Classification of Cardiac Arrhythmias using Machine learning techniques based on ECG Signal Matching

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Abstract

an electrocardiogram (ECG) signal becomes very important in diagnosing cardiac arrhythmias. The techniques that classify cardiac arrhythmias based on ECG-features still have poor accuracy and much learning time. In this paper, we proposed framework to drive the best classification technique that builds an accurate model for classifying cardiac arrhythmias based on ECG-signal matching. Our framework is consisted of two steps, the preprocessing step which is introduced to match the ECG-templates of the arrhythmias with ECG window beats to find the similarity between them and store these similarities in form of numeric dataset to be used later with classification techniques. The classification step uses four classification techniques and applied in the MIT-BIH-arrhythmias database to classify the numeric dataset so as to drive best technique. Our results proved that decision trees classifier has higher accuracy and lower learning time than other techniques and classification cardiac arrhythmias based on signal matching is better than classification cardiac arrhythmias based on features extraction.

Keywords

ECG, Cardiovascular disease, Classification ECG, Signal Matching.

1. Introduction

The cardiovascular disease becomes one of main diseases that threaten the human healthy especially in developing countries such USA and Canada. There are many ways to discover cardiac arrhythmias by using ECG signal. Electrocardiography is important device for recording electrocardiogram (ECG) signals and variability of bioelectric potential with respect to time as human heart beats. ECG is widely used for diagnosising heart activity among three features known as P, QRS and T waves. Also it gives us useful information about the functional aspect of the heart. The early detection of the cardiac arrhythmias can prolong life and enhance the quality of living through appreciates treatment. Therefore, we need many techniques that analyze the ECG signal to detect the heart diseases. The state of cardiac health is generally reflected in the shape of the ECG waveform and heart rate and contains important pointers to nature of the disease attacking the heart [1].

There are approaches have been developed for classifying cardiac arrhythmias based on ECG signal but still weak and have a poor accuracy because they depend on features extraction of ECG in order to classify cardiac arrhythmias.

In this paper, we proposed framework of driving the best classification technique that could build best accurate Classifier for classifying cardiac arrhythmias based on signal matching that works effectively and efficient. The remainder of this paper is organized as following; Section 2 describes the cardiac arrhythmias and techniques of ECG analysis for classifying cardiac arrhythmias. In section 3, we explain the related works focusing on the characteristics and advantages and disadvantages of the related works. Section 4 explains our framework in details. Section 5 explains our experimental results and performance evaluation. Finally, section 6 summarizes the results that we gained during our experimental results.

2. Cardiac Arrhythmias and Techniques

ECG provides the most accurate means of identifying cardiac arrhythmia (bad rhythm) which can be diagnosed easily when we understand electrophysiology of the heart which includes normal conduction pathways. Normally sanio-atrial (SA) node generates regular sinus rhythm that paces the heart. Each pacemaker impulse from SA node spreads through both atria as an advancing wave of depolarization. On ECG there is a consistent distance (duration) between similar waves during regular shapes a rhythm because the SA node's automaticity precisely maintains constant cycle duration between the pacing impulse that generates similar shapes.

The cardiac arrhythmias can be divided into number of categories according to the arrhythmia's mechanism of origin: irregular rhythm, escape, premature and tauchy-arrhythmias.There are many techniques that have been proposed for classifying cardiac arrhythmias based on features extraction. For example techniques that work based on detecting of single arrhythmia type and its discrimination from normal sinus rhythm or discrimination between two different types of arrhythmias such as time-domain analysis, sequences hypothesis testing algorithm, threshold-crossing intervals and artificial neural network and time frequency analysis. Other techniques classify beat by beat and focus on single beat classification such as artificial neural networks, fuzzy neural networks, mixture of experts approach, hermite function combined with self organizing maps and time-frequency analysis combined with knowledge based systems. But still now all those techniques suffer from accuracy of classification arrhythmias, learning time and the error rates are high because the ECG signal Contains many noises such as baseline wandering and artifacts beside the window size and scalability problems. Our motivation behind this research, firstly, in the literature, there many methods to classify cardiac arrhythmias depend on features extraction, but the features extraction from ECG still are difficult [2]. For example, there are previous methods that work on ECG based on intervals time between the features such as RR, PR and ST intervals, but the measurement of those intervals still are not accurate because of misdetection in features extraction algorithms [4] and there are some methods that classify arrhythmias based on the detection of variations between the intervals ,but the variations in these intervals between the wave are difficult to discover [5].Secondly, the process of ECG analysis in those methods takes long time which makes such methods not suitable for real time classification systems [3].

