Classification of Cardiac Arrhythmia using ID3 Classifier Based on Wavelet Transform

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Abstract

Accurate detection of Electro Cardio Graphic (ECG) features is an important demand for medical purposes, therefore an accurate algorithm is required to detect these features. This paper proposes an approach to classify the cardiac arrhythmia from a normal ECG signal based on wavelet decomposition and ID3 classification algorithm. First, ECG signals are denoised using the Discrete Wavelet Transform (DWT) and the second step is extract the ECG features from the processed signal. Interactive Dichotomizer 3 (ID3) algorithm is applied to classify the different arrhythmias including normal case. Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) Arrhythmia Database is used to evaluate the ID3 algorithm. The experimental result shows that the accuracy of ID3 is 92% in the case of Haar transform and 94% with Daubeshies4 transform.

Keywords: ECG classification, Discrete Wavelet transform (DWT), ID3.

تصنيف الاضطرابات القلبية بأستخدام المصنف ID3 وتحليل المويجة

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الخلاصة:

في الاغراض الطبية يكون الكشف الدقيق لخصائص الاشارة القلبية (ECG) مطلبا مهما لذلك نحتاج الى خوارزمية دقيقة لكشف تلك الخواص. في هذا البحث، في هذا البحث تم اقتراح نهج لكشف وتصنيف الاضطرابات القلبية بالاعتماد على تحليل المويجات. في الخطوة الاولى تم تقليل الضوضاء في الاشارة بأستخدام تحليل المويجات المتقطع (DWT) وفي الخطوة الثانية تم استخلاص الخصائص من الاشارة القلبية ثم طبقنا خوارزمية ID3 لتصنيف مختلف الاضطرابات القلبية مع الحالة الطبيعية للقلب. لتعليم واختبار الخوارزمية تمت الاستفادة من قاعدة البيانات MIT–BIH وللحصول على الاشارات الخاصة بالاضطرابات القلبية. ان النتائج العملية تبين ان دقة تصنيف الخوارزمية هو 92% عند استخدام تحويل Harr و94% بأستخدام تحويل Duabechies4.

1. Introduction

ECG stands for electrocardiogram: electro = electrical; cardio = heart; gram = recording[1]. The ECG is the recording of the heart's electric activity of depolarization and repolarization of the atrial and ventricular chambers of the heart. Depolarization is the sudden influx of cations when the membrane becomes permeable, and repolarization is the recovery phase of the ion concentrations returning to normal. A single normal cycle of the ECG represents the successive atrial depolarisation/repolarisation and ventricular depolarisation/repolarisation which occurs with every heart beat. These can

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be approximately associated with the peaks and troughs of the ECG waveform labelled P, Q, R, S and T [2]. Cardiac arrhythmia (also dysrhythmia) is a term for any of a large and heterogeneous group of conditions in which there is abnormal electrical activity in the heart. The heart beat may be too fast or too slow, and may be regular or irregular. Arrhythmia comes in varieties. It may be described as a flutter in chest or sometimes "racing heart". The diagnosis of Arrhythmia requires ECG. By studying ECG, doctors can diagnose the disease and prescribe the required medications [3]. This paper presents a classification approach based on Interactive Dichotomizer 3 (ID3).

The paper is organized as follows: Section 2 includes definition of ECG signals and describes each wave within the signal, section 3 includes works related to this paper the Section 4 contains an overview of the wavelet transform and the type of wavelet family. Section 5 illustrates the ID3 algorithm, while section 6 presents the proposed approach. Finally, sections 7, 8 and 9 demonstrate the performance measure and conclusion respectively.

2. ECG Signals

ECG is a nearly periodic signal that reflects the activity of the heart and gives important information of the health, and this information helps to diagnosis many heart diseases [4]. However, the ECG signals being non-stationary in nature, it is very difficult to visually analyze them. Thus the need is there for computer based methods for ECG signal analysis[3]. Any disorder of heart rate or rhythm, or change in the morphological pattern, is an indication of cardiac arrhythmia, which could be detected by analysis of the recorded ECG waveform. The ECG has components and different waves represent a normal signal of ECG, these components has been described in Figure (1).

