Machine Learning-based Classification of Ischemic and Non-Ischemic Exercise Stress Test ECG

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Abstract

Myocardial Ischemia (MI) is a fatal heart condition due to insufficient blood flow in the heart muscles, which may cause unexpected heart attacks. Exercise Stress Test (EST) Electrocardiogram (ECG) is a non-invasive diagnostic procedure that can help identify various disease conditions, including MI. This study aims to classify the ischemic and non-ischemic EST ECG using Machine Learning (ML) algorithms. EST ECGs for 152 patients (n=53 female) of mean age (50 ± 11.92 years) were used in this study. ST morphology changes, measured during pre-load, load, and recovery at J + (40, 60, and 80 ms) were utilized as input to 14 ML classifiers. 70% of the input data to the ML classifiers were considered as train data, and 30% of the input data as test. Random Forest (RF) was selected based on the most suitable output and was used to classify between ischemic and non-ischemic by considering the clinical features such as ST variations, Blood Pressure (BP), Metabolic equivalent (Mets), and Rate Pressure Product (RPP) as input for both lead-II and V5. The model accuracy, sensitivity, precision, and F1 score for lead-II were 93%, 89.17%, 93%, and 89.63%, respectively. For V5, the performance matrices were 91%, 80%, 95%, and 86.14%, respectively.

1. Introduction

Myocardial ischemia and stroke are the leading causes, accounting for more than 80% of deaths due to cardiovascular diseases [1]. Hence, the requirement for early detection of ischemia is highly recommended. Exercise Stress Test (EST) is a non-invasive, inexpensive, and preliminary diagnosis for detecting ischemia and various other cardiovascular diseases [2]. ST segment changes primarily seen in EST Electrocardiogram (ECG) could be the cause of myocardial ischemia [3,4]. ST segment changes are seen in the ventricular action potential plateau phase when the flow of currents called injury currents is produced due to voltage gradients across the border between ischemic and non-ischemic myocardial cells [3]. These variations are elevated ST segment and depressed ST segment with upsloping, down-sloping and horizontal depression. If ST alterations are permanent, they can indirectly indicate the degree and severity of myocardial ischemia injury and, eventually, cell death [5]. T- wave inversions, with the ST segment deviations were used as solid indications for ischemia [3]. Apart from ST segment changes, other features like Blood pressure (BP) response, Metabolic equivalent (Mets), exercise capacity, Heart Rate (HR), and angina are also essential biomarkers for detecting ischemia.

Comparing ST segment variations for detecting ischemia is time consuming and laborious. Hence, lately automated recognition of distinctive features from ECG waves, for example by using Machine Learning (ML) algorithms is critical in diagnosing myocardial ischemia [6].

2. Methodology

2.1. Study population

152 (53 women) volunteers (mean age 50 ± 11.92 years) underwent a stress test ECG under Bruce protocol, conducted using an ergometer. Age, sex, weight, maximum Mets, maximum BP, maximum HR, minimum (BP*HR), and end criteria, which are the causes for ending the EST, are the biomarkers noted in the test along with the ECG recordings.

2.2. Data acquisition and analysis

EST were recorded at a paper speed of 25 mm/s and 10 mm/mV using Standard 12 Lead in different stages which are supine, standing, pre walk, load 1, load 2, load 3, load 4, recovery 1, recovery 2, recovery 3, and at the end of test each for 3 minutes standard duration was used in this analysis. ST segment morphology changes in lead-II and V5 were measured during all the EST stages at 40 ms, 60 ms, and 80 ms after the J-point. ST morphological alterations, as well as other indicators, were considered clinical features in the self-created data set, which was subsequently analyzed and fed as input to the ML classification models.

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2.3. Characterization of ST segment

Figure 1 illustrates a typical up sloping ST depression in a single beat Standard 12-lead ECG at load 2 stage of EST. ST segment begins after J-point but the ST deviation from the isoelectric line is measured at J+(40, 60 and 80) ms.

