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ANALYSIS OF ACUTE MYOCARDIAL INFARCTION USING ECG SIGNALS AND MACHINE LEARNING ALGORITHMS

Vyacheslav V. Potekhin and Ogul Unal
Peter the Great St. Petersburg Polytechnic University

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Abstract

Heart attack, alternatively known as myocardial infarction (MI), covers various conditions that impact the heart and is one of the most common causes of death worldwide. Electrocardiogram (ECG) can be used as a way to examine the functionality of the cardiovascular system. Researchers apply several machine learning techniques to analyze medical data, helping healthcare professionals to predict heart diseases. The focus of most studies has been on classifying heartbeats or classifying healthy ECG signals on a dataset. In this paper, we propose two methods based on machine learning algorithms for the classification of healthy subjects, subjects who have a myocardial infarction, and analysis of ST elevated (STEMI) or non-ST elevated MI (NSTEMI). We evaluated the proposed method on PhysionNet's PTB Diagnostics dataset. The suggested method can make predictions with accuracies of 95.29% and 82.93% on healthy-MI classification and STEMI-NSTEMI classification, respectively.

Keywords: Machine Learning; Supervised Learning; Electrocardiogram; Myocardial Infarction; Neural Networks

1. Introduction

MI is defined as myocardial cell death due to prolonged ischemia in pathology. Electrocardiography, according to Britannica is a method of graphic tracing of the electric current generated by the heart muscle during a heartbeat [3]. Global Burden of Disease Study 2017 published that the cardiovascular diseases were responsible for 31.8% of all deaths worldwide [21]. The mortality rate of Acute MI remains high, and most deaths occur outside of the hospital. Cardiovascular heart disease represents the leading cause of death in both men and women older than 65 years.

Myocardial infarction (MI) can be recognized or defined as pathological by clinical features using electrocardiographic (ECG) findings, elevation of biochemical markers of myocardial necrosis, and imaging [10]. Machine Learning is a popular method to predict heart diseases, heartbeat classification or prediction of MI [19] [20]. The most challenging problem with the analysis of ECG signals, as with other time-series data, is the difficulty of classifying or detecting different morphology and waveforms in the signal. This is a time-consuming and challenging task that can cause errors. The medical data can be analyzed by different machine learning algorithms [23]. Datasets in

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various fields [22] such as in medicine can be used as training data therefore computers can learn to classify healthy subjects or subjects who have MI. In this research, we used PTB Diagnostic ECG Database.

Machine learning is a method that a computer gradually learns what parameters or weights fit the data best. In this study, two classification models were developed for Acute MI and also for its subcategories. Results of the algorithms were compared. In this paper, we propose two different machine learning methods for ECG signals that can analyze ECG signal to classify the subcategories of MI (STEMI and NSTEMI).

There are other heart diseases that can be detected utilizing ECG signals. In future work, we will further expand this research incorporating other machine learning techniques and heart diseases such as myocarditis or dysrhythmia and different features related to ECG.

2. Literature Review

2.1. Anatomy of the Heart

The heart is an organ that serves as a pump to circulate blood [1] situated between the two lungs. The heart consists of several layers of a muscle wall - the myocardium. A thin layer of tissue, the pericardium, covers the outer part, and another layer, the endocardium, lines the inner part. The heart cavity is divided in the middle into the right and left heart, which, in turn, are divided into two chambers. The upper chamber is called the atrium and the lower chamber is called the ventricle. The heart consists of four chambers: the atrium (right and left atria) and the ventricle (left and right ventricles) on the left and right. The mitral valve separates the left atrium and ventricle and the tricuspid valve separates the right atrium and ventricle [2].

The heartbeat is caused by changing contractions and relaxations of the myocardium. These contractions are stimulated by electrical impulses from a natural pacemaker, the sinoatrial, or SA, node located in the muscle of the right atrium [1]. The impulse from the SA node causes the two atria to contract, pushing blood into the ventricles. Ventricular contraction is controlled by impulses from the atrioventricular, or AV, node located at the junction of the two atria [1]. After contraction, the ventricles relax then the pressure inside the ventricles drops. The blood enters the atria again, and the pulse from S-A starts the cycle again. This process is called the cardiac cycle. The stimulus coming out of the sinus node spreads through both atria of the heart, along the conduction pathways specialized for this job, and with this stimulus, the atria contract and send the blood to the ventricles. Then the signal is sent to a certain area between the atria and the ventricles; comes to the atrioventricular (AV) node. The electrical message is held briefly in the atrioventricular node before being delivered to the ventricles. Thus, simultaneous contraction of the atria and ventricles is prevented.

The heart, by contracting and pumping the blood is caused by electrical currents. These currents are in the around millivolts [2]. These currents can be recorded with the help of an electrocardiogram or ECG by being amplified by specific devices.