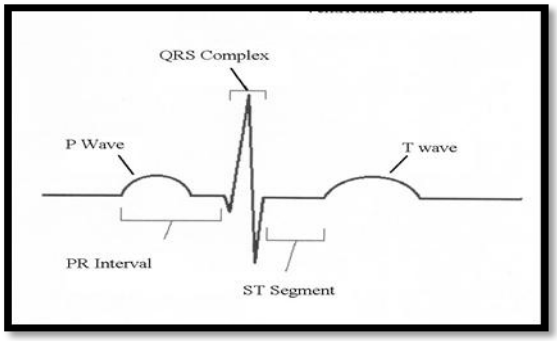

Figure 1- Normal ECG Signal and its various Components

The impulses of the heart are recorded as waves called P-QRS-T deflections.

The following is the description and significance of each deflection and segment:

P wave indicates atrial depolarization (and contraction).

PR Interval measures time during which a depolarization wave travels from the atria to the ventricles[5].

QRS Interval includes three deflections following P wave which indicates ventricular depolarization (and contraction).

Q wave is the first negative deflection while R wave is the first positive deflection.

S wave indicates the first negative deflection after R wave [3].

ST Segment measures the time between ventricular depolarization and beginning of repolarization.

T wave represents ventricular repolarization [5].

3. Related Work

Faiza Charfi and Ali Kraiem, 2012, [6] adopted a wavelet transform to extract the ECG signals wavelet coefficients as first features and utilize the combination of Principal Component Analysis (PCA) and Fast Independent Component Analysis (FastICA) to transform the first features into uncorrelated and mutually independent new features. Then use these features as inputs to C4.5 algorithm which is some decision tree methods to classify ECG signals. The MIT-BIH database that includes normal subjects and subjects is used. The results suggest the high reliability and high classification accuracy of C4.5 algorithm with the bootstrap aggregation.

P.D.Khandait., Nagpur and S.S.Limaye, 2012, [7] choose Daubechies4 (Db4) Wavelet for extracting ECG features. The main advantage of this kind of detection is less time consumption for long time ECG signal. Testing classification accuracy of 98.17% is achieved which is a promising result.

Vanisree K and Jyothi Singaraju, 2011, [8] removes Baseline Drift (De-trending) and noise (De-noising) from the signal. The proposed algorithm can be used to automatically detect R-peaks and R-R interval of ECG signals which reduces the time and increases the accuracy. Thus the performance of the proposed system is increased.

Sina Zarei Mahmoodabadi, Alireza Ahmadian, Mohammadjavad Abolhasani, Paul Babyn and Javad Alirezaie, 2010, [9] use beat locations to locate the peaks of the individual

waves present in each cardiac cycle. They are considered as ECG features. After feature extraction process, a fuzzy classifier is utilized for arrhythmia detection. The beat and arrhythmia detection algorithms present precision of over 99.8% for wavelet based methods.

4. The Wavelet Transform

Wavelet Transform is a time-frequency analyzing method that the window of time and the window of frequency can change, which uses the multi-resolution feature to extract original signals from signals mixed with the noise interference, and it is known as the "microscope" of signal analysis. One of the advantages of the Wavelet Transform is that it is able to decompose signals at various resolutions, which allows accurate feature extraction from non-stationary signals like ECG. Wavelet Transform has been used widely to process signals and images [10]. Wavelets are functions defined over a finite interval and having an average value of zero. The basic idea of the wavelet transform is to represent any arbitrary function of time as a superposition of a set of such wavelets or basis functions. These basis functions or baby wavelets are obtained from a single function ψ called the mother wavelet, by dilation (scaling) factor **a** and the translation (shifts) factor **b** as formulated in equation(1) [7][11][12]:

$$\psi_{a,b}(x) = |a|^{-1/2} \psi\left(\frac{x-b}{a}\right) \quad \ldots\ldots\ldots\ldots (1)$$

