Journal of Medical Systems (2019) 43: 191
https://doi.org/10.1007/s10916-019-1337-y

IMAGE & SIGNAL PROCESSING

Decision Tree Predictive Learner-Based Approach for False Alarm Detection in ICU

Tishya Manna[1] · Aleena Swetapadma[1] · Moloud Abdar[2]

Received: 14 March 2019 / Accepted: 13 May 2019 / Published online: 21 May 2019

Abstract

In this work, a novel method has been proposed for false alarm detection in Intensive Care Unit (ICU) during arrhythmia. To detect false alarm, various inputs are used such as electrocardiogram (ECG) signals, atrial blood pressure (ABP), photoplethysmogram signals (PLETH) and respiration (RESP). The inputs are given to decision tree predictive learner (DTPL) based classifier for thedetection of false alarm. The proposed method has an accuracy of 97% for prediction of false alarm in ICU. Theresult of the proposed method is promising which suggest that it can be used effectively for false alarm detection in ICUs. To the best of our knowledge, there is no such assumption based classification approach.

Keywords Arrhythmia · Machine learning · ECG · False alarm · ICU · Decision tree predictive learner

Introduction

Arrhythmia related adverse cardiological events are ventricular arrhythmias, super-ventricular arrhythmia, atrioventricular block, heartbeat failure which causes palpitation, orthopnea and sudden cardiological mortality. During diastolic shortest phase, blood flows in the coronary and then heart rate increases. But in the case of coronary heart patients, coronary blood flows less. In such diagnostic medical assessment treatment, patients should be taken under the observation of ECG assessment. This assessment translates the electrical impulsion and converted it into the series of wave format which is partitioned by depolarization and repolarization. From the previous study, the conventional idea has reported only right ventricle is involved in arrhythmogenic cardiomyopathy but there are some cases in which left ventricleis the part of it [1]. From the recent studies, it is noted that cardinal abnormalities and arrhythmia are under chronic obstructive pulmonary disease in which death has occurred in one-fourth of this case [2]. In another case affected lung function are considered that may increase the risk factor while arrhythmic pulmonary attack [3]. Global burden of disease (GBD) injured risk factor stated that atrial fibrillation leads to headache [4]. According to this surveyin 2010, an estimated result has shown 33.5 million are affected by atrial fibrillation over world which is 0.5% of the total population. In 2010, GBD has accumulated a statistical report on premature death regarding AF which is 18.8% and 18.9% rate increased correspond to man and woman.

In the preliminary stage of sudden cardiac heart attack, implantable cardioverter defibrillators (ICDs) treatment helps to survive potentially [5]. Considering all related parameters such as age and risk indication, the programmable device delivered the situation handling beneficial treatment with some restriction. For analyzing the sparsity of false heartbeat, long (30 min) and short (10 s) interval matric has been used for evaluating the algorithmic performance in [6]. But this work is limited within a short interval of 10s only. In [7], only 50% of among 40 types of notifications are truly detected by the medical stuff. All irrelevant alarms exceed the human audible range. This study is considered the threshold alarm, technical alarm, serious alarm, arrhythmia alarm. The reason is that there are various crucial parameters such as heart rate, respiration rate, oxygen saturation level and blood pressure in ICU. In a current medical situation, the patients are kept under the surveillance of severe health status narrating device which

This article is part of the Topical Collection on *Image & Signal Processing*

✉ Aleena Swetapadma
aleena.swetapadma@gmail.com

[1] School of Computer Engineering, KIIT University, Bhubaneswar, India

[2] Départementd'informatique, Université du Québec à Montréal, Montréal, Québec, Canada

works as a communicator between patients to nurse [8]. But threshold degradation occurs through a grating tone which creates a problem when it fails to notify in an adverse situation.

A recent study is trying is to improve the health status alerting notification which is generated through bedside monitor to convert the complex health stream to signal [9]. As the false alarm is a world burden till date and most of the studies are not meaningfully succeeded over it. In [10], a machine learning based algorithm has been used where 86.4% false alarm suppressed in asystole, 100% false alarm suppressed in bradycardia, 27.8% false alarm suppressed and 30.5% false alarm suppressed in ventricular tachycardia. In [11], ECG R-peak detection algorithm has been proposed. In [12], a mathematical morphology technique with the adaptive structural element has been proposed. To reduce false alarm, a QRS detection method and RR interval method have been proposed in [13]. To address false alarm, pulse features from ABP and PPG signal are extracted in [14]. In [15], a machine learning based technique has been proposed using random forest classifier for predicting five different types of models to detect five specific arrhythmic beats. Corrupted ECG signal may cause significant degradation of diagnostic accuracy. In [16], a Bayesian framework for decomposing ECG signal wasintroduced. In [17], forward search using ECG signal executed on the application specified integrated circuithas been proposed. This energy efficient android application detected the failure rate for bundle bunch block, hypertrophy, arrhythmia, and myocardial infarction. As ECG signal is an ensemble with noise and artifact, a model was proposed which automatically detect noise from ECG signal, extract features and classify in [18].

In [19], a diverse characteristic extended version of the oscillator model wasrepresented which has an ability to simulate realistic pacemaker represented with 12 lead ECG signal. In [20], a framework on the existing signal quality indiceswasproposed and false alarm reduction has experimented on the decision tree. In [21], a methodology for converting a rudimentary decision tree to an advanced model introducing multiple compact hash tableswas proposed. In another variant concept has been introduced by an oblivious decision tree with not more than 'k' number classification error in [22]. In this effort, only the incorrect classified elements are consideredrather than the class. In [23], a statistically analyzing decision tree in which fewer noise nodes are advised to fit into the deeper depth of the tree was considered. In [24], a fuzzy rule-based decision tree has been introduced. This method is also compared with the generic decision tree model through various online available dataset and produced highest accuracy. In [25], another part of the decision tree has been enlightened which has minimized wrongly classified cost and test set cost.

In response to the physionet challenge 2015, RR interval variation and QRS complex shape features for detecting true and false alarm have been recommended in [26]. Using ABP and PPG as input, a method was chosen based on decision tree predictive method against false alarm reduction in [27]. After observing the Korean patient's recorded PPG signal, classification accuracy among KNN, NN, and SVM was compared in [28]. In [29], CNN technique for automatic arrhythmia detection with 92.50% (2 s) and 94.90% (5 s) accuracy was represented. Another study has claimed to increase the true alarm by reducing the false alarm through noise classifier [30]. Electrocardiogram signal decomposition through 10 layers of CNN model for detecting myocardial infarction has been proposed in [31]. Comparing with other machine learning technique automatic feature extraction of CNN technique yields a magnificent accuracy by classifying 12 bit ECG signals. The training part of traditional CNN has redesigned by dropout technique. In this study, GPU accommodation issue has occurred which is very common to all deep learning mechanism. An advanced study using IDCNN which can classify 17 classes of arrhythmia with a satisfactory result has been proposed in [32]. This method has fulfilled very crucial factors such as classification speed, proficiency, compound ability, and usability. This experimental study has suggested long duration ECG is more potential in case of cardio disease analysis. As wavelet analyze the non-stationary signal more accurately with expanded function rather than trigonometric polynomial and scaled the signal with respect to time and frequency. Using this method an improvised feature recognition study has performed over bidirectional LSTM in [33]. Decomposed ECG sub-band frequency has been fed to the bidirectional LSTM to classify 5 types of heartbeat condition. The wavelet coefficient and raw ECG signal are used as input to LSTM that has enhanced the performance among the previous wavelet approaches. Another advantage of this approach is that the length of inputs does not a matter for network storage allocation. In [34], experimental study has sharpened the attenuation edges of ECG signals through Welch's method and discrete Fourier transformation analysis. A hybrid ensemble technique has presented using ensemble learning, deep learning, and evolutionary computational process. An improvised enhanced classification technique has introduced in [35] where the ensemble classification technique has proposed over 744 fragmented (10 s longer) ECG signal. This experimental strategy has achieved better performance in set optimization ensemble technique rather than class optimization ensemble technique.

