[1] Farheen Fathima
[2] Dr.Seetharam Khetavath

DconvNET Based Classification of ECG for heart attack detection: A Survey

Journal of Electrical Systems

Abstract: - The categorization of electrocardiogram (ECG) signals holds significant importance in the diagnosis of cardiac conditions. It's difficult to classify an ECG accurately. An overview of the categorization of ECG arrhythmias is presented in this work. Selecting the right course of treatment for a patient and identifying cardiac conditions depend on the timely and precise identification of various arrhythmia types. For the classification of ECG data, several classifiers are available. Artificial neural networks (ANNs) are the most extensively utilized and well-liked classifiers among all of them when it comes to ECG categorization. In order to address the challenges raised by ECG classification, this work gives a thorough assessment of preprocessing methods, ECG databases, feature extraction methods, ANN-based classifiers, and performance measurements. Additionally, our research provides a thorough analysis of the classifiers' output and input beat selection for each surveyed paper.

Keywords: ECG, artificial Neural Networks, Deep Learning, Artificial Intelligence, Classification

INTRODUCTION

An electrocardiogram (ECG) is a standard test that checks how the heart is working by measuring the electrical action of the heart [1] and [2]. Individuals with a heart related issues have the long record of ECGs for symptomatic purposes, which brings about the necessity of a lot of storage space. Subsequently there is a requirement for a framework which includes pressure of ECG signals alongside ECG investigation. ECG pressure is a superior technique for minimize computational many-sided quality as far as storage. Flag pressure and flag examination have request in numerous application territories particularly in biomedical zone [3]. ECG signals are diverse for every individual. ECG design acknowledgment is a standout amongst the most dependable coronary illness recognizable proof strategies. ECG is the standard tool for monitoring and diagnosing cardiovascular issues by measuring electrical movement of the heart [4]. The cathodes connected to the body identify the electrical movement of the heart. From every terminal the ECG signals will record and store for a drawn out stretch of time. Preparing of ECG flag by utilizing existing ECG library data comprises of ECG waveforms parameters like P wave, QRS complex and T wave [5], [6] and [7]. In this, QRS complex is most essential part which demonstrates the electrical depolarization of the ventricle muscles in the heart. The duration and stature of QRS gives critical measure of data to doctor in this manner he/she can undoubtedly comprehend the state of heart. A cardiovascular patient with the history of heart infections will dependably need to keep up a ton of ECG reports while going to a doctor for interview. We will likely outline a framework which includes pressure of ECG signals for ordering typical and strange classes of ECG signals. Digitizing the ECG flag will take care of the storage issue and it likewise gets to be practical when comes to sharing and finding.

The graphical recording of bioelectrical possibilities generated by heart on the surface of the body is called ECG (Electro-Cardio-Gram). An ordinary mechanized flag handling framework gets a lot of data that is hard to store and transmit. Here comes the significance of data pressure. Data pressure is the way toward recognizing and disposing of redundancies in a given data set. Through this data pressure method framework needs to accomplish greatest data volume lessening while protecting noteworthy data's. The requirement for flag pressure exists in many transmitting and storage applications. Expansive measure of ECG information needs to effectively store in healing facilities for monitoring reasons. The ECG monitoring gadget must have a memory limit of 200 Mbytes for a three lead recordings.

For all intents and purposes proficient data pressure might be accomplished just with lossy pressure techniques. On account of ECG flag pressure the primary target is to accomplish a minimum information rate by safeguarding the significant indicative information in the recreated flag. There is an expanding interest for long haul persistent monitoring of a patient's ECG and action, which offers the chance to assess the execution of the cardiovascular framework.

The ECG records the electrical activity of the heart, where each heart beat is displayed as a series of electrical waves characterized by peaks and valleys. Any ECG gives two kinds of information. One, the duration of the electrical wave crossing the heart which in turn decides whether the electrical activity is normal or slow or

[1] Research Scholar, Dept of ECE, CHAITANYA DEEMED TO BE UNIVERSIT, Hanmakonda, Warangal. Mail Id: farheenfathima794@gmail.com
[2] Professor & Head,ECE Department, CHAITANYA DEEMED TO BE UNIVERSITY, Hanmakonda,Warangal. Mail id : seetharamkhetavath@gmail.com

irregular and the second is the amount of electrical activity passing through the heart muscle which enables to find whether the parts of the heart are too large or overworked.
Normally, the frequency range of an ECG signal is of 0.05–100 Hz and its dynamic range – of 1–10 mV. The ECG signal is characterized by five peaks and valleys labelled by the letters P, Q, R, S, T. In some cases we also use another peak called U. The performance of ECG analyzing system depends mainly on the accurate and reliable detection of the QRS complex, as well as T- and P waves. The P-wave represents the activation of the upper chambers of the heart, the atria, while the QRS complex and T-wave represent the excitation of the ventricles or the lower chamber of the heart. The detection of the QRS complex is the most important task in automatic ECG signal analysis. Once the QRS complex has been identified a more detailed examination of ECG signal including the heart rate, the ST segment etc. can be performed. In the normal sinus rhythm (normal state of the heart) the P-R interval is in the range of 0.12 to 0.2 seconds. The QRS interval is from 0.04 to 0.12 seconds. The Q-T interval is less than 0.42 seconds and the normal rate of the heart is from 60 to 100 beats per minute. So, from the recorded shape of the ECG, we can say whether the heart activity is normal or abnormal. The electrocardiogram is a graphic recording or display of the time variant voltages produced by the myocardium during the cardiac cycle. The P-, QRS- and T-waves reflect the rhythmic electrical depolarization and re-polarization of the myocardium associated with the contractions of the atria and ventricles. This ECG is used clinically in diagnosing various abnormalities and conditions associated with the heart.

RELATED RESEARCH

In past, explores have proposed change techniques, for example, Fast Fourier Transform (FFT) [8] and [9], Discrete Cosine Transform (DCT) [10] and Discrete Wavelet Transform (DWT) [11]. FFT has the preferred standpoint that it lessens the quantity of calculations. FFT is utilized for the ECG flag pressure alongside zero associating limitation. For the most part ECG flag decay is thought to be time differing because of some heart variations from the norm. By utilizing general FFT conditions the Fourier arrangement coefficients are computed and this procedure must be performed on each recognized cycle. These Fourier arrangement coefficients are utilized to incorporate the first flag. The block chart demonstrates the pressure and reproduction arranges in the method. The primary stage is the change computation. At that point apply edge condition on change coefficients on the premise of vitality pressing effectiveness of coefficients, that makes settled number of edge esteem is set to zero. Versatile thresholding, settled thresholding or edge set by physically is likewise embraced. This esteem can be picked by considering the most extreme estimation of coefficient. Next stage is applying uniform quantization on these coefficients. The progression estimate esteem is acquired from the most extreme and minimum estimation of the flag framework. By setting step estimate the quantization levels are made and relating quantization tables are made to reproduce the first flag. The quantized data contains repetitive data which causes wastage of space.
With a specific end goal to defeat this disadvantage entropy encoding strategy known as Huffman coding is utilized [13]. In this stage the probabilities of event of the symbol in the flag are figured and in view of this esteem make another table. This table esteem gives the packed adaptation of ECG flag. For the characterization and investigation handle the table must save the information's with respect to the R peak and RR interval. From this, it is straightforwardly comprehend that quantized table is subject to the first ECG flag.

Fourier Transform

The sign can be broke down more adequately in frequency area than the time space, in light of the fact that the qualities of a sign will be more in frequency space. One conceivable approach to change over or transform the sign from time to frequency space is Fourier transform (FT). FT is a methodology which separates the sign into various frequencies of sinusoids and it is characterized as a scientific methodology for transforming the sign from time space to frequency area. FT has a downside that it will work out for just stationary signs, which won't change with the time frame. Since, the FT connected for the whole flag however not portions of a sign, on the off chance that we consider non-stationary sign the sign will fluctuate with the time frame, which couldn't be transformed by FT. also, one more downside that we have with the FT is we can't say that at what time the specific occasion will has happened.

