



## Heart Attack Risk Prediction with Duke Treadmill Score with Symptoms using Data Mining

Original  
Article

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The healthcare industry has a huge volume of patients' health records but the discovery of hidden information using data mining techniques is missing. Data mining and its algorithm can help in this situation. This study aims to discover the hidden pattern from symptoms to detect early Stress Echocardiography before using Exercise Tolerance Test (ETT). During this study, raw ETT data of 776 patients are obtained from private heart clinic "The Heart Center Bahawalpur", Bahawalpur, South Punjab, Pakistan. Duke treadmill score (DTS) is an output of ETT which classifies a patient's heart is working normally or abnormally. In this work multiple machine learning algorithms like Support Vector Machine (SVM), Logistic Regression (LR), J.48, and Random Forest (RF) are used to classify patients' hearts working normally or not using general information about a patient like a gender, age, body surface area (BSA), body mass index (BMI), blood pressure (BP) Systolic, BP Diastolic, etc. along with risk factors information like Diabetes Mellitus, Family History, Hypertension, Obesity, Old Age, Post-Menopausal, Smoker, Chest Pain and Shortness Of Breath (SOB). During this study, it is observed that the best accuracy of 85.16% is achieved using the Logistic Regression algorithm using the split percentage of 60-40.

**Keywords:** Duke Treadmill Score, Data Mining, ETT, Support Vector Machine, Logistic Regression, J.48, Random Forest, WEKA

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**Author's Contribution**

All authors have contributed equally.

### Conflict of interest

The authors declare no conflict of interest in publishing this manuscript in IJIST.



## Introduction

The Healthcare industry collects a large volume of data that needs to be mined to discover useful information for better decision making. Heart Disease is the major cause of mortality worldwide. Symptoms have a huge impact on heart disease. Some are more important and some are less. It is very important to detect the weightage of each attribute. More weighted symptoms have a high impact on disease prediction. For these reasons we are using data mining to check which attribute has more weightage to detect the duke treadmill score which is directly associated with heart attack chances [1]

Data mining helps to reduce the number of tests and early prediction of disease and avoid highly charged test costs and time to start treatment of a patient. Heart disease early prediction system is useful for medical experts and policymakers to avoid mortality with early treatment start based on symptoms. This paper presents the model and symptoms that help diagnose the patient's condition.

## Site Map

This study was conducted in Bahawalpur, Southern Punjab, Pakistan in the Faculty of Computing, The Islamia University of Bahawalpur, Bahawalpur.