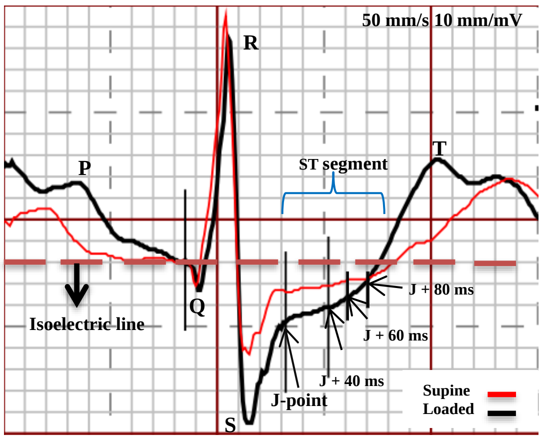

Figure 1. ST segment depression at J + (40, 60, 80) ms.

The data prepared is ST morphological alterations of both lead-II and V5, at J+(40, 60, 80) ms, which is supplied as input to 14 ML classifiers as feature sets, which identify volunteers as having elevated, depressed, or normal ST segment. Due to data imbalance, multiclass classification could not be performed at 40 ms after J-point. Hence ST alterations at only J+(60, 80) ms was taken as data input to ML classifiers. The classifiers that are compared are K nearest neighbors (KNN), Decision Tree Classifier (DT), Support Vector Machine (SVM), Extra Trees Classifier (ET), Random Forest Classifier (RF), Ridge Classifier (ridge), Linear Discriminant Analysis (LDA), Cat Boost Classifier (Catboost), Logistic Regression (LR), Ada Boost Classifier (ADA), Light Gradient Boosting Machine (Lgbm), Naive Bayes (NB), Extreme Gradient Boosting (XGboost), and Gradient Boosting Classifier (GB). Top 5 models listed according to their accuracy in descending order are selected for the particular intervals both for lead-II and V5. Among these classifiers, the most optimized model was RF.

Following this, the ST alterations at J+(60, 80) ms in both leads and the other biomarkers are used as input to the RF to classify volunteers as ischemic or non-ischemic. All the classifications are done, with 70% of the data being train data and 30% being the test data. A performance analysis has been done to find the optimum interval at which distinguishes patients with myocardial ischemia from non-ischemic with higher accuracy.

3. Results

Post comparison of the ML algorithms and selecting RF algorithm as optimum model, Table 1 displays the accuracy of the RF model in classifying volunteers into having elevated, depressed or standard ST segment both for lead-II and V5 at 60 ms and 80 ms after the J-point. Table 2 exhibits the performance analysis of RF classifier, which is used for binary classification, to differentiate ischemia from non-ischemic heart condition.

Table 1. Accuracy of RF model in classification of ST segment Variations at J+(60, 80) ms using RF model

Leads	Duration	Accuracy
Lead-II	60 ms	0.82
	80 ms	0.85
V5	60 ms	0.94
	80 ms	0.92

Table 2. Performance analysis to determine ischemia from non-ischemic heart conditions for lead-II and V5 at J+ (60, 80) ms

Leads	Duration	Accuracy	Recall	Precision	F1
Lead-II	60 ms	0.93	0.89	0.93	0.90
	80 ms	0.91	0.95	0.88	0.91
V5	60 ms	0.91	0.80	0.95	0.86
	80 ms	0.85	0.71	0.79	0.73

Higher accuracy shown at 60 ms after J-point could be potential interval for determination of ischemia. Figure 2 and Table 3 shows the confusion matrix and classification report in lead-II using RF classifier.