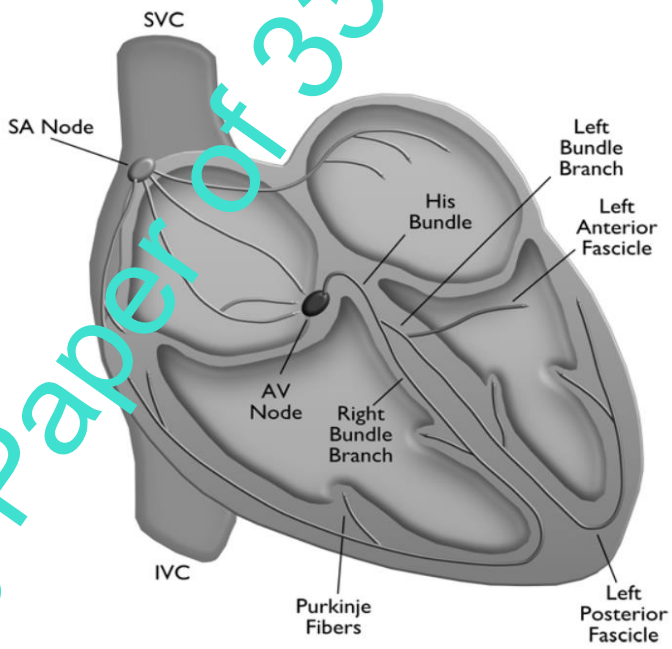

Fig. 1. Cardiac conduction system of heart

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2.2. ECG

Dutch physiologist Willem Einthoven developed the first electrocardiogram in 1903, and for many years the testing was called an EKG after the German Elektrokardiogramm [3]. ECG records of electrical changes that occur during the heartbeat can be used in the diagnosis of heart failure or detecting anomalies. Each heart cycle produces ECG waves called P, QRS, and T.

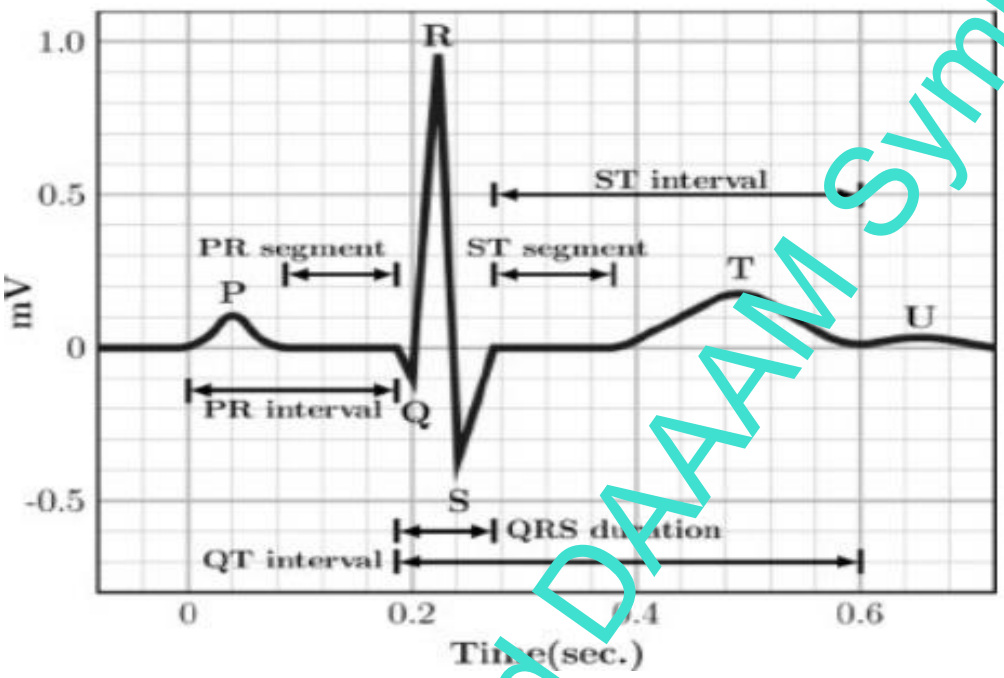

Fig. 2. Healthy ECG signal showing with PQRST complexes

Each wave or segment of the ECG corresponds to a certain event of the cardiac electrical cycle [4]. When the atria are full of blood, the SA node fires, and electrical signals spread throughout the atria and cause depolarization. This is represented by the P wave. Atrial contraction starts after the P wave begins. The PR interval is the time between the first deviation of the P wave and the first deviation of the QRS complex [5]. The PQ segment represents the time of signals travel from the SA node to the AV node. The QRS complex indicates the firing of the AV node and represents the ventricular depolarization:

- Q wave corresponds to depolarization of the interventricular septum.
- R wave is produced by depolarization of the main mass of the ventricles.
- S wave represents the last phase of ventricular depolarization at the base of the heart.

Atrial repolarization occurs during this time however the signal is not visible because of the large QRS complex. ST-segment reflects the plateau in the myocardial action potential [4]. This is when the ventricles contract and pump blood. The ST segment is the time interval between the end of the QRS complex and the start of the T wave. The T wave represents ventricular repolarization immediately before ventricular relaxation [6]. Thus the cycle repeats itself with every heartbeat.