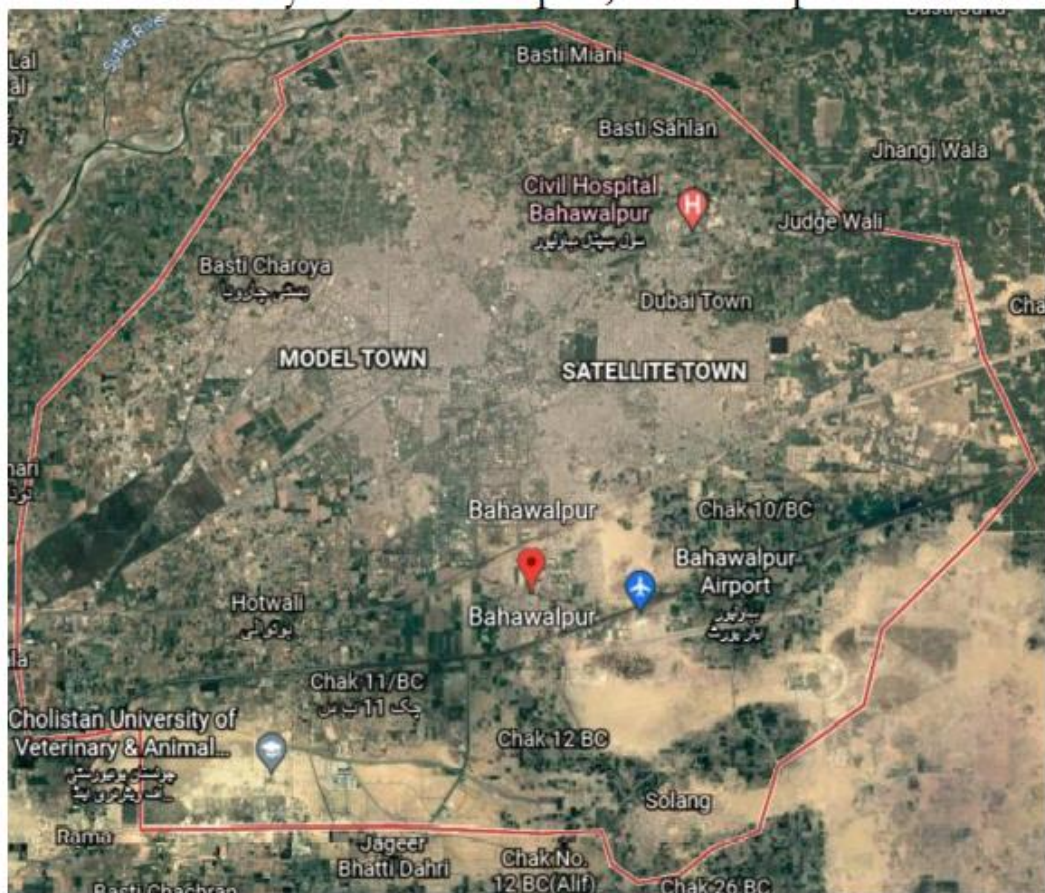


Figure 1. Study Site

## Literature Review

### Data mining and algorithms used in medical domain

Data mining was helpful in previous heart disease prediction systems [2, 3]. Logistic Regression, Support Vector Machine, J.48, KNN, K-Nearest, and Decision Table are powerful classification algorithms used to classify heart disease [4]. These algorithms are used to process the raw data and make some useful relationships between different attributes in data.

**Early study on Prediction of Duke Treadmill score**

Duke Treadmill Score (DTS) is a value that calculates from the exercise time, Angina Score, and ST Deviation [5]. DTS calculate with the following formula: exercise time – (5 × maximum ST deviation) – (4 × angina index). This formula generates an integer number that is further divided into categories. If the DTS value is greater than or equal to 5 then it considers as normal and if the value is less than 5 and greater than or equal to -10 then it considers as Moderate Risk for the patient and if the DTS value is below then -10 then it considers as High Risk for the patient. These exercise values come from exercises that are based on some protocol like Bruce, Modified Bruce or Naughton, etc. Some previous studies were done using DTS and other medical test results with data mining [6] which is used to predict different coronary arteries disease.

In this study, the duke treadmill score was categorized into two categories either normal or abnormal as shown in Table 1

**Table 1.** Duke Treadmill Score Categories

Sr.	Duke Treadmill Score	Category
1	>=5	Normal
2	<5	Abnormal

**Problem Statement**

Previously there are many reported research is presented on Duke Treadmill Score (DTS) but this test is difficult for everyone to achieve the standard of its protocol. Old age patients and kids who are not able to walk on the treadmill at a specific time to achieve targeted heart rate. In this work we are predicting patients’ heart condition as normal or abnormal without performing ETT and calculating DTS.

**Material And Methods**

**Data Set**

Dataset used in this study is constructed from patients' ETT data provided by Dr. Zafar Iqbal Jam (Cardiologist), The Heart Center Bahawalpur, Punjab, Pakistan. There were 776 patients’ data from the year 2016 to 2021. In this dataset, there are 15 attributes and each patient is classified as having normal or abnormal heart activity based on duke score. This data set contains 157 females and 619 male patients while their male patients’ age is from 18 to 75 years and female patients’ age is 26 to 72 years. Male patient’s BSA has range from 1.13 to 2.92 and in female patients’ BSA is from 1.29 to 2.49. Male patient’s BMI has ranged from 16.30 to 341.16 and in female patients it is 15.22 to 206.59. Two attributes are Blood Pressure Systolic from 90 to 180 and Blood Pressure Diastolic from 52 to 110. After these attributes of our dataset, nine attributes are risk factors in patients. Their statistics are as follows: Diabetes Mellitus is one of the major issues these days [7].

