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Detection of supraventricular tachycardia by Machine Learning

Sangram Nayak, Sritam Samal, Deeptansu Patro,
M.S.K.A Pavan kumar and Monalisa Mohanty*
ITER, Siksha 'O' Anusandhan (Deemed to be University)
Bhubaneswar, India
Sangramnayak0299@gmail.com, sritamsamal52@gmail.com, deeptansupatro1999@gmail.com, aravindpavan99@gmail.com, monalisamohanty@soa.ac.in

Abstract
Supraventricular tachycardia (SVT) means abnormally fast heartbeat. It often affects young, healthy people and it is generally caused by the fault in electrical signals in the heart. Supraventricular tachycardia (SVT) is one of the type of arrhythmias that is basically an abnormal heartbeat. Tachycardia means a rapid increase in the heart rate which is of more than 100 beats per minute. Electrocardiogram (ECG) is one of the most important diagnostic tool used for the detection of the health of a heart. The number of growing heart patients has made necessary development in the techniques of automatic detection for detecting the various types of abnormalities or the arrhythmias of the heart to basically reduce the pressure and share the load of the physicians. ECG recordings were taken from MIT-BIH supraventricular arrhythmia database (SVDB) of the Physionet repository. Each record contains ST, N and VB rhythm and of 30 minutes length. Then using feature extraction , we extracted features for ST,N and VF and finally put into classifier like decision tree(LMT) and functions(MLP) to classify the ECG signals.
Keywords: *Tachycardia, Supraventricular tachycardia, arrhythmias, decision tree classifiers.*

1. Introduction

Supraventricular arrhythmias occur due to irregular heart beat but often are not very serious but it may get serious in future if necessary medication is not taken in time. Here the patient may feel dizziness [1]. Few types of arrhythmias have no symptoms. Symptoms may comprise trembles or feeling a gap between heartbeats. In more intense situations, there may be light-headedness, passing-out, and shortness of breath or chest pain [2]. Now a days it can be caused by various things which are hard exercise, fever, fear, stress, certain medications, anxiety, and drugs which specifically leads to sinus tachycardia that is one of its types. In these days people consume a lot of caffeine due to smoke or drink too much alcohol, and hence are likely to have supraventricular tachycardia. Sometimes it is also due to heart attacks. Women and children are most affected by it.

Supraventricular tachycardia is a condition when the heart rate speeds up because the electrical signal misfires in the organs of upper chamber. It reduces the blood flow in the body because it couldn't filled with blood before it contracts due to the fast beating. The SVTs can be identified if the ventricular rate exceeds 100 beats/min along with a narrow QRS complex is the general way. Also, SVTs with a wide QRS complex can involve supraventricular tissue with conduction to the ventricle via abnormal myocardial fibers, as in the case of an accessory pathway connection [3].

Globally, cardiovascular diseases are the leading cause of death, causing around 17.9 million estimated deaths every year [4]. The majority of these deaths are due to tachyarrhythmia, or fast heart rates. When the heart rate is greater than 120 beats per minute, it belongs to tachycardia and when the rate is greater than 350 beats per minute, it belongs to fibrillation [5]. It can even leads to death when ventricular Tachycardia (VT) rapidly deteriorates to Ventricular Fibrillation (VF) [6]. Statistics shows that 1 in every 250 children can have supraventricular tachycardia (SVT), but its appearance is often unclear and the indications of SVT are incorrectly assigned to some other common paediatric conditions. Most children will go on to live normal healthy lives if the SVT is correctly identified on time. In most paediatric advanced practice nursing programs SVT not covered in depth, but it should be familiar to all paediatric major care providers because of its commonness [7].

This article has been organized as follows: section 2 gives a review of Supraventricular tachycardia. In the 3rd section, the methodologies are discussed. The 4th and 5th section belongs to results and conclusion respectively.