Short-Time Fourier analysis

To adjust the inadequacy in FT, Dennis Gabor in 1946 presented another technique called windowing, which can be connected to the sign to investigate a little area of a sign. This adjustment has been called as the Short-Time Fourier Transform (STFT), in which the sign will be mapped into time and frequency information.
In STFT, the window is altered. In this way, we this window won't change with the time of the sign i.e., for both tight resolution and wide resolution. Also, we can't anticipate the frequency content at every time interim segment.

Discrete Cosine Transform

DCT is one of the transformation technique used to decompose the host signal into several frequency bands, which makes a lot easier to do the compression of meta data, where the data can be converted in to spatial domain and will be divided into 8x8 blocks and the 1D DCT is applied to each block respectively. The two dimensional DCT is given by

$$C(0,0) = \frac{1}{N}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)$$

$$C(u,v) = \frac{1}{2N^3}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y) * [\cos(2x+1)u\pi] * [\cos(2y+1)v\pi]$$

Where, $u = 0,1,2,\ldots, M-1$,

$$v = 0,1,2,\ldots, N-1 \text{and} j = \sqrt{-1}$$

The inverse DCT (IDCT) is given by

$$f(x,y) = \frac{1}{N}C(0,0) + \frac{1}{2N^3}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(u,v) * [\cos(2x+1)u\pi] * [\cos(2y+1)v\pi]$$

Daamouche.A *et al.* (2012) proposed a new methodology for representation of ECG beats with wavelet. In this method, ECG beats were represented in terms of discrimination capability. A polyphase representation of wavelet filter bank was used to formulate the design problem within a particle swarm optimization (PSO) framework. MIT/BIH arrhythmia database was used for the development of this algorithm. The classification was done using support vector machine (SVM) classifier. This algorithm had achieved a higher accuracy and stability over the Daubechies and Symlet wavelets[14].

Banupriya, C. V. and Karpagavalli. S. (2014) employed a discrete wavelet transform (DWT) for extracting features from ECG signals. MIT-BIH Arrhythmia database was used for the development of this algorithm. The Machine Learning techniques such as Extreme Learning Machine (ELMand Support Vector Machine (SVM) were used to classify four different types of heart beats namely LBBB,PVC, RBBB and Normal heart beat. On analyzing the performance of the classifiers, it was observed that ELM-Radial Basis Function (RBF) Kernel took less time as compared to the other kernels in modelling[15].

Dutta, S *et al*. (2010) developed an automated medical diagnostic tool for the classification of ECG beats. This tool aided in an accurate and apt detection of cardiac arrhythmias. In this method the features were extracted using cross-spectral density approach which is also called as cross -correlation approach from ECG signals. These signals were classified using a least square support vector machine (LS-SVM) classification algorithm. The extracted features from the ECG beats were categorized into three categories such as PVC beats, normal beats, and other beats. About one third of the total samples were used for training set and the remaining were used for testing the developed algorithm. The accuracy of this algorithm falls in the range between 95.51–96.12%[16].

Khazaee, A., and Ebrahimzadeh, A. (2010) proposed an algorithm for the classification of five types of ECG beats. The classification was done using power spectral-based hybrid support vector machines-genetic algorithm (SVMGA). The classified beats include four manifestations of heart arrhythmia and a normal beat. Three phases were used in this work, namely a feature extraction phase, a classification phase and an optimization phase. In the feature extraction phase, the features such as spectral and three timing interval parameters from the EGC were extracted. This was done using Non-parametric power spectral density (PSD) estimation method. In the classification module, SVM classifier was used to classify the various types of heart beats. The optimization was done by tuning the various kernel function parameters. The evaluation of the algorithm was done using eight files obtained from the MIT–BIH arrhythmia database. The results concluded that the classification accuracy of the SVMGA approach provided superior classification rate than the SVM classifier[17].

Martis, R. J., *et al*.(2013) developed an algorithm to analyze five types of arrhythmia namely supra-ventricular ectopic beats, non-ectopic beats, ventricular ectopic beats, fusion betas and unclassifiable and paced beats. To reduce the dimensions, the dimensionality reduction algorithms such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) were applied independently on DWT sub bands. These reduced features were fed to the Support Vector Machine (SVM), neural network (NN) and probabilistic neural network (PNN) classifiers for automated diagnosis. Ten fold cross validation method was used for analysing the performance of the developed algorithm[18].

On observation, it was found that the combination of ICA features and PNN performed better than the PCA and LDA methods. An average specificity, sensitivity, positive predictive value (PPV) and accuracy obtained with these features were of 99.83%, , 99.97%, 99.21% and 99.28% respectively[19] .

Güler, I., & Beyli, E. D. Ü. (2007) implemented multiclass Support Vector Machine (SVM) with error correcting output codes (ECOC) for classification of ECG beats. In this , four types of ECG beats such as normal beat, ventricular tachyarrhythmia beat, congestive heart failure beat, atrial fibrillation beat were considered for analysis. Initially the decomposition of ECG signals weredone using discrete wavelet transform (DWT). The wavelet coefficients were then calculated for representing the signal in time-frequency domain.

The classification of ECG beats were done by the combination of wavelet coefficients and multiclass SVM. The final classification results produced by the algorithm were satisfactory[20].

NEURAL NETWORKS

Daqrouq, K., *et al*. (2014) developed a feature extraction technique to grab information from the ECG signals. This method used the average framing percentage energy (AFE) of terminal wavelet packet transform (WPT) sub signals in feature extraction. The extracted features were classified using Probabilistic Neural Network (PNN). The obtained results were compared with the existing work carried out by the researchers in the classification of heart arrhythmias. The performance of the developed algorithm was satisfactory and it produced an accuracy of 97.92 %[21].

Edenbrandt. L., *et al.* (1992) have used two thousand ST-T segments which were obtained from the 12-lead ECG. These segments were visually classified into 7 different groups. A software-based neural network has been used in this learning process. An average of 90–95% classification rate is obtained by this network with the individual ST-T segments in the test set[22].

Gupta, K. O., and Chatur, P. N. (2012) compared the existing techniques used for extraction of parameters from the ECG signal and arrhythmia classification. In this study the author proposed a novel classification algorithm which used Artificial

Neural Networks (ANN) and data mining techniques in arrhythmia detection. The final classification rate produced by the proposed algorithm was satisfactory [23].

Hedén, B. *et al.* (1994) have proposed an algorithm for the classification of ECG using neural networks. A total of 1107 ECG waveform samples were used to train and tested the developed algorithm. Various combinations of QRS and ST-T measurements were fed as input to the neural networks. One third of the total samples were used to train the developed algorithm and the remaining two third were used for the testing process. Anterior myocardial infarction was the major disorder taken for diagnosis in this algorithm. The sensitivity in the diagnosis of anterior myocardial infarction was 81%, while the specificity was 97.5% by this algorithm[24].

Hosseini H.G. *et al.* (2006) proposed an ECG signal classification with a two-stage feed forward neural network . Two network architectures in which one as one stage and the other as two stage feed forward neural networks were designed. The training and testing of this algorithm was done using ECG signals obtained from the MIT-BIH database. The input to the network comprised of 12 ECG features and 13 compressed components of each heart beat signal. This multi-stage network was named as NET_BST and it possessed the classification rate of around 93%[25].

Hu Y.H. (1993) developed an algorithm for electrocardiographic QRS detection and beat classification using an artificial neural networks. The QRS detection was done using an adaptive multilayer perceptron structure. This method aided in the detection of QRS complexes even in a noisy environment. For electrocardiographic QRS complex pattern classification, an artificial neural network adaptive multilayer perceptron was used to classify the QRS patterns into normal and abnormal beat patterns. The classification was done for 12 different abnormal beat morphologies. Preliminary results obtained using the MIT/BIH) arrhythmia database was encouraging[26].