By studying the literature, it can be observed thatall the methods either use complex methods or have less accuracy in detecting the false alarm. Considering the drawbacks of other methods, in this work, a novel method is proposed for false alarm detection in ICU for arrhythmia patients. To detect false alarm correctlyECG, ABP, PLETH,and RESP can be used as input as it contributes to the arrhythmia conditions more or less. The inputs are then given to the DTPL for false alarm detection. The advantage of the proposed method is that it can detect false alarm more accurately than other methods suggested to date. Yet another advantage of the proposed method is that it is simple, robust and easy to implement. The rest of the manuscript is organized as follows –section 2 contains description about DTPL, section 3 contains the proposed method, section 4 contains the results, section 5 contains the comparison with another method and section 6 contains the conclusion of the work.

Decision tree predictive learner

Among the various machine learning techniques, decision trees convert the hypothetical decisiveness to an automatic process. Another profound characteristic of the decision tree is that they can handle less or unpreprocessed raw data. A simple representation of a prediction based model is easy for understanding by data mining experts or even by non-experts. In the decision tree structure, the topmost part is considered as root. Just next level of the root is all possible outcomes of the roots called decision attribute and a leaf node which is the result of the classification. However, the important thing is splitting attribute and choosing the highest information gain. Any node that could not be further split, if that node contains the class label, the splitting recursion will stop. And for recognizing the unknown attribute,it traced the path started from root to leaf satisfying the condition and at last predict the class label for the unknown data [36]. Actually, the decision tree represents the visual structure of data containing in the database. First, it constructs as large as a tree but needs to put down the high computational cost. For finding a solution of over fitting of data, tree pruning was addressed to list out the least reliable attributes. There are two concepts of pruning, one is pre-pruning where the construction has stopped and pruned the existing one. Another is post-pruning which eliminates the branches after fully constructing the decision tree. Pre-pruning requires less computational time where post-pruning requires more. But post-pruning is more reliable than the previous one.

The potential characteristics of the decision tree are transparency, explicitly traced through all possible combination and at the end make a conclusion with leaf node attribute. Unambiguous features of the decision tree are capable of comprehensive decision making. For each condition, it will satisfy all possible no repeating path to get a final conclusion. Another more important feature is that continuous and categorical variablesare satisfiable by a decision tree. It would be required for one-time construction then it can manipulate all other condition through a conditional attribute. There are some variations in the decision tree such as ID3 which is a top-down order tree where information gain is considered as splitting criteria. ID3 is proposed for handling categorical value but cannot handle missing value condition. ID3 can only test one attribute at a time, hence pruning is not required. C4.5 is the improvised version of ID3 which can accept both continuous and discrete variable. In contrast with ID3, C4.5 is a bottom-up technique which has the ability to handle missing data. CART is a classification tree and also regression tree which has an internal node with two outgoing ages. Continuous and discrete both can be handled by CART. Another extended version of decision trees is the generic decision tree which can be converted to the multi compact hash table but gets the output from the final merged table. In another case, k error has to be predetermined where k should be an integer.

The generalize decision tree remodeled by evidence theory concept which is able to handle unsettled attribute and class level also called DTPL. Flow-chart influenced diagram of DTPL is represented through a square named as decision node, triangle named as an end node, and the circle represented as a chance node. This effective method of data mining is very easy to understand, free from ambiguity, missing value, robust method, comfortable with a discrete and continuous variable. It is also applicable for any type of conditional queries which will be solvable through a one way directed path. Figure 1 shows a simple decision tree predictive learner. X1, X2, and X5 are considered as conditional attributes which will always have either two or more optional criteria, are called as class label, is represented by path. Each decision path may or may not produce leaf node. Here leaf nodes are X3, X4, X6, and X7 which determine the outcome. In this work, DTPL is used to detect false alarm in ICU during arrhythmia.

Proposed method

Through the relevant feature selection, the computational cost might be reduced for a huge dataset in the complex classification problem. To get a more improvised accurate result against false alarm reduction in arrhythmia this effort has introduced a framework based on the decision tree predictive learner. Inputs such as ECG, PLETH, ABP, and RESP are given to the training module and trained with decision tree predictive learner. The tree formed is then pruned to get the optimal tree for better accuracy. After the model is trained, it is tested with unknown test samples. The outline diagram is shown in Fig. 2 which is described in the section below.

Inputs

To get the information for any heart-related diseases ECG is most important as it generates the depolarization and polarization of electrical impulsion of a resting body in the waveform structure with respect to time. This impulsion is displayed through the electrocardiogram in a non-invasive process. This waveform will provide heart rate, rhythm,

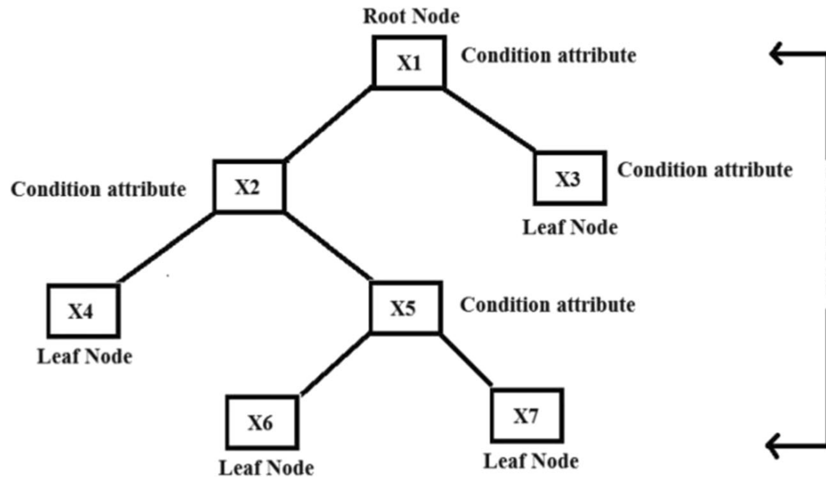

Fig. 1 Decision tree predictive learner

shapes, size of heart chambers, any significant hypertension and the evidence of previous sudden heart attack. Resting paced negatively charged heart try to release its negative charge through Na + and Ca++. This depolarization wave incidence sinoatrial node and passes through atrium and ventricle. The output is collected through the pair of the left arm, right arm, left leg and each pair are recorded as a lead.

The significant ECG signal parameters are RR interval (interval between one R wave to next R wave), QRS complex (rate of depolarization) rapidity between right and left ventricle, ST interval, T wave (the concept of ventricle's repolarization), QT interval. Physionet 2015 challenge dataset contains multimodal data whose sampling frequency is 250 Hz. Sampling time is reciprocal of sampling frequency which is 0.004 s. So, the sample interval between two inputs is 0.004 s. Figure 3 (a) shows the heart structure and components. Figure 3 (b) shows the functioning of the heart and the ECG generation.

Abnormal blood pressure for a long duration will tend to the adverse cardiovascular situation. Abnormal blood pressure fluctuation makes complication between heart, kidney, and lungs. Through the early diagnostic preventive treatment, some good levels of unhealthy blood pressure can be controlled. Critical patient needs to measure the blood pressure according to the gold standard rules. But the rather cases Korotkoff's sound measurement technique and oscillographic measuring process [37] was followed to make a report on blood pressure. In these two above method, pressure cuff has been tightly cuffed at the upper part of the arm to measure diastolic pressure and systolic pressure wherein normal healthy case diastolic measurement is less than 80 mmHg and systolic measurement is less than 120 mmHg.

Current study has explored that detecting and evaluating blood pressure through the atrial propagation theory [38–41] and photoplethysmogram morphological process [42–44] is more accurate than previous measuring technique called pulse transit time (PTT) [45]. PPP requires another two more signals ECG and PPG which has high operational cost. In another suitable study, estimating blood pressure is done by a smartphone-based optical technique which measures the changes in blood volume in the skin surface [46].