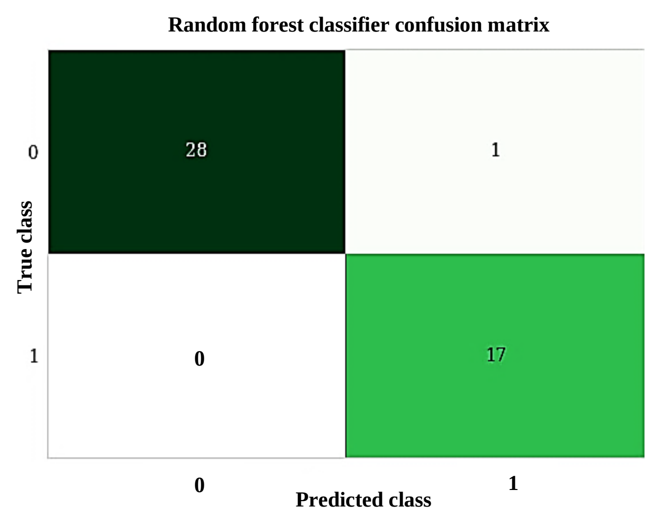

Figure 2. Confusion matrix for lead-II, where 0 represents non-ischemic and 1 represents ischemic heart condition.

Table 3. Classification report for lead-II to determine ischemia for each class at J+60 ms

Class	Precision	Recall	F1
Class 0**	1.00	0.97	0.98
Class 1**	0.94	1.00	0.97

****Class 0 represents non-ischemic and class 1 represents ischemic heart condition**

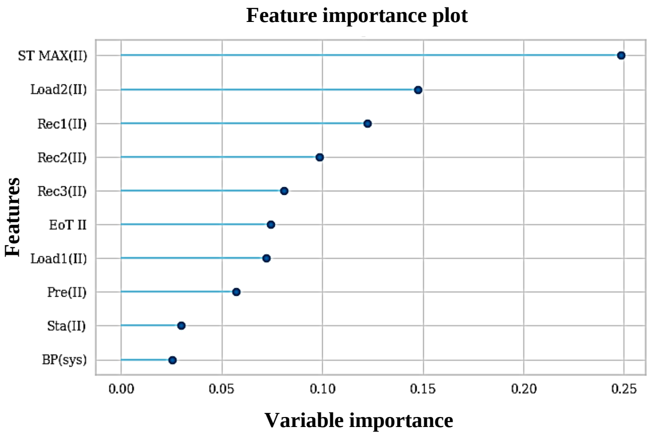

Figure 3. Feature importance plot for lead-II.

Figure 3 and Figure 5 shows the feature importance plot for lead-II and V5 at J+60 ms. In both the leads most important feature for classification is ST deviation at maximum load which is denoted by ST MAX. Figure 4 and Table 4 shows the confusion matrix and classification report in V5 using RF classifier.

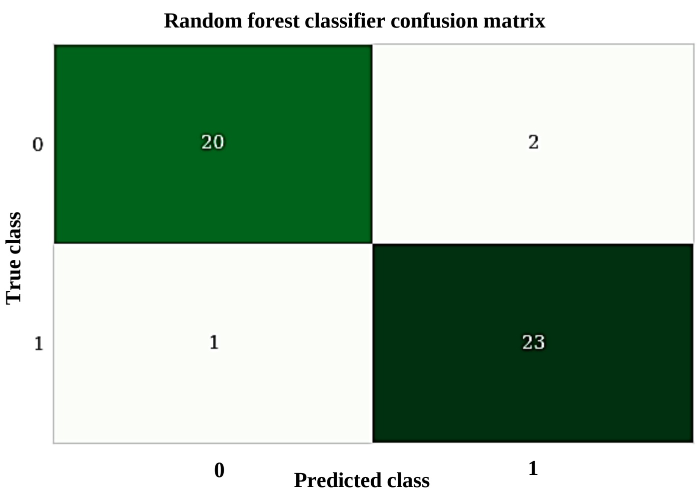

Figure 4. Confusion matrix V5, where 0 and 1 denotes non-ischemic and ischemic heart condition respectively.

The RF classifier training scores at 60 ms after J-point for both lead-II and V5 is 1 and the validation scores are 0.91 and 0.93 showing the data is well trained and comprehended with the test data.

