ECG Signals Classification for Arrhythmia Detection using Machine Learning Technique

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Abstract

Arrhythmia is a condition of ectopic (abnormal) heartbeats, which occurs due to irregular pumping of heart. The timely detection of arrhythmia can help the cardiologist in making decision for providing medical aid to the patients. In this work, electrocardiogram (ECG) signal analysis has been done to classify abnormal which are also known as ectopic heart beats and the normal heart rhythms. Mainly ectopic beats are of two types as premature supraventricular (psvc) and premature ventricular contractions, arrhythmia is also a condition of ectopic (abnormal) heartbeats. ECG signals are the graphical plot of heartbeat. It consist of mainly three types of waves. P waves, QRS complex and T wave. Linear Discriminant Analysis (LDA) based classifier has been used to detect abnormality in heartbeat signals automatically, which gave in accuracy, senstivity and specificity of 98.57, 98.7 and 98.2 % respectively. The proposed method has been tested using benchmark dataset, namely MIT-BIH Arrhythmia Data. Finally, the comparison of results of proposed method has been done with existing state of art using same database.

Keywords

Arrhythmia detection, Ectopic beats, Electrocardiogram (ECG), MIT-BIH Arrhythmia Database

Introduction

Electrocardiogram (ECG) is a quick and painless method to record electrical activities if heart i.e. normal, abnormal, and irregular heart rhythms in the form of waves [1]. Abnormal heart rates are changes in a heart rhythm conduction that is otherwise normal. This alteration tends to be fast and too slow or irregular heartbeats [2-5]. There is no clear found reason for abnormal electrical heart rhythms origin. Major categories of ectopic beats are [6-7]; atrial fibrillation are irregular types of heart rhythms, leads to poor blood flow. Atrial flutter is the condition where the upper chambers (atria) of human heart beats rapidly. As initial automatic abnormal rhythmic sensing and categorizing of Electrocardiogram waves is critical, easy to provide medical care diagnosis and treat patients suffering from critical ectopic heartbeats [8].

Ectopic or abnormal heartbeats are detect mostly by alter in the blood parameters, like a low mineral potassium level which is called hypokalemia; inconvenience in proper blood transportation supply. Abnormal heart rates can cause by stress, caffeine, alcohol, antidepressant medicines, and some not prescribed drugs [9-11].

These heartbeats are typical in youngsters who do not have congenital (existing at birth) cardiac disease. The majority of additional heartbeats in kids are PACs. These are typically described as innocuous. Also rare in grown up people, are abnormal heartbeats [12]. When they occur frequently, cardiologist should investigate the cause timely. The underlying cause and symptoms are the main targets of treatment. An inexpensive and non-invasive technique to determine these disorders is by analyzing ECGs [13]. As it is mentioned, when there are differences between patients in the ECG signals, the classifier algorithms have not worked well in practice, illustrating a frequent weakness of having an inconsistent performance when classifying a new patient's Electrocardiogram signals [14-15].

In past few years many researchers in the field of cardiovascular disease detection suggested different approaches based on their studies [3-21]. The statistical time growing neural network based technique was proposed by Gharehbaghi et. al. [3] and they examined different heart sound signals for detection of cardiovascular disease. With the help of convolutional neural network, Acharya et al.'s [5] classified ECG signals of atrial fibrillation, atrial flutter, and ventricular fibrillation classes to identify different arrhythmias. Andreao et al.'s [6] proposed an efficient arrhythmia identification algorithm uses the hidden Markov model to determine how similar the arrhythmias are.

In previous studies they have used many types of classifiers for example SVM (support vector machine classifier) [22], PNN (probabilistic neural network classifier), NN (neural network classifier) [24], PSC (patient specific classifier) [25] and CNN (convolutional neural network classifier) [26]. Different classifiers are used based upon their accuracy, specificity, and sensitivity factor. For example, support vector machine (SVM) classifier has more sensitivity than all other classifiers and Probabilistic neural network (PNN) has more accuracy and specificity than other classifiers [27]. The neural network classifier (NN) is important in applications such as pattern recognizing and classification of tasks. The neural network classifier (NN) is a feedforward than it provides more accuracy as compared to others but its efficient working depends on number of unseen layers and active function of neurons [24].

