Detection of Myocardial Infarction and Arrhythmia from Single-Lead ECG Data using Bagging Trees Classifier

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***Abstract*— Myocardial Infarction (MI) and Arrhythmia (AR) are serious heart diseases. Human identification of these diseases from raw electrocardiography (ECG) signals is tedious and expensive. In recent studies, these diseases have been identified and localized individually using multi-channel ECG data. We explored for the robust detection of both MI and AR from ECG signal using a minimalistic (single channel) ECG data. In this study, a total of 440 records from 12-lead ECG signals (79 Healthy Person, 346 MI, and 15 AR) have been used from "PTB Diagnostic ECG Database" of PhysioBank. The proposed algorithm automatically identifies P, Q, R, S, and T points of ECG signals, and then extracts 33 features: 15 interval type and 18 amplitude type. Bagging Tree, an ensemble method which is computationally efficient and at the same time can deal with the class imbalance problem within the data, is used for classification. During training, 10-fold cross validation is used to ensure generalization of the classifier and to remove over-fitting. Our study demonstrates that Bagging Tree is able to identify MI, AR and normal patients with the cross-validation accuracy of 99.7%, sensitivity of 99.4%, specificity of above 99.5%, precision of 99.32%, and F1 score of 99.36% from a single lead ECG data (Lead V4). The proposed algorithm uses a minimalistic single-channel ECG for robust detection of MI and AR that can be utilized in wearables for real-time patient monitoring.**

I. Introduction

Myocardial Infarction (MI) and Arrhythmia (AR) are two critical and common heart diseases. The shortage of blood flow to a location of the heart causes damage to the heart muscle and this phenomenon is called MI. AR occurs due to the problem in the electrical conduction system of the heart. If these diseases are not detected in time, the activity and the structure of the heart gets deteriorated quickly [1]. An estimated 0.9 million Americans experience different kinds of MI or AR in each year [2-4].

With the help of ECG, the presence of MI and AR can be detected [5-15]. Generally, in medical diagnosis system, the non-invasive 5 or 12-lead ECG system is used for precise signal analysis [5, 6]. Multi-lead ECG is frequently used to classify MI and AR from normal patients such as: MI was detected using temporal features with k-nearest neighbor classifier (KNN) [7], ST-segment polynomial coefficient features and the morphological features of ECG with neuro-fuzzy classifier [8], and Hermite expansion coefficient features of multi-lead ECG with neural networks [10]. AR could be classified using extracted ECG coefficients from the independent component analysis (ICA) and RR interval with the neural network [11], higher order statistical features, mixture modeling features with the ensemble method [12] and some other techniques. To reduce the cost, complexity, sensor burden and to bring portability, single-lead approaches have also been studied to detect these diseases separately [1, 5, 11, 15]. Even though detection of MI or AR is well investigated separately, according to our knowledge, no study was performed till date to classify both diseases from normal people using same feature vector from a single lead ECG data. As patients suffering from MI can also be affected by AR [16], therefore it is important to detect both diseases simultaneously to ensure correct diagnosis and better healthcare.

This work focuses on the detection of MI and AR from single-lead ECG data and compares different lead performances in order to find the most suitable lead so that any of these two diseases can be detected using a single classifier with minimum delay. To address the class imbalance issue and to reduce the computation, ensemble based bagging tree classifier is used. From the ECG signal of each lead, amplitude, amplitude difference, and time interval of the P, Q, R, S, T points are used to form the feature vector. Our results show that lead V4 performs the best to classify between MI, AR, and normal people among twelve leads in terms of cross-validation accuracy, sensitivity, specificity, precision, and f1 score.

II. Ensemble Classifier

The concept of ensemble classifiers evolved to make more certain and accurate prediction of the data [17]. Bagging trees are useful to deal with class imbalance issue [18]. We have used Bagging Trees from the ensemble classifier branch in this study. If our dataset size is D, then by sampling uniformly k sample from D with replacement p times creates p bootstrap samples. These p different models are fitted with p bootstrap samples. For an unseen predictor, the class has been defined from the votes of p models [19].

III. Method

In this analysis, the PTB Diagnostic ECG Database from the PhysioBank website has been used for this study [20, 21]. Total 440 records from healthy controls, different myocardial infarctions affected patients, and arrhythmia patients have been used from the database (Table I). Each record has 15 simultaneously measured signals from 15 leads. This dataset

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has data from the 12 conventional leads: lead i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6 and from 3 frank leads: lead vx, vy, vz. The sampling rate for capturing the data was 1000 Hz. The signal processing steps have been described in this section. A flowchart of the process is given in Fig. 1.