Generally the classification methods could be divided into three groups of systems: a) systems that record signals and perform classification off-line; b) systems that perform remote real-time classification and; c) systems that provide local real-time classification. For the last ones, we differentiate them taking into account the level of mobility.

The objective of this research is to drive the best technique from existing classification techniques in data mining to build accurate classifier so as to work on real-time effectively and efficient for classifying cardiac arrhythmias based on ECG signal matching Using DTW. Our goal behind this research is to use Signal matching instead of features extraction for classifying arrhythmias to avoid miss detection features, reduce error rates, learning time and increase the accuracy of classification for cardiac arrhythmias.

3. Related Work

There has been much works in the field of ECG classification and most works have been based on neural networks, markov chain model and support vector machine (SVM). The datasets used to train these methods are often small. In 2004, tsipoura proposed method for classifying arrhythmias based on RR-intervals used by the rules that were determined by the medical doctors [5].

Even though this method has high performance and easy to understand but has many problems such as time consuming, doesn't classify all cardiac arrhythmias. In 2005 yu hen hu and ramaswamy proposed methods for classifying arrhythmias. Those methods used artificial neural networks for classifying arrhythmias based on features extraction [6], [7] and they work very well in classification if and only if they are trained very well. The disadvantages of those methods, the time of training for neural networks and training dataset were small, ECG noises and they need adaptation of thresholds of weights. In 2004, Philip proposed method for classifying heart beats automatically using ECG morphology and heart beat interval features [8]. It classifies the heart beats automatically but it used static window size which produces some errors in heart beats which reduce the performance of the algorithm and generates errors which affect the measurement of RR-intervals. In 2000, p.de chazal used wavelet coefficient for classification ECG [9]. The performance of the wavelet was accurate comparing to other methods but it suffers from many problems such as consuming time, static window size and it depends on nominal features that make the analysis and classification very difficult. In 2007, iske classified the ECG signal by extracting the features in time domain and frequency domain and then he used support vector machine (SVM)[10].The problem in this method , SVM maps input vectors to the high dimensional space and makes a problem in ECG analysis because if the dimensional space is high the error rate will be high. Other disadvantage in SVM, it needs intervention from user to adapt the parameters of optimal model. In 2007, anversyeda tried to classify the ECG based on signal matching similarity [11].The problems of this method; it obtained the input as images and then converted into digital from hard copy of ECG paper which influenced on accuracy of the results, mismatching and time consuming. One of the main problems in ECG analysis is the window size [2] which decreases the accuracy.

All the methods that were mentioned above section are offline systems for classifying cardiac arrhythmias. The medical doctors found that offline systems don't work as they expected in emergence hospitals because the patients who have dangerous arrhythmias cardiac couldn't wait long time and die very quickly and the offline systems always delay in detecting the cardiac arrhythmia[4,5,6 and 7]..

In order to solve and avoid the problems in offline systems, they are many methods that have been developed to classify the cardiac arrhythmias using machine learning techniques based on features extraction on real time by using PDAs or embedded devices that could be carried by patients to monitor their rhythms on long time under different conditions. In 2004, jimena tried to drive approach that can build most accurate model for classifying cardiac arrhythmias based on features extraction using PDAs [12]. His work used many features from ECG signal such as P,QRS ,T , PR and QT intervals , the size of the P,QRS complex and T waves and the frequency of them and also ST and PQ segments as shown in Figure 1. Also he used ECGPUWAVE tool to extract the wave events of ECG signal beside built automata that divides the signal into sequence of beats. then he divided the dataset into random groups one training (66%) and another for validation(33%).The training dataset were used as input data for choosing the tool and method to build up the classification model. The data in second group were used to validate model. He used weka and answertree tool in his experimental results. 16 methods were used in the experiments as shown in table 1.

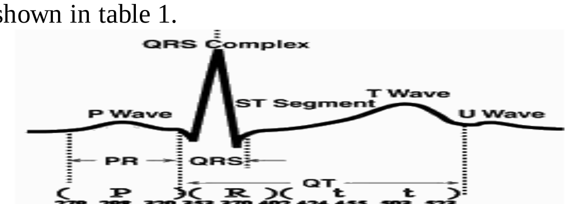

Figure 1.parts of beat

Table 1: List of experimental results of classification arrhythmias using features extraction.

