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# A Survey on ECG Signal Feature Extraction and Analysis Techniques

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**Abstract**: Electrocardiogram (ECG), a non-stationary signal, is extensively used to measure the rate and regularity of heartbeats. Comparison of overall ECG waveform pattern and shape enables doctors to diagnose possible diseases. Currently there is computer based analysis which employs certain signal processing to diagnose a patient based on ECG recording. Noise severely limits the utility of the recorded ECG and thus needs to be removed for better clinical evaluation. ECG feature extraction is also required because it plays a significant role in diagnosing most of the cardiac diseases. One cardiac cycle in an ECG signal consists of the P-QRS-T waves. The feature extraction scheme determines the amplitudes and intervals in the ECG signal or any other features of it for subsequent analysis. Recently, numerous research and techniques have been developed for analyzing the ECG signal. This proposed paper discusses various techniques and transformations proposed earlier in literature for feature extraction and analysis of ECG signals and makes comparison among them.

**Keywords**: ECG, processing, feature extraction, ECG signal analysis.

## I. INTRODUCTION

The improvement of ECG analysis which is part of bio-signal processing to obtain the heart disease classification has been studied by many researchers from the past decades up to now. Their studies have been carried out through experimental numerical works. In ECG analysis, the main idea is to make the analysis methods enhancement in the degree of accuracy in classifying the disease and increasing the number disease that can be classified. By finding the suitable analysis methods, the heart disease classification can be calculated accurately at a fast rate through the analysis process. Therefore, the past studies of the ECG analysis algorithms enhancement are an important topic that should be reviewed. This work is aimed at providing some of related information regarding the research carried out pertaining to the improvement of heart disease classification with the important roles played by ECG analysis, from different researchers across the globe. Philip de Chazal et al. in [1] illustrated that there are four major steps to the ECG signal recognition system, namely, the pre-processing of the signal, QRS complex and P ant T wave detection, feature extraction and ECG signal classification as shown in fig. 1.

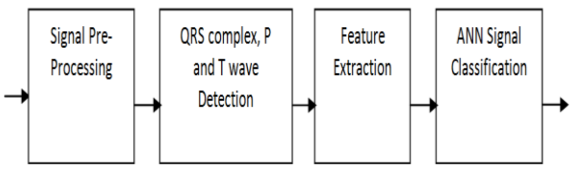


Fig. 1 Steps in ECG signal recognition system

## II. LITERATURE SURVEY

This survey begins by reviewing some of the previous studies in ECG signal feature extraction and analysis techniques. The survey is divided into feature extraction and classification techniques.

### *A.* ECG Feature Extractions

The first step in the analysis of ECG signal is the denoising of ECG signal. Denoising or pre-processing of ECG signal is important because noise severely limits the utility of the recorded ECG. After pre-processing, the second stage towards classification is to detect certain features of ECG signals mostly QRS complex, P and T waves. The features, which represent the classification information contained in the signals, are used as inputs to the classifier used in the classification stage.

The goal of the feature extraction stage is to find the smallest set of features that enables acceptable classification rates to be achieved. In general, the developer cannot estimate the performance of a set of features without training and testing the classification system. Therefore, a feature selection is an iterative process that involves training different feature sets until acceptable classification performance is achieved.

A. Coast Doughlas et al. in [2] described an approach to cardiac arrhythmia analysis using Hidden Markov Models. This technique classified by detecting and analyzing QRS complex and determining the R-R intervals to determine the ventricular arrhythmias. The Hidden Markov modeling approach combines structural and statistical knowledge of the ECG signal in a single parametric model. The Hidden Markov modeling addresses the problem of detecting low amplitude P waves in typical ambulatory ECG recordings.
C. Li et al. in [3] used the Wavelet Transform (WT) method including N.V. Thakor et al. [4], David Cuesta-Frau et al. [5], Louis C Pretorius and Cobus Nel [6] and S.Z. Mahmoodabadi et al. [7] because the results indicated that the Discrete Wavelet Transform (DWT)-based feature extraction technique yields superior performance.
C. Li et al. in [3] have done the ECG analysis using WT.


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This method can distinguish the QRS wave and P, T wave. This technique also can distinguish noise, baseline drift and artifacts. So it can characterize the signal information analysis very well and suitable to process time-varying biomedical signals. The WT also capable of representing signals in different resolutions by dilating and compressing its basis functions as explained by I. Clark in [8].