SVM are used for features which is linearly separable and has number of features in data. Probabilistic neural network classifier (PNN) is having to be trained first and once the probabilistic neural network classifier is trained then we just have to fed data to Probabilistic neural network classifier. It classifies the data then automatically [28].

The various methods makes algorithms tend to exhibit considerable variances in their accuracy and efficiency for bigger databases, making them untrustworthy for widespread usage in clinical or practical settings. Here, in this work we proposed an algorithm which can effectively classify the ECG signals for differentiating normal ECG signal and ectopic beat signals to detect arrhythmia.

EEG Dataset Used in Study

In the present work, the ECG signals are used in benchmark dataset known as MIT-BIH for ectopic beat detection[19]. The database acclimated in our study is from Massachusetts institute of technology and Beth Israel hospital (MIT-BIH), where signals were recorded using sampling frequency of 360Hz and it having more than 4000 long duration ECG signals. Table 1 shows the training test results of various samples obtained by HOLTER ECG. The present work has classified following types of ECG signals; Nc represent the non-ectopic beats (normal ECG), Sv represent the supraventricular ectopic beats, V represent the ventricular beats and Fs represent the fusion beats. Table 1 shows the summary of MIT-BIH ECG database.

Table 1: Training Test for Different Type of Beats to train our classifier for classification of ectopic beats.

DATABASE	Nc	Sv	V	Fs	REC.
MIT-BIH(ds-1)	45774	943	3556	312	20
MIT-BIH(ds-2)	44012	2042	3216	388	32
INCART	153542	1959	2000	303	73

SVDB	145437	10633	8284	21	90

In this work, the data of HOLTER ECG of many type of abnormal heart beat and also the disease caused by them are considered. Table 2 shows data of heart patients of many disease like atrial premature beat. In this table 0 is for Normal heart beat and 1 is for abnormal heart beat which is further classified into four types they are Ap (Premature atrial beat), Rb (Right bundle branch block beat), Vp (Premature ventricular beat) and Lb (Left bundle branch block beat).

TABLE 2: DATASET OF DIFFERENT PATEINTS SUFFERING FROM DIFFERENT TYPES OF ABNORMAL HEART BEATS USED IN PRESENT STUDY

	1	1	1	1	0
RECORDS	Ap	Vp	Lb	Rb	0
118	96	16	-	2166	-
107	-	59	-	-	-
109	-	38	2492	-	-
232	1382	-	-	397	-

METHODOLOGY

In this segment, we the methodology used to determine ectopic beats automatically from an ECG signals has been described in detail. The basic steps to classify abnormal heart rhythm is shown in Fig. 1. Firstly, we have to collect the dataset from an ECG machine and then we have to do pre-processing of that dataset using a specific type of filter. All the samples are pre-processed through a 200-millisecond width median for deduction of the P wave and QRS complex and for removing T wave a 600-millisecond width median filter. The resulted signals are known as baseline signals and these baseline signals are deducted from the actual signals to get the baseline corrected Electrocardiogram signals. Then a FIR filter with a 35Hz cut-off frequency is used to remove high-frequency (HF). Then, feature extraction has been done using the filtered data, then different linear and non-linear features were extracted. Eqn. 1 shows the formula for Euclidean distance, which has been used as feature from ECG signal analysis and it is represented as:

$$G(A[x],\ A'[y]) \ = (\Sigma(A(x+G) - A'(y+D))) \qquad [1]$$

Where, A[x] and A'[y] are ECG samples and l denotes the length that we are going to use from ECG sample. This Euclidean distance is a measure for ECG that length of ECG sample is sufficient or not for extracting information about the heartbeat such as, the position of the QRS complex and the corresponding fiducial points Q, R and S Fig.2. And limit of G tends to l.