Ince, T., *et.al.* (2009) presented an algorithm which was generic and patient-specific in nature for accurate detection of ECG heartbeat patterns. The feature extraction process in the system utilized morphological wavelet transform feature extraction technique. These features were projected onto a lower dimensional feature space using principal component analysis and temporal features from the ECG data. A feed forward and fully connected artificial neural network which was optimally designed for each patient with the proposed multidimensional particle swarm optimization technique was used for pattern recognition unit. The classification experiments were done using a benchmark database which, showed that, the proposed system achieved higher accuracy, better sensitivity that was better than most of the current state-of-the-art algorithms in the detection of ventricular ectopic beats (VEBs) and supra-VEBs (SVEBs). The algorithm when tested over the entire database, it produced an average accuracy-sensitivity of 98.3%-84.6% and 97.4%-63.5%in VEB and SVEB detections respectively. The algorithm, due to its parameter-invariant nature, was highly generic and thus applicable to any ECG dataset[27].

Jadhav, S. M., *et.al* (2010) proposed an automated Artificial Neural Network (ANN) for the classification of cardiac arrhythmia. This method used the signals acquired from standard 12 lead ECG recordings. The development of the algorithm focussed on achieving a much accurate arrhythmia classification system which could be applicable in diagnostic decision support systems. During the analysis of waveform for arrhythmia, some attribute values of a person would be missing. This was much unavoidable in most of the cases. To compensate these, the missing attributes have been replaced by the closest column value of the concern class. Then the classification was done using a Multilayer perceptron (MLP) feed forward neural network model which uses static back propagation algorithm for classification of arrhythmias. Networks models were trained and tested using UCI ECG arrhythmia data set. Six metric measures sensitivity, specificity, classification accuracy, mean squared error (MSE), receiver operating characteristics (ROC) and Area under the curve (AUC) classification were used to assess the performance of the developed algorithm. A classification accuracy of 86.67% was achieved by this algorithm[28].

Jaiswal G.K. and Paul R. (2014) focussed on the nonlinearity present in the ECG features. The five features of ECG signal such as P, Q, R, S, T were focussed in this work. The features from P-wave, PR segment, PR interval, QRS Complex, ST segment, ST-interval, T-wave, QT and QRS voltage from the ECG were extracted. The extracted features were examined for the diagnosis of heart beat disorders. Most of the data used in this work were obtained from Physio Data Net and MIT-BIH data base[29].

This study was carried out using ANN on patients who were admitted in the intensive care unit with some certain heart disorders. The states of the patients were classified into normal, abnormal and life threatening cases by this algorithm. Five features extracted from the ECG were fed as input parameters to the ANN for classification. This technique also identified the normal region for classification of abnormalities. This is because of ECG waveform normally varies from person to person at different conditions.

Javadi, M., *et.al.* (2011) used a combination of neural network model and stacked generalization method for classification of electrocardiogram (ECG) beats. In the earlier study using a stacked generalization method, the author mapped the base classifier output to the target. This helped to acquire knowledge about the input space and also supported in the proposal of a modified stacked generalization method.The error rate produced by the algorithm was 12.41 %.This was much less when compared with the popular classifier fusion methods[30].

Christov, I. *et al*. (2006) performed a comparative study with various classifiers in the detection of heart disorders. The classifiers used for the study were the K^{th} nearest neighbour rule, neural networks, discriminant analysis and fuzzy logic. 26 morphological parameters were the features taken for study. The above features were examined for the diagnosis of five types of ventricular complexes. These complexes were normal heart beats, premature ventricular contractions, left and right bundled branch blocks, and paced beats. One global, one basic and two local learning sets were used in this work. The learning set contains five types of QRS complexes which were collected from all patients in the MIT-BIH database. The data were either with or without applying the leave one out rule, thus representing the global and the basic learning set, respectively. The local learning set contains the heartbeats which were obtained only from the tested patient. These beats were taken either consecutively or at random. On testing high accuracy was obtained with the local learning sets, whereas on the other hand global learning sets yielded poor results[31].

Jiang W. and Kong S.G. (2007) presented an ECG heart beat pattern classification with evolvable block-based neural networks (BBNNs).This BbNN contains an array of 2-D modular component NNs with flexible structures and internal configurations. This methodology can be implemented using reconfigurable digital hardware such as field-programmable gate arrays (FPGAs). The internal configuration of a block as well as the overall structure of the BbNN were determined by the signal flow between the blocks..The optimization of the network structure and the weights were done using local gradient-based search. The inputs to the BbNN structure were the Hermite transform coefficients and the time interval between two neighbouring R- peaks of ECG signals. The optimization with the proposed evolutionary algorithm (EA) on BbNN paved the way in the development of a personalized heartbeat pattern classifier. This classifier can cope up with varying operating environments which were caused by individual difference and time-varying characteristics of ECG signals. Simulation of the algorithm was done using the MIT-BIH arrhythmia database and it produced a high average accuracies in the detection of supra ventricular ectopic beats (96.6%) and ventricular ectopic beats (98.1%) patterns for heartbeat monitoring[32].

Kumar, R. G., and Kumaraswamy, Y. S. (2013) developed a soft computing technique using Feed Forward Neural Network (FF-NN) for classification of the different types of arrhythmia using RR interval. The distance between the RR waves was the feature used in this work for arrhythmia classification. These features from the ECG were extracted using Discrete Cosine Transform (DCT) and were mapped against the trained features. A series of classifiers such as Classification and Regression Tree (CART), Radial Basis Function (RBF), Multi Layer Perceptron Neural Network (MLP-NN) and Feed Forward Neural Network (FF-NN) were used to obtain a better outfit with the extracted features. The analysis was done with the data from MIT-BIT arrhythmia database. On comparative study all the classification algorithm used in this work produced promising results[33].

Liu, S. H., *et.al*. (2013) presented an automatic method for the classification of normal sinus rhythm (NSR) and other four types of arrhythmia from the continuous ECG signals. A self-constructing a neural fuzzy inference network (ScNFIN) was used for classification.The ECG was classified into one of the five classes such as NSR and four arrhythmia types, including premature atrium contraction (PAC), premature ventricular contraction (PVC), left bundle branch block (LBBB), and right bundle branch block (RBBB). The classification results achieved an accuracy of 96.4%. This method was helpful for the development of a portable ECG monitor system[34].

M Jadhav, S., *et.al*. (2012) proposed an Artificial Neural Network (ANN) based system for the diagnosis of cardiac arrhythmia. This diagnostic system uses the signals obtained from standard 12 lead ECG signal recordings data. The signal from UCI ECG signal data was used to train and test the three different ANN models in this work. In this arrhythmia analysis, the closest column values of the concern class were used to replace some unavoidable missing attribute values. The diagnosis of cardiac arrhythmia was done by ANN models which were trained by static back propagation algorithm with momentum learning rule. With the aid of metric measures such as mean squared error (MSE), classification specificity, sensitivity, accuracy, receiver operating characteristics (ROC) and area under curve (AUC) the evaluation of the algorithm was done. Of the various ANN models, Multilayer perceptron ANN model produced an attractive classification results in terms of sensitivity and accuracy of 93.75% and 86.67% respectively. On the other hand, 93.1% classification specificity was achieved using Modular ANN[35].

Maglaveras N. *et al.* (1998) applied non-linear transformations on the ECG. In this, the data is mapped into the n-dimensional spaces using the component analysis. A neural network based pattern recognition and classification was followed in this work. The major issues considered in this work were recognition and classification of QRS/PVC, ischemic beats and episodes and the detection of atrial fibrillation. This algorithm was generated as a generalised algorithm in the classification of ECG as compared to the other algorithms. The performance evaluation was done using MIT- BIH database and the classification rate produced by this algorithm was satisfactory[36].

Mahajan, R., and Bansal, D. (2013) designed a higher order statistics based ECG Signal Analyser. In this a fourth order based, i.e. trispectrum dependant features were extracted from normal and abnormal waveforms. The extracted features were trained using Leven berg Marquardt training algorithm on feed forward neural network classifier. This algorithm was able to classify heart beats into three types , such as left bundle branch block, normal, and nodal escape beat. The overall classification accuracy achieved by the algorithm was 98 %. The MIT-BIH database was used for the development of this algorithm[37].

Martis, R. J., *et.al*. (2014) developed a classification method for classifying arrhythmia and normal sinus rhythm with the signals obtained from the ECG. MIT- BIH- an open source database was used in this work. QRS complex in this method was detected using Pan-Tompkins algorithm and principal component analysis (PCA). The performance was evaluated using a set of classifiers which includes k-means classifier, error back propagation neural network (EBPNN) classifier and optimized *k*-means clustering. The performance of the algorithm was assessed using M-fold cross validation method. On evaluation, the *k*-means classifier provided an average accuracy of 91.21 %, whereas EBPNN provided a greater average accuracy of 95.79 %. The optimized *k*-means classifier produced an accuracy of 95.79 %, which was same as the classification results obtained with EBPNN[38].