TABLE I. DESCRIPTION OF THE DATA CONSIDERED IN CLASSIFICATION

Class (11)	*No. of Records (421)*	*Diagnostic Class*
1	79	Healthy Controls
2	44	Anterior
3	44	Anterior Lateral
4	77	Anterior Septal
5	89	Inferior
6	56	Inferior Lateral
7	19	Inferior Posterior Lateral
8	3	Lateral
9	4	Posterior
10	10	Posterior Lateral
11	15	Arrhythmia

A. ECG Signal Preprocessing

ECG signal can easily get contaminated by high frequency and low-frequency noises. Sources of high frequency noise can be electromyogram, power line interferences, mechanical forces acting on electrodes and sources of low-frequency noise can be respiration, motion of patients, and motion of instruments [22]. For filtering the noise, a bandpass filer has been used. A Butterworth filter of 3rd order having (0.5-45) Hz bandwidth [23] is used for this purpose.

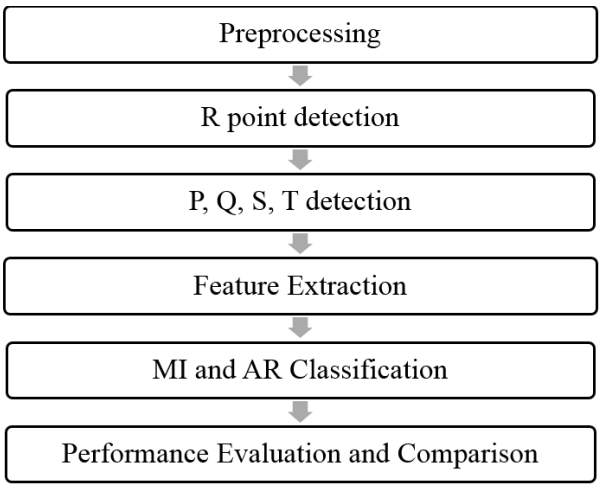

Fig. 1: Processing of ECG data for MI and AR detection

B. R point detection

For the detection of the prominent point like P, Q, R, S, T, T´ first, the detection of R point is important. For the detection of R point, the Pan Tompkin's algorithm has been used [24]. To implement this, pan_tompkin.m code has been used from MATLAB file exchange which has been contributed by Hooman Sedghamiz.

C. P, Q, S, T, T´ detection

After the detection of R point, RR interval and mean RR interval is calculated for every dataset. Then using this information, the rest of the prominent points like Q, R, S, T, and T´ has been calculated by using the information given in Table II:

TABLE II. CRITERIA USED FOR DETECTING P, Q, S, T

Point	Criteria
Q	Minima in between 1/8 of RR interval before each R point to R point
S	Minima in between each R point to ¼ of RR ahead of each R point
P	Maxima from 3/8 of RR before each R point to Q point
T	Maxima after ¼ of RR interval of each R point to the 3/8 of RR of each R point
T´	Minima after ¼ of RR interval of each R point to the 3/8 of RR of each R point

D. Feature Extraction

For the extraction of features, two nature of parameters are considered: interval and amplitude. The interval features are P-P, Q-Q, R-R, S-S, T-T, T-T´, P-Q, P-R, P-S, P-T, Q-R, Q-S, Q-T, R-S, S-T. The amplitude features are P, Q, R, S, T, T´, PQ, PR, PS, PT, PT´, QR, PR, PS, PT, PT´, QR, QS, QT, QT´, RS, ST, ST´. Total 33 features are extracted from each lead. Among them, 15 are interval type and 18 are amplitude type. Feature extraction process runs for every two beat and every time it finishes the processing, it shifts by one beat.

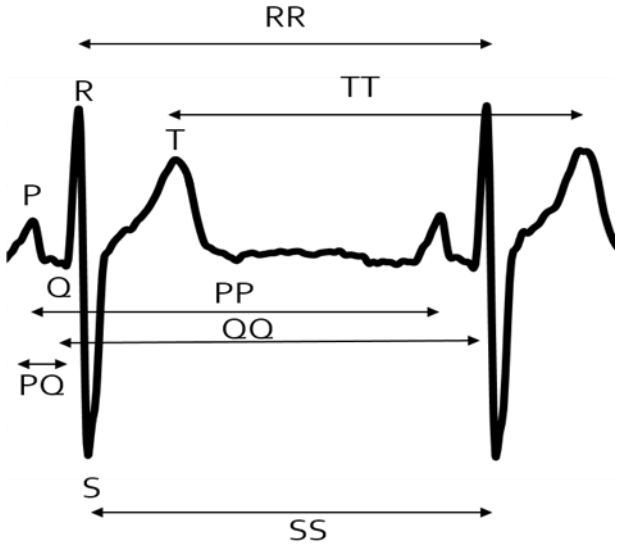

Fig. 2: Some of the key ECG Features

E. Classification

The size of the extracted feature vector is 66634 × 34. The methods used for the classification is bagging trees from Classification Learner Toolbox of MATLAB 2016a version. For training the model, 10-fold cross validation technique is used. The number of splits and the number of learners are kept 20 and 30, respectfully.