4.1 The Discrete Wavelet Transform (DWT)

The discrete wavelet transform (DWT) of a signal **x** is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response **g** resulting in a convolution of the two as shown in equation (2):

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k].g[.n-k] \quad \ldots. (2)$$

The signal is also decomposed simultaneously using a high-pass filter **h**. The outputs giving the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). By using decimation process the filter outputs are then down sampled by 2, as shown in equations 3and 4 respectively:

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k].g[2.n-k] \quad \ldots\ldots (3)$$

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k].h[2.n-k] \quad \ldots\ldots (4)$$

This decomposition has halved the time resolution since only half of each filter output characterizes the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled[13]. As shown in Figure (2).

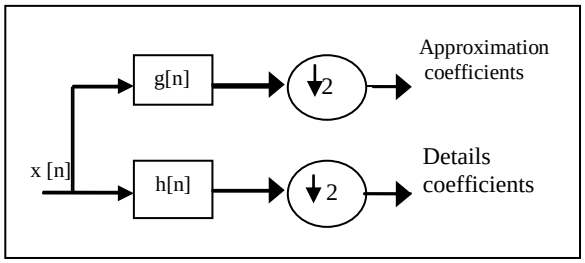

Figure 2- Block diagram of filter analysis

4.2 Wavelet Selection

The use of the Wavelet Transform has gained popularity in time-frequency analysis because of the flexibility it offers in analyzing basis functions. The selection of relevant wavelet is an important task before starting the detection procedure. The choice of wavelet depends upon the type of signal to be analyzed. There are several wavelet families like Harr, Daubechies, Biorthogonal, Coiflets, Symlets, Morlet, Mexican Hat, Meyer etc. However, Daubechies (Db4) Wavelet has been found to give details more accurately than others. Moreover, this Wavelet shows similarity with QRS complexes and energy spectrum is concentrated around low frequencies. Therefore, (Db4) Wavelet is chosen for extracting ECG features [10].

5. ID3 Algorithm

Decision-tree learning is one of the most successful learning algorithms, due to its various attractive features: simplicity, comprehensibility, no parameters, and being able to handle mixed-type data. In decision-tree learning, a decision tree is induced from a set of labeled training instances represented by a tuple of attribute values and a class label [14]. The basic idea of ID3 algorithm is to construct the decision tree by employing a top-down, greedy search through the given sets to test each attribute at every tree node. Information gain metric is used to select the attribute that is most useful for classifying a given sets. To find an optimal way to classify a learning set, what we need to do is to minimize the questions asked (i.e. minimizing the depth of the tree). Thus, we

need some function which can measure which questions provide the most balanced splitting. The information gain metric is such a function.

5.1 Entropy

ID3 algorithm uses entropy to calculate the homogeneity of a sample or characterizes the impurity of an arbitrary collection of examples. If the sample is completely homogeneous the entropy is zero and if the sample is an equally divided it has entropy of one. Equation (5) calculates the entropy for dataset.

$$Entropy(S) = \sum_{i=1}^{C} -P_i \log_2 P_i \quad \ldots (5)$$

Where, S is a collection of samples represents the training dataset, c is the classes number contained in the dataset, while P_i represents the proportion of S belonging to class i [15].

5.2 Information Gain

Measuring the expected reduction in Entropy to minimize the decision tree depth, when we traverse the tree path, we need to select the optimal attribute for splitting the tree node, which we can easily imply that the attribute with the most entropy reduction is the best choice. We define information gain as the expected reduction of entropy related to specified attribute when splitting a decision tree node.

$$Gain(S, A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v) \cdots \quad (6)$$

Where,

Values(A) : is the set of all possible values for attribute *A.*

S_v : is the subset of *S* for which attribute *A* has value *v.*

$Entropy(S)$: is the entropy of the original collection *S.*

$\sum_{v \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v)$: is the expected value of the entropy after *S* is partitioned using attribute *A.*