Tool	Method	Algorithm based on	Validation	CPU Time
Weka	j48.Part	C4.5(decision trees)	92.73 %	8m 11s
Weka	IB1	nearest neighbor classifier	92.26 %	12m
Weka	NeuralNetwork	uses backpropagation	91.61 %	2h 10m
Weka	LogitBoost	for boosting any classifier	91.53 %	8m 20s
Weka	kstart.KStart	entropic distance measure	90.59 %	50m
Weka	KernelDensity	kernel density classifier	90.54 %	7m 43s
Weka	DecisionTable	decision table	90.51 %	3m 28s
AnswerTree	DecisionTree	decision tree	89.05 %	4m
Weka	OneR	1R	83.86 %	3s
Weka	NaiveBayes	Bayesian classifier	70.12 %	5s
Weka	DecisionStump	decision stump	67.55 %	4s
Weka	AdaBoostM1	Boosting a classifier	59.52 %	1s
Weka	Bagging	bagging a classifier	59.52 %	1s
Weka	ZeroR	using a 0-R classifier	59.52 %	1s
Weka	VFI	Voting feature interval	49.92 %	1s
Weka	HyperPipes	hyperPiper classifier	15.16 %	1s

His result proved that decision trees (C4.5) had better performance than other methods. Even though it drives the best techniques from existing techniques which has high accuracy for classifying cardiac arrhythmias based on features extraction but it suffers from time consuming, battery life, CPU time and computing process which are very heavy for PDAs capacity.

In 2005, thara used machine learning techniques for classifying arrhythmias specially tachycardia automatically using ECG signal [13]. The objective of this work was to drive a classification approach which can be encoded as embedded software. The work evaluated three standard machine algorithms OneR, J45 and naïve bayes applied to classify cardiac arrhythmias. He evaluated those algorithms based on accuracy and Learning Time shown in table 1.

This work reported that three machine learning methods were applied on the task of classifying arrhythmia and most accurate learning methods were evaluated. Experiments were conducted on the cardiac arrhythmias in fully automatic manner using machine learning algorithms. Its experiments proved that OneR and naïve bayes have the most stable accuracy rate. This is not true for decision trees (J45).The advantages of this work are to drives approach that could build model for classifying tachycardia with high accuracy using embedded devices in order to reduce power consuming.

But the disadvantages of this work, its dataset contains miss values and has 279 attributes, 206 attributes are linear values and the rest are nominal which make the analysis of ECG dataset is very complicated. Because the ECG analysis based on features extraction suffers from problems in different levels of processing such as errors that produced by algorithms of detecting features, classification techniques and errors that produced by algorithms of features selection that beside the ECG noises and window size. All those errors make variation in the results between the ECG analysis as shown in the methods [12] and [13] in classifying arrhythmias.

In order to avoid the problems that mentioned in the above section we are suggesting a frame work based on ECG signal matching for classifying cardiac arrhythmias using DTW similarities.

4. Our Frame Work

In this paper, we are going to classify cardiac arrhythmias based on signal matching using DTW and existing classification techniques in data mining to drive best technique that could build classification model which gains high accuracy when applied on real time applications without any consuming time.

Our goal is to use signal matching instead of feature extractions is to decrease the learning time and increase the accuracy of classifying cardiac arrhythmias.

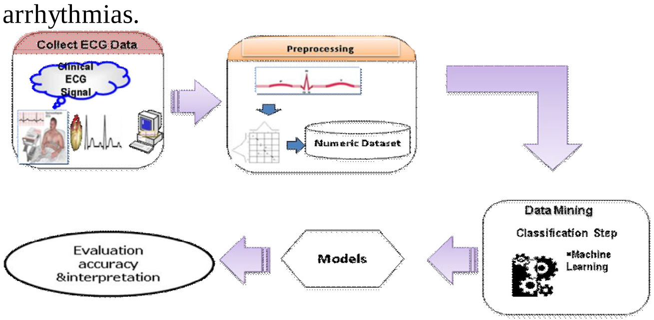

Figure 2. Frame work steps.

In order to Collect ECG signals from human bodies we usually use the leads. The standard ECG is composed of 12 leads, six limb leads are recorded by using arm and leg electrodes, and other six chest leads are recorded using electrodes at six different positions on chest. Now days there are many resources for ECG data such as physionet [14], Framingham Heart Study [15], Risk Assessment Tool [16]. In our framework, we are going to use MIT-BIH Arrhythmia Database. Our frame work is consisted from two steps, preprocessing step and classification step as shown in figure 2.