A total of 144 patients has this risk factor where 104 are male patients and 40 are female patients. Family history is another risk factor in patients which indicates that other family members have heart problems. In this dataset, 136 patients have a family history of CHD where 105 are male patients and 31 female patients. Next, the Hypertension risk factor has in 335 patients where 239 patients are male and 96 patients are female. Hypertension is more common in old age people. Mortality in heart patients has increased due to hypertension [8]. The next risk factor of this dataset is obesity. There are 169 obese patients in a dataset where 116 are male and 53 are female. The next risk factor in this dataset is Old Age. Patients with an old age risk factor are 74 where 56 are male patients and 18 are female patients. Attribute Old age decided by the doctor.

A patient has any heart problem due to age factor considered as an Old Age risk factor. The next risk factor is Smoking. Smoking has dangerous side effects on heart patients. There are a lot of previous researches that prove that smoking is a serious cause and risk factor for heart patients [9]. 152 patients are smokers where 151 patients are male patients and only one patient is a female smoker. The next risk factor is Post-menopausal. There is 19 patient with this risk factor all are females. The next attribute is Chest pain, a total of 708 patients have a primary indication of chest pain where 566 are male patients and 142 are female patients. Chest pain is the primary indication

of CHD. A lot of studies have been conducted to prove the chest pain is an indication of CHD [10, 11]. Shortness of Breath (SOB) is a condition of the patient when he/she run or even walks sometimes and starts a problem in breathing. But some are severe cases where patients start shortness of breath by just walking some steps and sitting up and down [12]. 13 patients have SOB where 9 are male patients and 4 are female patients.

