuthai P, 2015][131], aimed initially on denoising the ECG signal using filters and detect the PQRS waveforms. ECG signal is analyzed or classify using Extreme Learning Machine (ELM) and it is compared with Support Vector Machine (SVM) and Back Propagation Neural Network (BPN). The classification of the ECG signal is done in two classes, Normal and Abnormal. ECG waveform is detected and analyzed using the 48 records of the MIT-BIH arrhythmia database. The classifier performance is measured in terms of Sensitivity (Se), Positive Predictivity (PP) and Specificity (SP).

[Padmavathi S, and Ramanujam E, 2015][132], proposes the methodology of Multivariate Maximal Time Series Motif with Naïve Bayes Classifier to classify the ECG abnormalities. The proposed model of predicting Time Series Motif is evaluated with the dataset contains the collection of ECG signals of patients recorded using Holter Monitor.

[Kelwade J.P,Salankar S.S, 2015][133],aimed on artificial neural network (ANN) as a classifier to predict cardiac arrhythmias into five classes. The HRV data, RR interval time series is obtained using the Electrocardiogram (ECG) data from the MIT-BIH Arrhythmia Database. The linear and nonlinear parameters are extracted from RR intervals and are used to train Multi-Layer Perceptron (MLP) neural network. The neural network for time series i.e. RR interval time series, the prediction of Normal Sinus Rhythm (NSR), Premature Ventricular Contraction (PVC), Atrial fibrillation (AFIB), Left bundle branch block (LBBB) and Second degree block (BII) can be done. The 70% of the datasets are used to train MLP neural network.

III. PROBLEM IDENTIFICATION AND PROPOSED APPROACH

Studies on references from literature revealed that there are number of challenges in providing Classification of Cardiac Arrhythmia for Medical Applications. Although many researchers, over the years have suggested various approaches to resolve them, still there are requirements for invention and improvements.

Accurate estimation of Cardiac Arrhythmia is critical in diagnosing Heart diseases by using ECG signal. The extraction of QRS complexes of ECG signal is difficult and which may leads to wrong diagnosis. Studies conducted in this thesis work to carry out these individual optimization techniques which did not give the desired identification accuracy. The system is advised based on universal filtering, pulse identification, clustering, categorization of signal with small delay can be done to identify the life threatening arrhythmia. In response to industry demand, a myriad of Classification of Cardiac Arrhythmia techniques have been proposed during the last three decades.

In this context, the present thesis work takes the following approach for effective Classification of Cardiac Arrhythmia techniques using Computational Intelligence strategies.

1. Study Discrete and Multi Wavelet Transformations and examine the probability of improving by

introducing some modifications to Cardiac Arrhythmia for the extraction of QRS complexes in ECG signal.

2. Study Double differentiation and Multi-Discrete Wavelet Transformations and examine the probability of improving by introducing some modifications in Cardiac Arrhythmia and the results are trained using Neural Networks to improve the classification and accuracy.
3. To apply Wavelets and Probabilistic Neural Networks for Classification of Cardiac Arrhythmia and which would generate more accuracy and sensitivity for identification of normal and abnormal ECG.

As the efficacy of the techniques is always crucial in any study and in order to assess the suitability of these proposed techniques in the thesis, from a diverse selection, their performance and relative merits are compared in each chapter, with several existing models in the literature by conducting the experiments on MIT-BIH database.

CONCLUSION

In this paper we briefly present the various Cardiac Arrhythmia Techniques in ECG Signalwhich are found in the literature and outline the proposed approach of the present research work. Finally identified that that Computational Intelligence techniques are giving the better results

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