5. Preprocessing step

The goal of this step is to convert the ECG in suitable format in order to be used in classification step. Most of Previous works was using features for classifying heart arrhythmia beats. In order to use signal matching, we need first to determine the window size for reading heart beats accurately from ECG signal based on the heart rate variability to make the window size dynamic.

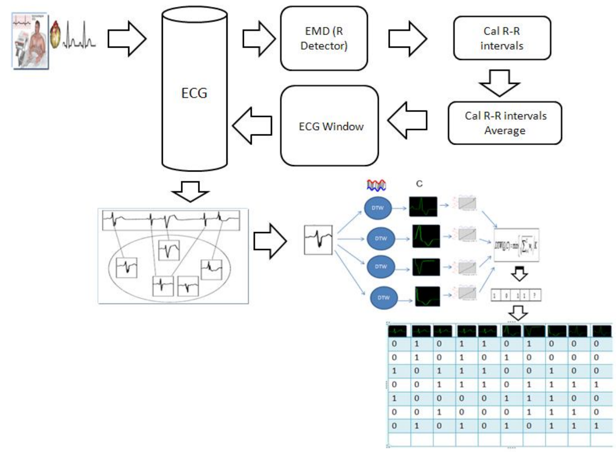

Figure 3. Preprocessing steps in our frame work.

The following steps explain the determination of the window size from the heart rate variability. First step we detect R wave in order to calculate the heart rate variability using empirical mode decomposition (EMD) [17].

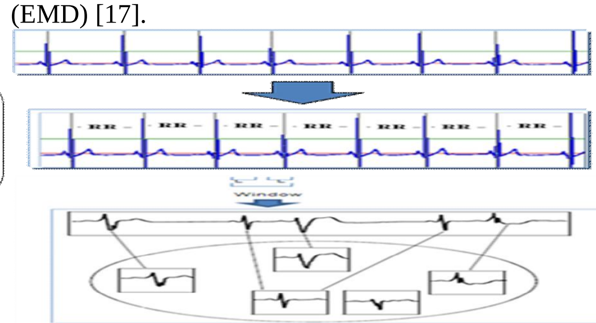

Figure 4. Steps of determining window size.

After detecting the R waves, we need to measure the time interval between successive R waves as it is shown in figure 4. In order to find the window size from heart rate variability, we calculate the mean of R-R intervals using the following Equations:

$$Mean(RR) = \sum_{i=0}^{n} (RR) / N - 1 \quad (1)$$

$$L = Mean(RR)/2 \quad (2)$$

$$WindowSize = [L(ms) + Rwave + L(ms)] \quad (3)$$

After calculating the mean of RR- intervals, we calculate the window size by dividing the mean of RR-intervals into half as shown in equation 2. The window size will be taken for every beat L milliseconds before every R wave and L milliseconds after the R wave as shown in equation 3.After that, we determine the ECG templates of shapes. We extracted specific patterns for specific heart arrhythmias specifically premature ventricular contraction (PVCs) and normal patterns or normal beats (N). Every heart cardiac arrhythmia makes specific shape on ECG that changes the amplitude of ECG signal on ECG paper as shown in figure 5.

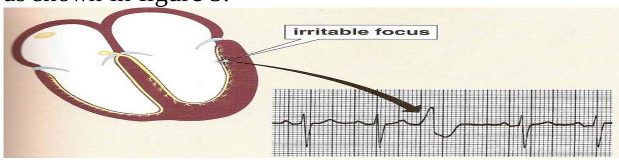

Figure 5. PVC arrhythmia changes the normal shape.

PVC originates suddenly in irritable ventricular automaticity focus and produces again and shapes ventricular on EKG.

The PVCs occur early on the cycle easily recognized by great width and enormous amplitude (high and depth), they are usually opposite to the polarity of the normal QRS as shown in fig 5. We extracted manually different templates from real ECG signal and from phyionet dataset for PVCs and N beats as shown in figure 6.

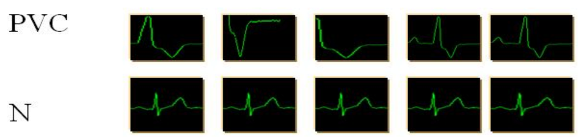

Figure 6. Extraction template shapes of PVCs and N beats from ECG signal.