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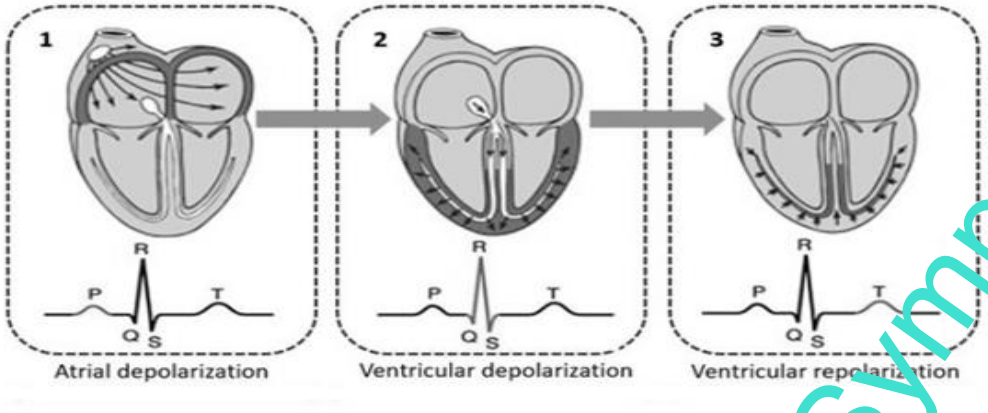

Fig. 3. Stages of depolarization and repolarization

The 12-lead ECG provides spatial information about the electrical activity of the heart in 3 orthogonal directions. Each of the leads represents a particular orientation in space [7].

- Bipolar limb leads are; Lead 1(Right Arm(-) to Left Arm(+)), Lead 2 (Right Arm(-) to Left Leg(+) and Lead 3 (Left Arm(-) to Left Leg(+)).
- Augmented unipolar limb leads are; Lead aVR (Right Arm (+) to (Left Arm & Left Leg(-)), Lead aVL (Left Arm(+) to (Right Arm & Left Leg(-)), Lead aVF (Left Leg (+) to (Right Arm & Left Arm(-))
- Unipolar chest leads are; V1, V2, V3 (posterior anterior) and V4, V5, V6 (Right, Left or Lateral)

In a 12-lead ECG, there are 12 leads calculated using 10 electrodes. The last electrode is placed on the right leg which is earth. The 12-lead ECG provides more information from a larger surface area surrounding the heart [8].

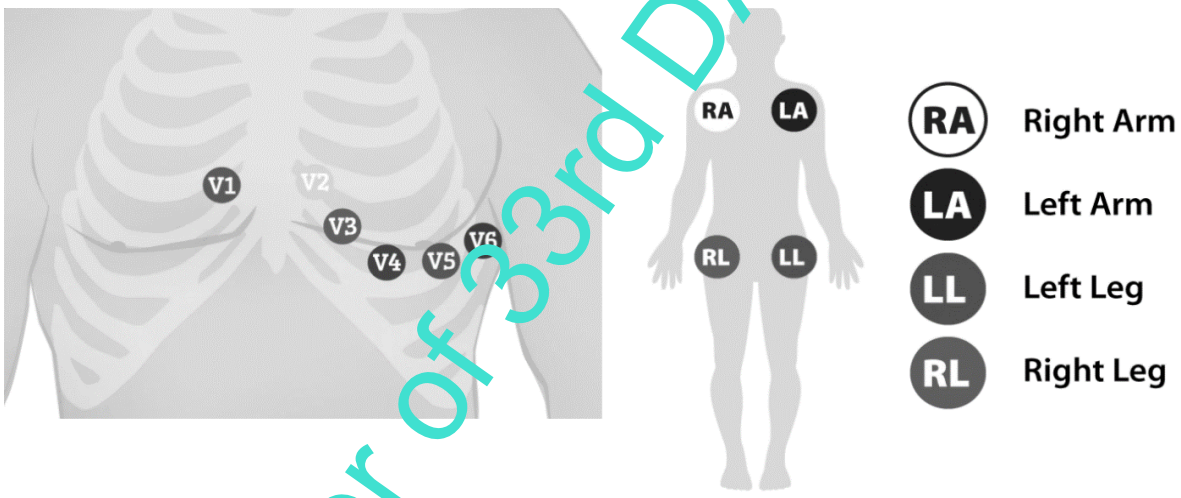

Fig. 4. Electrodes and their placement

2.3. Myocardial Infarction

The myocardium is heart muscle, myocardial infarction is defined pathologically as myocyte necrosis due to prolonged ischemia [9]. Ischaemia is the condition of restriction or reduction of blood flow in some part of the body. The heart muscle begins to die due to lack of oxygen caused by a blockage in the arteries (blood supply for the heart). Therefore it is crucial to restoring blood flow to prevent permanent damage to heart tissue [10].

Non-ST-segment elevation myocardial infarction(NSTEMI) is a type of MI that occurs on the inner layer of the ventricular wall. The ECG Electrode sees the damaged area after the intact myocardial tissue in between, the ST segment collapses. Thus, ECG changes may include ST-segment depression or T segment inversion.

ST-segment elevation myocardial infarction (STEMI) extends the entire thickness of the myocardium. ECG shows the ST elevated results because If the electrode directly sees the damaged area, the ST segment is elevated. In this research, Normal, STEMI, and NSTEMI (with ST depression) were used [18].