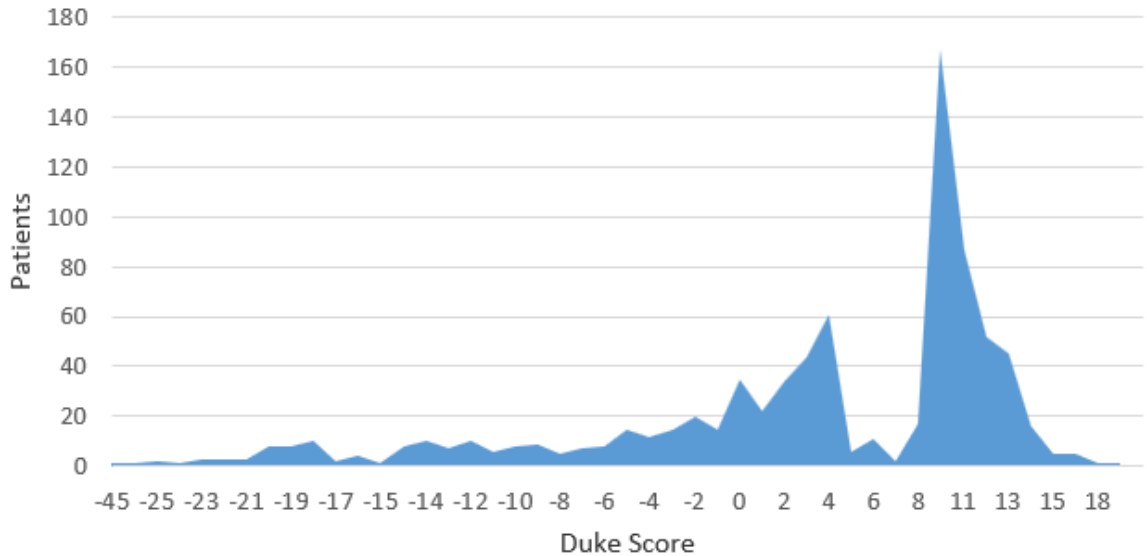
**Table 2.** Data Set Attributes

Sr.	Attribute	Description	Total	Division
1	Gender	Gender attribute represent the Sex either male or female 1=Male 0=Female	776	<b>619-Male, 157-Female</b>
2	Age	Age is number in years	776	<b>Male(18-75), Female (26-72)</b>
3	BSA	BSA is Body surface area.[13]	776	<b>Male (1.13-2.92), Female (1.29-2.49)</b>
4	BMI	Body mass Index [14]	776	<b>Male (16.30-341.16), Female (15.22-206.59)</b>
5	BP Systolic	Blood pressure systolic.	776	<b>Male (90-179), Female (92-180)</b>
6	BP Diastolic	Blood pressure Diastolic.	776	<b>Male (52-110), Female (53-108)</b>
7	Diabetes Mellitus	Diabetes Mellitus normally called diabeted. 1= Diabetes Mellitus 0= No DM	144	<b>Male=104, Female=40</b>
8	Family History	Family history means any heart disease patients in parents or grandparents. 1= Family Has History 0=No Risk of family.	136	<b>Male=105, Female=31</b>
9	Hypertension	Hypertension means high blood pressure. 1=Patient has hypertension 0= patient does not have hypertension	335	<b>Male=239, Female=96</b>
10	Obesity	Obesity means patient has more weight then normal 1=Patient has obesity RF 0=Patient does not have RF of obesity	169	<b>Male=116, Female=53</b>
11	Old Age	Patient's age is above 50-years consider as an old age patient. 1= Patient is old age. 0= Patient is not old age.	74	<b>Male=56, Female=18</b>
12	Post-menopausal	Post-menopausal is a risk factor for females 1=Patient has PM risk factor. 0=Patient has not risk factor of PM.	19	<b>Male=0, Female=19</b>
13	Smoker	Patient has smoking habit is called smoker. 1= Smoker 0= Not Smoker	152	<b>Male=151, Female=1</b>

14	Cheast Pain	Cheast pain has all type of cheast pain either cardiac or non cardiac. 1= Patient has Cheast pain. 0= Patient doest not have Cheast pain.	708	<b>Male=566, Female=142</b>
15	SOB	Shortness of breath. 1= Shortness in breath 0= Patient has no shortness in breath.	13	<b>Male=9, Female=4</b>

**Data Preparation**

In this study, for experiments purpose WEKA version 3.8.2 is used. Duke score for each patient is shown in histogram Figure Duke Score already discussed in Early study on Prediction of Duke Treadmill score.



**Figure 2.** Distribution of patients by DTS

The patients’ data were collected by the Doctor mentioned in Data Set section in his medical clinic. Each patient is classified as having a normal or abnormal heart condition based on the Duke results obtained by ETT examination. During ETT a patient has to walk on the treadmill using according to certain protocols as discussed in Early study on Prediction of Duke Treadmill score.

During ETT a patient is required to achieve some specific heart rates, blood pressures, etc. are monitored. Initially, the provided data was in SQL format where a few columns contain multi-value attributes like risk factors and primary indications. These columns are normalized by spreading these into multiple columns. Furthermore, the data is manually observed and a few columns with less than 15 occurrences in a complete column are removed. All the columns for risk factors and primary indicators are in binary form. The data is labeled manually into two classes which are normal and abnormal based on samples’ duke score. The samples having equal or more than 5 duke scores are labeled normal else labeled abnormal.

By using the above mansion risk factors and primary indications we want to predict patients’ heart condition before performing ETT. In terms of this prediction, we are using WEKA’s Algorithms.

- Logistic Regression Algorithm, Logistic regression is a classifier with binary classification technique. Logistic Regression is a formula that came from statistics. It is like linear regression. It works with binary values based on some specified set of dependent or independent variables[15, 16].

- Random Forest Algorithm, Random forest is rapidly used and helpful in previous studies for decision making. Yeshvendra K. Singh uses this algorithm to predict Heart Disease with 85% correct prediction [17, 18].
- J.48 Algorithm, J.48 is a famous classifier for data mining. J.48 used in many previous studies to predict heart disease and some other diseases using symptoms of data[19, 20].
- SVM, a Support vector machine (SVM) is another powerful tool for using classification and regression. This algorithm is also used to analyze data and pattern recognition. SVM is a mathematical function for creating a model for real-world data. This is already proved by Mythili T. in [21] and Chandra Babu Gokulnath in [22] with the highest accuracy of SVM being 83% in his study.

**Results**

Results prepared in this section with the above-mentioned algorithms with two different strategies and will compare all results at the end. Cross-Validation and Percentage Split will be used for each algorithm. Each algorithm discusses separately with these strategies.