2. Literature Review

The death cause of one of the worldwide leading diseases which is cardiovascular disease was analysed by Gao *et al.* in year 2019. Now a days, approximately 5 million cases of heart failure (52.9% men and 47.1% women), and approximately three million American adult women aged 20 and older are suffering from heart failure [8]. Srinivasam *et al.* has described supraventricular tachycardia as one among the most common disorders which requires the emergency medical cardiac care in the neonates. Atrioventricular tachycardia using atrioventricular bypass tract is most common type of supraventricular tachycardia in the period of neonatal [9]. In year 2015, Chu *et al.* have developed a method for the treatment of SVTA for infants and have obtained the overall recurrence of SVTs [10]. In year 2019, Mohanty *et al.* have represented an organized view on the present method that are used for detecting the cardiac arrhythmia using the signals of ECG which involves feature extraction, approaches of machine learning and signal decomposition [11]. Guandalini *et al.* in year 2019 have approached four different basic techniques of mapping which can be used to guide the Ventricular Tachycardia (VT) ablation and the four are entrainment, substrate mapping, activation and pace [12]. DeSimone *et al.* in year 2018 have structured a way which helped in easily recognizing and classifying arrhythmias and also illustrated the mechanism for these arrhythmias which provided an understanding of the interventions generally used [13].

In year 2013, Escudero *et al.* has invented a treatment option for the children with SVT and reviewed the mechanism of action, classification of systems, pharmacodynamics and pharmacokinetics of the current available antiarrhythmic used in the paediatric SVT [14]. Lee *et al.* in year 2008 provided a great thesis about deapth theory of history, treatment strategies, mechanism and the presentation of the upcoming commonly encountered SVT's and the related syndromes that are in details [15]. Schelchte *et al.* in year 2008 has primarily focused on children with SVT's and has provided common mechanism with their age related presentation, diagnosis, management and advanced practice nursing programs [16]. In year 1993, Wathen *et al.* described about the classification of the supraventricular tachycardia (SVT) and how it evolved. He proposed a method that attempts incorporate virtues and he also provided the design because the new information on the mechanism and the clinical characteristics should be additive but not disruptive [17]. Wong *et al.* in year 2019 have provided some deep learning techniques which would solve the problem for classification of physiological signal in ventricular tachycardia, since the deep learning techniques can obtain incredible performances in many of the medical applications [18]. Ichikawa *et al.* has emphasized the usage of the mechanical circulatory support in the life threatening SVT cases with the help of theophylline toxicity and has also represented about a case where the man takes the theophylline and was later admitted to the hospital with supraventricular tachycardia (SVT) and also congestive heart failure [19].

Mohanty *et al.* in the year 2018 developed a method to detect VT and VF arrhythmias using temporal, spectral and statistical feature. They have realized that sudden cardiac arrest are causing a lot of deaths in the world and so the technique has to be developed to identify ventricular tachycardia and ventricular fibrillation to prevent from ventricular arrhythmia. They took 57 records of ECG recordings and after feature extraction and C4.5 classification, they got the sensitivity of 90.97%, specificity of 97.86% and accuracy of 97.02%.which was better than SVM classification . The system data that was obtained could be an aid to clinician for precise detection of ventricular arrhythmias [20]. Mohanty *et al.* in the year 2019 using machine learning developed an automated system that can be used for the detection of ventricular arrhythmia. The ECG recordings were taken from the PhysioNet database. Then they did feature extraction and then classified using C4.5 classifier. With 5 second window length they obtained a sensitivity of 97.97%, specificity of 99.15% and accuracy of 99.18% for C4.5 classifier which was better than SVM classifier. Though this type of method has been established earlier but not through machine learning. The machine learning develop an automated system for the detection of ventricular arrhythmia which makes it more useful [21].