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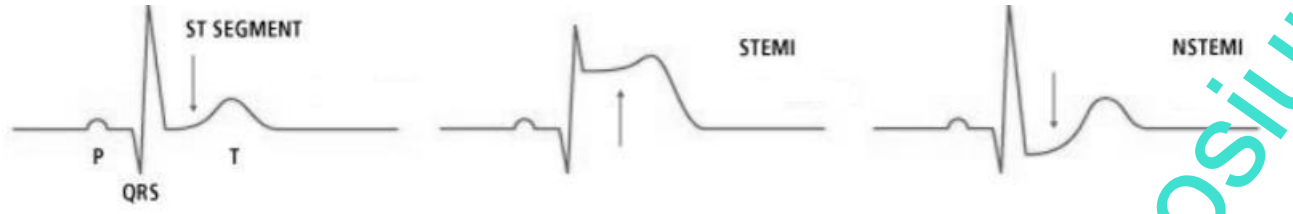

Fig. 5. Healthy, STEMI and NSTEMI ECG changes

3. Methods & Materials

3.1. PTB Dataset

The database contains 549 records from 290 subjects (aged 17 to 87) Each subject is represented by one to five records [11].The conventional 12 leads (i, ii, iii, aVR, aVL, aVF, v1, v2, v3, v4, v5, v6) together with the 3 Frank lead ECGs (vx, vy, vz). Each signal is digitized at 1000 samples per second, with a 16-bit resolution over a range of ± 16.384 mV [11]. The dataset was separated into two classes. 20 Healthy and 20 subjects with MI were selected. ECG signals with only acute MI were used in this research. The Myocardial Infarction class was separated into two sub-classes as STEMI and NSTEMI. ECG signals and leads chosen in this research have been approved by a medical expert to create correct dataset labels for classification algorithms. Leads 1, 2, aVF, v2, v3, v4 have been chosen to classify healthy or MI subjects. Afterward, leads v1, v2, v3, and v4 were used to classify STEMI and NSTEMI ECG signals. The dataset is balanced and contains six STEMI and seven NSTEMI ECG signals. Python waveform-database (WFDB) package was used to visualize results (4500 ms for visualization below).

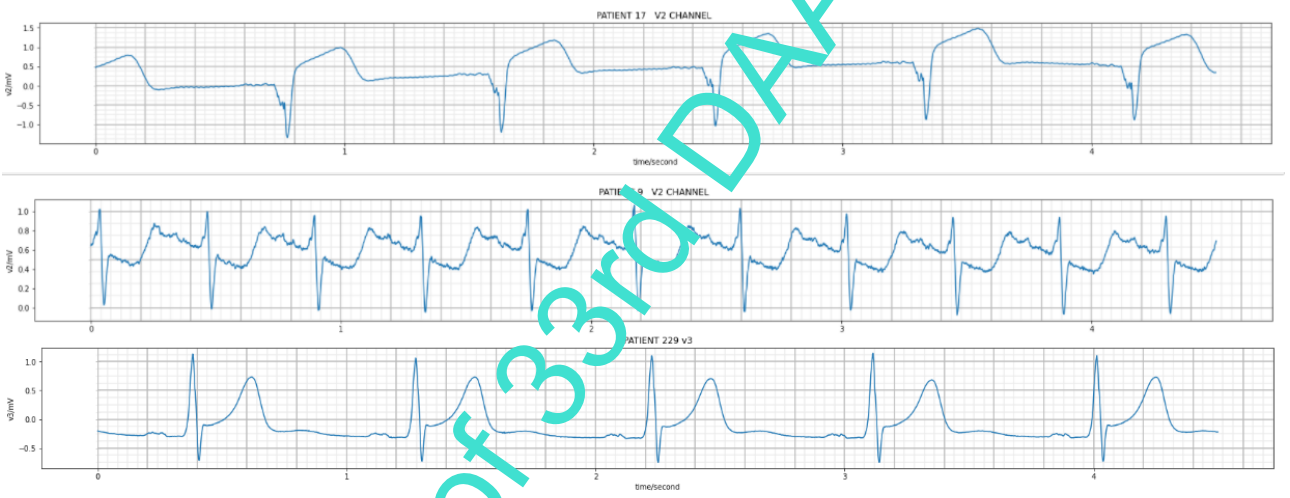

Fig. 6. ECG signals are shown as STEMI, NSTEMI, and non-MI respectively

3.2. Preprocessing

Raw ECG signals were preprocessed using delineation on signals. The wavelet algorithm was used to delineate the ECG dataset.

The continuous-time signal is the "function of continuous-time variable that has an uncountable or infinite set of numbers in its sequence.

Wavelet transform is a mathematical approach widely used for signal processing applications. It can decompose special patterns hidden in the mass of data. Wavelet transform has the ability to simultaneously display functions and manifest their local characteristics in the time-frequency domain. CWT (Continuous Wavelet Transform) is where the scale and translation are set arbitrarily [12]. CWT (1) provides a description of the signal in the time-scale domain, allowing the representation of the temporal features of a signal at different resolutions; therefore, it is a suitable tool to analyze the ECG signal [13].

$$CWT(\alpha,\tau) = \int_{-\infty}^{\infty} f(x)\,\frac{1}{\alpha}\;\Psi^{*}\left(\frac{x-\tau}{\alpha}\right)dx \quad (1)$$

The wavelet transform is a mathematical technique that can decompose a signal into multiple lower resolution levels by controlling the scaling and shifting factors of a single wavelet function.