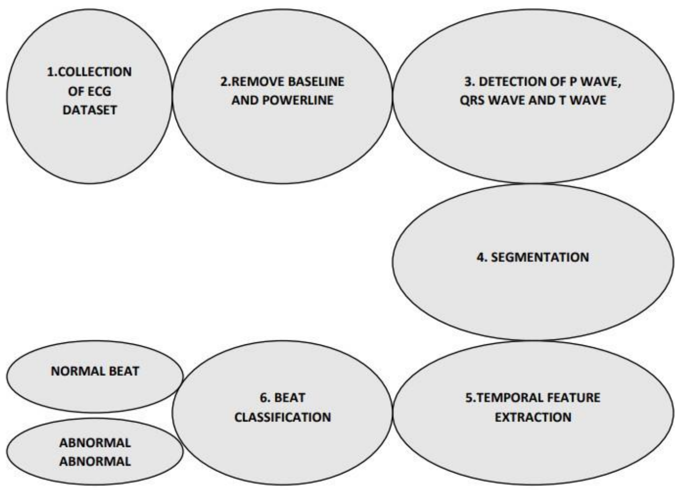


Fig. 1. Proposed Methodology For Ectopic Beat Classification using MIT-BIH dataset.

The extracted features have been fed to the LDA classifier which is employed for classification of different types of ECG signals (Nc, Sv, V, Fs). The LDA approach is used in disease detection to identify a linear combination of attributes that distinguishes or defines two or more sets of occurrences. The goal of LDA is to combine the original samples to produce a new test features space. As demonstrated in Fig. 2, it maximizes the difference between the predefined classes with regard to the new test feature space. 70% of the signals have been used for training the model and remaining 30% were used for testing the model performance. 5 fold cross validation technique has been used.

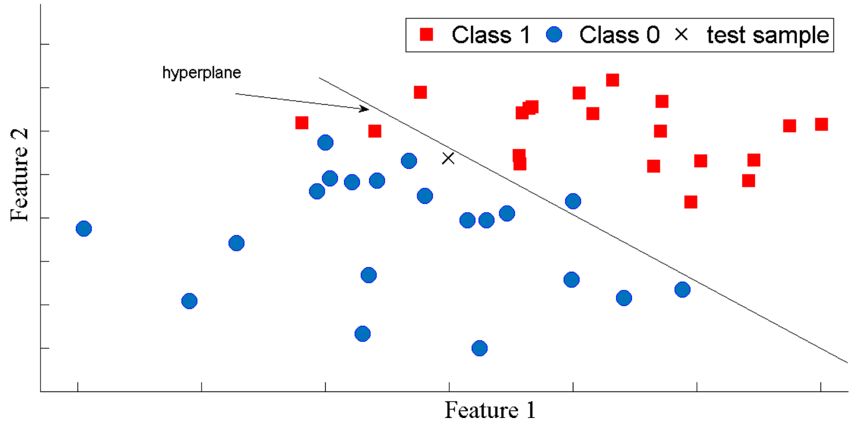


Fig. 2: Effect of linear discriminant analysis over the features. Where Class 0 represents normal ECG and Class 1 represents abnormal ECG signals

RESULT AND DISSCUSSION

Based on detected or undetected signals four parameters are there which helps us to get performance analysis of classifiers. They are True positive which describes positive samples correctly detected, True negative describes the negative correctly detected, False positive are the negative samples falsely detected and False negative are positive not detected as positive. Accuracy (Ac), Specificity (Sp) and Sensitivity (S) of classifier are depends on above mentioned four parameters[24][29] and are calculated as below:

