Application of Machine Learning to Predict the Occurrence of Complications after Myocardial Infarction

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Abstract:

Myocardial Infarction (MI), more commonly known as a heart attack, is a condition that occurs when the heart is unable to recieve blood flow due to blockage. This condition is one of the more challenging problems of modern medicine due to its complex nature and serious complications that occur. In a healthcare setting, machine learning has quickly become one of the popular approaches to develop models used for predicting various healthcare problems. The deadly nature of MI makes it of utmost importance to predict the complications and outcomes early on in the diagnosis. Machine learning algorithms can be useful in predicting MI outcomes with the use of existing data from health reports. The motive of this research is to predict the occurrence of chronic heart failure after the first heart attack. The machine learning algorithms used are Decision Tree, Random Forest, Support-Vector Machine (SVM), and Logestic Regression to implement a model to predict chronic heart failure. By predicting the occurrence of chronic heart failure after MI early on, patient outcomes can be improved. Therefore, this study intends to predict factors that are most predictive of the occurrence of chronic heart failure following a MI, and how accurately can the presence or absence of these complications be predicted in patients using UCI machine learning repository and various classification algorithms. By tuning hyperparameters for all the machine learning models, it can be reasonably predicted that the Support Vector Machine model will outperform the other ML models due to its advantage of being highly effective in high dimensional spaces.

Introduction:

Myocardial infarction, or a heart attack, is undoubtedly a medically serious condition. Although there are current treatments, such as Percutaneous coronary intervention (PCI), and preventative measures available, its prevalence is still relatively high (10). This is because plaque that has built up inside the coronary artery lumen ruptures during a myocardial infarction episode, and causes the formation of a blood clot. The blood clot then limits the flow of blood to the heart, resulting in a heart attack. Heart attacks can occasionally be silent, go undiagnosed, or be catastrophic, leading to atypical frontal hemodynamic decline and unintentional death. According to the Angiography Registry reports, the 1-year mortality rate for AMI patients is still 10% (11).Therefore, pinpointing the causes of chronic heart failure after MI and forecasting its recurrence in MI patients can inform physicians and enhance patient prognosis. Previous research studies lack an extensive and multidimensional systematic assessment of patients with chronic heart failure in the acute phase of MI and are instead restricted to a small number of factors. The GRACE risk score is the most used systematic assessment approach for MI patients, yet its accuracy in predicting chronic heart failure may not remain high since it is primarily used to predict mortality (12). As a result, developing a predictive model of chronic heart failure following MI plays a crucial role in guiding doctors' choices. Traditional risk models are frequently based on statistical techniques, which can only assess the correlations between a number of elements in a linear fashion. Researchers will pre-select variables to fictitiously exclude probable risk factors. It has higher requirements for handling multi-factor and multi-level interactions in complicated disorders such as acute myocardial infarction. Recently, machine learning algorithms have gained a lot of popularity for predictive studies in the healthcare field. Medical research has gradually incorporated machine learning, the most significant branch of artificial intelligence, into their methodology (13). The limits of human components and variables in traditional analysis are successfully overcome by machine learning, which automatically extracts information from massive clinical data for learning by replicating human learning activities (14). The application of ML to the cardiovascular field has proven successful in a number of areas, including predicting diseases and diagnostic classification. Predicting patient death has been the main focus of recent research on machine learning in myocardial infarction (15).

Proposed Work and Analysis

The work performed in this report primarily focuses on using various machine learning classification algorithms for Myocardial Infarction prediction. In this research, the data used has a total of twelve cardiac complications and the target complication is chronic heart failure. Chronic heart failure is a serious long-term condition that slowly gets worse over time.

Patient cohort

This research applied the suggested methodology to a publicly available clinical dataset of moderate size. The dataset, Complications of myocardial infarction, contained data from 1,700 patients at their time of admission to the hospital to 72 hours after admission to the hospital.

Variable Selection

All variables that pertained to the time of admission were used in the machine learning algorithms. A total of 115 variables were collected immediately after hospitialization, and after eliminating patients with more than 20% of missing data and attributes with more than 20% of data, 103 variables were left in the dataset. The analysis only focused on the prediction of the complication of chronic heart failure so the other 11 possible complications were also removed. Therefore, the analysis was performed with 92 attributes and 1,444 patient samples.