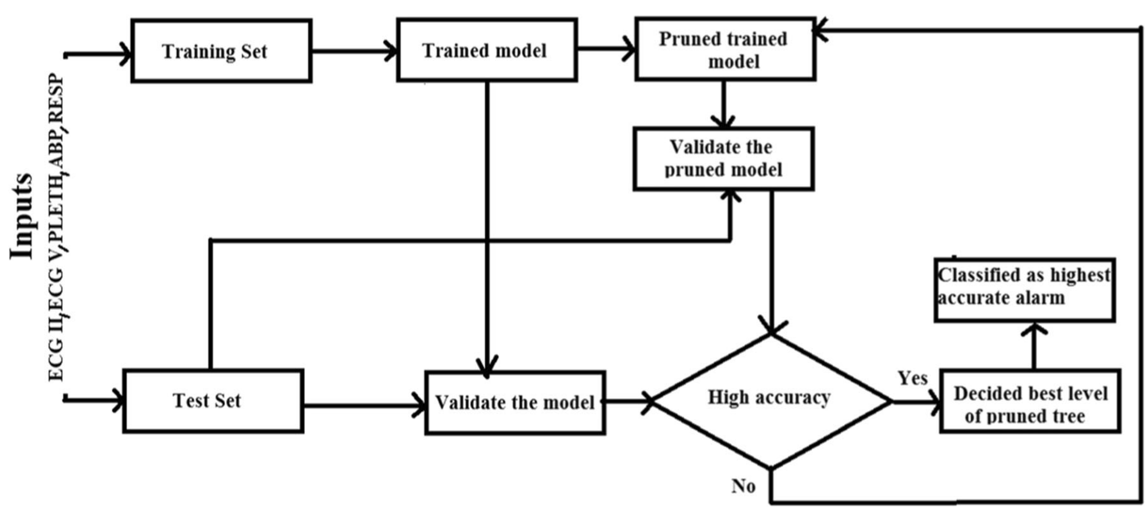

Fig. 2 Flowchart of DTPL based method

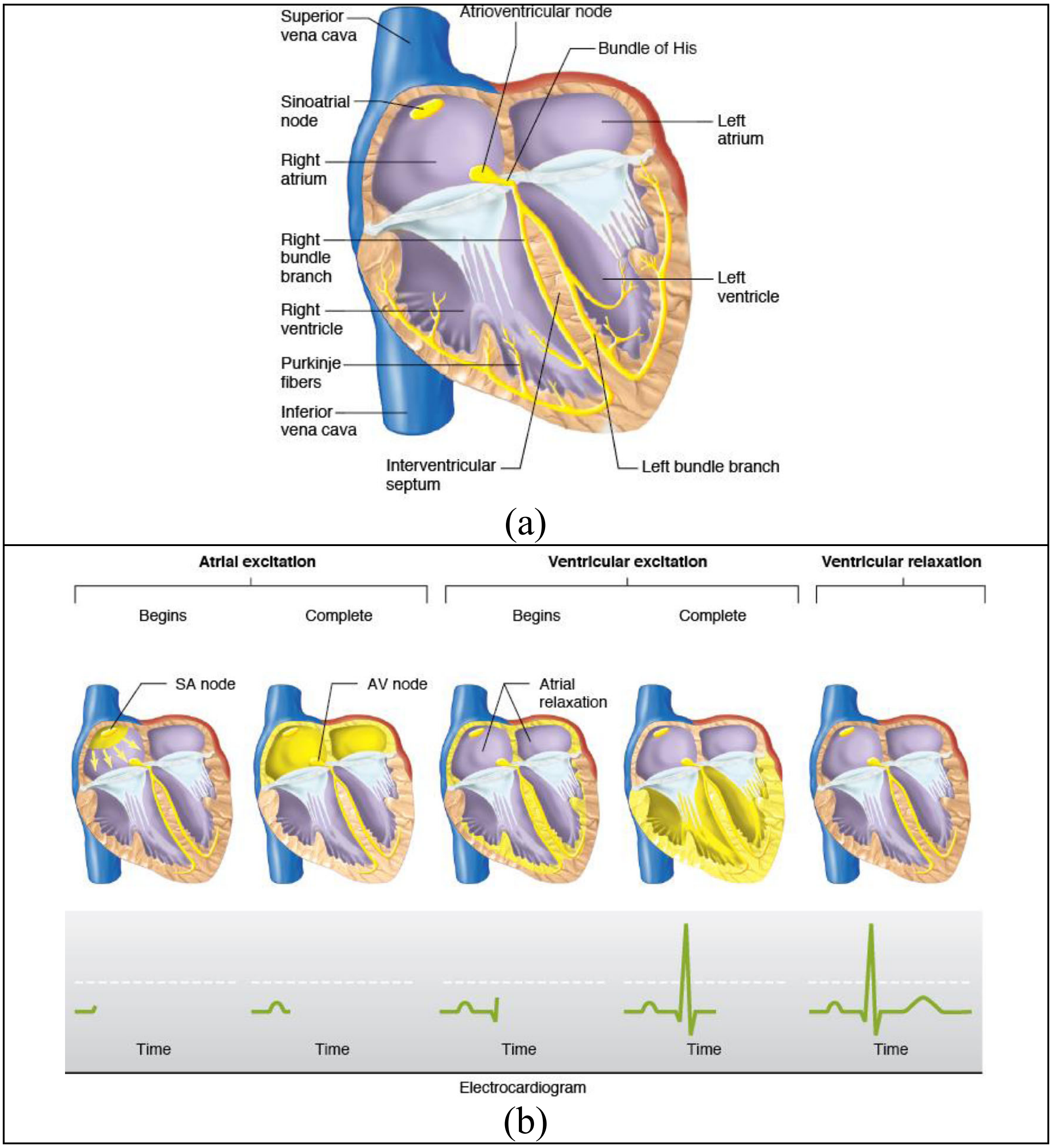

Fig. 3 (a) Components of heart (b) Functioning of heart and ECG generation (https://physicaltherapyreviewer.files.wordpress.com/2015/04/conduction-system-2.png)

The respiratory rate is a significant measurement of human health deterioration status. It fluctuates within as little as accounting with time which is considered as an unhealthy condition. According to the Resuscitation Council UK, the respiratory rate was measured by combining heart rate, blood pressure measurement, health temperature, and oxygen saturation level. RR is commonly varied with age. But commonly 12 to 25 bpm RR is considered as the normal range for people greater than 65 years old age and 10 to 30 bpm is considered as normal for 80 or more year's persons. The inputs used in this work for false alarm detection are ECG, ABP, PLETH and RESP. Figure 4 shows the various input signals such as ECG, PLETH and ABP obtained during tachycardia for true and false alarm. Figure 5 shows the various input signals such as ECG, PLETH and RESP obtained during tachycardia for true and false alarm. These signals are then given as input to the DTPL based classifier for false alarm classification.