**Logistic Regression**

Firstly Logistic regression is used to analyze and classification using WEKA. Initially, Logistic regression is applied with no filter with split data of 60% as training data and 40% as test data. With this algorithm total, 129 patients are correctly identified as normal but 20 patients are normal but identified as abnormal patients. Same as with abnormal patients, 135 patients are correctly identified as abnormal but 26 patients are abnormal but identified as normal patients. With this algorithm, 264 patients are correctly identified out of 310 patients test data. The overall accuracy for this algorithm is 85.16%. Detail about the algorithm classification in below Table 3.

This classifier shows the accuracy of both classes' values Normal and Abnormal. Normal Accuracy is 86.6% and abnormal accuracy is 83.9%. Detail accuracy of this algorithm is shown in the below Table 3.

**Table 3.** Logistic Results of Percentage Split

Detailed Accuracy By Class					
	Precision	Recall	F-Measure	MCC	ROC Area
Normal	83.20%	86.60%	84.90%	70.40%	89.70%
Abnormal	87.10%	83.90%	85.40%	70.40%	89.70%

The logistic algorithm is again applied with cross-validation with 10-Fold. With this algorithm total, 306 patients are correctly identified as normal but 73 patients are normal but identified as abnormal patients. Same as with abnormal patients, 320 patients are correctly identified as abnormal but 77 patients are abnormal but identified as normal patients. With this algorithm, 626 patients are correctly identified out of 776 patients' data. The overall accuracy for this algorithm is 80.67%. Detail about the algorithm classification in below Table 4.

This classifier shows the accuracy of both class values Normal and Abnormal. Normal Accuracy is 80.70% and abnormal accuracy is 80.60%. Detail accuracy of this algorithm is shown in the below Table 4.

**Table 4.** Logistic Results Of Cross Validation

Detailed Accuracy By Class					
	Precision	Recall	F-Measure	MCC	ROC Area
Normal	79.90%	80.70%	80.30%	61.30%	89.30%
Abnormal	81.40%	80.60%	81.00%	61.30%	89.30%

**Random Forest**

The second algorithm used for classification is Random Forest. Initially, Random Forest is applied with no filter and split data of 60% as training data and 40% as test data. With this algorithm total of 122 patients are correctly identified as normal but 27 patients are normal but identified as an abnormal patients. Same as with abnormal patients, 137 patients are correctly identified as

abnormal but 24 patients are abnormal but identified as normal patients. With this algorithm, 259 patients are correctly identified out of 310 patients' test data. The overall accuracy for this algorithm is 83.55%. Detail about the algorithm classification in below Table 5 .

This classifier shows the accuracy of both classes' values Normal and Abnormal. Normal Accuracy is 81.90% and abnormal accuracy is 85.10%. Detail accuracy of this algorithm is shown in the below Table 5

**Table 5.** Random Forest Results of Split Percentage

Detailed Accuracy By Class					
	Precision	Recall	F-Measure	MCC	ROC Area
Normal	83.60%	81.90%	82.70%	67.00%	89.20%
Abnormal	83.50%	85.10%	84.30%	67.00%	89.20%

Random Forest algorithm is again applied with cross-validation with 10-Fold. With this algorithm total of 296 patients are correctly identified as normal but 83 patients are normal but identified as abnormal patients. Same as with abnormal patients, 331 patients are correctly identified as abnormal but 66 patients are abnormal but identified as normal patients. With this algorithm, 627 patients are correctly identified out of 776 patients' data. The overall accuracy for this algorithm is 80.80%. Detail about the algorithm classification in below Table 6.

This classifier shows the accuracy of both classes' values Normal and Abnormal. Normal Accuracy is 78.10% and abnormal accuracy is 83.40%. Detail accuracy of this algorithm shown in the below Table 6.