When the heart beat is road from ECG signal, it is going to be matched with all the shapes that were extracted for PVC and N beats. To find the similarity between the template shapes and heart beat. We use DTW algorithm which was explained in [18][19] to find the similarity between two signals (time series) that should be computed by aligning significant patterns as shown in figure 7.

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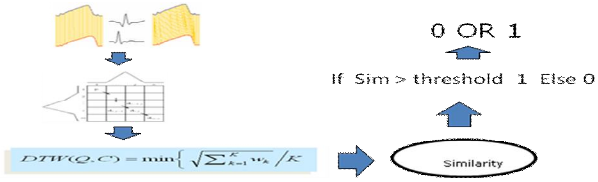


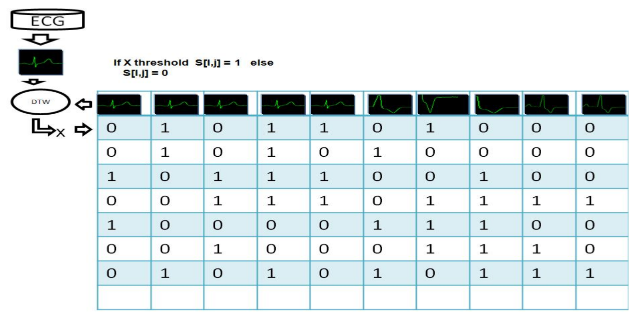
Figure 7. Steps for finding the similarity between two ECG signals.

Our frame work tries to find the similarities between all the templates and every heart beat. Those similarities equal to the number of ECG templates that were extracted. In order to avoid consuming time in calculating similarities using DTW, we use recursive function which gives us the minimum cost path as it shown in equation 4:

$$\gamma(x, y) = d(q_i, c_i) + \min(\gamma i\, i-1, j-1), \gamma(i-1, j), \gamma\gamma i\, j-1)) \quad (4)$$

Where q, c are ECG signals.

To avoid the fuzziness in the similarities, we normalize the similarities into zero or one values based on threshold value which is determined 0.06. After normalizing step, we put the similarity values into numeric dataset which is considered as input for classification step as shown in figure 8.



0	1	0	1	1	0	1	0	0	0
0	1	0	1	0	1	0	0	0	0
1	0	1	1	1	0	0	1	0	0
0	0	1	1	1	0	1	1	1	1
1	0	0	0	0	1	1	1	0	0
0	0	1	0	0	0	1	1	1	0
0	1	0	1	0	1	0	1	1	1

Figure 8. Output dataset from preprocessing step.

6. Classification Step

The goal of this step is to apply the classification techniques and generate models .the best model will be selected based on the accuracy, learning time.

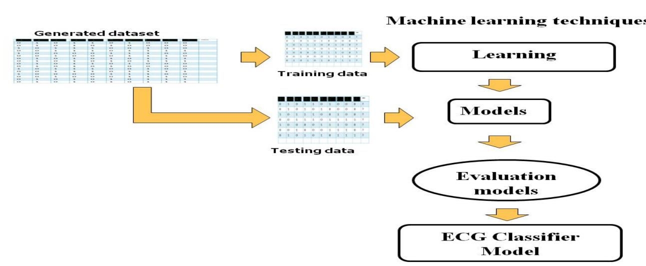


Figure 9. Classification steps.

In this paper, we selected four standard machine learning algorithms applied to classify cardiac arrhythmias such like decision tree (DT), bayes naïve (BN) classifier, support vector machine (SVM) and artificial neural network (ANN). We divide the generated dataset into training dataset and testing dataset under different percentages of splitting as shown in figure 9.

7. Experiment Results

The hardware platform under which we have conducted the experiments consists of one computer with CPU 2.80 GHZ, RAM 1.0 GIGA, HD 80 GIGA and operating system windowXP service pack2. In preprocessing step, we wrote program using Microsoft visual studio C++/C and open graphical language (openGL) to visualize and match the ECG signal beats with ECG templates using DTW. We used Cygwin environment tool and physionet toolkit for accessing MIT-BIH Arrhythmia Database. We used Clementine 12.0 tool which provides methods and algorithms for the classification step.