Table 4. Classification report for V5 to determine ischemia for each class at J+60 ms

Class	Precision	Recall	F1
Class 0**	0.95	0.91	0.93
Class 1**	0.92	0.96	0.94

****Class 0, and Class 1 implies non-ischemic and ischemic heart condition respectively**

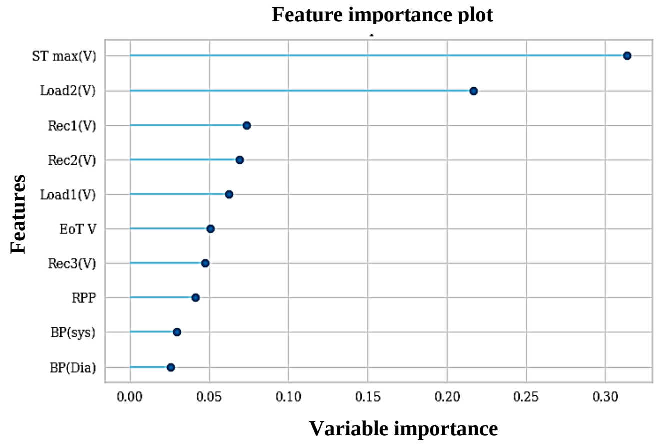

Figure 5. Feature importance plot for V5.

4. Discussion

ST segment variations in lead-II and V5 of EST ECG were identified as data inputs for 14 ML algorithms at J+(40, 60, 80) ms to classify patients having elevated, depressed, and standard ST change. The threshold for ST variations for abnormal changes was ± 0.1 mV for both the leads [3,4,7]. There is a requirement for inputs to ML models to balance the attributes; otherwise, it becomes challenging for traditional ML models to show unbiased results [8]. Hence, results from ST variation at J+40 were discarded for further analysis since they could give biased results due to an imbalanced dataset for both lead-II and V5. Data at J+(60, 80) ms were taken as input to ML classifiers, also considering the fact that these are significant intervals for detecting ST abnormalities as proclaimed by authors [4,9,10]. Splitting data into test and train and following 10-fold cross-validation provided unbiased evaluation [11]. This study used a comparison of ML algorithms to classify ST variations, and further classify ischemic heart condition whereas previous study [12] compared ML algorithms for predicting mortality risk in patients with myocardial infarction. The RF classifier, chosen as the optimum model, was then used among all ML classifiers to determine ischemic heart conditions in volunteers. ST segment deviations and other biomarkers were fed as input to the RF model and were then used to classify ischemic from non-ischemic cardiac conditions. As reported by the authors [9,10], ST variations at intervals J+(60, 80) ms were chosen for having high accuracy in determining ischemia. Table 2 shows the performance of RF with higher accuracy at J+60 ms, thus confirming the most accurate recognition of ischemia in this interval [13]. Figures 2 and 4 display the confusion matrix, which gives information about the true positive, true negative, false positive, and false negative outcomes of the test data in both lead-II and V5. Tables 3 and 4 show the classification report for class 0, the non-ischemic group, and class 1, the group with ischemia in both lead-II and V5. The feature importance plot in Figures 3 and 5 in lead-II and V5, shows that maximum ST deviation is an essential feature. All these parameters imply the robustness of the RF classifier and the high accuracy and importance of ST deviations at J+60 ms for classifying ischemic and non-ischemic heart conditions.

5. Conclusion

The characteristics of the ST segment after performing EST were analyzed in detail as this segment is of utmost importance for diagnosing a variety of fatal heart diseases. The ST segment elevation or depression should be greater than 0.1 mV. During EST, the ST segment is studied for each phase of the test. Manual classification of the variations could be tedious and erroneous therefore ML models are used for automated classification with less time consumption. 14 ML models were compared, and RF was chosen as the optimum model for classifying ST variations. Following that, the RF classifier was utilized in this experimentation to identify ischemic from non-ischemic individuals based on EST data. 60 ms after J-point was considered as the optimum interval after J-point to determine ischemic patients accurately. The RF model accuracy, sensitivity, precision, and F1 score for lead-II were 93%, 89.17%, 93%, and 89.63% respectively. For V5, the performance matrices were 91%, 80%, 95%, and 86.14%, respectively at J+60 ms. Thus, conveying RF as the optimum and 60 ms after J-point as most accurate for determining ischemic heart condition.

Acknowledgments

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