Melgani F. and Bazi Y. (2008) developed a particle swarm optimization (PSO) based SVM classification algorithm for classification of ECG signals. The features extracted from the normal and the abnormal beats, which were tuned as linear discriminant functions were used as the input parameters for the classifiers. The performance of the developed classifiers was compared with SVM classifier, k-nearest neighbour (k-NN) classifier and radial basis function (RBF) neural network classifier. The training was done using three varieties of beats (250,500 and 750). On evaluation, the combination of PSO-SVM yielded an overall accuracy of 89.72% on 40438 test beats selected from 20 patient records. On the other hand, the classification rate obtained with SVM, k-NN and RBF were 85.98%, 83.70%, and 82.34% respectively[39].

Osowski S. and Linh T.H. (2001) presented electrocardiographic (ECG) beat recognition and classification by applying the fuzzy neural network. The features obtained from the higher order statistics was used to train the network. The feature selection was done using the cumulants of the second, third, and fourth orders. The

classifier used in this work was the hybrid of fuzzy and neural network. It employs a cascaded fuzzy self-organizing sub network with the multilayer perceptron.. The developed algorithm was able to recognize the different types of ECG beats and achieved good efficiency[40]. Osowski S. *et al*. (2011) proposed an algorithm by fusing the various neural classifiers into one ensemble system. The system was developed for recognition and classification of arrhythmia. The performance analysis of this developed algorithm was done by comparing the performance of other classification methods such as majority and weighted voting method, Kullback–Leibler divergence method and modified Bayes classification method. MIT-BIH AD database was used for the development and testing in this work. The performances obtained with the fused classifiers were much more efficient than the individual classifiers in terms of accuracy[41].
Acharya U.R *et.al. (*2003) used artificial neural network (ANN) and fuzzy equivalence relations for the classification of certain diseases. The heart rate variability was used as the base signal from which certain parameters are extracted and presented to the ANN for classification. The same data was also used for fuzzy equivalence classifier. 85 % of the test cases were seen to be correct with the feed forward architecture ANN classifier 90 % of correct classification was achieved using fuzzy classifier over these test cases[42].
Übeyli, E. D. (2009) presented the classification of ECG signals using the adaptive neuro-fuzzy inference system (ANFIS) .Two stages such as feature extraction and classification were involved in decision making. Feature extraction was done by computation and classification was done by ANFIS which was trained using back propagation gradient descent method. The algorithm was developed for the classification of four types of ECG beats. They were the normal beat, congestive heart failure beat, ventricular tachyarrhythmia beat, and atrial fibrillation beat. The samples of these beats were obtained from the Physio Bank database. The extracted features were classified by four ANFIS classifiers. The outputs of these classifiers were fed as input to the fifth ANFIS classifier. This was done to improve the diagnostic accuracy. This ANFIS model combined the adaptive capabilities of the neural network and the qualitative approach of the fuzzy logic. The results confirmed that the proposed ANFIS model has potential in classifying the ECG signals with a high degree of accuracy[43]. Yu, S. N., and Chen, Y. H. (2009) presented a classification method for noise-tolerant electrocardiogram (ECG) using higher order statistics (HOS) of sub- band components. In this method, five levels of discrete wavelet transform (DWT) were applied to decompose the signal into six sub-band components. Higher order statistics were used to calculate four sets of HOS features from the three mid-band components, which together with three RR interval-related features constructed the primary feature set. A feature selection algorithm based on correlation coefficient and Fisher discriminality was then exploited to eliminate redundant features from the primary feature set. A feed forward back propagation neural network (FFBNN) was employed as the classifier. Two sample selection strategies and four categories of noise artifacts were utilized to justify the capacity of the method. More than 97.5% discrimination rate was achieved, no matter which of the two sampling selection strategies was used. By using the feature selection method, the feature dimension can be readily reduced from 30 to 18 with a negligible decrease in accuracy. This method improved the sensitivities of most beat types resulting in an elevated average accuracy. Also, this method was tolerant to environmental noises. Even in noisy conditions an accuracy of 91% was retained[44].

NEAREST NEIGHBOUR CLASSIFIER

Castillo, O., *et.al*. (2012) developed a system for the classification cardiac arrhythmias using a hybrid intelligent system. In this method, the sample of ECG signals subjected to RBBB, LBBB, PVC and fusion paced arrhythmia were taken for training and testing process. A group of normal heart beats were also taken to differentiate the above mentioned arrhythmias from the normal heart beats. Segmentation was done on the ECG signals of different types of arrhythmias. These segmented signals were subjected to classification. Three classifiers such as Fuzzy K- Nearest Neighbors, Multi Layer Perceptron with Gradient Descent and momentum Backpropagation, and Multi Layer Perceptron with Scaled Conjugate Gradient Backpropagation were used for classification. The output from the individual classifiers were fused using a Mamdani type fuzzy inference system. The classification rate achieved with this algorithm is 98 %[45].
Mishra, A. K., and Raghav, S. (2010) developed an algorithm using local fractal dimension based nearest neighbour classifier for the classification of arrhythmia. The Local Fractal Dimension (LFD) from a sample point of the ECG waveform was used as the feature. The class of the extracted features in feature space was estimated using Nearest neighbour algorithm. Euclidean distance based on the R- R interval information was used to estimate the closest feature in the feature space. This distance between the closest features were applied on two classification algorithms namely, variance and fractal dimension estimation based nearest neighbour classifier and power spectral density and fractal dimension estimation based nearest neighbour classifier. Based on the figure of merit between the extracted feature and the closest feature, the final classification results obtained with both the classifiers were satisfactory. MIT-BIH Arrhythmia dataset was used for the development and validate this algorithm[46].
Owis M.I. *et al* (2002) proposed an alternate method for the diagnosis of ECG signals. The data from the ECG waveform were subjected to two types of blind source separation techniques. They were Principal Component

Analysis (PCA) and Independent Component Analysis (ICA). The features from five different ECG signal types which include normal, ventricular couplet, ventricular tachycardia, ventricular bigeminy and ventricular fibrillation were taken for analysis. The intervals between the peaks were windowed using either a rectangular or a Hamming window and applied to nearest neighbour classifier. On observation by using rectangular window, specificity of 100% and a sensitivity of 98% were obtained using nearest neighbour classification and ICA features. On the other hand, with Hamming window, a lower classification rate was obtained using the features from either PCA or ICA for the same classifier[47].

AUTOMATIC CLASSIFICATION METHODS

Charfi, F., and Kraiem, A. (2012) developed an algorithm for an automated analysis of different types of ECG signals. Atrial fibrillation and right bundle branch block were the two major pathologies taken for the development of this algorithm. Data mining decision tree process was applied to grab the information from the ECG signals. Decision making algorithms such as C4.5, CHAID (Chi square Automatic Interaction Detector) and improved CHAID were applied on the extracted features. On observation the C4.5 classifier produced higher accuracy rate of 96.87%. This accuracy was higher as compared with the other classification algorithms used in this work[48].

De Chazal, P. and Reilly R.B. (2003) developed an automated diagnostic algorithm for diagnosing the premature ventricular contraction and fusion beat types from the normal heart beats. Linear discriminant model and feed forward networks were the classification models used in this work. A classification rate of 89 % was achieved with this algorithm with the features obtained from the ECG waveform shape and heart intervals. The data base used in this work was an MIT-BIH arrhythmia database[49].