6. The Proposed Cardiac Arrhythmia Classifier

In this section a proposed classification of cardiac arrhythmia based wavelet transform will be given. As shown in Figure (3) the system consists of three main blocks. The first stage take several cardiac signals of length 5 second (1800 sample), and a zero-padding which is a simple scheme based on signal extension on the boundaries used to get enough samples to compute the output corresponding to the data points near the boundaries. The second stage includes computation of the one dimensional wavelet transform of all input ECG signals once using Haar filter and again using Daubechies4 filter to extract a vector of five features of selected signal.

The third stage uses the vectors of features resulted from the second stage and represent them in the form of nominal values within a nominalization sub stage and then use this data as training inputs for ID3 algorithm to produce a decision tree (classifier). Then convert this classifier to a set of rules which it is used to classify five types of ECG arrhythmias including normal case: Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Premature Ventricular Contraction (PVC), Paced beats, Normal case a. Figure (3) describes the block diagram of the Proposed Cardiac Arrhythmia Classifier. The following subsections clarify each stage in details.

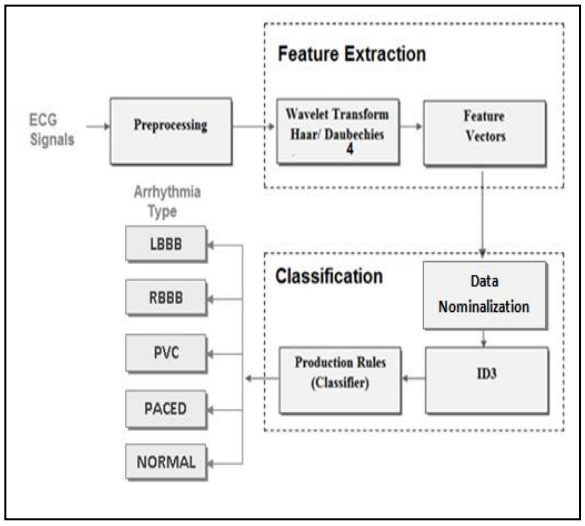

Figure 3- The Proposed Cardiac Arrhythmia Classifier

6.1. Feature Extraction.

The original ECG signals are one dimensional array and they are large and redundant as features, the features is being extracted from the preprocessed ECG signals using methods described as follow:

A. Detecting R Peaks in the Down Sampled Signal

First, find the values which are greater than 60% of the maximum value of the down sampled signal (or 14% in case of paced arrhythmia signal). Invariably these are R peaks. As the decomposed signals are noise free signals, first R peak needs to be detected in the noise free signal. The sample locations in

original signal are different than the decomposed signal. So the strategy here will be first to detect the R peaks in the down sampled signal and then cross verify those points in the actual signal. Detection of R-Peaks in the down sampled signal processed in algorithm (1).

Algorithm (1) detect R-Peaks in the down sampled signal

Input*: Y , R_Threshold* *// Y* array of down sampled signal *//*
Output*: P1* *// P1* array of R-Peak locations in *Y//*
Begin*:*
let *P*, *P1* arrays of integers.
let *MaxValue* = maximum value of *Y.*
let *m1 = MaxValue – MaxValue*R_Threshold.*
Find all values in *Y* that are greater than or equal to *m1* and store their locations in *P.*
//start to remove points that are too close in *P* //
P1=null
j=0
last=P[0]
P1[j]=last
For *i* = 1 ***to*** length(*P*)-1 ***do***
If *P*[*i*] > *last*+10 ***Then***
last=P[i]
j= j+1
P1[j]=last
EndIf
EndFor
Return *P1* *// P1* is the R-Peaks positions in the 2nd level decomposition signal //
End

B. Detecting R Peaks in the Original Signal

To search for the position of all the locations in the original signal to the approximation coefficient of the second level decomposed signal was adopted, therefore R-peaks in the down sampled signal is at least 1/4th of the actual R location of the same point. Therfore, the detected positions will be mapped to original signal by multiplying with 4. Down sampling process always deviate the signal positions. Therefore searching for the maximum value in the original signal will be needed in a window of ±20 samples from the reference R point obtained. Algorithm (2) describes the search strategy.