Machine Learning

Feature Selction

Feature selection was performed after fine-tuning the hyperparameters that were defined as model parameters with arbitrary values before the start of the learning process. During training, a Random Forest classifier was used to fit the number of decision tree classifiers on a subset of the data. Random forests achieve a reduced variance by checking the binary results of the combined diverse trees and then selecting the results after averaging their probabilistic prediction (1). All features were run through a brute-force exhaustive search paradigm called grid search (2). A list of values for different hyperparameters were specified and the model performance for each combination was evaluated to obtain the optimal combination of values (2). Based on this evaluation, reduced Gini Impurity was chosen as the criterion to minimize the probability of misclassifications. The importance of each feature in a random forest or decision tree is often calculated by ranking them based on the reduction in Gini impurity they achieve. By measuring the change in Gini impurity that results from removing a specific feature and comparing the results of that to the overall reduction in Gini impurity when all features are used, the importance of features can be determined. The features that resulted in higher reductions contributed more to the model's ability to make accurate predictions and are of more importance. Table 1 indicates the specific parameters used to get the importance ranking of features. In addition to making the machine learning model more interpretable, the top 15 variables were selected and used for comparative purposes. The feature importance ranking can be found in the appendix in Table A2.

Random Forest Parameters	
Criterion	**Gini**
Max Depth	1
Min Samples Leaf	3
Max Features	None
N Estimators	500
N Jobs	2

Table 1: The specific Random Forest parameters used for feature selection

Model Construction

The predictive classifiers were developed based on data from the training set using 4 supervised ML methods: Decision Tree, Random Forest, Support Vector Machine, and Logistic Regression. The data split was chosen to be 80% training and 20% testing. The training set then had the tenfold cross-validation technique performed on it. This technique split the training set randomly into 10 equal folds, with approximately the same number of events. This validation experiment is then repeated 10 times with each fold being used in turn as the validation set, and the remaining 9 folds being used as the training set (3). The 20% testing set is used to evaluate the model performance. The workflow is described in Figure 1 below. The parameters for each model found using grid search can be found in the Appendix in Table A1.

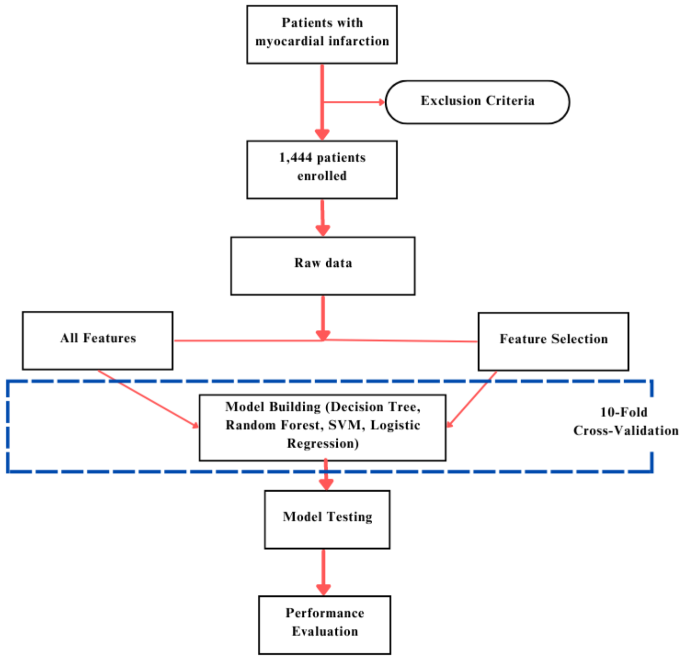

Figure 1: The flow diagram showing the process for evaluating the performance of machine learning methods

First, all the variables were fed into machine learning to build the prediction model. However, taking into consideration that healthcare providers will have difficulty considering all 92 variables in a clinical setting, a simplified model is derived from the complete model. The simplified model includes the top 15 variables selected based on the Random Forest. The overall prediction performance of the machine learning models on the test set were evaluated by calculating the accuracy, precision, and the area under the curve (AUC). Receiver operating characteristic (ROC) curves were drawn for all models and the probability threshold was the default 0.5 on the classification efficiency. The machine learning techniques were implemented in the Python 3 (ipykernal) environment.

Results

ML Analysis

Feature Selection

Machine learning extracted the top 15 feature-ranking with the Random Forest for further modeling. After interpreting the model, some of the most important features are the presence of heart failure, white blood cell count, age, diabetes, and blood pressure. All the top 15 important features can be found in the Appendeix in Table A2 with their respective value of importance.

Model Evaluation and Comparison

Four machine learning algorithms were used to build a predictive model of chronic heart failure after myocardial infarction. Whether it was all the variables or the 15 most important variables, the Decision Tree classifier and the Logistic Regression model had the best performance in comparison to the other algorithms. The results of the model evaluations are shown in Table 2 and the Decision Tree model (for all features and select features) and the Logistic Regression model (select features) had an weighted accuracy of 77% with a weighted precision of 83%. This is indicative of a moderately good performance for the machine learning algorithm.