3. Methodology

The work is focused on the supraventricular tachycardia detection and classification using machine learning techniques. The block diagram of the proposed work has been shown in Fig.1. The raw ECG signals have been acquired from SVDB databases with a sampling frequency of 128Hz. The ECG signals are pre-processed for removal of artifacts and the simulation wave- forms. Out of the two channels of SVDB database, the first channel has been selected for the work. A window technique has been used here for extraction of useful features in different domains. A window length of 2s has been chosen for this work. In total, a set of 11 features has been extracted for precise classification of SVTA. The features are norm entropy, log entropy, kurtosis, shan entropy, covariance, sure entropy, permutation entropy, threshold entropy, skew, hurst, and ratio [21]. The extracted features have been evaluated and ranked according to their weightage value using the Weka software which is a best suited software environment for machine learning. The ranked features have been used as the inputs for decision tree classifiers in this work.

Two different classifiers such as Logistic Model Tree (LMT), and Multi-Layer Perceptron (MLP) have used for a comparative analysis of classification performance. Using LMT classifier, the accuracy and sensitivity values have been found to be 99.23 % and 98.64% respectively. Similarly using MPL classifier, the accuracy and sensitivity values have been found to be 98.73 % and 98.39% respectively.

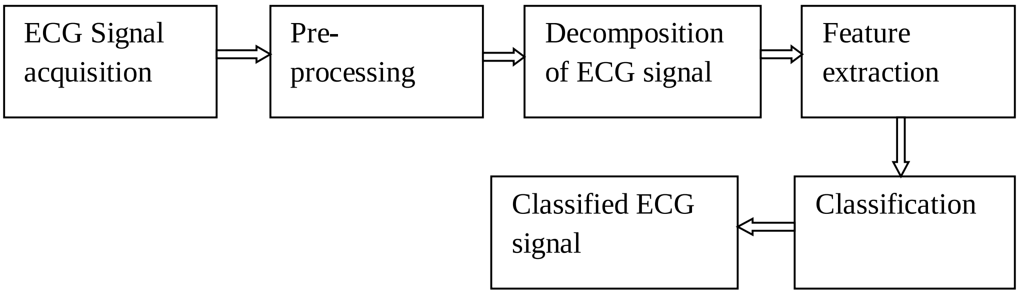


Fig.1. Block diagram of SVTA arrhythmia classification

3.1. Logistic Model Tree (LMT)

In computer science, a logistic model tree (LMT) is a classification model with an associated supervised training algorithm that combines logistic regression (LR) and decision tree learning [22]. Logistic model trees are based on the earlier idea of a model tree: a decision tree that has linear regression models at its leaves to provide a piecewise linear regression model (where ordinary decision trees with constants at their leaves would produce a piecewise constant model). In the logistic variant, the LogitBoost algorithm is used to produce an LR model at every node in the tree; the node is then split using the C4.5 criterion. Each LogitBoost invocation is warm-started [vague] from its results in the parent node. Finally, the tree is pruned. The basic LMT induction algorithm uses cross-validation to find a number of LogitBoost iterations that does not overfit the training data. A faster version has been proposed that uses the Akaike information criterion to control LogitBoost stopping.

3.2. Multi-Layer Perceptron (MLP)

A multilayer perceptron (MLP) is a class of feedforward artificial neural network (ANN) [23]. The term MLP is used ambiguously, sometimes loosely to refer to any feedforward ANN, sometimes strictly to refer to networks composed of multiple layers of perceptrons (with threshold activation); see § Terminology. Multilayer perceptrons are sometimes colloquially referred to as 'vanilla' neural networks, especially when they have a single hidden layer. An MLP consists of at least three layers of nodes: an input layer, a hidden layer and an output layer. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron. It can distinguish data that is not linearly separable.

4. Results

We have considered the SVDB database from PhysioNet repository. The acquired ECG signal have been pre-processed for removal of unwanted noises and interferences. A window of size 2s has been chosen for extraction of features in various domains. The SVDB databases is having a sampling frequency of 128Hz. After the feature extraction is done, the extracted features are set with ranks for the evaluation done by the attribute evaluator as shown in Table.1. The Table.2 and Table.3 shows the analysis of each individual features by LMT and MLP classifiers respectively with a window size of 2s. Table.4 and Table.5 shows the performance evaluation using LMT and MLP classifiers respectively for different combination of features. These comparative analysis indicates that the LMT gives better results as compared to MLP classifier in terms of accuracy and sensitivity as shown in Fig 2(a) and 2(b) respectively.