**Table 6.** Random Forest Results With Cross Validation

Detailed Accuracy By Class					
	Precision	Recall	F-Measure	MCC	ROC Area
Normal	81.80%	78.10%	79.90%	61.60%	89.00%
Abnormal	80.00%	83.40%	81.60%	61.60%	89.00%

**J.48**

The third algorithm used for classification is J.48. Initially, J.48 is applied with no filter and split data of 40% as training data and 60% as test data. With this algorithm total of 189 patients are correctly identified as normal but 46 patients are normal but identified as abnormal patients. Same as with abnormal patients, 175 patients are correctly identified as abnormal but 56 patients are abnormal but identified as normal patients. With this algorithm, 364 patients are correctly identified out of 466 patients' test data. The overall accuracy for this algorithm is 78.11%. Detail about the algorithm classification in below Table 7.

This classifier shows the accuracy of both classes' values Normal and Abnormal. Normal Accuracy is 80.40% and abnormal accuracy is 75.80%. Detail accuracy of this algorithm is shown in the below Table 7.

**Table 7.** J.48 Results with Split Percentage

Detailed Accuracy By Class					
	Precision	Recall	F-Measure	MCC	ROC Area
Normal	77.10%	80.40%	78.80%	56.30%	79.90%
Abnormal	79.20%	75.80%	77.40%	56.30%	79.90%

J.48 algorithm is again applied with cross-validation 15-Folds. With this algorithm total, 295 patients are correctly identified as normal but 84 patients are normal but identified as abnormal patients. Same as with abnormal patients, 315 patients are correctly identified as abnormal but 82 patients are abnormal but identified as normal patients. With this algorithm, 610 patients are correctly identified out of 776 patients' data. The overall accuracy for this algorithm is 78.61%. Detail about the algorithm classification in below Table 8.

This classifier shows the accuracy of both class values Normal and Abnormal. Normal Accuracy is 77.80% and abnormal accuracy is 79.30%. Detail accuracy of this algorithm is shown in the below Table 8

**Table 8.** J.48 Results With Cross Validation

Detailed Accuracy By Class					
	Precision	Recall	F-Measure	MCC	ROC Area
Normal	78.20%	77.80%	78.00%	57.20%	79.90%
Abnormal	78.90%	79.30%	79.10%	57.20%	79.90%

**Support Vector Machine**

The last algorithm for classification is SVM. Initially, SVM is applied with no filter and split data of 40% as training data and 60% as test data. With this algorithm total, 127 patients are correctly identified as normal but 22 patients are normal but identified as an abnormal patient. Same as with abnormal patients, 128 patients are correctly identified as abnormal but 33 patients are abnormal but identified as normal patients. With this algorithm, 255 patients are correctly identified out of 310 patients' data. The overall accuracy for this algorithm is 82.26%. Detail about the algorithm classification in below Table 9.

This classifier shows the accuracy of both class values Normal and Abnormal. Normal Accuracy is 85.20% and abnormal accuracy is 79.50%. Detail accuracy of this algorithm is shown in the below Table 9

**Table 9.** SVM Result with Split Percentage

Detailed Accuracy By Class					
	Precision	Recall	F-Measure	MCC	ROC Area
Normal	79.40%	85.20%	82.20%	64.70%	82.40%
Abnormal	85.30%	79.50%	82.30%	64.70%	82.40%

SVM algorithm is again applied with cross-validation 5-Folds and random seed 2 from detail settings. With this algorithm total of 310 patients are correctly identified as normal but 69 patients are normal but identified as abnormal patients. Same as with abnormal patients, 314 patients are correctly identified as abnormal but 83 patients are abnormal but identified as normal patients. With this algorithm, 624 patients are correctly identified out of 776 patients' data. The overall accuracy for this algorithm is 80.41%. Detail about the algorithm classification in below Table 10

This classifier shows the accuracy of both class values Normal and Abnormal. Normal Accuracy is 81.80% and abnormal accuracy is 79.10%. Detail accuracy of this algorithm is shown in the below Table 10

**Table 10.** SVM Results with Cross Validation

Detailed Accuracy By Class					
	Precision	Recall	F-Measure	MCC	ROC Area
Normal	78.90%	81.80%	80.30%	60.90%	80.40%
Abnormal	82.00%	79.10%	80.50%	60.90%	80.40%

**Discussions**

After applying all the algorithms one by one with both Split Percentage in Figure 3. Results accuracy of each algorithm with split percentage

Table 11 and Cross-validation in Table 12, now we have the best performance of each algorithm. The highest performance comes from Logistic Regression Algorithm with a split percentage, which is 85.16% overall. Now we compare all results into summarized form.