Algorithm (2) : R-Peak detection in the original signal

Input: *P1, WinFrom, WinTo, A* *//WinFrom=-20, WinTo=+20//*
Output: *RLoc* *//RLoc* an array of real R-Peaks locations//
Begin
//Map the detected locations to original Signal//
For *i*= 0 to Length(*P1*)-1 ***do***
*P2[i]=P1[i]**4
EndFor
// Search for the maximum value within each cardiac cycle of the original signal//
For *i*= 0 to Length(*P1*)-1 ***do*** // for each cardiac cycle//
Define and assign *Range* array to all indices in the original signal *A* bounded by the limits *P2[i]+WinFrom* to *P2[i]+WinTo* window.
Define and assign *aR* array to all values in the original signal *A* from the location *P2[i]+WinFrom* to location *P2[i]+WinTo.*
Find the maximum value of *aR* array and store its index to *idx*.
Range[idx] is the real location of R-Peak of *ith* cardiac cycle.
Store the location of R-Peak of the *ith* cardiac cycle into the *RLoc* array.
EndFor
Return *Rloc*
End

Figure 4- shows the R-Peaks in the original signal after applying the R-Peak detection algorithm.

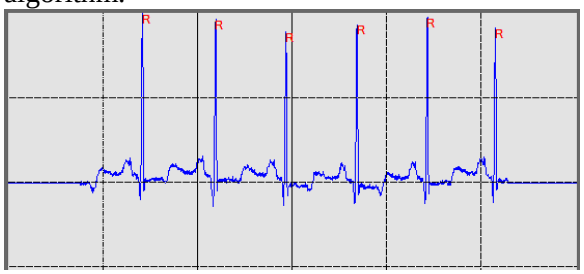

Figure 4- R-Peaks in the original signal

Algorithm (3) : P-Peak detection in the original ECG signal

Input: *RLoc , WinFrom, WinTo, A* // *WinFrom=-100, WinTo=-10//*
Output: *PLoc* //*PLoc* array of P-Peaks locations//
Begin:
// Search for the maximum value within the region which is located before R-Peaks //
For *i*= 0 to Length(*RLoc*)-1 **do** //for each cardiac cycle //
Define and assign *aP* array to all indices in the original array signal *A* bounded by the limits *RLoc[i] + WinFrom* to *RLoc[i] + WinTo*.
Define and assign *TP* array to all values in the original signal *A* from the location *RLoc[i] +WinFrom* to
location *RLoc[i]+WinTo*.
Find the maximum value of *TP* array and store its index to *idx*.
aP[idx] is the location of P-Peak of *ith* cardiac cycle.
Store the location of P-Peak into the *PLoc* array
EndFor
Return *PLoc*
End

The Q, S and T peaks can be found in the same way of detecting P Peaks. Figure (5) shows P, Q, R, S, T peaks in the original ECG signal after applying the detections algorithms.

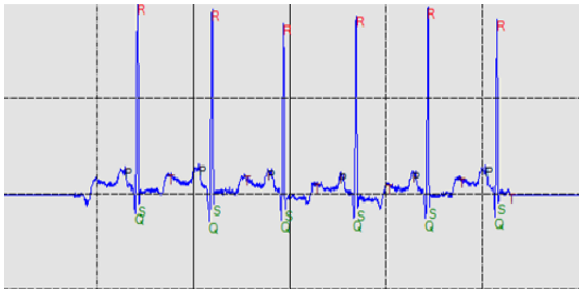

Figure 5- P, Q, R,S and T peaks

6.2 The Five Features Vector

After detection the five peaks as explained in the previous sections (see Figure 6). A five features are selected from five peaks (R, P,Q, S, T) to represent the ECG signal. These features are formulated as shown in equations (7, 8, 9, 10 and 11):