Franc Jager in [9] developed a new approach to feature extraction which is Kahunen Lo'eve Transform (KLT) which is an attractive and powerful approach to the feature extraction and shape representation process. It has the solution if the probability densities of population of pattern vectors of a problem domain are unknown. The problem about this method is, it is too sensitive to noisy pattern of ECG signal.

According to P. Ranjith et al. [10] which used WT to detect myocardial ischemia, the WT is obtained using the quadratic spline wavelet. These correspond to the detection of T wave and P wave. Their methods showed a comparatively higher sensitivity and nominal positive predictivity value. It can be easily extended to detect other abnormalitites of the ECG signal. But this method also has the limitation that computations required are higher than those required by other methods.

According to M. H. Kadbi et al. in [11] highlighted those three features for feature extraction stage which are time frequency, 2-time domain features and 3-statistical feature. These features have been used in their project because these features can overcome the limitations of other methods in classifying multiple kinds of arrhythmia with high accuracy at once. These methods have been combined with PCA method to reduce the redundancy caused by the frequency coefficient in the feature dimension to make sure the average of the classification accuracy can be increased.

G.G. Herrero et al. in [12] used the independent component analysis and matching pursuits for the features extraction for extracting additional spatial features from multichannel electrographic recordings. It test the classification performance of 5 largest classes of heart beats in the MIT-BIH arrhythmia database which are normal sinus beats (NSB), left bundle branch block (LBBB), right bundle branch block (RBBB), premature ventricular contraction (PVC) and paced beats (PB). The performance of the system is remarkably good, with specificities and sensitivities for the different classes. They have a problem because the complicated separation between ventricular PBs and PVCs because of the inverted T wave.

A. Ahmadian et al. in [13] proposed a new piecewise modelling for approximation of ECG signal using Hermitian Basis. This method uses only the $5^{th}$ order Hermitian basis functions. This method yields to weighing the approximation error of each segment base on its importance throughout the ECG complex. This method shows the total error obtained in this method is almost halved in comparison with similar non-segmented method. The disadvantage of this method is that small error could mislead the diagnosis.

K.S. Park et al. [14] applied two morphological feature extraction methods which are higher order statistics and Hermite basis function. Their research results showed that hierarchical classification method gives better performance than the conventional multiclass classification method. They used the support vector machines to compare the feature extraction methods and classification methods to evaluate the generalization performance. But the use of higher order models need more computation cost and caused over fitting problem in generalization performance. In terms of accuracy, they found that their hierarchical classification method showed better classification performance than the conventional multiclass classification method despite the loss in accuracy and sensitivities with certain class.

## B. ECG Training and Classification Algorithms

In ECG training and classification analysis stages, some researchers have tried to maximize the detection level of accuracy in many different ways. The performance of the developed detection systems is very promising but they need further evaluation. The automatic detection of ECG waves is important to cardiac disease diagnosis. A good performance of an automatic ECG analyzing system depends heavily upon the accurate reliable detection of the disease.

Neural Network

The classification of the ECG using NNs has become a widely used method in recent years. The network architectures for modelling process modelling in NNs include the feed forward network, the radial basis function (RBF) network, recurrent network, and other advanced network architecture as explained by the Centre for Process Analytics and Control Technology (1999) and Sjoberg in [15]. The efficiency of these classifiers depends upon a number of factors including network training. It has the inputs models in the training parameters and the output indicated the point at which training should stop. Simple feed forward neuron model was shown by Dayong Gao et al. in [16]. Researcher from Harvard University, M. Sordo in [17 indicated that the training and testing of the models was based on the results from the signal database of the normal patient and heart disease patient.

Rosaria Silipo and Carlo Marchesi in [18] also developed an automatic ECG analysis based on ANN. This project presented the result by carrying out the classification tasks for the most common features of ECG analysis which are arrhythmia, mycordial ischemia and chronic alterations and achieved high classification accuracy.

Kei-ichiro Minami et al. in [19] developed a method to discriminate life threatening ventricular arrhythmias by observing the QRS complex of the electrocardiogram

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(ECG) in each heartbeat. Changes in QRS complexes due to rhythm origination and conduction path were observed with the Fourier transform, and three kinds of rhythms were discriminated by a neural network. In this paper, the potential of their method for clinical uses and real-time detection was examined using human surface ECG's and intra cardiac electrograms (EGM's). The method achieved high sensitivity and specificity (≥ 0.98) in discrimination of supra ventricular rhythms from ventricular ones. They also presented a hardware implementation of the algorithm on a commercial single-chip CPU.