DTPL based method

Among couple of classification algorithms, a decision tree predictive learner for predicting the accuracy in five types of arrhythmiawas chosen. DTPL approach is based on supervised learning technique. A model must be assembled on the trusted data which is big enough than the non-classified portion. But there is no exact recommended value of percentage

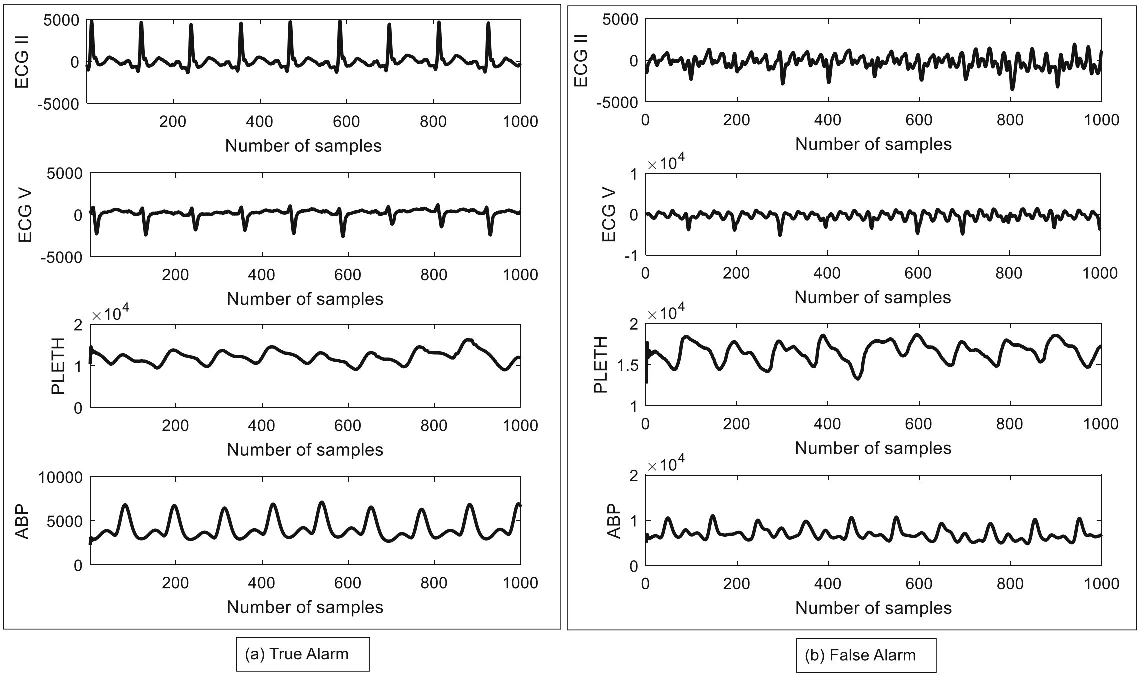

Fig. 4 Input signals ECG, PLETH, ABP obtained during tachycardia condition (a) True alarm (b) False alarm

for dividing primary dataset as training data and testing data. DPTL model should be generalized one, otherwise it could produce partial class label output. Non-generalized small training bucket DPTL model would tend to over fit. And another important point is, this partitioning should very concrete. Sometimes highest accuracy is the result of leaked out test set into the training set. For small dataset 90/10 partition is good enough. For huge dataset, the optimal proportion between training and testing may be 70/30 for achieving good prediction accuracy. So, for this experiment, the later one has been

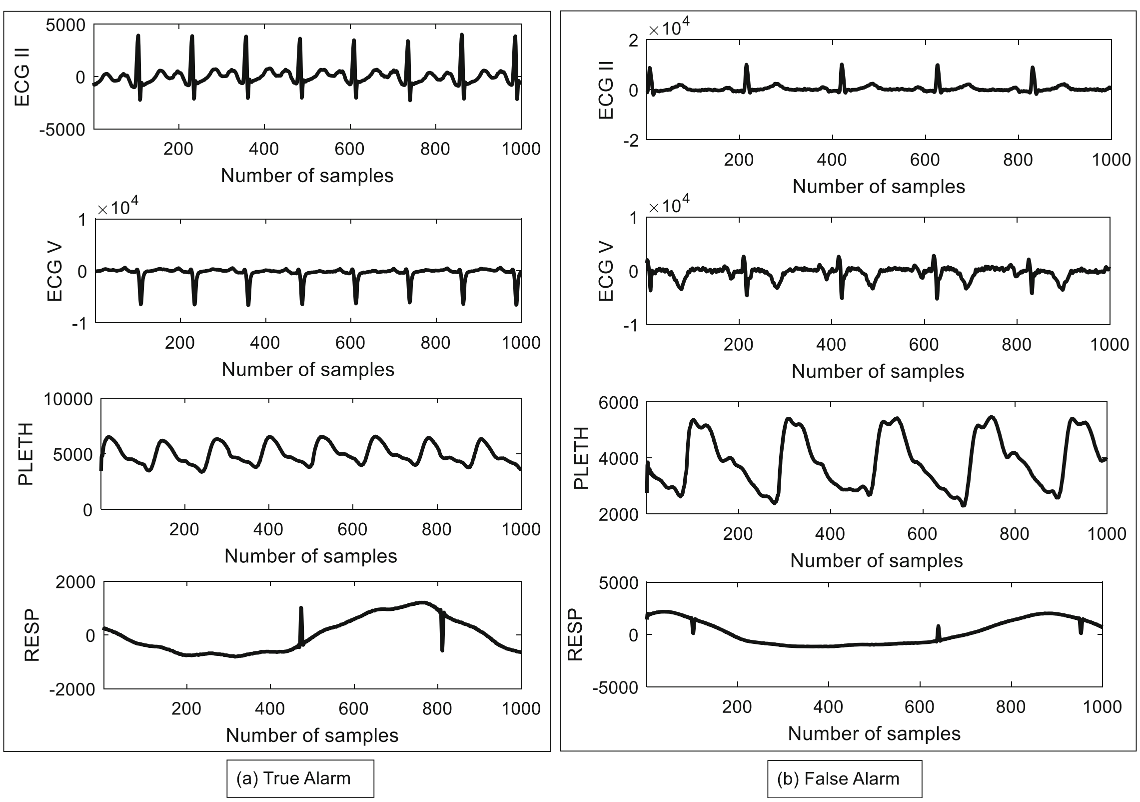

Fig. 5 Input signals ECG, PLETH, RESP obtained during tachycardia condition (a) True alarm (b) False alarm

considered which can make an impact on the statistical meaningful result. In this methodology first, a primary predicting tree using the training set and previously defined target value which is considered as a class labelwas implemented. Then the model is verified upon the test set of data and produced accuracy analysis is carried out through the confusion matrix. After the primary phase, this model needs to be pruned because if the better accuracy achieved by the pruned tree then there is no necessity to keep the primary one. So, the tree is pruned and again tested on the dataset for better accuracy. And most of the cases pruned tree gives better accuracy depending on the levels the tree had been pruned. In this study, it has been observed that at a certain level, tree has got the highest accuracy and that level needs to be marked. After achieving the highest accuracy at some level,the accuracy of the modelwill move to down at certain level. Among all combinations of input signals, in some cases there is no need to prune the primary tree as it is already at the optimal level. Figure 6 shows the optimal decision tree obtained for tachycardia where ×1 isECG II, ×2 is ECG V, ×3 is ABP and ×4 is RESP. Training performance of all types of arrhythmia is shown in Table 1 and Table 2 for real and retrospective phase respectively. Table 1 shows the accuracy and level of tree obtained for various types of inputs used. From Table 1 it can be observed that the accuracy of the training has been improved after pruning. In some cases, the same accuracy has been obtained in lower level trees which are more efficient. After designing the training modules, it has been validated with various test samples. Results of the proposed method have been discussed in the next section.

The rules extracted from decision tree for tachycardia condition are shown below.