C. Detecting P, Q, S and T Peaks

From R-Peak previously obtained, traverse Forth and Back and search for minima and maxima, these are P, Q, T, S peaks respectively. Algorithm (3) shows the method to detect the P-Peaks within each cardiac cycle.

$$D_{PR} = \frac{\sum_{i=1}^{n}((Offset(Ri) - Offset(Pi))}{n * fs} \quad \ldots. (7)$$

$$D_{QRS} = \frac{\sum_{i=1}^{n}((Offset(Si) - Offset(Qi))}{n * fs} \quad \ldots\ldots. (8)$$

$$A_{QS} = Max((Amplitude(Si+1) + Amplitude(Qi+1)) - (Amplitude(Si) + Amplitude(Qi))) \quad (9)$$

$$A_{RS} = \frac{\sum_{i=1}^{n}(Amplitude(Ri) + Amplitude(Si))}{n} \quad \ldots(10)$$

$$A_{RT} = \frac{\sum_{i=1}^{n}(Amplitude(Ri) - Amplitude(Ti))}{n} \quad .(11)$$

Where
R_i,P_i,Q_i,S_i,and T_i are the peaks of the *ith* ECG cycle.
$Offset(Xi)$ denotes to position of Xi peak of *ith* ECG cycle.
fs is the sampling frequency , equal 360 HZ. D_{PR} is the average of PR intervals. D_{QRS} is the average of QRS durations. A_{QS} is the maximum QS amplitudes between each two successive ECG cycles. A_{RS} is the average of RS amplitudes. A_{RT} is the average of RT amplitudes.

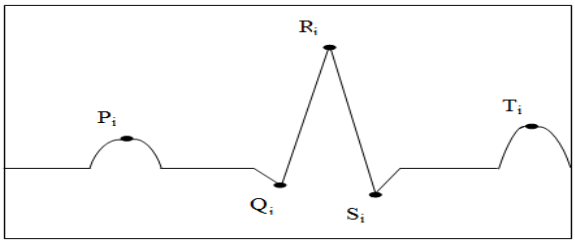

Figure 6- The Detected P, Q, R, S, and T points in ECG Signal.

6.3 Classification Stage

After obtaining the real values of five features it should be described as nominal values and arranged in a structured database comprised of attribute-value pairs; each row of the database is a sample and each column is an attribute taking on different values. One of the attributes in the database is designated as the class attribute; the set of possible values for this attribute is the classes which represent the ECG arrhythmias being classified. We wish to predict the class of a sample by viewing only the non-class attributes. This can be used to predict the class of new samples for which the class is unknown.

In this dataset, there are six categorical attributes using D_{PR}, D_{QRS} , A_{QS}, A_{RS}, A_{RT} and Arrhythmia class attribute, these attributes are the input of the ID3 algorithm to learn and produce the decision tree which will enable us to recognize the arrhythmia class of the new samples, the arrhythmia class can be one of these five ECG cases LBBB, RBBB, PVC, PACED and NORMAL. Algorithm (4) is used to build the decision tree to classify the five ECG cases.

Algorithm (4) : The ID3 Algorithm for Decision Tree Learning

Input: ***Examples*** *// training data set //*
,Target_attribute *is the attribute whose value is to be predicted by the tree.*
,Attributes *is a list of other attributes that may be tested by the learned decision tree.*
Output: *decision tree that correctly classifies the given* ***Examples.***
Begin:
Create a ***Root*** node for the tree.
If *all* ***Examples*** have the same value of the target attribute, **Return** the single node tree ***Root*** with label =
the value of target attribute.
If ***Attributes*** is empty, **Return** the single node tree ***Root*** with label = most common value of ***Target_attribute*** in ***Examples.***
Else
Begin
Let ***A*** **=** the attribute from ***Attributes*** that best classifies ***Examples.***
Let the decision attribute for ***Root = A.***
ForEach possible value, ***vi,*** of ***A***
Add a new tree branch below ***Root*** corresponding to the test ***A*** = ***vi.***
Let $Examples_{vi}$ be the subset of ***Examples*** that have value ***vi*** for ***A.***
If $Examples_{vi}$ is empty **Then**
Add a leaf node with label = most common value of ***Target_attribute*** in ***Examples*** to the new
branch.
Else
Add a subtree ***ID3(*** $Examples_{vi}$ ***, Target_attribute,Attributes*** *– {A})* below this new branch.
EndFor
End
Return ***Root***
End