De Chazal, P. and Reilly R.B. (2006).studied the patient-adapting heartbeat classifier using ECG morphology and heartbeat interval features. An adaptive system for automatic processing of the electrocardiogram (ECG) for the classification of heartbeats into one of the five beat classes recommended by ANSI/AAMI EC57:1998 standard was presented. The heartbeat classification system processed an incoming recording with a global-classifier to produce the first set of beat annotations. After an expert validation and if necessary a fraction of the beats of the recording were corrected. The system was then adapted by first training a local-classifier using the newly annotated beats and combined this with the global-classifier to produce an adapted classification system. The adapted system was then used to update beat annotations. The results of this study show that the performance of a patient, adaptable classifier increased with the amount of training of the system on the local record. The performance of the system can be significantly boosted with a small amount of adaptation even when all beats used for adaptation are from a single class. This study illustrated the ability to provide highly beneficial automatic arrhythmia monitoring systems[50].

De Lannoy, *et al*. (2011) proposed a method for the automatic classification of heartbeats in an ECG signal. This work was based on specific characteristics. Some of them were time dependences between observations and a strong class unbalance. To resolve this, a specific classifier was developed. This classifier was evaluated in real time ECG signals from the MIT arrhythmia database[51].

This classifier used in this work was a weighted variant of the conditional random field classifier. Experiments showed that this method outperformed well over the existing heartbeat classification methods.

Ge, D., *et.al.* (2002). proposed autoregressive (AR) modelling technique for the classification various cardiac arrhythmias. The beats such as normal sinus rhythm (NSR) atrial premature contraction (APC), premature ventricular contraction (PVC), super ventricular tachycardia (SVT), ventricular tachycardia (VT) and ventricular fibrillation (VF) were taken for diagnosis. The AR coefficients in this work were computed using Burg's algorithm. The AR coefficients were classified using a generalized linear model (GLM) based algorithm in various stages. The accuracy in the detection of NSR, PVC, APC, SVT, VT and VF were in the range of 93.2% to 100% using the GLM based classification algorithm[52].

Martínez.J.P., *et al.* (2004) developed a system using the wavelet transform (WT). The QRS complexes were identified and delineated. The delineation was done by detecting the peaks of the individual waves, complex onset and end. Finally the determination of P and T wave peaks, onsets and ends were done. The evaluation of the developed algorithm was done on various databases such as MIT-BIH Arrhythmia, QT, European ST-T and CSE databases. This algorithm achieved a sensitivity of 99.66% and a positive predictivity of 99.56%.On the other hand, with the well known MIT-BIH Arrhythmia data base a specificity of 99.8% was attained. For the delineation of ECG waves, the computation of the mean and standard deviation between the automatic and manual annotations was done. The mean error obtained with the WT approach does not exceed one sampling interval, while the standard deviations obtained were within the accepted tolerance limit as suggested by the expert physicians. Promising results of were obtained with this developed algorithm over other well known algorithms, especially in determining the end of T wave[53].

Khadra L. *et al.* (2005) has focused cardiac arrhythmia classification using higher order spectral analysis. The analysis was done using the bispectral technique in which, the autoregressive model was used to estimate the frequency of the bi- spectrum. This frequency was used as a quantitative measure to classify atrial and ventricular tachy arrhythmias. This algorithm showed a noticeable difference in the parameter values were observed for different arrhythmias. Moreover the bi-coherency spectrum showed a difference in the bi-coherency values between the normal and tachycardia patients[54].

Lin K.P. and Chang W.H. (1989) have used non linear transformation method to extract ECG features. In this method every residual error signal was transformed to a set of three states pulse-code train which were relative to the original ECG signal. The flexibility in the implementation of pulse-code train in digital hardware circuits helped in automated ECG diagnosis. The feature extraction technique of this algorithm performed well in feature extraction for arrhythmia detection. 92 percent sensitivity was achieved with this algorithm in the detection of PVC (premature ventricular contraction). The development of this algorithm was done by using an MIT/BIH database[55].

FUZZY BASED DIAGNOSIS

Exarchos T. P. *et. al.* (2007) performed the classification of ischaemic and arrhythmic beats using fuzzy expert systems in ECG recordings. The ST-T database obtained from the European Society of Cardiology was used to the train the developed algorithm. The testing was done using MIT-BIH data base. The specificity and the sensitivity reported for ischaemic beat classification were 92 % and 91 % respectively. The developed fuzzy expert system reported a sensitivity of 96% and specificity of 99% for all categories of arrhythmic beat classification[56].

Ozbay Y. *et al.* (2006) compared the classification accuracy of combined fuzzy clustering NN architecture (FCNN). This was developed for early diagnosis of arrhythmias from the ECG signals. MIT-BIH data base was used in this work. Five types of signals obtained from normal sinus rhythm, sinus bradycardia, ventricular tachycardia, sinus arrhythmia, atrial premature contraction, paced beat, right bundle branch block, left bundle branch block, atrial fibrillation and atrial flutter were used for analysis. The results concluded that the developed FCNN architecture produced comparatively better results than the MLP architecture[57].

Yeh, Y. C., Wang, *et.al*. (2010) performed classification of ECG beats of various heart disorders using the fuzzy c-means method. This diagnostic methods has a few advantages such as good detection results, less mathematic computations, low memory space utilization and low time complexity. On observation, the FCMM could able to accurately classify and distinguish the difference between normal and abnormal heartbeats. This classification of heart beats contains the following steps. (i) Detection of QRS waveform using the Difference Operation Method (ii) Qualitative feature selection using the Range-Overlaps Method of ECG signals (iii) Computation of cluster centre for each class and (iv) Determination of heartbeat class for the patient. The results showed that the sensitivities were 98.28%, 86.97%, 90.35%, 92.19%, and 94.86% for NORM, RBBB, LBBB, VPC and APC respectively. The total classification accuracy with this algorithm was 93.57%[58].

Yeh, Y. C., *et.al*. (2010) proposed a Range-Overlaps Method for extracting features from ECG signals. This method was a simple and reliable feature extraction method. This method has the merits of good detection results, least mathematical computations, less memory space and low time complexity. The performance evaluation was done using both cluster analysis and fuzzy logic methods. The total classification accuracy with this algorithm was 93%[59].

OTHER DIAGNOSIS ALGORITHMS

Afonso,V.X. *et al*. (1999) have used a multi rate digital signal processing method to detect heartbeats in the ECG. To decompose the ECG into sub bands with uniform frequency intervals a filter bank (FB) was incorporated in this algorithm. The algorithm aided for time independent and frequency analysis to be performed on a signal. Features extracted from a set of sub bands were used to make computations. The decision making was done using the heuristic detection strategy from multiple one-channel beat detection algorithms. A sensitivity of 99.59% and a positive predictivity of 99.56% were produced by this algorithm against the MIT/BIH database[60].

Banerjee, S., and Mitra, M. (2014) used a cross wavelet transform (XWT) for the analysis and classification of electrocardiogram (ECG) signals. Using the cross correlation the similarity between two ECG waveform in time domains was estimated[61].

On applying continuous wavelet transform to two time series and on examining the decompositions. It was observed that the two decompositions yielded a wavelet cross spectrum and wavelet coherence. This aided in estimating the localized similarities in time and frequency. The ECG data when analysed using XWT explored the resulting spectral differences in the signal. For analysis, a normal beat ensemble was selected as the absolute normal ECG pattern template. All other normal and abnormal patterns were compared from the template pattern. By analysing the differenc of patterns in the QT zone, the presence of inferior myocardial infarction was detected. On observation, the wavelet cross spectrum and wavelet coherence of various ECG patterns showed distinguishing characteristics over two specific regions R1 and R2, where R1 was the QRS complex area and R2 was the T-wave region. The evaluation of the developed algorithm was done using the Physikalisch-Technische Bundesanstalt diagnostic ECG database. The overall accuracy, sensitivity, and specificity obtained with this developed algorithm were 97.6%, 97.3% and 98.8% respectively[62].

Bortolan G. *et al.* (1990) have used a simple feed forward neural network structure for the detecting the various complexes in the ECG. The various metric measures such as specificity, sensitivity total and partial accuracy were used for the assessment of the developed algorithm. On evaluation, satisfactory results were produced by this algorithm[63].