F. Performance Evaluation

For performance measure, we have used cross-Validation accuracy, sensitivity, specificity, precision, f1 score to determine the best performing method. 10-fold cross validation accuracy is a measure for generalization and

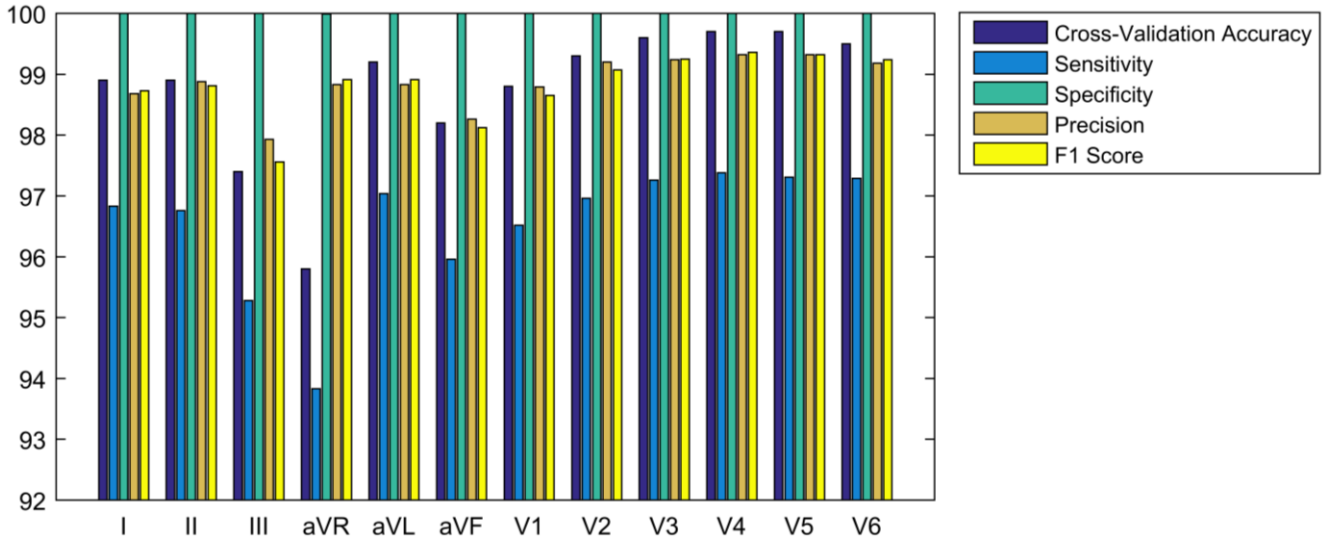

Fig. 3: Performance Comparison of Different Leads (x-axis: name of the lead, y-axis: performance metrics in percentage)

TABLE III. SUMMARY OF LEAD 10 PERFORMANCE

Class	Sensitivity	Specificity	Precision	F1 Score
Healthy Controls	99.4	100	99.4	99.40
Anterior	99.4	100	99.4	99.40
Anterior Lateral	99.4	100	99.4	99.40
Anterior Septal	99.4	100	99.4	99.40
Inferior	99.4	100	98.26	99.40
Inferior Lateral	99.4	100	98.79	99.40
Inferior Posterior Lateral	99.4	100	99.20	99.40
Lateral	99.4	100	99.24	99.40
Posterior	100	100	99.32	100.00
Posterior Lateral	100	100	99.32	99.70
Arrhythmia	99	100	99.18	99.00

overfitting, whereas sensitivity, specificity, precision are the measures to see the effect of false positive or negative in the performance. F1 score is the score to view the balance between precision and recall or sensitivity.

IV. RESULT

For measuring the overall efficacy in the detection of diseases, 10-fold cross-validation accuracy, sensitivity, specificity, precision, and f1 score are measured and presented in fig.3. We have observed that lead V4 performed the best among all other leads in distinguishing normal, 9 types of MI, and AR patients (fig.3) in terms of cross-validation accuracy, weighted sensitivity, specificity, precision, and f1 score. We have measured the cross-validation accuracy which determines how good a classification model might perform in real time or how well a model deals with overfitting. Cross-validation accuracy of lead V4 and V5 is 99.7% which is the highest among all other leads. To find how well the lead detects a disease when it is actually present, sensitivities for all classes are measured. According to the weighted sensitivity, lead V4 performs the best by giving 99.4% while the second best is 99.32% by lead V5. Specificity is used to measure how good a lead is in diagnosing a class as negative when it is actually absent. All lead performs well in terms of specificity. Precision helps us to compare how much relevant result a lead might produce in real time. The best precision score is 99.32% by lead V4 and V5. The balance between the precision and the recall can be understood from the f1 score and the more is the f1 score, the better it the balance is. The lead V4 again produces the best f1 score (99.36%).