Table.1 Ordered ranking of selected features by the correlation attribute evaluation with ranker search method.

Ranking weight	Feature rank	features
0.6808	1	Norm entropy
0.6731	2	Log_entropy
0.5772	3	kurtosis
0.5646	4	Shan_entropy
0.5621	5	Co-variance
0.5394	6	Sure_entropy
0.4777	7	perm
0.4328	8	Threshold frequency
0.3884	9	skewness
0.1794	10	Hurst exponent
0.0491	11	Ratio

Table 2. Analysis of each individual features by LMT with a window size of 2s.

	Tp rate	Fp rate	precision	recall	F measure	mcc	Roc area	Prc area
1	0.973	0.017	0.974	0.973	0.973	0.958	0.985	0.967
2	0.973	0.017	0.974	0.973	0.973	0.958	0.985	0.967
3	0.982	0.009	0.986	0.986	0.986	0.978	0.995	0.991
4	0.984	0.009	0.986	0.986	0.986	0.978	0.995	0.991
5	0.985	0.009	0.986	0.985	0.985	0.977	0.995	0.991
6	0.981	0.012	0.982	0.981	0.981	0.971	0.989	0.978
7	0.986	0.009	0.986	0.986	0.986	0.978	0.995	0.991
8	0.980	0.012	0.981	0.980	0.980	0.970	0.989	0.977
9	0.976	0.015	0.977	0.976	0.976	0.963	0.988	0.976
10	0.960	0.025	0.963	0.960	0.960	0.939	0.990	0.981
11	0.950	0.030	0.952	0.950	0.950	0.924	0.982	0.970

Table 3. Analysis of each individual features by MLP with a window size of 2s.

	Tp rate	Fp rate	Precision	Recall	F measure	Mcc	Roc area	Prc area
1	0.980	0.013	0.981	0.980	0.980	0.969	0.989	0.980
2	0.979	0.013	0.980	0.979	0.979	0.967	0.989	0.978
3	0.973	0.017	0.975	0.973	0.973	0.959	0.989	0.978
4	0.973	0.017	0.974	0.973	0.973	0.958	0.986	0.972
5	0.973	0.017	0.975	0.973	0.973	0.959	0.986	0.970
6	0.969	0.020	0.971	0.969	0.969	0.952	0.979	0.949
7	0.969	0.020	0.970	0.969	0.969	0.952	0.980	0.950
8	0.969	0.020	0.971	0.969	0.969	0.952	0.980	0.949
9	0.969	0.020	0.971	0.969	0.969	0.952	0.980	0.950
10	0.945	0.034	0.948	0.945	0.944	0.916	0.980	0.957
11	0.945	0.035	0.949	0.945	0.944	0.916	0.981	0.962

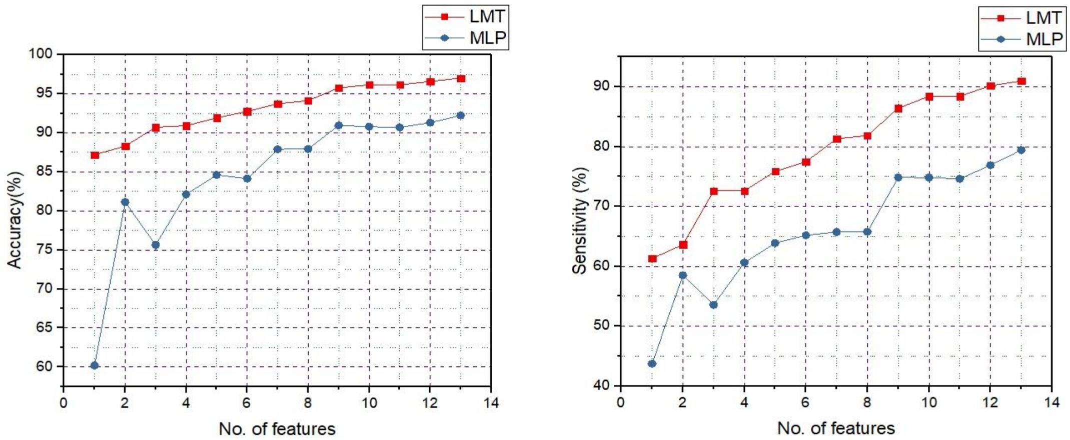
Table.4. Performance evaluation using LMT for different combination of features.