We selected three datasets from MIT-BIH Arrhythmia Database 100, 200 and 222 [14] and entered them with ECG templates of PVCs and N rhythms our C program that visualizes and calculate the similarities dataset for every ECG dataset individually by using DTW as shown in figure 8.

The original datasets were chosen such like 100,200 and 222 and partitioned i manually into percentages of 50%50, 70%30, 80%20% and 66% 33% disjoint sets: training set and testing set. The training set was used to train the models that were generated by algorithms. The methods that used in classification steps were DT, SVM, BN and ANN.

Every generated dataset which contains 20 attributes.

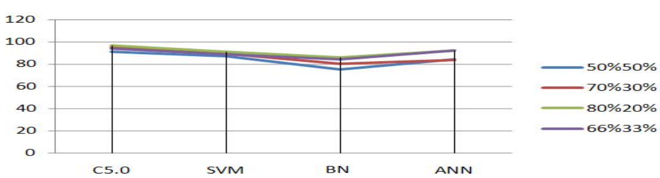


Figure 10. The accuracy of classification methods using dataset 100.

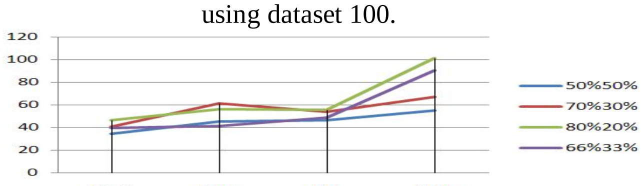


Figure 11. The learning time of classification methods using dataset 100.

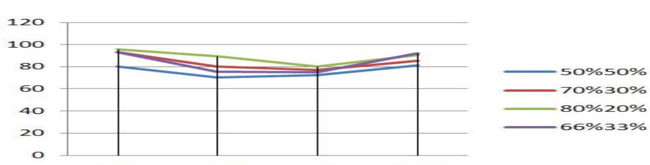


Figure 12. The accuracy of classification methods using dataset 200.

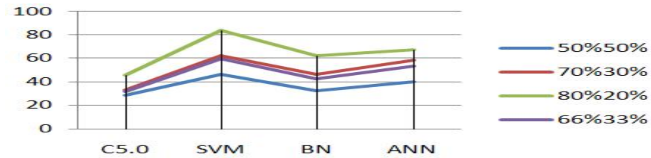


Figure 13. The learning time of classification methods using dataset 200.

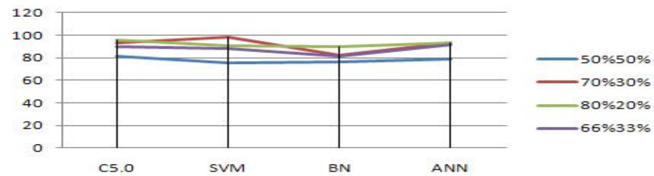


Figure 14. The accuracy of classification methods using dataset 222 .

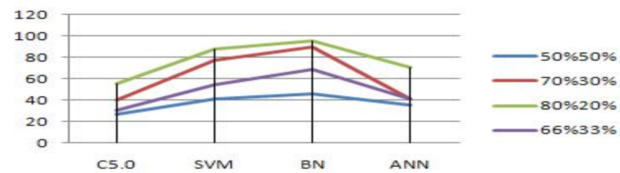


Figure 15. The learning time of classification methods using dataset 222.

Our experimental results proved that decision tree classifier (C5.0) has high accuracy comparing to SVM, NB, ANN as shown in figures 10 and 12.

And also it has less learning time as shown in figures 11, 13 and 15.

Also our experimental results proved that ANN has better accuracy than decision trees classifier (C5.0) when the ECG dataset contains noise as shown in figure 14. But the learning for decision trees classifier (C5.0) is still better than ANN as shown in figure 15.

We compared our experimental results with related Works [12] and [13] and we found that our Classification arrhythmias using ECG Signal matching is better than classification arrhythmia using Features extractions [12,13] as it is shown in figure 16.

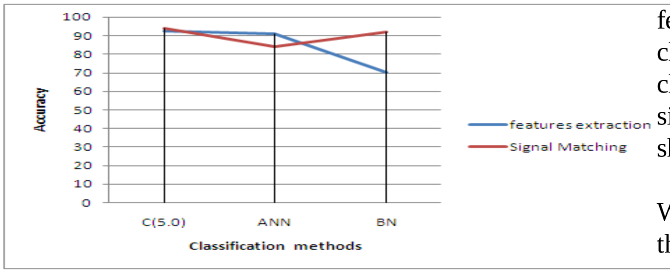


Figure 16. Accuracy comparison between features extraction and Signal Matching shapes using dataset 100.