Costas Papaloukas et al. in [20] developed an automated technique for the ischemic detection based on the recordings from European Society of Cardiology (ESC) ST-T database in order to train the network for beat classification also achieved high accuracy rate.

Dayong Gao et al. [16] from the National University of Ireland have developed a diagnostic system for cardiac arrhythmias form ECG data, using an 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 signal. This system consists of three basic modules which are a Server, multiple Client Machines and BAN-Hubs which use real time patient bio-signal data provides earlier information and high classification accuracy.

T. Inan et al. [21] believed that morphological information must be coupled with timing information, which is more constant among patients, in order to achieve high classification accuracy for larger data sets. With this approach, they combined wavelet-transformed ECG waves with timing information as feature set for classification. They used selected waveforms of 18 files of the MIT/BIH arrhythmia database, which provides an annotated collection of normal and arrhythmic beats, for training our neural-network classifier. The accuracy was 95.16% over 93,281 beats from all 40 files, and 96.82% over the 22 files outside the training set in differentiating normal, PVC, and other beats.

Jiang et al. in [22] presented evolvable block-based neural networks (BbNNs) for personalized ECG heartbeat pattern classification. A BbNN consists of a 2-D array of modular component NNs with flexible structures and internal configurations that can be implemented using reconfigurable digital hardware such as field-programmable gate arrays (FPGAs). Simulation results using the Massachusetts Institute of Technology/Beth Israel Hospital (MIT-BIH) arrhythmia database demonstrate high average detection accuracies of ventricular ectopic beats (98.1%) and supraventricular ectopic beats (96.6%) patterns for heartbeat monitoring, being a significant improvement over previously reported electrocardiogram (ECG) classification results.

Indu Saini and B. S. Saini in [23] used NN technique with error back propagation method to classify 4 different types of arrhythmias namely LBBB, RBBB, APB and PB with normal ECG signal. MLP network was used, 20 hidden nodes with sigmoid activation function was used. Input layer neuron 3 and output layer neuron fixed to 5. The three morphological feature RR interval, R peak amplitude and QRS duration of ECG signal were used for arrhythmia classification. The classification results obtained in this work show that the neural classifier has achieved very good accuracy level in distinguishing various arrhythmias.
Maedeh Kiani Sarkaleh and Asadollah Shahbahrami in [ 24] used DWT for processing ECG recording and extracting some features and the MLP NN performs the classification task. Two types of arrhythmia can be detected by the proposed system. The extracted feature vector consists of 24 statistics over the set of wavelet coefficients from first level to eight levels. The set of features used are, maximum of the wavelet detail coefficients in each level, minimum of the wavelet coefficients in each level and variance of the wavelet detail coefficients in each level. The simulation results demonstrated that the system could be employed for the classification of the ECG arrhythmias with recognition rate of 96.5%, when 13 neurons were in the hidden layer in traingdx, 11 neuron in trainrp algorithm and 14 neurons in trainlm.

Neuro-Fuzzy Approach

The idea of the ECG analysis and classification using Neuro Fuzzy has been started around 1990, yet it remains one of the most important indicators of proper heart disease classification today. The most difficult problem faced by an automatic ECG analysis is the large variation in the variations in the morphologies of ECG waveforms, it happens not only for different patients or patient group but also within the same patient. So the Neuro Fuzzy is the most suitable technique because it is more tolerance to morphological variations of the ECG waveforms.

Tran Hoai Linh et al. in [25] have studied in depth on the Neuro-Fuzzy approach to the recognition and classification of heart rhythms on the basis of ECG waveforms. It uses the new approach of heart beat recognition. This project is the resolution for the problem of less sensitivity to the morphological variation of the ECG. It combines two techniques which are characterization of the QRS complex of ECG by Hermite polynomials and using the coefficients of Hermite kernel expansion as the features of the process and the application of the modified neuro-fuzzy TSK network for ECG pattern recognition and classification.

The Neuro-Fuzzy techniques which refers to the combinations of fuzzy set theory and neural networks with the advantages of both which can handle any kind of information, numeric, linguistic, logical, imperfect information, resolve conflicts by collaboration and aggregation, self-learning, self-organizing and self-tuning capabilities, no need of prior knowledge of relationships of data, mimic human decision making process and fast computation using fuzzy number operation in order to do the classification task.