Chen, Y. H. and Yu. S. N. (2012) proposed three Non linear correlation- based filters (NCBFs) for the diagnosis of heart disorders. Among these three, two (NCBF1 and NCBF2) were used to estimate the feature – feature correlation. The other SUFCO was used to skip the redundancy reduction process. It supports in selecting the features based only on the feature–class correlation. The performance of these filters was compared with another nonlinear feature selection method called Relief-F. The evaluation was done with the discriminality and the redundancy of the retained features. The performance of most effective NCBF was compared with the linear correlation-based filter (LCBF). The results concluded that NCBF1 and NCBF2 outperformed well over the SUFCO and Relief-F methods. About eight features were considered for classification and an accuracy of 96.34% was obtained with this method[64].

Christov I. *et al.* (2006) compared the various heart beat classification abilities. The techniques such as QRS pattern recognition and matching Pursuit algorithm were used for the computation of morphological descriptors and for the calculation of expansion coefficients. The computed features aided in the classification normal and the abnormal heart beats. The K-Nearest neighbour classification algorithm was used for classification. The algorithm was able to successfully classify the normal, left and right heart beat types. The classification rate produced by this method was also satisfactory[65].

De Chazal, P. and Reilly R.B. (2006) classified heart beats of different classes in accordance with ANSI/AAMI EC57:1998 standard. Beats such as normal beat, ventricular ectopic beat (VEB), supraventricular ectopic beat (SVEB), fusion of a normal and a VEB, or unknown beat type was taken for analysis. The ECG data obtained from 44 non pacemaker recordings were used in this work. Among these 44 data recordings, 22 were used to build the classifier and the other were used in analysing the performance of the developed algorithm. The classification was done by using the morphology of the ECG, heart beat intervals and R-R intervals. On evaluation, the algorithm produced a sensitivity of 75.9%, a positive predictivity by 38.5%, and a false positive rate of 4.7% for the SVEB class. With the VEB class, it produced a sensitivity of 77.7%, the positive predictivity of 81.9%, and the false positive rate of 1.2%[66].

Dinh. H. A.N. *et. al.* (2001) have examined the effects of wavelet properties such as linearity and time/frequency localization on the accuracy of QRS detection. The sum of false negatives and false positives was the criterion used for determining the efficiency of wavelet function. The work reported a significant reduction of error in the QRS complex detection. The mean error was reduced to 0.75%. This was achieved with the use of Cubic Spline wavelet - a biorthogonal third order wavelet. This study reported that, the error in the detection of QRS complexes can be reduced with the use of wavelets[67].

Haque, A. F. *et al*. (2009) proposed a wavelet based method to detect small variations of ECG features. These small variations in ECG signals cannot be visualised manually. Hence forth a signal processing method is needed for the analysis of these parameters. The FFT and wavelet were used to estimate the minute variations in simulated normal and noise corrupted ECG signal. On observation, it was studied that the wavelet was more accurate over the FFT in projecting the small abnormalities in ECG signal[68].

Hu Y.H. *et al.* (1997) developed a customized ECG beat classifier called as "mixture-of-experts" (MOE) for classifying ECG beats. The patient specific ECG data helped in the development of this small customized classifier .When thsese individual classifier were combined with a global classifier, it turned in to a large ECG database of many patients, to form a MOE classifier structure. The developed algorithm when tested with MIT/BIH arrhythmia database produced enhanced results over the existing algorithm[69].

Jane R. *et al.* (1992) have used a cascade adaptive filter for removing the baseline wander and for preserving the low-frequency components in the ECG. An adaptive notch filter at zero frequency was used in the first stage and a QRS detector was used in the second stage to detect the occurrence of QRS peaks in the ECG. With these, all the signal components correlated with the QRS complex were preserved. The analysis was done over the frequency response of the filter. This type of the filter can be called as a comb filter without DC lobe. This method was tested using ECG signals from the MIT-BIH database. The classification performance was compared with the cubic spline approach. The advantage observed with this method was, this method could able to remove baseline wander in real time without much calculation of isoelectric levels during the preservation of low-frequency ECG clinical information[70].

Javadi, M. *et al.* (2013) proposed an ECG arrhythmia signal classification method by using the complementary features of Mixture of Experts (ME) and Negatively Correlated Learning (NCL). In this the various error functions were utilized by Negative Correlation Learning and Mixture of Experts methods. For training,the control parameter for NCL was incorporated in the error function of ME. This was done to establish a balance in bias-variance-covariance trade-offs. The test data in this work was obtained from the ECG records from the MIT-BIH arrhythmia database. The final results produced by this work were satisfactory[71].

Rieta, J. J. *et al.* (2004) used independent component analysis (ICA) to reduce the blind source separation (BSS) problem in the ECG. The three key components, namely 1) AA and ventricular activity (VA) generated by sources of independent bioelectric activity; 2) AA and VA present non-Gaussian distributions and 3) the generation of the surface ECG potentials from the cardio electric sources aided in the application of ICA in analysing heart beats. The proposed ICA was applied on the recording obtained from seven patients. In the study it was concluded that the AA source can be identified using a kurtosis-based reordering of the separated signals followed by spectral analysis of the sub-Gaussian sources. With the BSS-based approach it was able to obtain a unified AA signal by exploiting the atrial information present in every ECG lead. This resulted in an increased robustness with respect to electrode selection and placement[72].

Kavitha, R., and Christopher, T. (2014) proposed a technique to examine electrocardiogram (ECG) signal, by taking the features from the heart beats. The classifications were done with the ECG signals collected from the MIT-BIH database. The heart rate was used as the base signal from which certain parameters are extracted and presented to the network for classification. This survey provided an overview for classification of the heart rate[73].

Kiranyaz, S. e*t.al.* (2011) developed a personalized long-term electrocardiogram (ECG) classification framework. The work aimed at the classification of the ECG beats in Holter register in which the ECG recordings from an individual patient were used for analysis. The visual inspection of the Holter register was quite difficult due to the storage of large amounts of ECG recordings in it. This problem was resolved by using K- means clustering technique in this work. This determines the optimal number of key beats with the master key beat. This developed algorithm was compared with the ECG beats that were manually classified by the physicians. The accuracy produced by the algorithm was 99 %. This algorithm aided the physicians to diagnose heart disease of any kind within a short span of time[74].

Li C.*et.al.* (1995) have developed an algorithm based on wavelet transforms (WT's) for detecting ECG characteristic points. By using the multi scale feature of WT's, the QRS complex can be distinguished from high P or T waves, noise, baseline drift, and artifacts. The detection rate of QRS complexes with this method was above 99.8% when tested over MIT/BIH database. The advantage of this method is that, the detection of P and T waves is possible even with serious base line drift and noise[75].

Llamedo, M., & Martínez, J. P. (2011) focussed on the development of a generalised and a simple heartbeat classifier. Here the features obtained from the RR series and the features computed from the ECG samples using wavelet transform were taken for diagnosis. The classification performance was evaluated using three databases such as MIT-BIH Arrhythmia, the MIT-BIH Supraventricular Arrhythmia, and the St. Petersburg Institute of Cardiological Technics (INCART) databases. The best fit was obtained using floating feature selection algorithm and the same is used for generalizing models in the training and validation sets for different search configurations. The evaluation of the developed algorithm was done using MIT-BIH Arrhythmia databases. An accuracy of 93% for normal beats, sensitivity of 95%, positive predictive value of 98% was obtained for supraventricular beats. On the other hand, for ventricular beats, it produced a positive predictive and sensitivity value of 87% and 81% respectively[76].

Manikandan M. S. and Dandapat S. (2008) proposed an ECG compression algorithms for real-time applications. The compression of ECG signal was done with a simple distortion level (SDL) and target data rate (TDR) wavelet threshold method. ECG data from various databases such as the MIT-BIH Arrhythmia (mita) (Fs ¼ 360 Hz, 11 b/sample), the Creighton University Ventricular Tachyarrhythmia (cuvt) (Fs ¼ 250 Hz, 12 b/sample) and the MIT-BIH Supraventricular Arrhythmia (mitsva) (Fs ¼ 128 Hz, 10 b/sample), were used in this work. The data rate variability, signal reconstruction quality and the number of iterations needed for convergence, were the parameter considered for the evaluation of the developed algorithm. The evaluation was done using percentage root mean square difference (PRD) and root mean square error (RMSE) measures. Satisfactory compression was attained with TDR algorithm over the TDL algorithm. The diagnosis rate of 100% was achieved in CR _12, CR _ 8 and CR _ 4 for datas obtained from mita, cuvt and mitsva databases respectively. The experimental results concluded that the proposed TDR algorithm performed well than TDL for in real-time application[77].