Figure 16 shows the accuracy comparisons of classifying cardiac arrhythmias between features extraction and signal matching.We observe that decision tree(C5.0) and bayes naïve(BN) classifiers in signal matching have better results than decision tree and bayes naïve classifiers in features extraction. This is not true for artificial neural network (ANN).

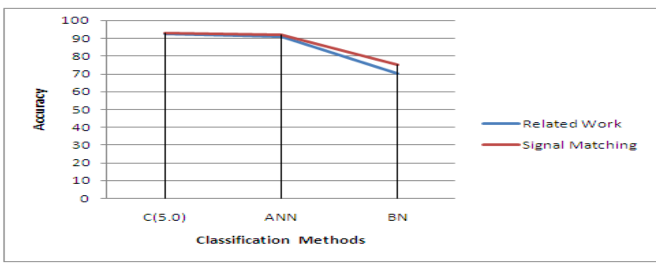


Figure 17. Accuracy comparison between features extraction and Signal Matching shapes using dataset 200.

Our experimental results using dataset 200 proved that decision trees classifier (C5.0), artificial neural network (ANN) and bayes naïve classifiers have better results in signal matching than features extraction as shown in figure 17.

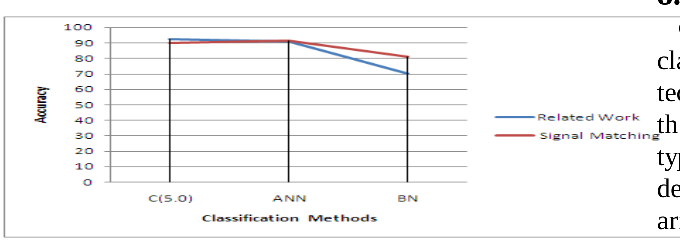


Figure 18. Accuracy comparison between features extraction and Signal Matching shapes using dataset 222.

Our experimental results by using dataset 222 which contains noise proved that decision trees (C5.0) has less accuracy in signal matching than the accuracy in features extraction and opposite to bayes naïve classifier (BN). In the artificial neural network classifier (ANN), we observed its results are very similar in features extraction and signal matching as shown in figure 18.

We summarized that our experimental results proved that:

1)Classification arrhythmia using classification techniques in data mining based on Signal Matching have better results than classification arrhythmia using features extraction as shown in figures 16, 17 and 18.
2) Decision trees is the best technique comparing to other for building classifier that could be used to classify cardiac arrhythmia when the dataset doesn't contain more noise as shown in figures 16 and 17.
3)Proved that training dataset size could effect the accuracy and learning time. We noticed that when the training dataset increased, it is going to increase the learning time in SVM, BN, ANN, and decrease the error rates of those techniques and we observe that decision tree technique has lower learning time and high accuracy compare to other.
4)Our experimental results agreed to JIMANA [12] which also proved that decision trees method is more suitable method that could be used to build classifier for classifying arrhythmia based on features extraction. But JIMANA [12] didn't take the ECG noise factor into account and our experimental results agreed [12] when the dataset is not affected by the noise.
5)Our experimental results also proved that ANN neural network has better accuracy than decision trees (C5.0) when the ECG signal has more noise as shown in figure 18.

8. Conclusion

Classifiers that perform a complete ECG classification on real time using machine learning techniques for patients are of great interest because they allow reducing the risks of the human life.Those types of classifiers could be embedded on small devices such as mobiles, PDAs for classifying cardiac arrhythmias without any time consuming.
In this paper, we developed framework for driving best technique from machine learning techniques in order to build a complete ECG classifier that based on ECG signal matching. We selected four standard methods decision trees, support vector machine, naïve bayes and artificial neural network. We evaluated them using three datasets from MIT-BIH Arrhythmia

Database based on signal matching using DTW for classifying arrhythmias specifically PVC and N rhythms. The obtained results for those methods proved that decision trees classifier is best technique that could be used for classifying on real time without any consuming time based on signal matching. In the particular, decision trees method provides a very good accuracy for classifying arrhythmias.
As future work, we plan to solve the memory problem and increase the number of arrhythmias and improve the accuracy of system applied for monitoring the heart health in real time

9. Acknowledgement

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