Models	**Weighted Accuracy (F1)**	**AUC**	**Weighted Precision**	**Specificity**	**False Positive Rate**	**False Negative Rate**
All Features						
Decision Tree	0.77	0.62	0.83	0.89	0.11	0.20
Random Forest	0.77	0.68	0.80	0.76	0.24	0.19
SVM	0.66	0.60	0.58	0	0	0.24
Logestic Regression	0.77	0.55	0.83	0.32	0.68	0.23
Feature Selection						
Decision Tree	0.77	0.62	0.83	0.89	0.11	0.20
Random Forest	0.77	0.68	0.80	0.76	0.24	0.19
SVM	0.66	0.52	0.58	0	0	0.24
Logestic Regression	0.67	0.52	0.65	0.29	0.71	0.24

Table 2: The predictive performance of all machine learning models

ROC curves were drawn from all the models. Figure 2 is the ROC curve obtained by the decision tree learning two types of data sets. Figure 3 is the ROC curve obtained by the Random Forest learning two types of data sets. Figure 4 is the ROC curve obtained by the SVM learning two types of data sets. Lastly, Figure 5 is the ROC curve obtained by the Logestic Regression learning two types of data sets. It can be seen that the highest value of the area under the ROC curve of the model constructed by the Random Forest with both sets of data is 0.677.

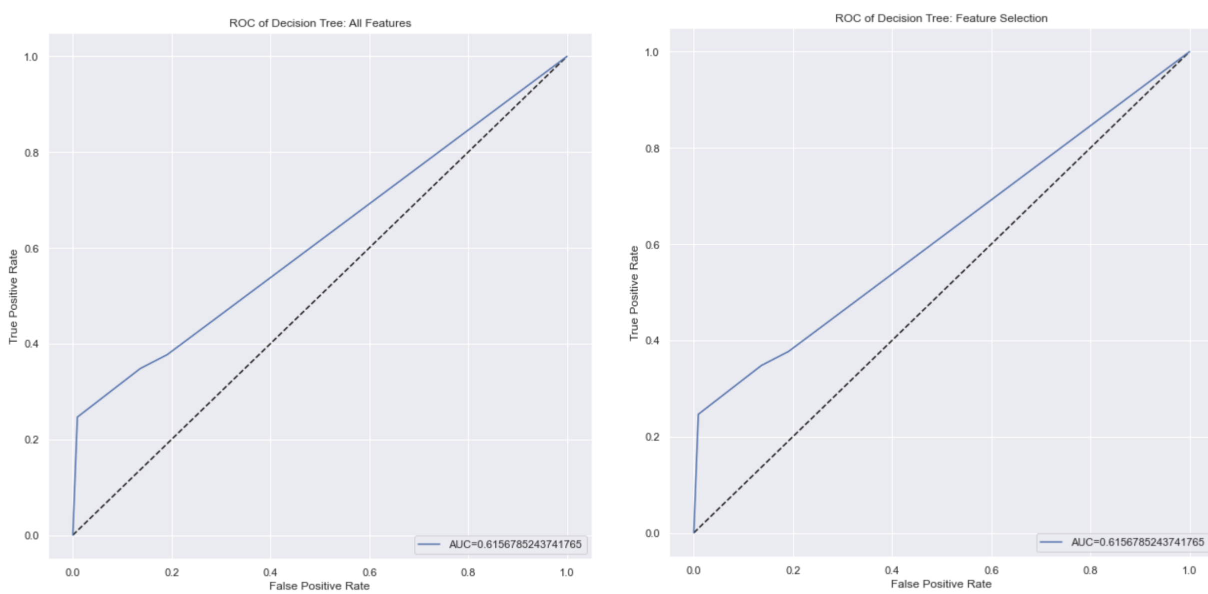

Figure 2: The ROC curves of the Decision Tree models: **(Left)** Decision Tree- All Feature Model; **(Right)** Decision Tree- Select Feature Model