Mar T, *et al.* (2011) proposed an enhanced method named as sequential forward floating search (SFFS) for efficient ECG classification. The method was based on linear discriminant analysis. This function was used as a measure for the evaluation SFFS algorithm. The performance of the algorithm was compared with Multilayer perceptron algorithm to evaluate the classification performance. The evaluation results showed that SFFS was much more robust than the MLP model in ECG classification. The algorithm was formulated in compliance with the standards suggested by Association for the Advancement of Medical Instrumentation standard EC57:1998[78].

Matsuyama A. *et al*. (2007) developed a method to distinguish between normal beats and abnormal beats in an ECG signal. Initially the decomposition of ECG signals were done using wavelet transform. This decomposition helped in extracting the feature vectors in terms of normalised energy and entropy. For better classification of the feature vectors extracted from normal and abnormal beats, the normal beats which occur before and after the abnormal beats were eliminated from the group. The combination of wavelet decomposition and the classification aided in identifying the normal and the abnormal beats from the ECG signals. This elimination of normal beats also helped in reducing the size of normal beats cluster[79].

Oweis R. and Hijazi L. (2006) have designed a tool to detect heart defects such as arrhythmias and heart blocks from the ECG signal. The relation between the time domain representation of the signal and the frequency-domain spectrum aided in the diagnosis of arrhythmias. Based on these spectrums, an ECG tool was designed, implemented and tested on a large number of samples. The classification rate obtained with this tool was 99%[80].

Pal, S., and Mitra, M. (2010) proposed a multi-resolution wavelet transform based system for detecting and evaluating of ECG characteristic points like QRS complex, P and T waves. In this, a coefficient method was used for proper identification of the optimum set of wavelet coefficients. These coefficients helped to reconstruct a wave from the ECG signal. The performance of this system was done with the aid of 12 lead ECG recording collected from the physionet diagnostic database. For testing the accuracy of the developed algorithm, the measured values were cross examined with the values that were determined manually. The test result showed over 99% positive detection rate for R peak and base accuracy of 97%, 96%, 95%, 98% of heart rate, P wave, QRS complex and T waves respectively[81].

Pan J. and Tompkins W. J. (1985) have developed a real time algorithm which detects the QRS complex from ECG signals. This real time algorithm detected QRS complex using amplitude, slope and width information. A digital band pass filter was used to reduce the error in detection caused by interference in this system. To increase the detection sensitivity, low threshold values has been used. The MIT-BIH arrhythmia database was used for the development of this algorithm. An accuracy of 99.3% was achieved in the identification of QRS complexes by this algorithm[82].

Ahmeda, S. M., & Abo-Zahhad, M. (2001). described a hybrid technique to achieve ECG data compression. The compression was achieved using a combination of wavelet transform and linear prediction methods. Initially wavelet transform was applied in the ECG signals using four different discrete wavelet transforms (Daubechies, Coiflet, Biorthogonal and Symmlet). These wavelet transform decompose the ECG signals into five detailed levels and one approximation. This aids in the linear prediction of the wavelet coefficients and also aid in the minimising the error in classification. In order to increase the compression rate further, the residual sequence obtained after linear prediction was coded using a newly developed coding technique. With all these steps, a compression ratio (Cr) of 20 to 1 was achieved with percentage root mean square difference (PRD) less than 4%[83].

Senapati, M. K., *et.al* (2014) proposed the detection and classification cardiac arrhythmias from the ECG signal acquired from the patients. The R-peak was detected by a modified Pan-Tompkins approach. A Linear Discriminate (LD) function scaled conjugate gradient method and Naive Bayes Classifier approaches were used in this work for classification of cardiac arrhythmias. The arrhythmias are classified into four classes such as R-R interval, QRS interval, QRS morphology and T-wave morphology by extracting the features from each cardiac cycle. The test data were obtained from the MIT-BIH Arrhythmia database and performance of the three classifiers was verified using the test data. Satisfactory results were produced by these classifiers in arrhythmia classification[84].

Senhadji L. *et al.* (1995) used wavelet transforms to describe and recognize isolated cardiac beats. The energy based representation and distribution estimated at each decomposition level that were assessed using principal component analysis were used in this work. These features were then subjected to linear discriminant analysis.This work leads to the identification of the most relevant resolution levels[85].
Sidek, K. A., and Khalil, I. (2013) proposed an ECG data analysing technique Hermite interpolation (PCHIP) and piecewise cubic spline interpolation (SPLINE). A sample of 70 ECG recordings which were from 4 different public ECG databases were used for the development and evaluation of the algorithm. Feature extraction was done by an analytical method. The extracted features were subjected to Cross Correlation (CC), Percent Root-Mean-Square Deviation (PRD) and Wavelet Distance Measurement (WDM) methods. The performance evaluation was done in two conditions viz. with and without applying interpolation techniques. The experimentation suggested that biometric matching with interpolated ECG data achieved higher matching percentage value of up to 4% for CC, 3% for PRD and 94% for WDM. These results were compared with the existing method which used ECG recordings with lower sampling frequency. A higher classification accuracy of up to 99.1% for PCHIP and 99.2% for SPLINE with interpolated ECG data as whereas the classification accuracy of 97.2% was obtained without interpolation of ECG data. These results revealed the application of interpolation techniques will enhance the quality of the ECG data[86].
Shen, M., *et.al*. (2010) used an Electrocardiogram (ECG) classification method using domain knowledge and morphology information. The extraction of features from ECG was done using Principal Component Analysis and Independent Component Analysis methods. The extracted features were classified using the SVM classifier. The performance of the classifier was evaluated with the manual diagnosis methods done by the experts. A total of 94325 heart beats from the MIT-BIH Arrhythmia Database and 289 12-lead records from Chinese Cardiovascular Disease Database were used in this work to verify the classification model .The final results produced by the SVM classifier resembles with the results produced by the physicians[87].
Yeh, Y. C. *et al.* (2009) described a Linear Discriminant Analysis (LDA) method to analyze ECG signals to and also for effective diagnosis of cardiac arrhythmias. This method could be able to accurately classify and differentiate between normal (NORM) and abnormal heartbeats. The abnormal heartbeats which were diagnosed by this algorithm includes left bundle branch block (LBBB), right bundle branch block (RBBB), ventricular premature contractions (VPC) and atrial premature contractions (APC). This method of ECG signal analysis comprises of three main stages: (i) QRS waveform detection; (ii) qualitative feature selection; and (iii) heartbeat case determination. The evaluation of the developed algorithm was done using ECG records in the MIT-BIH arrhythmia database. Experimental results show that the correct diagnosis rates produced by this were 98.97%, 95.09%, 91.07%, 92.63% and 84.68% for NORM, RBBB, LBBB, VPC and APC respectively[88].
Wiggins M. *et al.*(2008) presented a methodology for classifying ECG recording using the statistical features extracted from ECG signals. The extracted feature was classified using a genetically evolved Bayesian network classifier. Continuous signal feature variables were converted to a discrete symbolic form by thresholding to lower the dimensionality of the signal. This reduction in dimensionality reduced the complex calculations in conditional probability tables for the classifier. The comparison of data between the trained features and testing features was done using hill climbing technique and genetic algorithm techniques. On analysis it was observed that the evolved Bayesian network performed better (86.25% AUC) than both the one developed using the greedy algorithm (65% AUC) and the naive Bayesian classifier (84.75% AUC)[89].
Yeh Y.C. and Wang W.J. (2008) proposed a Difference Operation Method (DOM) for detecting the QRS complex of an electrocardiogram (ECG) signal. The proposed methodology has two stages. The first stage is to find the point R. This was done by applying the difference equation operation to an ECG signal. The second stage is to localization of the points Q and S with respect to the point R in order to diagnose the QRS complex. The existing methods support to obtain the T wave and P wave form the QRS complex. The work was carried out using MIT-BIH arrhythmia database. The results concluded that more precise and faster detection rate was obtained using DOM than the other heart disorder detection methods[90].
Yeh, Y. C., *et.al*. (2012) utilized cluster analysis method for analyzing ECG signal to diagnose cardiac arrhythmias. This method was followed to accurately classify and distinguish the difference between normal and abnormal heartbeats. The abnormal heart beats includes left bundle branch block (LBBB), right bundle branch block (RBBB), ventricular premature contractions (VPC) and atrial premature contractions (APC). This method involves three major stages in the analysis of ECG signals. They were (i) detecting the QRS waveform; (ii) selecting qualitative features; and (iii) determining heartbeat case. The reference data used in this work were the ECG signals stored in the MIT-BIH arrhythmia database. On evaluating the developed algorithm, it produced a sensitivity of 95.59%, 91.32%, 90.50%, 94.51%, and 93.77% in heartbeat case NORM, LBBB, RBBB, VPC, and APC, respectively. The total classification accuracy (TCA) was around 94.30%[91].
Yu S.N. and Chou K.T. (2007) proposed a switchable scheme to discriminate different types of electrocardiogram (ECG) beats. This differentiation was done using independent component analysis (ICA). The RR-interval in the waveform helps to indicate between the longer (1.0 s) and the shorter (0.556 s)