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Hidden Markov Models

This technique was successfully used since the mid 1970s to model speech waveforms for automatic speech recognition. The Hidden Markov modeling approach combines structural and statistical knowledge of the ECG signal parametric model. The model constructed contains multiple states per excitation field, model parameter ant training algorithms as explained by K. Seymore et al. in [26].

A. Coast Douglas et al. in [2] described an approach to Cardiac Arrhythmia Analysis using Hidden Markov Models. This technique classified by detecting and analyzing QRS complex and determining the R-R intervals to determine the ventricular arrhythmias. The Hidden Markov modeling approach combines structural and statistical knowledge of the ECG signal in a single parametric model. Model parameters are estimated from training data using an iterative, maximum likelihood re-estimation algorithm. This method has ability of beat detection, segmentation and classification, with highly suitable to the ECG problem. Its approach addresses a waveform modeling, multichannel beat segmentation and classification, and unsupervised adaptation to the patient's ECG.

W.T. Cheng and K.L. Chan in [27] have discovered the method of Hidden Markov Model (HMM) in classifying arrhythmia. They have developed a fast and reliable method of QRS detection algorithm based on a one-pole filter which is simple to implement and insensitive to low noise levels. The disadvantage are that the observations are very sensitive to baseline wander, DC drift and heart rate variation. The HMM method also is not sufficient to represent one particular type of beat. This is because some beats exhibit large variations in the morphologies of their ECG signals. Therefore, several HMMs are needed for certain some beats.

Support Vector Machine

The Support Vector Machine based Expert System that have been described by C.J.C. Burges [28], Stanislaw Osowski et al. [29] and Van der C. M Walt and E. Barnard [30] also the best method to apply in ECG analysis. The recognition system that uses the support vector machine (SVM) working in the classification mode. Support vector machine map input vectors to a higher dimensional space where a maximal separating hyperplane is constructed. Two parallel hyperplanes are constructed on each side of the hyperplane that separates the data. The separating hyperplane shows the maximize distance. The larger the distance between these parallel hyperplanes, the better the generalization error of the classifier.

Stanislaw Osowski et al. [29] performed their studies of Heartbeat Regulation using SVM based Expert System. This recognition system has used the different preprocessing methods for generation of features which are higher order statistics (HOS) while the second is the Hermite characterization of QRS complex for the registered ECG waveform. Their paper presented the combination of multiple classifiers by the weighted voting principle. In their studies, stated that a good recognition system should depend on the features representing the ECG signals in such a way, that the differences among the ECG waveforms are suppressed for the waveforms of the same type but are emphasized for the waveforms belonging to different types of beats. It is an important item, since the observed signal is a high variation of signals among the same type of beats. These two different preprocessing methods of the data, cooperating with SVM classifier, that have been integrated into one expert system have proven in improve the overall accuracy of heartbeat recognition.

S. S. Mehta and N. S. Lingyat [31] indicated the application of SVM on QRS detection using entropy criterion. The advantages of using SVM are the ability to find a hypeplance that divides samples in two classes with the widest margin between them, and the extension of this concept to a higher dimensional setting using kernel function to represent a similarity measure on that setting. This algorithm performs better as compared with published results of other QRS detectors tested on the same database and depends strongly on the selection and the variety of the ECG included in the training set, data representation and the mathematical basis of the classifier.must be numbered using uppercase Roman numerals. Table captions must be centred and in 8 pt Regular font with Small Caps. Captions with table numbers must be placed before their associated tables, as shown in Table 1.

Self-Organizing Map

Meanwhile in the ECG analysis of the Ischemia detection with a self organizing map supplemented by supervised learning has been developed in 2001 by Papadimitriou et al.. It is to solve problem of maximizing the performance of the detection of ischemia episodes. The basic self-organizing map (SOM) algorithm modified with a dynamic expansion process controlled with entropy based criterion that allows the adaptive formation of the proper SOM structure. This extension proceeds until the total number if training patterns that are mapped to neurons with high entropy reduces to a size manageable numerically with a capable supervised model. Then, a special supervised network is trained for the computationally reduced task of performing the classification at the ambiguous regions only. The utilization of SOM with supervised learning based on the radial basis functions and SVMs has resulted in an improved accuracy of the ischemia detection.