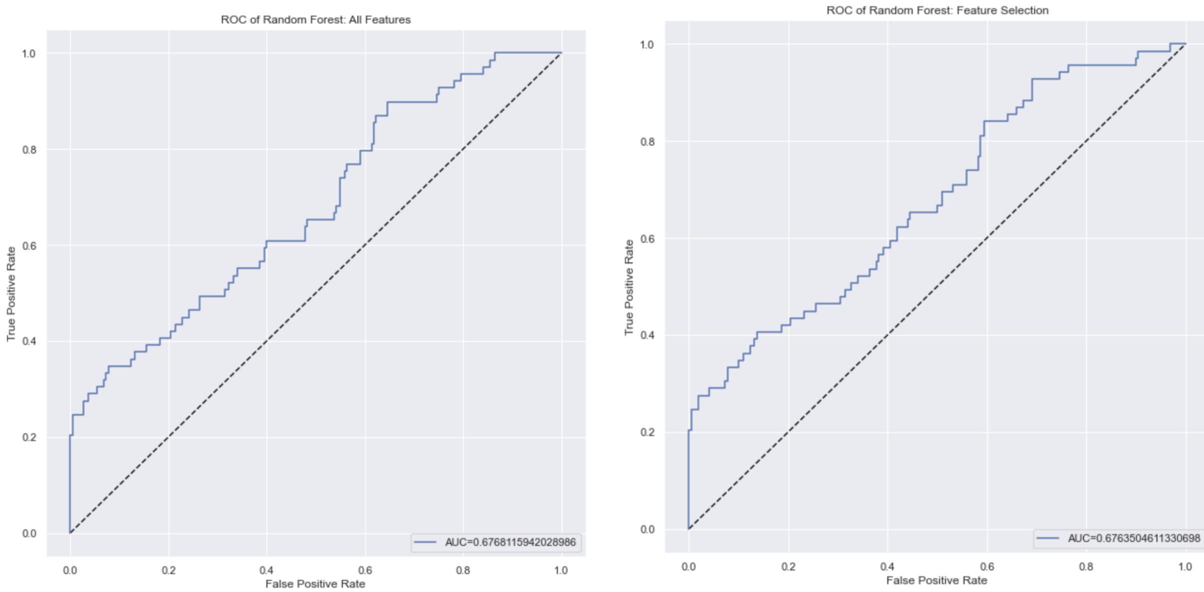

Figure 3: The ROC curves of the Random Forest models: **(Left)** Random Forest- All Feature Model; **(Right)** Random Forest- Select Feature Model

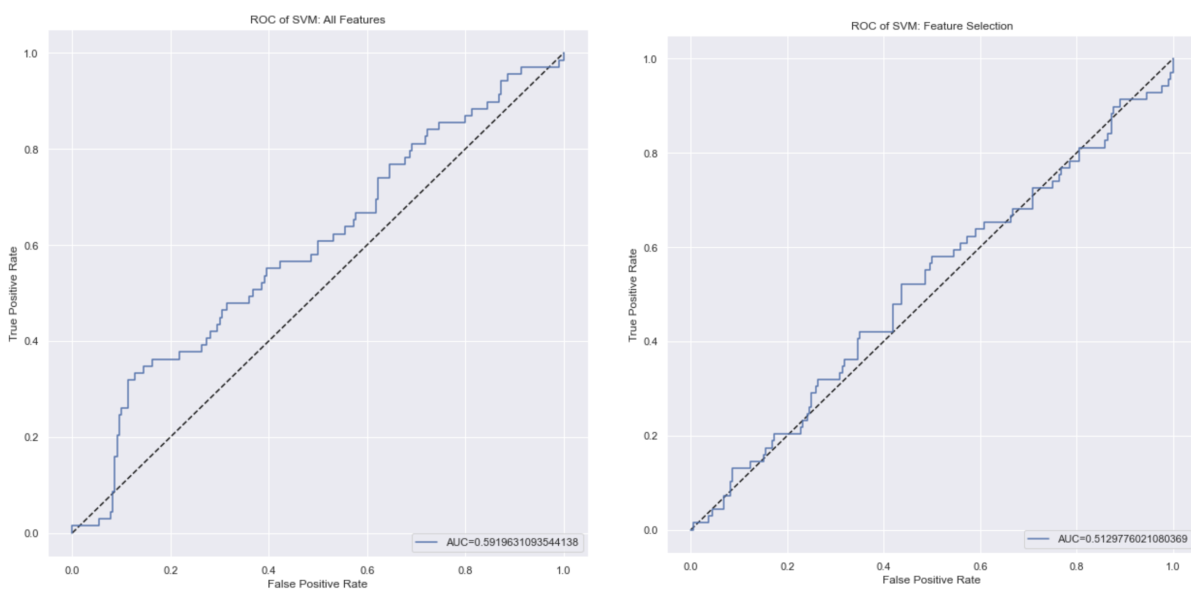

Figure 4: The ROC curves of the SVM models: **(Left)** SVM- All Feature Model; **(Right)** SVM- Select Feature Model