1. if ×2 < 4877.5 then node 2 elseif ×2 > =4877.5 then node 3 else 0
2. if ×1 < 7650.5 then node 4 elseif ×1 > =7650.5 then node 5 else 1
3. if ×3 < 5521 then node 6 elseif ×3 > =5521 then node 7 else 0
4. if ×2 < 4265.5 then node 8 elseif ×2 > =4265.5 then node 9 else 1
5. if ×2 < 815.5 then node 10 elseif ×2 > =815.5 then node 11 else 0
6. Then node 6 is class = 1
7. Then node 7 is class = 0
8. if ×2 < 4134 then node 12 elseif ×2 > =4134 then node 13 else 1
9. if ×1 < 3153 then node 14 elseif ×1 > =3153 then node 15 else 1
10. Then node 10 is class = 1
11. Then node 11 is class = 0
12. if ×4 < 4311 then node 16 elseif ×4 > =4311 then node 17 else 1
13. if ×1 < 4575.5 then node 18 elseif ×1 > =4575.5 then node 19 else 1
14. Then node 14 is class = 1
15. Then node 15 is class = 0
16. if ×2 < 3605.5 then node 20 elseif ×2 > =3605.5 then node 21 else 1
17. if ×2 < 3482.5 then node 22 elseif ×2 > =3482.5 then node 23 else 1
18. Then node 18 is class = 1
19. Then node 19 is class = 0
20. Then node 20 is class = 1

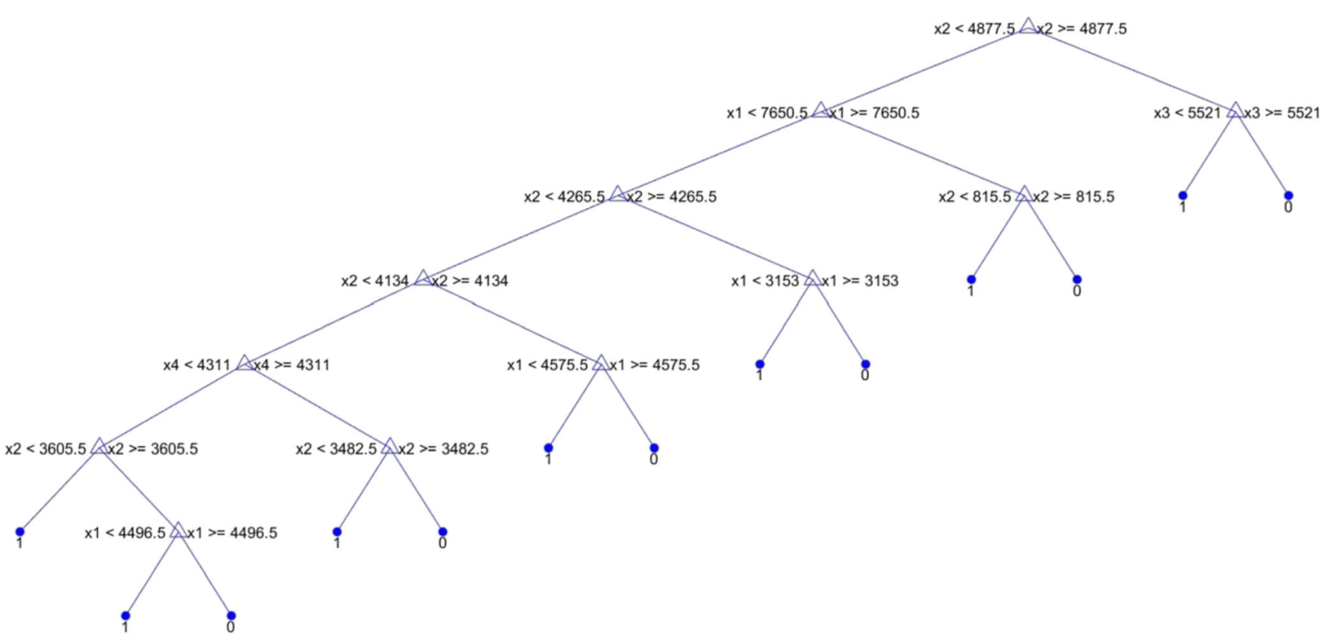

Fig. 6 Decision tree obtained for tachycardia

Table 1 Training performance of real phase

Type of Arrhythmias	Pruning	ECG II, ECG V, ABP, RESP Level	ECG II, ECG V, PLETH, ABP Level	ECG II, ECG V, PLETH, RESP Level	ECG II, ECG V, PLETH Level
Asystole	Pre-pruning	106	66	302	118
	Post-pruning	95	62	300	50
Bradycardia	Pre-pruning	NA	1	371	464
	Post-pruning	NA	–	140	265
Tachycardia	Pre-pruning	8	82	237	104
	Post-pruning	6	75	220	102
Ventricular Tachycardia	Pre-pruning	230	204	320	188
	Post-pruning	130	115	315	170
Ventricular flutter	Pre-pruning	NA	317	NA	NA
	Post-pruning	NA	300	NA	NA

*NA –Not Available,'-'means did not change

21. if ×1 < 4496.5 then node 24 elseif ×1 > =4496.5 then node 25 else 1
22. Then node 22 is class = 1
23. Then node 23 is class = 0
24. Then node 24 is class = 1
25. Then node 25 is class = 0

Results

The performance of the proposed DTPL based method for false alarm detection in ICU has been evaluated. The results obtained for various types of arrhythmia such asasystole, bradycardia, tachycardia, ventricular flutter,and ventriculartachycardiaare discussed below.

Performance of real phase

Performance of the proposed method has been checked using various inputs for all types of arrhythmia condition in real phase. The accuracy of the proposed method has been given in Table 3 for both pre-pruning and post-pruning. Figure 7 shows the highest accuracy obtained for various types of arrhythmia conditions. The highest accuracy obtained for asystole condition is 99.2% using ECG II, ECG V, and PLETH as input before pruning. The highest accuracy obtained for asystole condition is 99.3% using ECG II, ECG V, and PLETH as input after pruning. The highest accuracy obtained for bradycardia condition is 100% using ECG II, ECG V, PLETH and ABP as input before and after pruning. The highest accuracy obtained for tachycardia condition is 99.9% using ECG II, ECG V, ABP and RESP as input before pruning. The highest accuracy obtained for tachycardia condition

Table 2 Training performance of retrospective phase

Type of Arrhythmias	Pruning	ECG II, ECG V, ABP, RESP Level	ECG II, ECG V, PLETH, ABP Level	ECG II, ECG V, PLETH, RESP Level	ECG II, ECG V, PLETH Level
Asystole	Pre-pruning	61	113	170	166
	Post-pruning	60	105	165	120
Bradycardia	Pre-pruning	134	170	205	319
	Post-pruning	130	–	200	310
Tachycardia	Pre-pruning	14	NA	261	NA
	Post-pruning	10	NA	–	NA
Ventricular Tachycardia	Pre-pruning	36	123	355	293
	Post-pruning	30	120	340	250
Ventricular flutter	Pre-pruning	NA	1	NA	28
	Post-pruning	NA	–	NA	26

Table 3 Performance of real phase

Type of Arrhythmias	Pruning	ECG II, ECG V, ABP, RESP		ECG II, ECG V, PLETH, ABP		ECG II, ECG V, PLETH, RESP		ECG II, ECG V, PLETH	
		Accuracy	Level	Accuracy	Level	Accuracy	Level	Accuracy	Level
Asystole	Pre-pruning	92.8	106	60.8	66	72.6	302	99.2	118
	Post-pruning	94.5	95	60.7	62	74.7	300	99.3	50
Bradycardia	Pre-pruning	NA	NA	100	1	76.0	371	80.4	464
	Post-pruning	NA	NA	–	–	77.4	140	82.9	265
Tachycardia	Pre-pruning	99.9	8	97.1	82	63.4	237	95.5	104
	Post-pruning	100	6	97.6	75	67.8	220	96.5	102
Ventricular Tachycardia	Pre-pruning	93.7	230	97.8	204	85.8	320	97.9	188
	Post-pruning	94.2	130	98.3	115	86.9	315	98.6	170
Ventricular flutter	Pre-pruning	NA	NA	83.0	317	NA	NA	NA	NA
	Post-pruning	NA	NA	93.2	300	NA	NA	NA	NA

*NA –Not Available

is 100% using ECG II, ECG V, ABP and RESP as input after pruning. The highest accuracy obtained for ventricular tachycardia condition is 97.9% using ECG II, ECG V, and PLETH as input before pruning. The highest accuracy obtained for ventricular tachycardia condition is 98.6% using ECG II, ECG V, and PLETH as input after pruning. The highest accuracy obtained for ventricular flutter condition is 83.0% using ECG II, ECG V, PLETH and ABP as input before pruning. The highest accuracy obtained for ventricular flutter condition is 93.2% using ECG II, ECG V, PLETH and ABP as input after pruning. It can be observed that the accuracy of the method did not change much for real phase after pruning. But the level of the tree decreases ultimately decreasing the complexity of the method.