Fuzzy Logic

W. Zong and D. Jiang in [32] described the method of fuzzy logic approach single channel ECG beat and rhythm detection. The method summarized and makes use of the medical knowledge and diagnostic rules of cardiologists. Linguistic variables have being used to represent best features and fuzzy conditional statements perform reasoning. The algorithm can identify rhythms as well as individual beats. This method also handling the beat features and reasoning process is heuristic and seems more reasonable as stated in their paper. It also presented that this method may be of great utility in clinical applications such as multi-parameter patient monitoring systems, where many physiological variables and diagnostic rules exist.

Bayesian Method

Dayong Gao et al. in [16] pointed out that the Bayesian network are improved methods in determining the arrhythmia diagnosis system. This method is able to deal with nonlinear discrimination between classes, incomplete or ambiguous input patterns, and suppression of false alarms. It develops new detection schemes with a high level of accuracy. This approach is potentially useful for generating a pattern recognition model to classify future input sets for arrhythmia diagnosis.

M Wiggins et al. in [33] evolved a Bayesian classifier for ECG classification. The patients classification was according to statistical features extracted from their ECG signals using a genetically evolved Bayesian network classifier and the identification depend on the variables of interest. The Bayesian network has an ability to handle missing data points and its lower requirement of information based on a priori knowledge of the system's variable dependencies is its major benefits. It is relatively new tool that identifies probabilistic correlations in order to make predictions or assessments of class membership that could solve many complex problems exist and identifies the data for the variables of interest. This method shown it is very easy to implement and one of the research area that are good to be discovered. The limitation of their studies has been the method for binary discretization used after feature extraction because of small size of the data set.

Genetic Algorithm

Chris D Nugent et al. in [34] reported in depth on the prediction models in ECG classifiers using genetic programming approach. In their studies they developed the prediction models to indicate the point at which training should stop for NN based ECG classifiers in order to ensure maximum generalization. According to them, this good wave prediction could exhibit good generalization. They found that it could give benefit to developers of NNs, not only in the presented case of NN based ECG classifiers, but indeed any classification problems.

Autoregressive Model

Dingfei Geo et al. [35] have extended the study of cardiac arrhythmia classification using autoregressive modeling. This computer-assisted arrhythmia recognition have been proposed to classify normal sinus rhythm (NSR) and various cardiac arrhythmias including atrial premature contraction (APC), premature ventricular contraction (PVC), super-ventricular tachycardia (SVT), ventricular tachycardia (VT) and ventricular fibrillation (VF). Their studies have shown the AR coefficients were classified using a generalized linear model (GLM) based algorithm in various stages. From their study, they found that the AR modeling is useful for the classification of cardiac arrhythmias, with reasonably high accuracies. From the study, they found that AR modelling based classification algorithm has demonstrated good performance in classification. The algorithms are also easy to implement and the AR coefficient can be easily computed. AR modelling can lead to a low cost, high performance, simple to use portable telemedicine system for ECG offering a combination of diagnostic capability with compression. Therefore, it revealed that enhancement is suitable for real time implementation and can be used for compression as well as diagnosis.

## III. CONCLUSION

In the literatures, most researchers have developed the system based on the various techniques and algorithms. Each technique presented in the previous project of ECG analysis has their advantages and disadvantages. Table I summarizes various approaches in ECG signal analysis. The performance of the developed detection system is very promising but they need further evaluation. The automatic detection of ECG waves is important to cardiac disease diagnosis. A good performance of an automatic ECG analyzing system depends heavily upon the accurate and reliable detection of the QRS complex, as well as the T and P waves and most of the researchers only depend on certain disease.

From the reviewed, for ECG analysis in feature extraction and classification techniques, it is found that ANN and hybrid methods is one of the latest ECG analysis techniques particularly in bio-signal processing for medical application which are being carried out by biomedical researchers. Therefore, this type of research is definitely worth for further study. Research should mainly aim to use the selected algorithms for feature extraction and classification task to enhance the result of accuracy and extend the types of heart disease that can be classified. An ECG analysis system that is fast and simple can be developed.