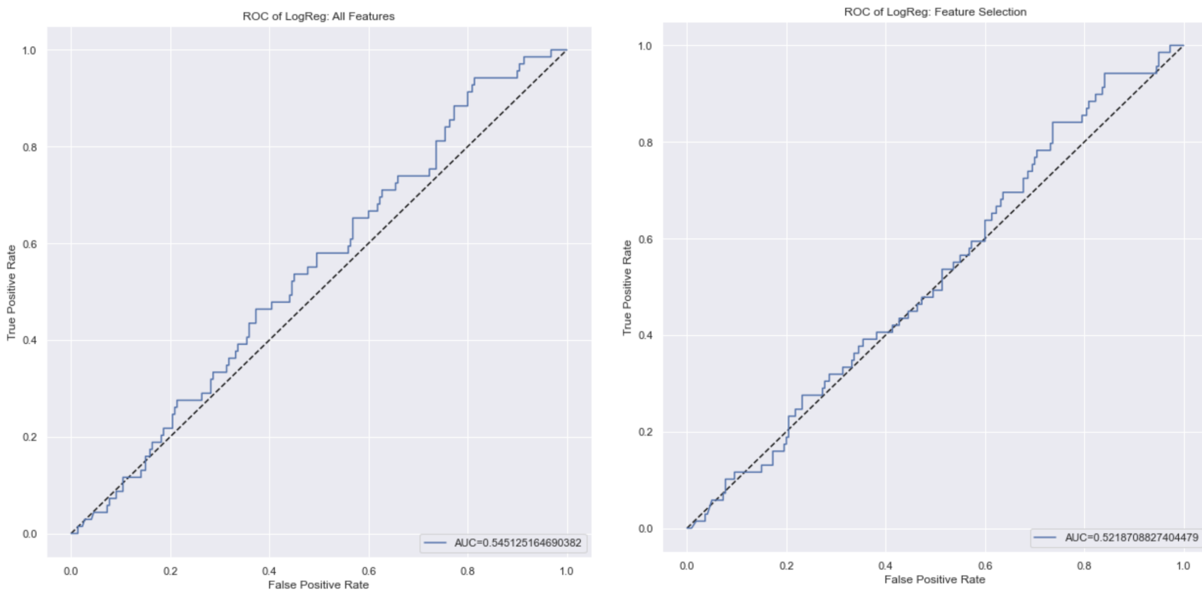

Figure 5: The Roc curves of the Logistic Regression models: **(Left)** Logistic Regression- All Feature Model; **(Right)** Logistic Regression- Select Feature Model

Discussion & Conclusion

Despite the advances in treatment of acute myocardial infarction, MI remains one of the most common causes of heart failure (4). The factors that contribute to the pathogenesis of heart failure development at the time of hospitilization include myocardial compromise due to necrosis, stunning, and mechanical complications such as papillary muscle rupture, ventriclar septal defect, and ventricular free wall rupture (4). This causes myocardial ischemia to occur since the blood and oxygen flow is decreased to the heart muscle (5). Progression of myocardial ischemia leads to cardiomyocyte death. The infammatory response to myocyte death after a heart attack can contribute to heart failure development. Other factors that can trigger heart failure progression include anaemia, chronic kidney disease, or chronic obstructive pulmonary disease (4). The proportion of heart failure cases at MI hospital admission has increased from 4% to 12-13% in the last decade. This is due to the development of heart failure after MI having a significant impact on outcomes and increasing the need for urgent medical help. Therefore, the American Heart Association has deemed heart failure prevention an urgent public health need (4). Heart failure screening and prevention is of particular importance to the population of patients who experienced a myocardial infarction because they are at high risk for heart failure development. By delaying the diagnosis of MI, the patient prognosis is more likely to be disreputable. This emphazises the need for a clinical model that can predict the occurrence of chronic heart failure after MI as early as possible. The most commonly used current clinical risk model for acute myocardial infarction is the GRACE risk score (6). This model, however, is mainly used to assess the mortality rate of the patient and may not accuratly predict the occurance of chronic heart failure. In addition, this model also is constructed using traditional statistical methods that linearly analyzes the relationship between a few factors, and it does not analyze the potential prognostic value of the interaction of weaker risk factors and the outcome (3). Complex diseases, such as myocardial infarction, need to have their multi-factor and multi-level interactions analyzed to increase the accuracy of the prediction model. Machine learning has played a key role in the study of cardiovascular diseases. Machine learning has been used for disease classification and diagnosis, medical image analysis, and predictive modeling construction (7,8). Currently, researchers have related machine learning and acute myocardial infarction to predict patient mortality (8). In this study, the clinical data of 1,700 MI patients were collected and machine learning was applied to create a predictive model of the occurrence of chronic heart failure after myocardial infarction.