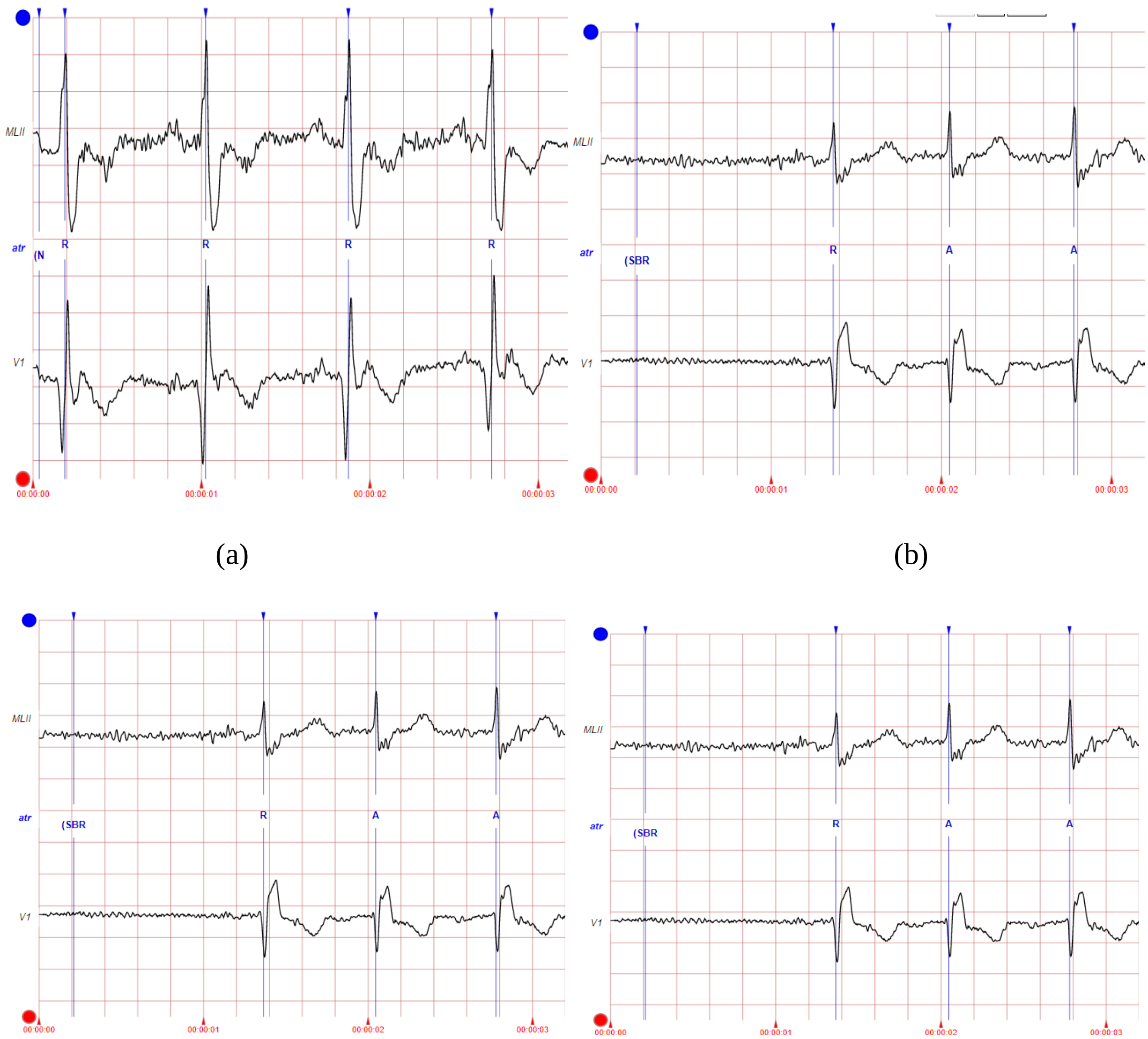
$$S = (++) * 100 / (++) + (--) \tag{2}$$

$$Sp = (+-) * 100 / (+-) + (-+) \tag{3}$$

$$Ac = [(++) + (+-)] * 100 / (++) + (--) + (+-) + (-+) \tag{4}$$

Where, ++ is true positive, -- is false negative, +- is true negative and -+ is false negative.