TABLE IV. RANKING OF LEADS BASED ON PERFORMANCES

Rank	Lead	Cross-validation Accuracy	F1 Score
1	V4	99.7	99.36
2	V5	99.7	99.32
3	V3	99.6	99.25
4	V6	99.5	99.24
5	V2	99.3	99.07
6	avl	99.2	98.91
7	ii	98.9	98.81
8	i	98.9	98.73
9	V1	98.8	98.65
10	avf	98.2	98.12
11	iii	97.4	97.56
12	avr	95.8	98.91

The sensitivity for detecting Posterior and Posterior Lateral is 100% while features from lead V4 were used (TABLE III). The sensitivity for the detection of Control, and some of the MI (Anterior, Anterior Lateral, Anterior Septal, Inferior, Inferior Lateral, Inferior Posterior Lateral, Lateral) is above 99%. The true negative rate (measured by specificity) and the relevance of the detection (measured by precision) are more than 99% for different MI, AR, and control for Lead V4. The balance of precision and recall is also higher than 99% for all

the classes and 100% for posterior MI while lead V4 is used. (TABLE III)

The ranking of the leads based on their performance is given in TABLE IV. TABLE IV gives us an idea that which location helps to detect MI, AR efficiently if we use a single lead system. Most of the Precordial leads (V2 …V6) could be better options for portable single lead system because they remain in the top of the table. Augmented limb and limb leads perform less superior than those precordial one.
patient management.

V. Discussion

We have compared our results with the existing research in terms of sensitivities for this study, Acharya et al [1], and Tripathy et al [23] respectively.
Except lateral myocardial infarction, for all other types this

TABLE V. Sensitivity Comparison

Approach	[1]	[23]	Our approach
Healthy Controls	97.6	90.6	99.4
Anterior	98.9	-	99.4
Anterior Lateral	97.7	-	99.4
Anterior Septal	97.2	-	99.4
Inferior	95.9	-	99.4
Inferior Lateral	97.6	-	99.4
Inferior Posterior Lateral	98.9	-	99.4
Lateral	99.9	-	99.4
Posterior	99.9	-	100
Posterior Lateral	99.8	-	100
Arrhythmia	-		99
MI	-	95.2	99.4

method outperforms in terms of sensitivity. Acharya et al [1] has followed single lead approach whereas Tripathy et al [23] has followed multi-lead approach. The best results from different approaches of Acharya et al [1] and Tripathy et al [23] have been chosen for the comparison task.

The comparison of our algorithm with the algorithms existed in the professional devices of the current commercial brands is not possible due to their proprietary nature.

The database has no specific information regarding the type of AR (ventricular or auricular) for patients. Therefore, our algorithm cannot distinguish between them.

We have followed ten-fold cross-validation for the evaluation purpose and to build a model to deal with overfitting at its best. However, due to a low number of records (440), we did not apply the final model to an independent dataset. This will be investigated in future, however, in this study, our target was to find some common features and proper classifier which will discriminate AR and different MIs from single lead for the future implementation in portable applications. In future, we have an interest for implementation of this work for portable applications involving microcontrollers and a smartphone app.

VI. Conclusion

The development of an algorithm for the detection of MI, AR using minimal features from a single lead is challenging. In this paper, an automated algorithm is proposed to deal with the classification of normal, different MI patients, AR patients using 33 time-domain features from single channel ECG data. The lead-wise comparison has been done among 12 leads (i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6) in order to find the best performing lead. We have chosen bagging tree, an ensemble method as a classifier which can help in efficient training and can deal with the class imbalance problem. According to our study, the performance from lead v4 was the best among other leads in terms of the cross-validation accuracy, sensitivity, specificity, precision, and f1 score. We got 99.7% 10-fold cross-validation accuracy with overall 99.41% sensitivity and 100% specificity from lead V4 in separating normal, different MI and AR patients. Also we have found that the data from the precordial leads are able to perform better in detecting these serious heart diseases (MI and AR) than the data from limb, or augmented limb leads. The proposed automated system is implementable in real time situation as it does not need human intervention. Physicians and other medical personal might be benefitted from real time classification along with the raw data. This work might help to reduce human error involved in manual detection and diagnose technique of ECG signal. Furthermore, utilizing single lead (lead V4), the number of channels required for monitoring would be minimal. As this method has less complexity in feature calculation and can give satisfactory performance with single-lead data, this might enhance the application of ECG monitoring system as a wearable for daily monitoring of patients to improve their quality of lives and

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