Before machine learning, 92 variables and 1,444 patients based on a previous study conducted at the University of Leicestera were included after preprocessing the data set (9). First we applied all 4 ML techniques (Decision Tree, Random Forest, SVM, and Logestic Regression) and combined it with the 92 variables to assess the risk of chronic heart failure after MI. The goal was to accuraly predict the patient's outcome of chronic heart failure with as few features as possible, so the top 15 predictive variables were used to build ML models as well. It was found that, when compared with the other machine classifiers, the Decision Tree algorithm had better predictive ability in both the full-variable model and the feature selection model. This is due to the higher accuracy and precision values in comparison to the other models. In terms of variable selection, advanced ML algorithms were combined to perform complex nonlinear analysis on important variables with significant predictive capabilities. The results show that the overall performance of machine learning was moderate. Tables A3 through A6 show the respective confusion matrix and classification report metrics. Therefore, it probably cannot replace diagnostic or risk estimators that further workup can provide. However, it could be used to refine and supplement the current acute myocardial risk score to help healthcare providers perform a more accurate risk assessment.

Limitations

This observational study has the same inherent limitations as any other observational study. However, the data-driven methodologies of machine learning are primarily focused on this kind of extensive retrospective study. Before being used in clinical settings, this machine learning strategy still needs more model training, validation, and tuning. Another drawback is the fact that all of the patients in this dataset were registered at a Russian hospital. The main finding of the current investigation found that the Decision Tree Algorithm demonstrated the highest prediction performance. An alternative interpretation of the results can be that the models could be used as a basis for future work and modified to fit their specific research interest. In future work, larger, more diverse data sets can be used. Overall, prediction models based on machine learning could be a fantastic addition to improve risk assessment and even clinical alarms for patients following myocardial infarction.

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Appendix

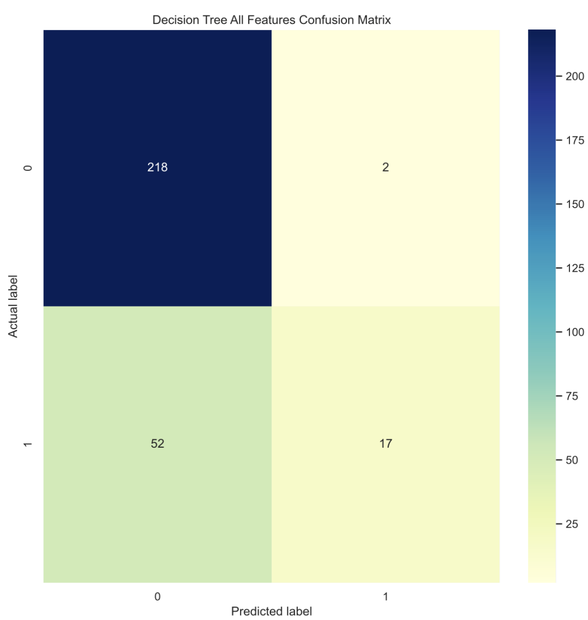
Model	Parameters
All Features	
Decision Tree	Criterion: Entropy, Max Depth: 2, Max Features: None, Min Sample Leaf: 1, Random State: 1
Random Forest	Criterion: Gini, Max Depth: 5, Max Features: None, Min Sample Leaf: 3, Random State: 1
SVM	C: 0.0001, Kernal: Linear
Logistic Regression	C: 0.05, Random State: 0, Penalty: L2, Max Iter: 1000
Feature Selection	
Decision Tree	Criterion: Entropy, Max Depth: 2, Max Features: None, Min Sample Leaf: 1, Random State: 1
Random Forest	Criterion: Gini, Max Depth: 6, Max Features: None, Min Sample Leaf: 4, Random State: 42
SVM	C: 0.0001, Kernal: Linear
Logistic Regression	C: 0.05, Random State: 0, Penalty: L2, Max Iter: 1000

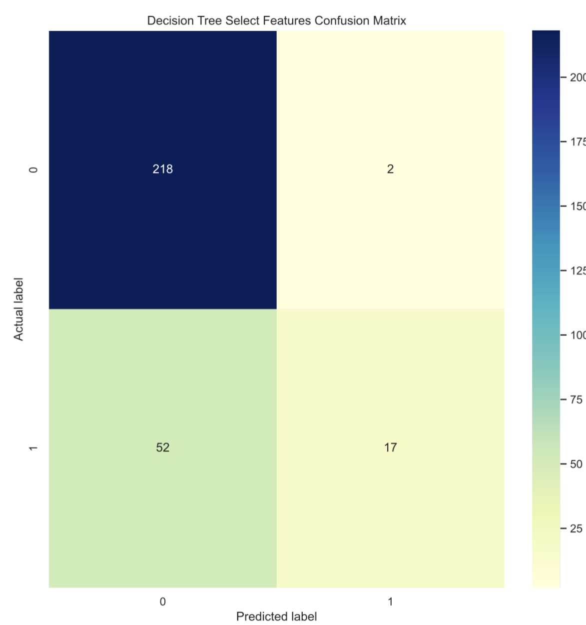
Table A1: The hypertuned parameters used for each machine learning model