Performance of retrospective phase

Performance of the proposed method has been checked using various inputs for all types of arrhythmia condition in retrospective phase. The accuracy of the proposed method has been given in Table 4 for both pre-pruning and post-pruning. Figure 8 shows the highest accuracy obtained for various types of arrhythmia conditions. The highest accuracy obtained for asystole condition is 99.0% using ECG II, ECG V, ABP and RESP as input before pruning. The accuracy after pruning is also the same as before with decreased level. The highest accuracy obtained for bradycardia condition is 97.5% using ECG II, ECG V, ABP and RESP as input before pruning. The accuracy after pruning is also the same as before with decreased level. The highest accuracy obtained for tachycardia condition is 99.3% using ECG II, ECG V, ABP and RESP as input before pruning. The accuracy after pruning is also the same as before with decreased level. The highest accuracy obtained for ventricular tachycardia condition is 97.5% using ECG II, ECG V, PLETH and ABP as input before pruning. The accuracy after pruning is also the same as before with decreased level. The highest accuracy obtained for ventricular flutter condition is 100% using ECG II, ECG V, PLETH and ABP as input before and after pruning. It can be observed that the accuracy of the method did not change much for real phase after pruning. But the level of the tree decreases ultimately decreasing the complexity of the method.

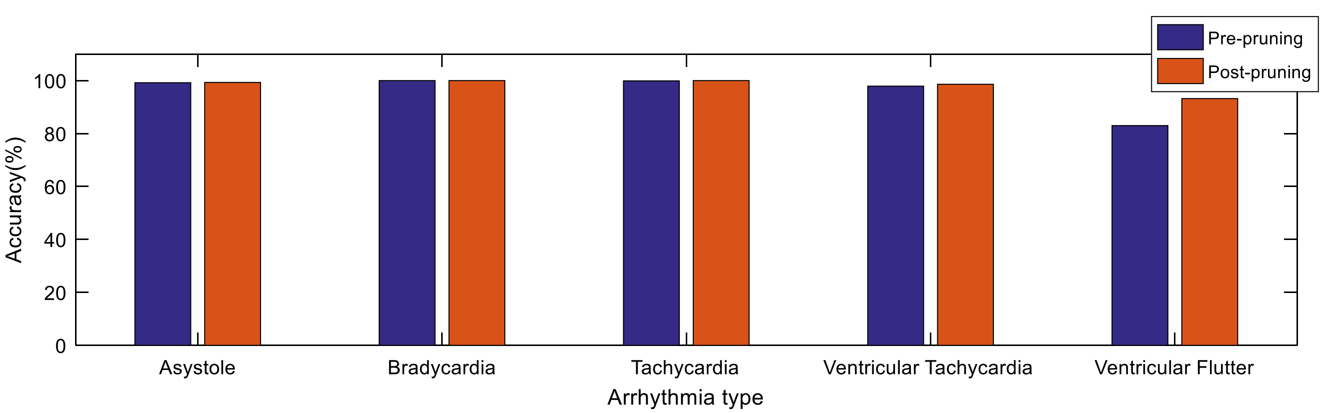

Fig. 7 Accuracy obtained pre and post-pruning in real phase

Table 4 Training performance of retrospective phase

Type of Arrhythmias	Pruning	ECG II, ECG V, ABP, RESP		ECG II, ECG V, PLETH, ABP		ECG II, ECG V, PLETH, RESP		ECG II, ECG V, PLETH	
		Accuracy	Level	Accuracy	Level	Accuracy	Level	Accuracy	Level
Asystole	Pre-pruning	99.0	61	73.9	113	82.6	170	97.6	166
	Post-pruning	99.0	60	73.9	105	82.6	165	97.6	120
Bradycardia	Pre-pruning	97.5	134	93.0	170	85.4	205	78.1	319
	Post-pruning	97.5	130	–	–	85.4	200	78.1	310
Tachycardia	Pre-pruning	99.3	14	NA	NA	64.4	261	NA	NA
	Post-pruning	99.3	10	NA	NA	–	–	NA	NA
Ventricular Tachycardia	Pre-pruning	96.3	36	97.5	123	74.2	355	82.5	293
	Post-pruning	96.3	30	97.5	120	74.2	340	82.5	250
Ventricular flutter	Pre-pruning	NA	NA	100	1	NA	NA	99.2	28
	Post-pruning	NA	NA	–	–	NA	NA	99.2	26

Comparison with other methods

Various researchers over the yearshave studied false alarm detection in ICU during. Table 5 describes a comparative study of various works proposedin terms of datasets used, the algorithm used, arrhythmia types detected and accuracy. The study [26] has mostly analyzed on the minimization of true alarm recognition error on the occurrenceof ventricular tachycardia by observing the variation of RR interval and QRS complex. And otheralarm types are experimented on the quality index value of ABP and threshold value of PPG. This studyhas claimed that the proposed method is able to reduce the false alarm occurrence up to 42.7% for all arrhythmia types. In [27] same algorithm has been used but has achieved less accuracy than the presentstudy. In all types of arrhythmia cases considering only ABP and PPG as an input. Whereas ECG ismost crucial for detecting the quality of heartbeat as well as manipulating the false alarming conditions. Try to classify Atrial fibrillation, [28] has introduced three comparative classification algorithms as KNN,NN, and SVM and among these three methods NN has achieved highest accuracy where it was trained by the back-propagation algorithm. This research study has proposed an ensemble of three methodswhere each method compromises the other's disadvantages and the combination of all methods make it more powerful than individual classifier. Further CNN is a smart choice in classification where thereduction of false arrhythmia alarm becomes more complicated. It's self-learning and self-organizing property is much more advanced than supervised learning methodology. Using only the ECGsignal as input the study in [29] has achieved better performance than the conventional classifier but not in comparison to the proposed method. Here, [30] has deployed a method where the combination of multimodal waveforms such as ECG, BP, and PPG has examined through the noise classifier to increasetrue alarm incidence as well as to reduce the false alarming condition. All these related studies are appliedto the content of false alarm reduction. But this study, which is performed on decision treepredictive learner method, has achieved the highest performance on the basis of accuracy. Implicit featureselection, robust to missing value problem and nonlinear data representation makes it more perfect forclassification purpose. From Table 5 it can be observed that the proposed DT-based method has highlighted as the highest accuracy among all the