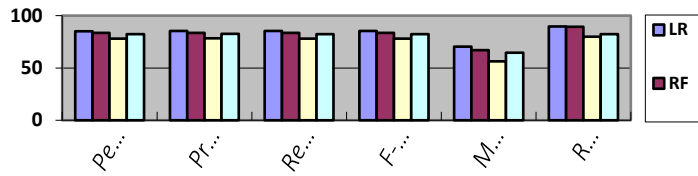


Figure 3. Results accuracy of each algorithm with split percentage

Table 11. Split Percentage of Each Algorithm

Detailed Accuracy By Algorithm (All values are in %)						
	Overall Accuracy	Precision	Recall	F-Measure	MCC	ROC Area
LR	85.16	85.20	85.20	85.20	70.40	89.70
RF	83.55	83.50	83.50	83.50	67.00	89.20
J.48	78.11	78.20	78.10	78.10	56.30	79.90
SVM	82.26	82.50	82.30	82.30	64.70	82.40

Table 12. Cross Validation of Each Algorithm

Detailed Accuracy By Algorithm (All values are in %)						
	Overall Accuracy	Precision	Recall	F-Measure	MCC	ROC Area
LR	80.67	80.70	80.70	80.70	61.30	89.30
RF	80.80	80.80	80.80	80.80	61.60	89.00
J.48	78.61	78.60	78.60	78.60	57.20	79.90
SVM	80.41	80.50	80.40	80.40	60.90	80.40

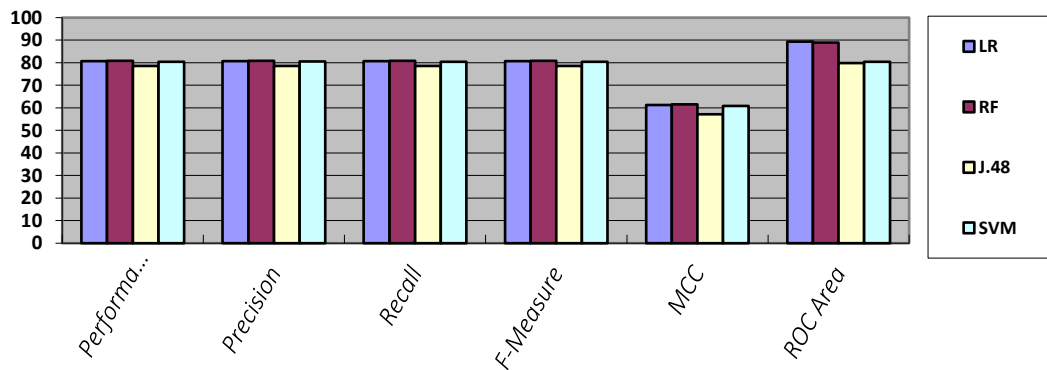


Figure 4. Results accuracy of each algorithm with cross validation

Table 13 and Table 14 shows statistical results of used algorithms. According to these LR with split percentage has showed maximum agreement of 0.7. This results is in accordance to the previous results.

Table 13. Algorithm results with split percentage results

Algorithm Stats With Split Percentage Results		
	Kappa Statistic	Mean Absolute Error
LR	0.7032	0.2501
RF	0.6702	0.2778
J.48	0.562	0.2627
SVM	0.6456	0.1774

**Table 14.** Algorithm results with cross validation results

<b>Algorithm Stats With Cross Validation Results</b>		
	<b>Kappa Statistic</b>	<b>Mean Absolute Error</b>
LR	0.6133	0.2594
RF	0.6154	0.2732
J.48	0.5719	0.2647
SVM	0.6084	0.1959

## Conclusion & Future Work

All the results are shown in detail in the previous section LR Algorithm with these parameters can correctly predict the patient condition 85%. To date, this is the first study to predict patients' heart condition using their general condition and symptoms without performing ETT and calculating DTS. In future work, we will try to improve accuracy by adding more features to the dataset. Patients with an abnormal heart condition can be further classified into moderate and high-risk patients.

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