Top Features	Importance
1) Presence of chronic Heart failure (HF) in the anamnesis	0.418150
2) White blood cell count (billions per liter)	0.064798
3) Age	0.063547
4) Serum AlAT content	0.051284
5) Diabetes mellitus in the anamnesis	0.043374
6) ESR (Erythrocyte sedimentation rate)	0.029034
7) Serum AsAT content	0.028614
8) Presence of a lateral MI (left ventricular)	0.025512
9) Systolic bp according to ICU	0.024143
10) Exertional angina pectoris in the anamnesis	0.023190
11) Time elapsed from the beginning of the attack of CHD to the hospital	0.022686
12) Diastolic bp according to ICU	0.020555
13) Quantity of MIs in the anamnesis	0.018495

14) Persistent form of atrial fibrillation on ECG at the time of admission	0.016817
15) Chronic bronchitis in the anamnesis	0.013107

Table A2: The top 15 important features and their value of importance in predicting chronic heart failure





All Features Decision Tree	Select Features Decision Tree
Weighted F1 Score: 0.77	Weighted F1 Score: 0.77
Weighted Recall Score: 0.81	Weighted Recall Score: 0.81
Weighted Precision Score: 0.83	Weighted Precision Score: 0.83

Table A3: The Decison Tree classifier confusion matrix and classification metrics for **(Left)** All Features and **(Right)** Feature Selection.

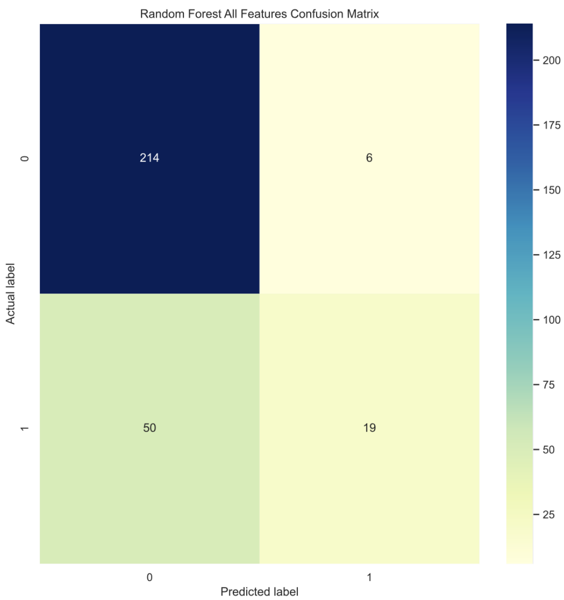
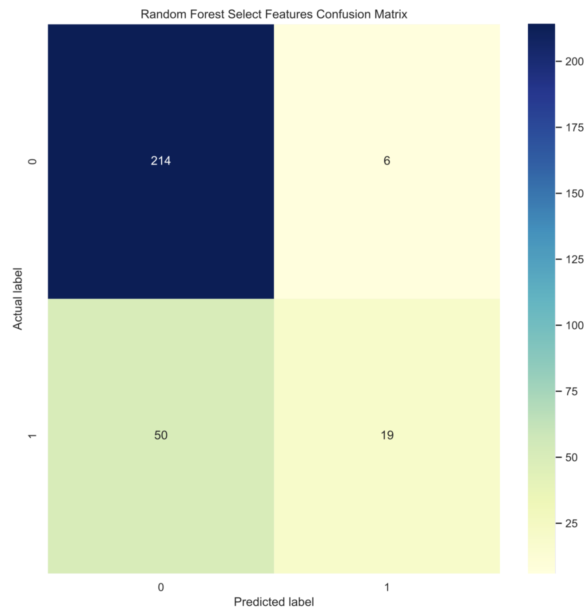
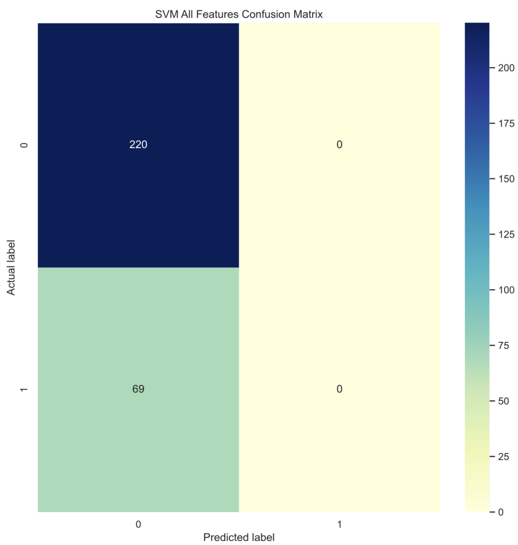
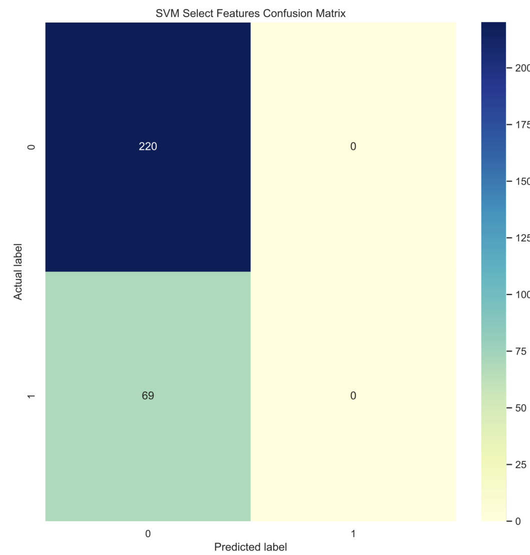
	