Fig. 3 shows the sample ECG signals from each class (a) is for Premature Atrila Beat (Av), (b) is for Right Bundle Branch Block Beat (Rb), (c) is for Premature Ventriculer Beat(Vp) , (d) is for Left Bundle Branch Block Beat(Rb).



(a) (b)

(c) (d)

Fig. 3: Sample ECG signals of different diseases (a) Premature Atrila Beat (Av), (b) Right Bundle Branch Block Beat (Rb), (c) Premature Ventriculer Beat(Vp) , (d) Left Bundle Branch Block Beat(Rb)

Table 3 gives the comparative analysis of proposed machine learning based technique for ectopic beat detection with the other available techniques. For the comparison purpose all studies incorporated in this table used the same MIT-BIH database. As it is observed from this table that difference in accuracy, senstivity and specificity of different classifier for example the accuracy of RNN is 85.4 [3] and of CNN is 97.30, if they used both then accuracy is 95.90 [1]. The proposed method achieved the accuracy, senstivity and specificity of 98.57, 98.7 and 98.2 % respectively which is better than other available methods.

TABLE 3: Comparison Table for different reference papers with respect to their used classifier and accuracy, sensitivity and specificity factor.

YEAR	PAPER	CLASSIFIER	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)
2004	Chazel et al. [25]	SVEB	94.60	74.9	38.50
2006	De chazel et al. [35]	PSC	97.4	94.4	98.4
2007	Jiang and kang et al.[38]	VEB	98.8	94.3	99.4
2011	Mar et al. [39]	SVEB	93.3	83.2	93.7
2013	R marti set al. [28]	SVM, NN AND PNN	99.28	99.97	99.83
2015	A. elhag et al. [24]	SVM	98.91	98.91	97.85
2018	G sannio et al.[8]	GE	75.3	69.6	76.6
2019	Sharma et al. [7]	KNN	98	85.33	98.22
2019	W zhu et al.[30]	SVM	91.43	99.27	98.48
2020	Z ebrahimi et al. [3]	RNN	85.4	80.6	85.7
2020	Xue xu et al. [1]	CNN AND RNN	95.90	95.90	96.30
2022	D l tai wong et al. [4]	CNN	97.30	91.30	98.1
	This work	**LDA**	**98.57**	**98.7**	**98.2**

As we have discussed computer aided disease detection technique for heartbeat classification using ECG signals used different methods using a series of classifiers like SVM, PNN, and NN [25]. All those specifiers has good specificity, sensitivity and accuracy. Abnormal beats leads to additional electrical impulses enforce by another latent pacemaker.

CONCLUSION

Cardiologists' workloads can be significantly reduced in medical field by computer-aided diagnosis of cardiac arrhythmias, allowing them to timely treat the disease without wasting time in diagnosis. In this work, an effective ECG classification system based on machine learning technique is developed to perform automatic ECG arrhythmia diagnosis by categorizing patient ECGs into four different cardiac conditions: premature atrial beat, right bundle branch block beat, premature ventricular beat and left bundle branch block beat.

The proposed method gave promising results accuracy (about 98.57%) and sensitivity (98.7%) showed how effective the present method is for automatically detecting cardiac arrhythmias. Additionally, use of linear discriminant analysis for reduces the need complex level of other machine learning techniques which are more time consuming and difficult to implement in real time environment.

We have discussed many research works of previous years and we can see that the usage of classifiers vary as per the data collected for classification of ECG signals but they take data from same hospital i.e. MIT-BIH[23]. So in future work the same algorithm can be used with other datasets also for detecting different types of heart diseases which are not included in this work.

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