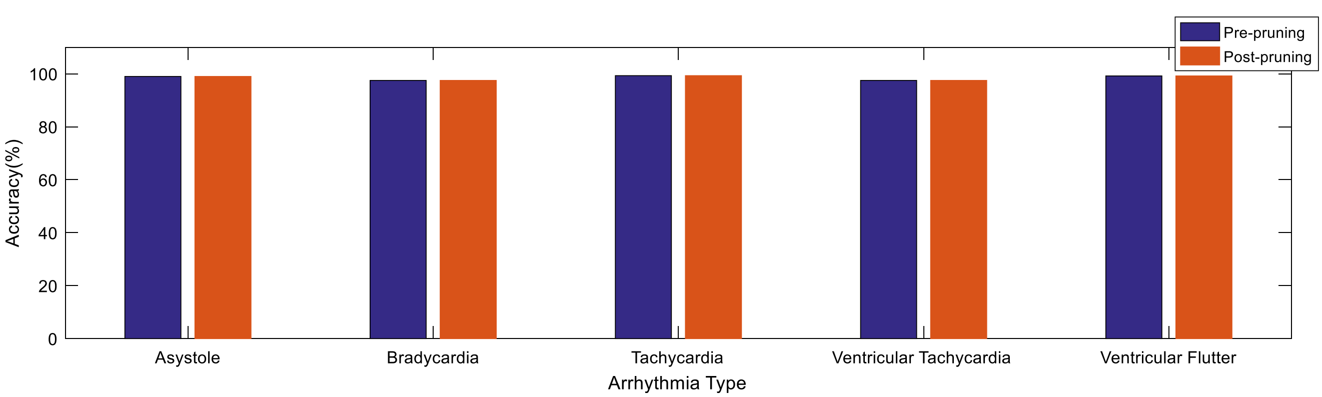

Fig. 8 Accuracy obtained pre and post-pruning in the retrospective phase

Table 5 Comparison of various methods

Authors	Dataset Used	Algorithm Used	Phase	Arrhythmia Type	Accuracy
Serackis et al. [26]	Computing in Cardiology 2015 Challenge (ECG II, ECG III)	RR interval variation and QRS complex shape Features	–	Asystole	92
				Bradycardia	93
				Tachycardia	95
				Ventricular Flutter	85
				Ventricular Tachycardia	44
Caballero et al. [27]	Computing in Cardiology 2015 Challenge (ABP,PPG)	Decision tree	Unofficial phase	Asystole	68.59
				Bradycardia	69.91
				Tachycardia	86.18
				Ventricular Flutter	64.86
				Ventricular Tachycardia	44.94
		Pruned Decision tree and added domain knowledge	Official phase	Asystole	76.57
				Bradycardia	84.76
				Tachycardia	86.18
				Ventricular Flutter	67.74
				Ventricular Tachycardia	55.22
Le et al. [28]	MIT-BIH arrhythmia database (ECG and PPG)	k-nearest neighbor (kNN), Neural network (NN) and Support vector machine (SVM)	–	Atrial Fibrillation (AF)	99.32
Acharya et al. [29]	CUDB, MITDB, VFDB (ECG)	11 layers of Convolution neural network (CNN)	–	Shockable and non-shockable ventricular arrhythmias	93.18
Daluwatte et al. [30]	Computing in Cardiology 2015 Challenge (ECG, BP and/or PPG)	Multimodal physiological waveforms Algorithm	Testing	Asystole	77.8
				Bradycardia	43.8
				Tachycardia	84.2
				Ventricular Flutter	85.5
				Ventricular Tachycardia	70.8
Proposed Method	Computing in Cardiology 2015 Challenge	Decision tree predictive learner	Testing	Asystole	99.3
				Bradycardia	97.5
				Tachycardia	100.0
				Ventricular Flutter	98.6
				Ventricular Tachycardia	100

other methods. Hence the proposed method can be implemented in real hospitals efficiently.

Conclusion

This study introduces a classification method regarding the reduction of false arrhythmia alarm by using decision tree predictive learner (DTPL). This supervised learning method makes a decision on behalf of checking attribute's condition. To the best of our knowledge, there is no such assumption based classification approach. In the first phase of the study create a decision making a tree on the trained dataset then it is verified by the tested dataset and accuracy has compared at various level in the pre-pruning and post-pruning. After checking the pre-pruning accuracy, to enhance the performance of the resultant predictive model has needed to implement the post-pruning tree by decreasing level up to the best level. In this study, the proposed method has tested through all five types of arrhythmia among which bradycardia has achieved the highest accuracy in real phase and tachycardia has achieved 99.3% accuracy in retrospective phase. This demonstration has been limited between intra-database studies. Moreover, the proposed work will extend for checking the potentiality of DTPL method over the inter-database.

References

1. Amadu, A. M., Baritussio, A., Dastidar, A. G., Garate, E. D., Rodrigues, J. C. L., Biglino, G., Lyen, S., Diab, I., Duncan, E., Nisbet, A., Thomas, G., Angelini, G. D., and Bucciarelli-Ducci, C., Arrhythmogenic right ventricular cardiomyopathy (ARVC) mimics: The knot unravelled by cardiovascular MRI. *Clin. Radiol.* 74:228–234, 2019. https://doi.org/10.1016/j.crad.2018.12.002.