No. of Features	TP	FP	FN	TN	ACC	SE	SP	PPV(PR)
1	846	35	35	2525	98.18	97.32	98.52	97.73
1,2	846	35	35	2525	98.18	97.32	98.52	97.73
1,2,3	849	18	18	2542	99.06	98.61	99.23	98.84
1,2,3,4	849	18	18	2542	99.06	98.61	99.23	98.84
1,2,3,4,5	**848**	**19**	**19**	**2541**	**99.23**	**98.64**	**99.29**	**98.86**
1,2,3,4,5,6	849	24	24	2536	98.75	98.14	98.98	98.47
1,2,3,4,5,6,7	848	27	27	2533	98.59	97.92	98.85	98.26
1,2,3,4,5,6,7,8	849	25	25	2535	98.70	98.07	98.93	98.41
1,2,3,4,5,6,7,8,9	847	31	31	2529	98.39	97.62	98.68	98.00
1,2,3,4,5,6,7,8,9,10	845	51	51	2509	97.34	96.10	97.84	96.77
1,2,3,4,5,6,7,8,9,10,11	837	64	64	2496	96.67	95.06	97.34	95.63

Table.5. Performance evaluation using MLP for different combination of features.

No. of Features	TP	FP	FN	TN	ACC	SE	SP	PPV(PR)
1	848	26	26	2534	98.65	98.00	98.89	98.32
1,2	849	27	27	2533	98.59	97.91	98.85	98.29
1,2,3	847	34	34	2526	98.23	97.39	98.56	97.78
1,2,3,4	847	35	35	2525	98.18	97.31	98.51	97.76
1,2,3,4,5	**847**	**34**	**34**	**2526**	**98.73**	**98.39**	**98.96**	**98.82**
1,2,3,4,5,6	844	40	40	2520	97.92	96.82	98.30	97.45
1,2,3,4,5,6,7	844	40	40	2520	97.92	96.82	98.31	97.42
1,2,3,4,5,6,7,8	844	40	40	2520	97.92	96.82	98.30	97.47

1,2,3,4,5,6,7,8,9	844	40	40	2520	97.92	96.82	98.30	97.47
1,2,3,4,5,6,7,8,9,10	839	71	71	2489	96.30	94.50	97.01	95.43
1,2,3,4,5,6,7,8,9,10,11	840	71	71	2489	96.30	94.46	97.00	95.55



(a) Plot of accuracy for different feature combinations using classifiers.

(b) Plot of sensitivity for different feature combinations using classifiers.

Fig.2. Comparative analysis of accuracy and sensitivity of two classifiers.

5. Conclusion

The research work approached in this work has been related in the development of new ways like machine learning to detect the cardiac arrhythmias. In the past few years we have seen an exponential increase in deaths due to cardiac arrest with some cases of unexpected deaths as it occurs within minutes after the symptoms occur. Our motivation was to come up with the new way to detect supraventricular tachycardia even before the symptoms occur. In this work we have gone through various ECG signals, to use it further we have used a window technique for the ECG signals and extracted the features and classified with LMT and MLP classifiers respectively. We have achieved better result with LMT having an accuracy of 99.23%. So, as shown that the detection method has high accuracy and can be used to detect the SVTA by which we can actually save a life.

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