All Features Random Forest	Select Features Random Forest
Weighted F1 Score: 0.77	Weighted F1 Score: 0.77
Weighted Recall Score: 0.81	Weighted Recall Score: 0.81
Weighted Precision Score: 0.80	Weighted Precision Score: 0.80

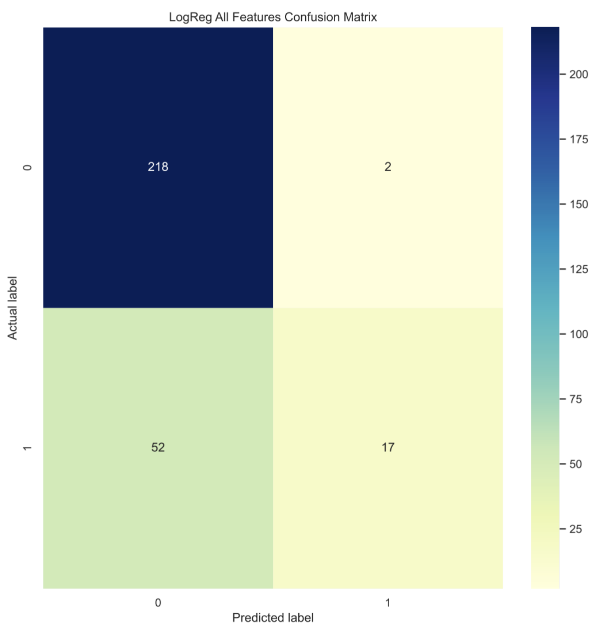
Table A4: The Random Forest classifier confusion matrix and classification metrics for **(Left)** All Features and **(Right)** Feature Selection.

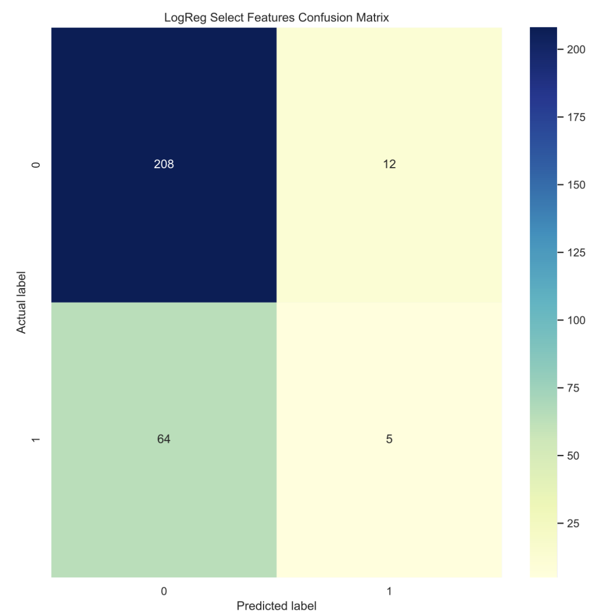




SVM All Features	SVM Select Features
Weighted F1 Score: 0.66	Weighted F1 Score: 0.66
Weighted Recall Score: 0.76	Weighted Recall Score: 0.76
Weighted Precision Score: 0.58	Weighted Precision Score: 0.58

Table A5: The SVM confusion matrix and classification metrics for **(Left)** All Features and **(Right)** Feature Selection.





All Features Logistic Regression	Select Features Logistic Regression
Weighted F1 Score: 0.77	Weighted F1 Score: 0.67
Weighted Recall Score: 0.81	Weighted Recall Score: 0.74
Weighted Precision Score: 0.83	Weighted Precision Score: 0.65

Table A6: The Logistic Regression confusion matrix and classification metrics for **(Left)** All Features and **(Right)** Feature Selection.