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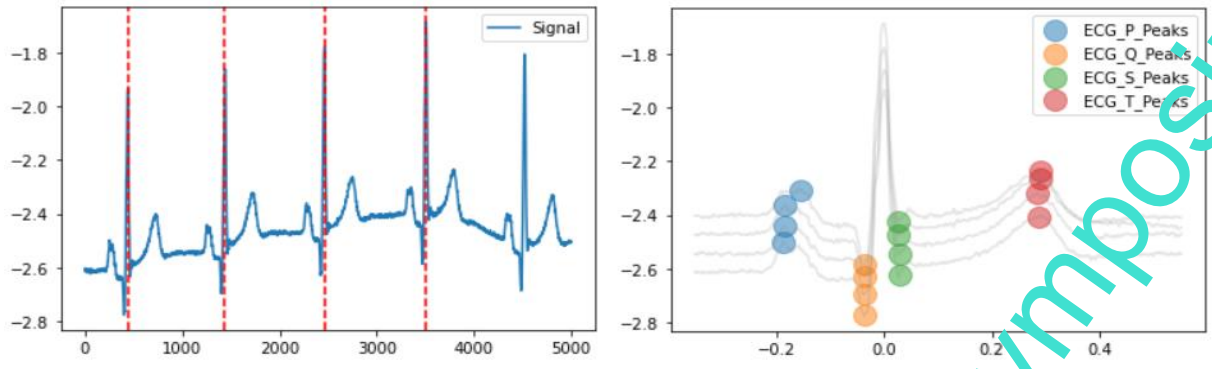

Fig. 7. Detected R peaks and delineated ECG signals using CWT (1000 sampling rate)

To identify MI S-T differences were detected and calculated. Extracted S-T onset and S-T-peak differences were used for related ECG leads. (1, 2, aVF, v2, v3, v4 for healthy-MI classification, v1, v2, v3, v4 for STEMI-NSTEMI).

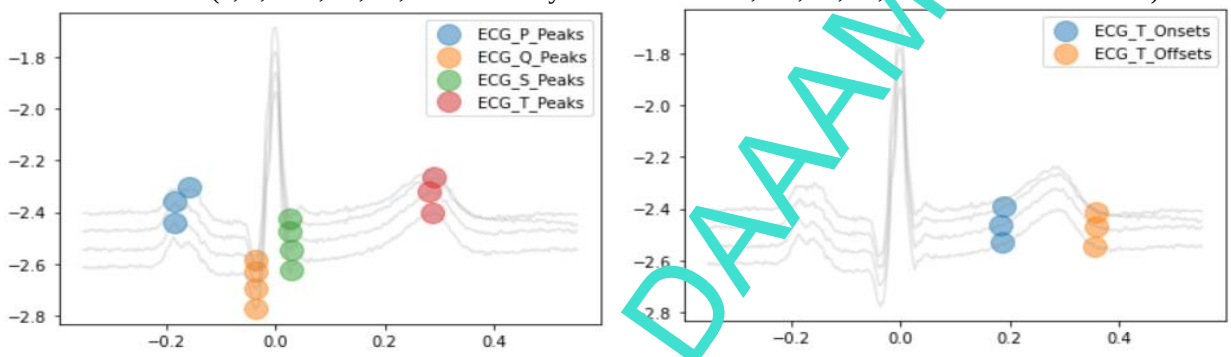

Fig. 8. S peaks, T peaks, and T onsets were extracted

After applying feature extraction new dataset that contained missing values was created, missing values in the dataset were filled with zeroes, and KNN (K nearest neighbor) imputer was used. The KNN is not robust to the input matrix with missing values, which may lead to the loss of effectiveness. [14] Therefore missing values were replaced with zeroes.

3.3. Algorithms

Machine learning is a process that which the computer gradually learns what parameters or weights fit the training data best. In this research, Support Vector Machine, Dense Neural Network using Keras and Torch, Random Forest, and XGBoost were used.

Support Vector Machine

SVMs have been used to solve many pattern recognition and classification problems and have been applied to the problems of prediction, forecasting, and implementing intelligent machines. The main goal of SVM is to find the optimal hyperplane for correct classification between data points of different classes (Figure 10). The dimension of the hyperplane is equal to the number of input objects minus one [15]. Data points on one side of the hyperplane will be classified for a certain class, while data points on the other side of the hyperplane will be classified for another class. The distance between the hyperplane and the first point (for all different classes) on both sides of the hyperplane is a measure of the algorithm's confidence in its classification decision. The greater the distance and the more confident we can be, SVM makes the right decision [15]. The data points closest to the hyperplane are called support vectors. The reference vectors determine the orientation and position of the hyperplane to maximize the classifier margin [15]. The number of support vectors that the SVM algorithm should use can be arbitrarily selected depending on the applications.

Neural Networks

Neural networks simulate the work of the human brain, allowing computer programs to find patterns and solve standard tasks in the field of AI, ML and deep learning. Neural Networks provide nonlinearity using activation functions (Relu and Sigmoid in this research). Keras provides a Python interface for artificial neural networks. Torch provides modules and classes torch.nn, torch.optim, Dataset, and DataLoader to create and train neural networks. Adam optimizer, Binary-Cross-Entropy loss function, Dropout=0.2, L2 regularization have been used. Dataset was split into training (70%), testing (15%), and validation (15%) sets. Drop out and regularization was applied to prevent overfitting.

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XGBoost

XGBoost is an implementation of decision trees with improved (boosting in ensemble learning) gradient, designed to improve performance and speed [16]. The model implementation supports the functions of the scikit-learn and R implementations with regularization. It is possible to overfit the model using XGBoost therefore, four different algorithms were used in this research.