2. Desai, R., Patel, U. K., Singh, S., Bhuva, R. K., Fong, H. K., Nunna, P., Zalavadia, D., Dave, H., Savani, S., and Doshi, R. K., The burdenand impact of arrhythmia in chronic obstructive pulmonary disease: Insights from the National Inpatient Sample. *Int. J. Cardiol.* 281:49–55, 2019. https://doi.org/10.1016/j.ijcard.2019.01.074.
3. Zaghla, H., Atroush, H. A., Samir, A., and Kamal, M., Arrhythmias in patients with chronic obstructive pulmonary disease. *Egypt J. Chest. Dis. Tubercul.* 62:377–385, 2013. https://doi.org/10.1016/j.ejcdt.2013.05.005.
4. Chugh, S. S., Rothy, G. A., Gillumx, R. F., and Mensah, G. A., Global burden of atrial fibrillation in developed and developing nations. *Global Heart* 9:113–119, 2014. https://doi.org/10.1016/j.gheart.2014.01.004.
5. Rosa, S. A., Cunha, P. S., Lousinha, A., Valente, B., Delgado, A. S., Pimenta, R., Bras, M., Cruz, M. C., Portugal, G., Monteiro, A. V., Oliveira, M., and Ferreira, R. C., Importance of monitoring zones in the detection ofarrhythmias in patients with implantablecardioverter-defibrillators under remote monitoring. *Revista Portuguesa de Cardiologia.* 38:11–16, 2019. https://doi.org/10.1016/j.repc.2018.05.015.
6. Daluwatte, C., Vicente, J., Galeotti, L., Johannesen, L., Strauss, D. D. G., and Scully, D. C. G., A novel ECG detector performance metric and its relationship with missing and false heart rate limit alarms. *J. Electrocardiol.* 5:68–73, 2018. https://doi.org/10.1016/j.jelectrocard.2017.08.030.
7. Siebig, S., Kuhls, S., Imhoff, M., Langgartner, J., Reng, M., Scholmerich, J., Gather, U., and Wrede, C. E., Collection of annotated data in a clinical validation study for alarm algorithms in intensive care—A methodologic framework. *J. Critic. Care* 25: 128–135, 2010. https://doi.org/10.1016/j.jcrc.2008.09.001.
8. Solet, J. M., and Barach, P. R., Managing alarm fatigue in cardiac care. *Progress Pediatr. Cardiol.* 33:85–90, 2012. https://doi.org/10.1016/j.ppedcard.2011.12.014.
9. Hu, X., Sapo, M., Nenov, V., Barry, T., Kim, S., Do, D. H., Boyle, N., and Martin, N., Predictive combinations of monitor alarms preceding in-hospital code blue events. *J. Biomed. Inform.* 45:913–921, 2012. https://doi.org/10.1016/j.jbi.2012.03.001.
10. Li, Q., and Clifford, G. D., Signal quality and data fusion for false alarm reduction in the intensive care unit. *J. Electrocardiol.* 45: 596–603, 2012. https://doi.org/10.1016/j.jelectrocard.2012.07.015.
11. Clifford, G. D., Silva, I., Moody, B., Li, Q., Kella, D., Shahin, A., Kooistra, T., and Perry, D., Mark RG (2015) the PhysioNet/computing in cardiology challenge 2015: Reducing false arrhythmia alarms in the ICU. *Comput. Cardiol.* 42:273–276, 2015.
12. Fallet, S., and Yazdani, S., Vesin JM (2015) a multimodal approach to reduce false arrhythmia alarms in the intensive care unit. *Comput. Cardiol.* 42:277–280, 2015.
13. Plesinger, F., Klimes, P., and Halamek, J., Jurak P (2015) false alarms in intensive care unit monitors: Detection of life-threatening arrhythmias using elementary algebra, descriptive statistics and fuzzy logic. *Comput. Cardiol.* 42:281–284, 2015.
14. Zong, W., Reduction of false critical ECG alarms using waveform features of arterial blood pressure and/or Photoplethysmogram signals. *Comput. Cardiol.* 42:289–292, 2015.
15. Eerikainen, L. M., Vanschoren, J., Rooijakkers, M. J., Vullings, R., and Aarts, R. M., Decreasing the false alarm rate of arrhythmias in intensive care using a machine learning approach. *Comput. Cardiol.* 42:293–296, 2015.
16. Roonizi, E. K., and Sassi, R., A signal decomposition model-based Bayesian framework for ECG components separation. *IEEE Trans. Signal Process.* 64:665–674, 2016. https://doi.org/10.1109/TSP.2015.2489598.
17. Jain, S. K., and Bhaumik, B., An energy efficient ECG signal processor detecting cardiovascular diseases on smartphone. *IEEE Trans. Biomed. Circ. Syst.* 11:314–323, 2017. https://doi.org/10.1109/TBCAS.2016.2592382.
18. Satija, U., and Manikandan, S. M., Automated ECG noise detection and classification system for unsupervised healthcare monitoring. *IEEE J. Biomed. Health Inform.* 22:722–732, 2018. https://doi.org/10.1109/JBHI.2017.2686436.
19. Quiroz-Juárez, M. A., Jiménez-Ramírez, O., Vázquez-Medina, R., Ryzhii, E., and Ryzhii, M., Cardiac conduction model for generating 12 Lead ECG signals with realistic heart rate dynamics. *IEEE Trans. Nanobiosci.* 17:525–532, 2018. https://doi.org/10.1109/TNB.2018.2870331.
20. Liu, F., Liu, C., Zhao, L., Jiang, X., Zhang, Z., Li, J., Wei, S., and Zhang, Y., Dynamic ECG signal quality evaluation based on the generalized bSQI index. *IEEE Access* 6:41892–41902, 2018. https://doi.org/10.1109/ACCESS.2018.2860056.
21. Qu, Y. R., and Prasanna, V. K., Compact hash tables for decision-trees. *Parallel Comput.* 54:121–127, 2016. https://doi.org/10.1016/j.parco.2015.12.003.
22. Saettler, A., Laber, E., and Pereira, F. A. M., Decision tree classification with bounded number of errors. Inform. Process. Lett. 127: 27–31, 2017. https://doi.org/10.1016/j.ipl.2017.06.011.
23. Liua, X., Lia, Q., Lib, T., and Chen, D., Differentially private classification with decision tree ensemble. *Appl Soft Comput.* 62:807–816, 2018. https://doi.org/10.1016/j.asoc.2017.09.010.
24. Wang, X., Liu, X., Pedrycz, W., and Zhang, L., Fuzzy rule based decision trees. *Pattern Recogn.* 48:50–59, 2015. https://doi.org/10.1016/j.patcog.2014.08.001.
25. Chen, Y. L., Wu, C. C., and Tang, K., Time-constrained cost-sensitive decision tree induction. *Inform. Sci.* 354:140–152, 2016. https://doi.org/10.1016/j.ins.2016.03.022.
26. Serackis, A., and Abromavicius, V., Gudiskis a (2015) identification of ECG signal pattern changes to reduce the incidence of ventricular tachycardia false alarms. *Comput. Cardiol.* 42:1193–1196, 2015.
27. Caballero, M., and Mirsky, G. M., Reduction of false cardiac arrhythmia alarms through the use of machine learning techniques. *Comput. Cardiol.* 42:1169–1172, 2015.
28. Lee, K., Choi, H. O., Min, S. D., Lee, J., and Gupta, B. B., A comparative evaluation of atrial fibrillation detection methods in Koreans based on optical recordings using a smartphone. *IEEE Access* 5:11437–11434, 2017. https://doi.org/10.1109/ACCESS.2017.2700488.
29. Acharya, U. R., Fujita, H., Lih, O. S., Hagiwara, Y., Tan, J. H., and Adam, M., Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network. *Inform. Sci.* 405:81–90, 2017. https://doi.org/10.1016/j.ins.2017.04.012.
30. Daluwatte, C., Johannesen, L., Vicente, J., Scully, C. G., and Galeotti, L., Strauss DG (2015) heartbeat fusion algorithm to reduce false alarms for arrhythmias. *Comput. Cardiol.* 42:745–748, 2015.
31. Baloglu, U. B., Talo, M., Yildirim, O., San Tan, R., and Acharya, U. R., Classification of myocardial infarction with multi-lead ECG signals and deep CNN. *Pattern Recogn. Lett.* 122:23–30, 2019. https://doi.org/10.1016/j.patrec.2019.02.016.
32. Yıldırım, O., Pławiak, P., Tan, R. S., and Acharya, U. R., Arrhythmia detection using deep convolutional neural network with long duration ECG signals. *Comput. Biol. Med.* 102:411–420, 2018. https://doi.org/10.1016/j.compbiomed.2018.09.009.
33. Yildirim, O., A novel wavelet sequence based on deep bidirectional LSTM network model for ECG signal classification. *Comput. Biol. Med.* 96:189–202, 2018. https://doi.org/10.1016/j.compbiomed.2018.03.016.
34. Pławiak, P., and Acharya, U.R., Novel Deep Genetic Ensemble of Classifiers for Arrhythmia Detection Using ECG Signals. 2019. doi: https://doi.org/10.1007/s00521-018-03980-2.

35. Pławiak, P., Novel genetic ensembles of classifiers applied to myocardium dysfunction recognition based on ECG signals. Swarm Evol. Comput. 39:192–208, 2018. https://doi.org/10.1016/j.swevo.2017.10.002.
36. Han, J., Kamber, M., and Pei, J., (Third edition) data mining concepts and techniques. Morgan Kaufmann.
37. Salvetti, A., Personal view: A centenary of clinical blood pressure measurement: A tribute to Scipione Riva-Rocci. *Blood Press.* 5: 325–326, 1996.
38. Mukkamala, R., Hahn, J. O., Inan, O. T., Mestha, L. K., Kim, C. S., Toreyin, H., and Kyal, S., Toward ubiquitous blood pressure monitoring via pulse transit time: Theory and practice. *IEEE Trans. Bio-Med. Eng.* 62:1879–1901, 2015.
39. Messas, E., Pernot, M., and Couade, M., Arterial wall elasticity: State of the art and future prospects. *Diagn. Interv. Imaging* 94: 561–569, 2013.
40. Ding, X. R., Zhang, Y. T., Liu, J., Dai, W. X., and Tsang, H. K., Continuous Cuffless blood pressure estimation using pulse transit time and Photoplethysmogram intensity ratio. *IEEE Trans. Bio-Med. Eng.* 63:964–972, 2016.
41. Poleszczuk, J., Debowska, M., Dabrowski, W., Wojcik-Zaluska, A., Zaluska, W., and Waniewski, J., Subject-specific pulse wave propagation modeling: Towards enhancement of cardiovascular assessment methods. *PLoS ONE* 13, 2018. doi: https://doi.org/10.1371/journal.pone.0190972.
42. Yoon, Y. Z., Kang, J. M., Kwon, Y., Park, S., Noh, S., Kim, Y., Park, J., and Hwang, S. W., Cuff-less blood pressure estimation using pulse waveform analysis and pulse arrival time. *IEEE J. Biomed. Heal. Inf.* 22:1068–1074, 2018.
43. Xing, X., and Sun, M., Optical blood pressure estimation with photoplethysmography and FFT-based neuralnetworks. *Biomed. Opt. Express* 7:3007–3020, 2016.
44. Li, Y., Wang, Z., Zhang, L., Yang, X., and Song, J., Characters available in photoplethysmogram for blood pressure estimation: Beyond the pulse transit time. *Australas. Phys. Eng. Sci. Med* 37: 367–376, 2014.
45. Ding, X., Yan, B. P., Zhang, Y. T., Liu, J., Zhao, N., and Tsang, H. K., Pulse transit time based continuous cufflessblood pressure estimation: A new extension and a comprehensive evaluation. *Sci. Rep.* 7:11554, 2017. https://doi.org/10.1038/s41598-017-11507-3.
46. Rundo, F., Ortis, A., Battiato, S., and Conoci, S., Advanced bio-inspired system for noninvasive cuff-less bloodpressure estimation from physiological signal analysis. *Computation* 6:46, 2018. https://doi.org/10.3390/computation6030046.