beats. Six ECG beat types which include 13900 samples extracted from 25 records in the MIT-BIH database was utilized in this study. Three conventional statistical classifiers were employed to testify the discrimination power of this method. The final accuracy produced in this work was 99%[92].

Zeraatkar, E *et al*. (2011) proposed arrhythmia detection on the basis of morphological and time-frequency features of t-wave in an ECG. 22 features from T wave which includes 5 wavelet features and 17 morphological were extracted from normal and abnormal records. The extracted features from T wave were pre-processed and classified using Multi Layer Perceptron (MLP) algorithm. The ECG signals obtained from 142 patients (40 normal, 47 LQT and 55 TWA) were used for the study. The specificity factor obtained with normal, TWA and LQT waves were 99.89%, 99.43%, and 99.90%, respectively[93].

Here it is dealing with the experimental analysis of proposed DCA algorithm to compress the ECG signal data which have been done in MATLAB environment. MATLAB is a high level technical computing language that is used to develop signal processing algorithms. It has many advantages over conventional programming languages such as C, C++, JAVA, FORTAN, COBALT, VHDL and VERILOG. We have considered MIT-BIH ECG database for testing the proposed algorithm. Original ECG signal data has been shown in figure 1. Output of DCA scheme has been shown in figure 4, where the most of the signal energy has been sequenced in coefficients less than 1100.

In figure 5 it has shown that the reconstructed signal compared with the original signal after applying inverse DCA scheme by considering only 1024 coefficients, which indicates that the signal will be compressed almost 4 times to the original ECG signal data that means the compression ratio is 4:1.

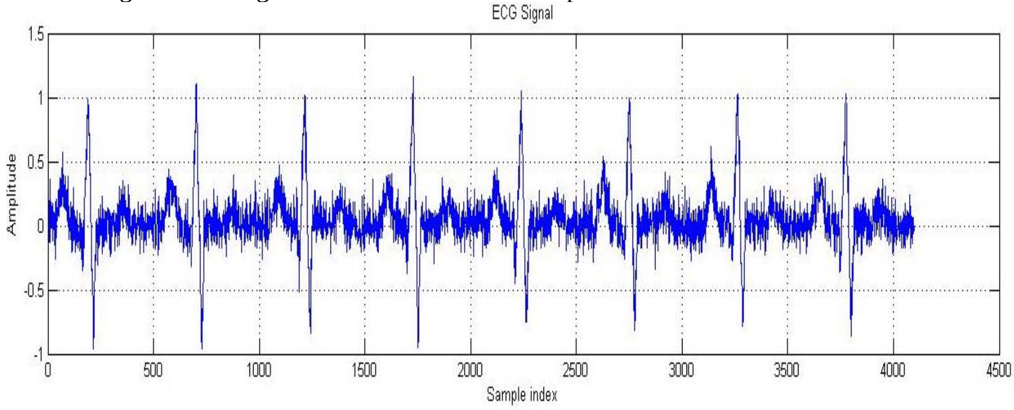

Fig.1 Input ECG signal

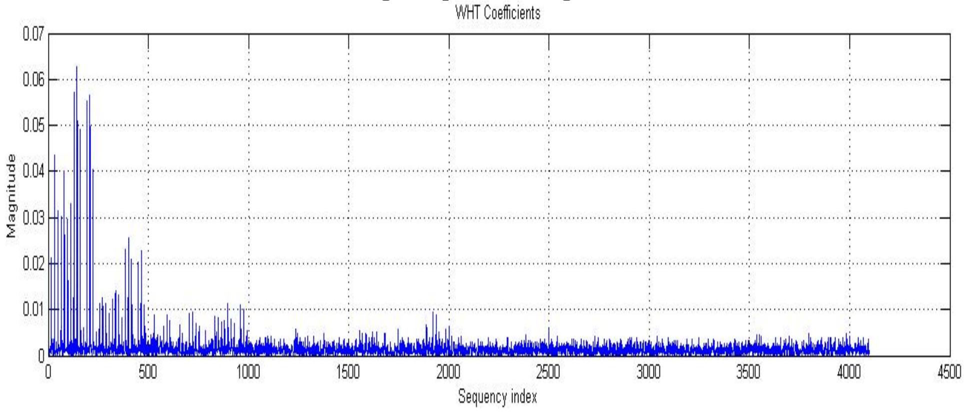

Fig. 2 Coefficients after applying DCA scheme

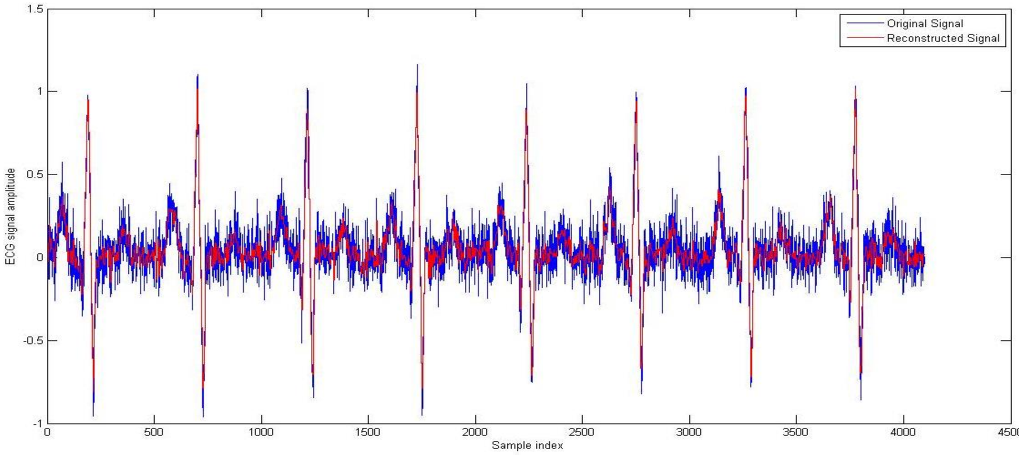

Fig.3 Comparison of original and reconstructed signal using DCA scheme

CONCLUSION

Categorizing ECG signals is a demanding endeavor. In order to address this issue, a proposed method has been put forward and thoroughly examined in previous chapters. This algorithm is built using medical signal processing and pattern recognition techniques. The algorithm's development relies on the utilization of the MIT-BIH database. The many phases of progress of this study are outlined as follows. This research is built upon previous efforts to classify ECG signals. The study outlined the tough issues involved in diagnosing ECG signals and stated the purpose of the effort. The project commenced by proposing a novel approach for categorizing ECG signals through the utilization of feature extraction and classification algorithms. This portion of the endeavor utilizes various feature extraction approaches such as Morphology, Trispectrum, and Wavelet methods. The FFNN was utilized as the classifier, and its weights were optimized using a Backpropagation algorithm during this part of the project. An analysis is conducted using the results obtained from each feature extraction technique and FFNN. Upon review, it is noted that the findings obtained using Trispectrum features exhibit favorable properties. Upon analyzing these data, it was shown that a greater number of characteristics contributed to improved classification.

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