In the beginning, hyperparameters were optimized using optuna library automatically. Afterward, they were manually adjusted to get better results. Chosen hyperparameters are: n_estimators: 200, max_depth: 5, reg_alpha: 3, reg_lambda: 2, min_child_weight: 1, gamma: 10, learning_rate: 0.01, colsample_bytree: 0.64

Random Forest

RF is an ensemble learning method, namely a random forest model consisting of a large number of small decision trees (estimators) that creates their own predictions. The RF combines the result to obtain accuracy (bagging in ensemble learning). A random forest builds trees in parallel, while boosting builts trees sequentially [17]. Hyperparameters chosen for RF algorithm: max_depth = 5, max_features=4, min_samples_leaf=2.

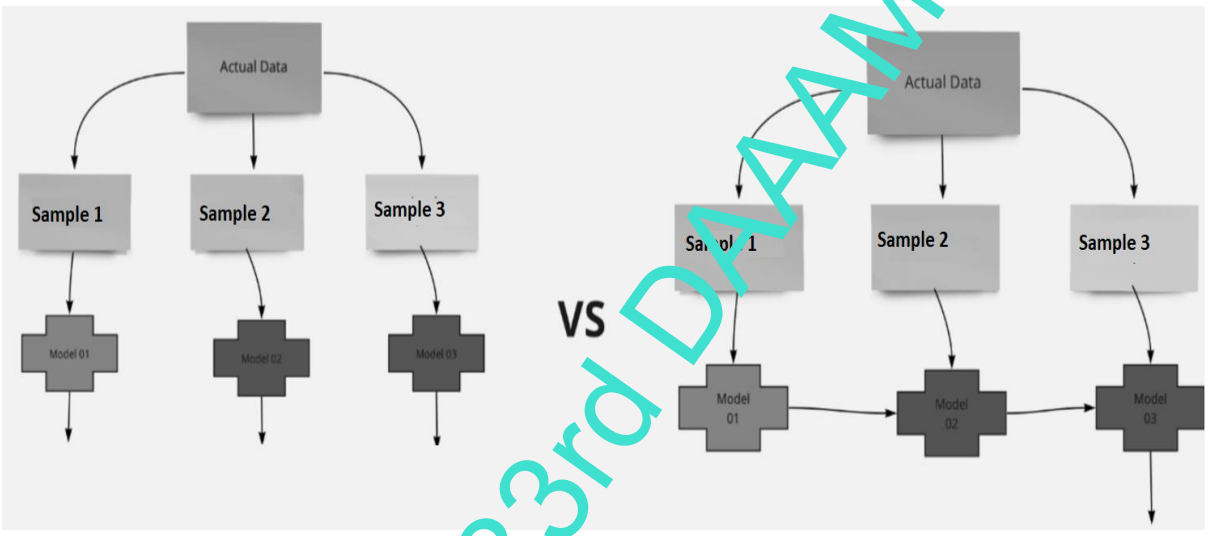

Fig. 9. Random Forest (bagging) and XGBoost (boosting)

4. Results

In this research, four different algorithms have been used. Same algorithms were applied to healthy-MI classification and STEMI-NSTEMI classification. For each algorithm, test accuracies and their confusion matrix are shown. Each figure has Predicted values for Healthy or MI binary classification on the left. On the right, classification results for STEMI or NSTEMI are shown. The XGBoost algorithm gave the highest accuracy for Healthy or MI classification (95.29). In the second classification (STEMI-NSTEMI). Random Forest gave the highest accuracy with 82.93%. Finally, SVM gave the worst results having 75.95% for the first and 70.03% accuracy for the second classification.

Before using any algorithm, all ECG signals were preprocessed (delineated with CWT). S – T onset and S – T peaks were extracted and used as key features. For Healthy-MI classification, 12 features were used as; S-T differences of 1, 2, aVF, v2, v3, and v4. Eight features (S-T differences of v1, v2, v3, and v4 for STEMI-NSTEMI) were extracted. After preprocessing, missing values were replaced with zeroes.

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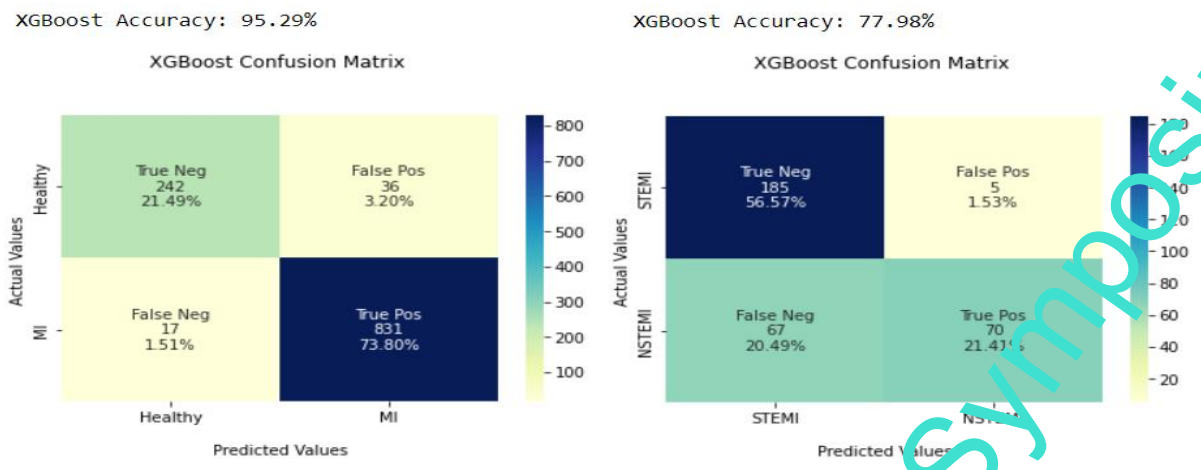