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TABLE I: SUMMARY OF APPROCHS FOR ECG SIGNAL ANALYSIS

| Method | Reasearcher | Comment and Description | Overall Performance |
|---|---|---|---|
| Karhumen Lo'eve Transform | Franc Jager (2002) | Attractive and powerful approach to the feature extraction process. It has the solution if the probability densities of pattern vectors population of a problem domain are unknown | Accuracy 80% |
| Wavelet transform | N.V. Thakor et al., 1993; C. Li et al.,1995; David Cuesta-Frau et al., 2002; Louis C Pretorius et al., 2002; S.Z. Mahmoodabadi et al., 2005 | Time frequency analysis. Ability to reconstruct the signal from the wavelet decomposition and preserve the energy under transformation. | Accuracy more than 90% |
| | | By decomposing signals into elementary building blocks that are well localized both in time and frequency, the WT can characterize the local regularity of signals. | Sensitivity attained more than 90% |
| Artificial Neural Netwok (ANN) | B. Heden et al. (1995) | ANN method can enhance the sensitivity of the conventional P wave's detection. The conventional criteria had a much lower sensitivity in the absence of P wave data which is 30.9 %. | Accuracy 80% to 90% |
| | | The corresponding sensitivity for the ANN is 94.5% | Sensitivity more than 90% |
| | Indu Saini and B. S. Saini (2012) | Classified four types of arrhythmias apart from normal signal. Used three morphological feature to train the NN. | Accuracy and Sensitivity more than 95% |
| | M. K. Sarkaleh and A. Shahbahrami (2012) | Classified two types of arrhythmias, Pb and APB apart from the normal signal. Used detail coefficients obtained by eight level decomposition of ECG signal. | Attained total recognition rate of 96.5% |
| | Rosaria Silipo and Carlo Marchesi (1998) | This approach capable of dealing with the ambiguous nature of ECG signal. | Accuracy 80% to 90% |
| | Costas Papaloukas et al. (2002) | Obtained 80% to 90% accuracy | Sensitivity more than 90% |
| | Dayong Gao et al. (2004) | The results presented in this project shows that more than 90% prediction accuracy may be obtained | |
| | He et al. (2006) | Exhibited the best performance and excellent model for the computer-aided diagnosis of heart disease. | Reached an overall accuracy of 95.5%. |
| | | A widely used method in recent years. The efficiency of these classifiers depends upon a number of factors including network training. | |
| | Jiang and Seong G. Kong (2007) | Used block-based neural networks for personalized ECG signal classification | Detection accuracies of ventricular ectopic beats was 98.1% and for supraventricular ectopic beats was 96.6%. |
| Hidden Markov Model | A. Coast Douglas et al. (1990) | P-wave detection results show an accurate detection of the low amplitude P-wave in ECG | Specificity 90% Accuracy 50% to 80% and |

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| | | | |
|---|---|---|---|
| | | recordings. | Sensitivity 80% to 95% |
| | Bardonova (2000) | The Hidden Markov Models which applied wavelet transform can improve the bio-signal analysis. | |
| | N. P. Hughes et al. (2003) | It is significantly better than similar models trained on the raw time ECG series data. | |
| | | Hidden Markov Modeling can address the problem of detecting low amplitude P-waves in typical ambulatory recordings. | |
| | V. Rodrigo et al. (2006) | This system combining WT and Hidden Markov Models, it obtained high beat detection performance with sensitivity of 99.79% and a positive predictivity of 99.96% | |
| Support Vector Machine | Stanislaw Osowski et al. (2004) | The results of the performance recognition of heart rhythm types confirmed the reliability for the approach. | Accuracy attained over 80% |
| Fuzzy Logic | M.G. Tsipouras et al. (2007) | Performed a good efficiency of the recognition of the normal and different types of beats representing the arrhythmias**.** | Specificity more than 90% Sensitivity 60% to 70% |
| Fuzzy Hybrid Neural Network | Tran Hoai Linh and Osowski (2003) | This method shows the simplicity, good recognition rate, and fast performance. Perform a good efficiency of the recognition for the different types of heart beats. | |
| Bayesian Method | M. Wiggins et al., 2005; M. Popescu et al., 1998 | A new tool to make predictions or assessment of class membership. The Bayesian Network (BN) is an excellent method for making decisions based on collected information and makes those decisions in very similar way to that of a physician: by taking each individual piece of information and assessing probabilities of how it affects the final diagnosis. | Accuracy above 80% |
| | | The only difficulty with a BN is determining the structure that produces the highest possible classification and/or prediction accuracy. | |
| Genetic Algorithms | Y. Goletsis et al., 2004; Chris D Nugent Nugent et al., 2002 | It obtained performance 91% in terms of both sensitivity and specificity. Need to combine different classifiers to obtain a better result. | Specificity 90% |
| | | | Sensitivity more than 90% |
| Self Organizing Map | S. Papadimitriou et al. (2001) | The average beat classification accuracy is 76.51% | Accuracy more than 70% |

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