This process above continues until the tree perfectly classifies the training examples, or until all attributes have been used [16].

7. Performance measure

The performance of the proposed ECG classifier is estimated statistically using classification elapsed time, classification accuracy and features extraction time measures.

1. Elapsed Time (*CEpTime*) measures the average classifier time.
2. Classification Accuracy (*Acc*) measures the overall performance over all classes of

arrhythmias. It is the ratio of correctly classified patterns to the total number of pattern classified.

$$Acc(\%) = \frac{T}{T+F} \times 100$$

Where,
T =Number of true arrhythmia detected.
F = Number of false arrhythmia detected.
3. The Feature Extraction Time (*FETime*) is the time elapsed for computing the five features of the selected ECG sample.
The performance using Haar and Daubechies4 transforms can be shown in Table 1- & figure 7.

The average of Feature Extraction Time (*FETime*) is estimated 750 ms using Haar while in Daubechies4 is estimated 660 ms.

Table 1- Classification Performance of the Proposed Cardiac Arrhythmia Classifier.

Class Type	No. of cases used in testing	Haar		Db4	
		Acc(%)	*CEpTime (ms)*	*Acc(%)*	*CEpTime (ms)*
LBBB	10	90%	0.00425	100%	0. 00528
RBBB	10	70%	0. 00402	90%	0. 00401
PVC	10	100%	0. 00485	100%	0.00460
Paced	10	100%	0. 00521	80%	0. 00367
Normal	10	100%	0.00441	100%	0.00430
Average		92%	0.0063	94%	0.0046

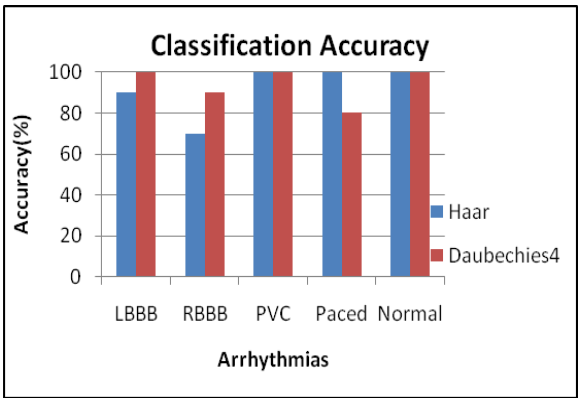

Figure 7- Classification Accuracy of the Proposed Cardiac Arrhythmia Classifier

8. Conclusion

The ECG signal can be used as a reliable indicator of heart diseases and the ID3 classifier is presented as the diagnostic tool to aid the physician in the analysis of cardiac abnormalities and it is helps in learning process. In the case of using Db4 transform the ID3 classifier concluded that three of the five extracted features can be used to classify the ECG arrhythmias. The two features (maximum QS amplitudes between each two successive ECG cycles, average of RT amplitudes) are redundant features in the case of Daubechies4 transform. Hence the ID3 with Daubechies4 help to reduce the features will be used in a classification process. The experimental result shows that the ID3 classifier achieves accuracy of 92% in the case of Haar transform and 94% with Daubeshies4 , the average of classification time is estimated 0.0063*ms* for Haar and 0.0046*ms* for Daubechies4 and the average of consuming time to extract features was 750 *ms* for Haar , while it is equal 660 *ms* by Daubechies4 transform. Hence the ID3 with Daubechies4 transform shows better results as compared with Haar transform.

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