Fig. 10. Xgboost test accuracies and confusion matrix

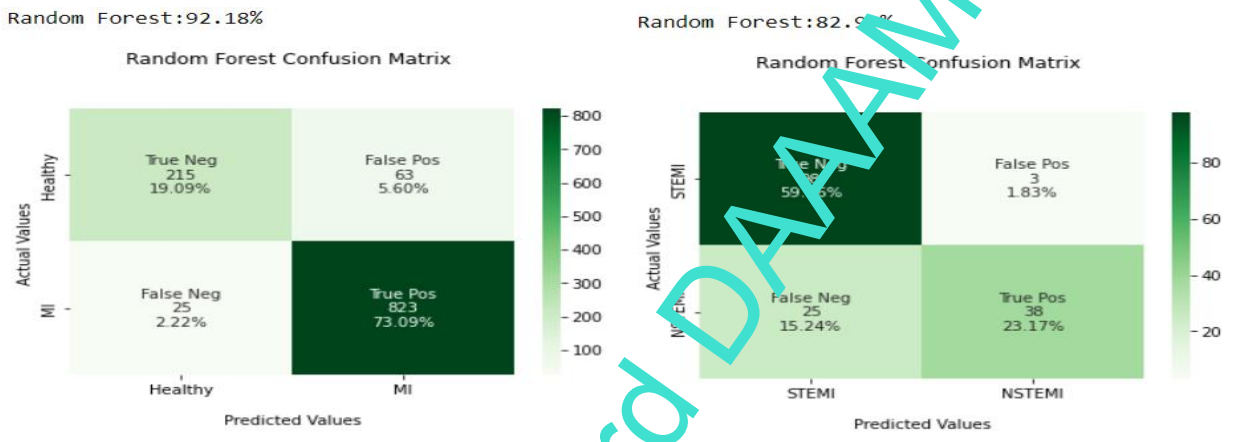

Fig. 11. Random Forest results

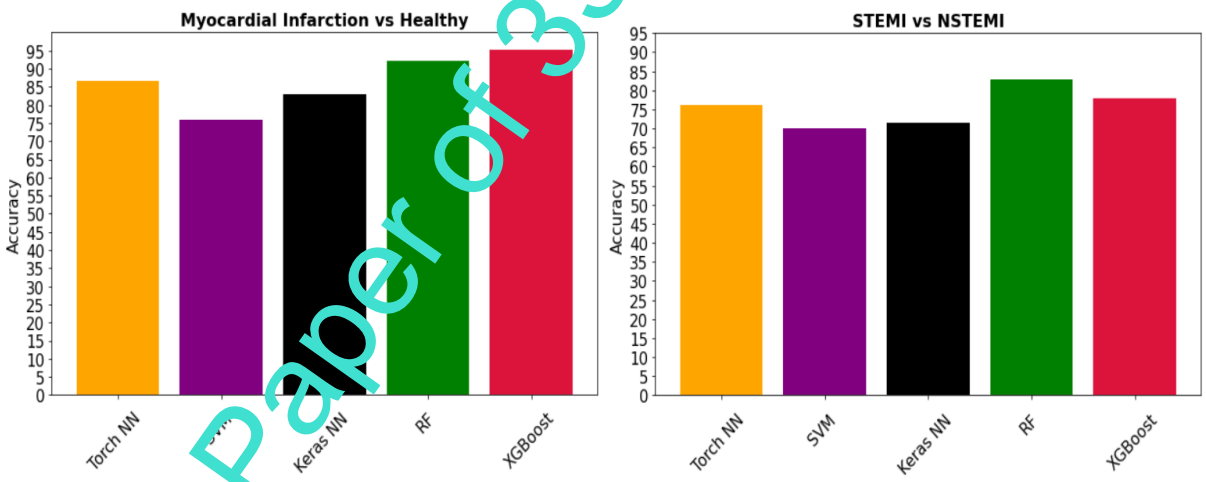

Fig. 12. Test accuracies for each algorithm

5. Discussion

In this research we analyzed Myocardial Infarction ECG signals to apply machine learning for classification. Data for MI represents Acute MI syndrome that occurred in the anterior part of the heart (formed mainly by the right atrium and ventricle). Thus Leads 1, 2, aVF, v2, v3, v4, and leads v1, v2, v3, v4 were chosen for both classification tasks. Chosen ECG signals were approved by a medical expert.

S-T differences differ in healthy subjects and subjects who have MI. Thus, extracted differences were used in the dataset for each chosen ECG lead. S-T differences might represent MI because electrical current will be able to bypass the necrosed area causing ST-segment to increase. Intact myocardial tissue in between the electrode damaged area causing

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the S-T segment to collapse. To classify STEMI and NSTEMI same approach was applied. In this case, S-T elevation or depression represents MI, as S-T elevation means STEMI and S-T depression means NSTEMI (sub-categories of MI).

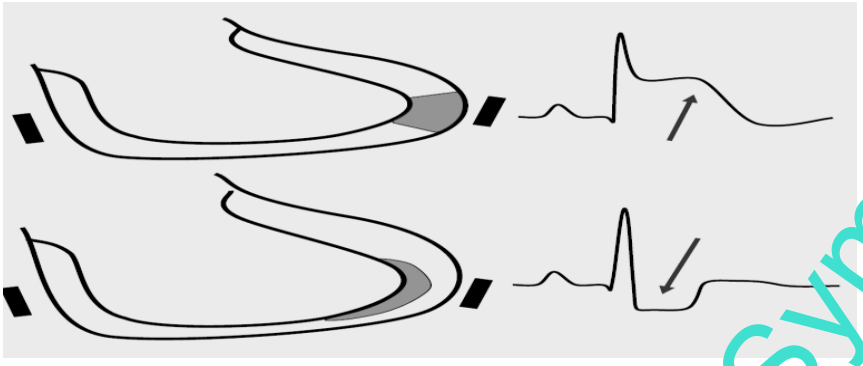

Fig. 13. Necroses (darker color on tissue) cause STEMI (above) and NSTEMI (below) ECG ST differences

The created dataset was in numeric format (contains missing values) and applied to several different machine learning algorithms. In both cases, the Neural network did not perform better than Xgboost and the Random forest algorithm due to having medium-sized data. Neural networks can perform better when utilizing bigger datasets and Ensemble learning can be more effective in this situation. To prevent overfitting, validation data (0.15) and a dropout value of 0.2 were chosen. Without overfitting, the neural network was able to train the model with around 80% accuracy, on the other hand, ensemble learning algorithms trained with 92% (shown in the previous section). All test accuracies drop approximately 10% when classifying STEMI-NSTEMI. The second classification has drawbacks as it is difficult to find appropriate ECG signals for the STEMI-NSTEMI classification. Model for healthy and MI ECG signals gave higher accuracies because S-T differences, in this case, were clearer in features. Another difficulty was during the training using ensemble learning algorithms, it is possible to overfit the model, and to prevent this, hyperparameters were tuned manually. The misuse of the max_depth parameter can cause overfitting even with shuffled validation sets. When the max_depth is greater than 5 for healthy-MI and more than 3 for STEMI-NSTEMI causing an overfitting model. As shown below, Log-loss was higher in the latter classification. As a result, lower ratios for colsample_bytree, training instances, lower values of max_depth, larger values of gamma, and lower values of learning rate were chosen to avoid over-fitting.

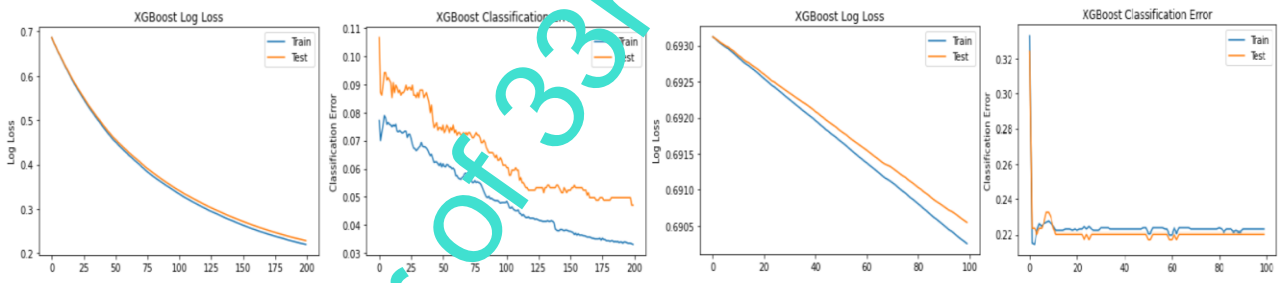

Fig. 14. Xgboost logloss and classification error for healthy-MI and STEMI-NSTEMI respectively

6. Conclusion

In this paper anatomy of the heart and characteristics of ECG signals were analyzed. Heart muscles work together to pump blood throughout our body. Every heartbeat can be recorded and compared to detect heart diseases.

S-T segments in PQRST, represent either non-ST elevated or ST elevated Myocardial Infarction. Continuous wavelet transform were used to prepare new features for the dataset. S-T differences were extracted and used in two different ML models to classify healthy and MI subjects. Latter, S-T elevated and, Non-S-T elevated ECG signals were classified using ML algorithms. XGBoost and Random Forest gave high accuracies on test data. To evaluate the model, parameters were chosen manually and tested to prevent overfitting the ML models. Using ECG signals, it is possible to characterize signals because feature extraction can be performed with the help of PQRST locations and CWT. Binary classification models for healthy-MI gave 95.29%, model for STEMI-NSTEMI had 82.93% accuracy.

Many patients suffer from acute MI. Thus it can be helpful to detect it using a machine. Detecting S-T and Non-S-T elevated MI can be useful to classify different types of systemic heart diseases. The proposed methodology has achieved higher accuracy in healthy-MI classification. Considering the limitations of this study, there is a need to implement more complex models and use combination of datasets and features to increase the accuracy and classify other heart diseases.

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