Heart Disease Prediction by Using ML

Submitted in partial fulfillment of the
requirement for the award of the degree of
BACHELOR OF ENGINEERING IN
COMPUTER SCIENCE &ENGINEERING

Under The Supervision of

Mr. S. Rakesh Kumar

Submitted By

S.NO	ENROLLMENT NUMBER	ADMISSION NUMBER	STUDENT NAME	Degree	Sem
1	19021011788	19SCSE1010631	RITIKA ROY	B.TECH	5
2	19021011528	19SCSE1010344	VANDANA RAI	B.TECH	5

SCHOOL OF COMPUTING SCIENCE AND ENGINEERING
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
GALGOTIAS UNIVERSITY, GREATER NOIDA

SCHOOL OF COMPUTING SCIENCE AND ENGINEERING
GALGOTIAS UNIVERSITY, GREATER NOIDA

CANDIDATE'S DECLARATION

We hereby certify that the work which is being presented in the HEART DISEASE PREDICTION USING ML in partial fulfillment of the requirements for the award of the BTECH submitted in the School of Computing Science and Engineering of Galgotias University, Greater Noida, is an original work carried out during the period of month, Year to Month and Year, under the supervision of Mr.S.RAKESH KUMAR, Department of Computer Science and Engineering/Computer Application and Information and Science, of School of Computing Science and Engineering , Galgotias University, Greater Noida

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Supervisor Name
MR.S.RAKESH KUMAR

CERTIFICATE

Certified that this project report "HEART DISEASE PREDICTION " is the bonafide work of RITIKA ROY AND VANDANA RAI who carried out the project work under the supervision of MR. S.RAKESH KUMAR

Signature of Supervisor(s)

Signature of Dean

Date:
Place: Greater Noida

Table of Contents

ABSTRACT

This report represents the mini-project assigned to Fifth semester students for the partial fulfillment of COMP 484, Machine Learning, given by the department of computer science and engineering, GU. Cardiovascular diseases are the most common cause of death worldwide over the last few decades in the developed as well as underdeveloped and developing countries. Earlydetection of cardiac diseases and continuous supervision of clinicians can reduce the mortalityrate. However, it is not possible to monitor patients every day in all cases accurately andconsultation of a patient for 24 hours by a doctor is not available since it requires more sapience,time and expertise. In this project, we have developed and researched about models for heartdisease prediction through the various heart attributes of patient and detect impending heart diseaseusing Machine learning techniques like backward elimination algorithm, logistic regression andREFCV on the dataset available publicly in Kaggle Website, further evaluating the results usingconfusion matrix and cross validation. The early prognosis of cardiovascular diseases can aid inmaking decisions on lifestyle changes in high risk patients and in turn reduce the complications,which can be a great milestone in the field of medicine.

Keywords: Machine Learning, Logistic regression, Cross-Validation, Backward Elimination, REFCV, Cardiovascular Diseases

LIST OF FIGURES:

LIST OF TABLES:

LIST OF ABBREVIATIONS:

1 IDE: Integrated Development Environment
2.REFCV: Recursive Feature Elimination using Cross-Validation
3.CV: Cross Validation
4.RFE:Recursive Feature Elimination

CHAPTER 1: INTRODUCTION

According to the World Health Organization, every year 12 million deaths occur worldwide dueto Heart Disease. The load of cardiovascular disease is rapidly increasing all over the world fromthe past few years. Many researches have been conducted in attempt to pinpoint the mostinfluential factors of heart disease as well as accurately predict the overall risk. Heart Disease iseven highlighted as a silent killer which leads to the death of the person without obvious symptoms.The early diagnosis of heart disease plays a vital role in making decisions on lifestyle changes inhigh-risk patients and in turn reduce the complications. This project aims to predict future HeartDisease by analyzing data of patients which classifies whether they have heart disease or not usingmachine-learning algorithms.

1.1 Problem Definition

The major challenge in heart disease is its detection. There are instruments available which can predict heart disease but either they are expensive or are not efficient to calculate chance of heartdisease in human. Early detection of cardiac diseases can decrease the mortality rate and overallcomplications. However, it is not possible to monitor patients every day in all cases accurately andconsultation of a patient for 24 hours by a doctor is not available since it requires more sapience,time and expe
rtise. Since we have a good amount of data in today's world, we can use various machine learning algorithms to analyze the data for hidden patterns. The hidden patterns can beused for health diagnosis in medicinal data.

1.2 Motivation

Machine learning techniques have been around us and has been compared and used for analysisfor many kinds of data science applications. The major motivation behind this research-based project was to explore the feature selection methods, data preparation and processing behind thetraining models in the machine learning. With first hand models and libraries, the challenge weface today is data where beside their abundance, and our cooked models, the accuracy we seeduring training, testing and actual validation has a higher variance. Hence this project is carriedout with the motivation to explore behind the models, and further implement Logistic Regression

model to train the obtained data. Furthermore, as the whole machine learning is motivated todevelop an appropriate computer-based system and decision support that can aid to early detectionof heart disease, in this project we have developed a model which classifies if patient will haveheart disease in ten years or not based on various features (i.e. potential risk factors that can causeheart disease) using logistic regression. Hence, the early prognosis of cardiovascular diseases canaid in making decisions on lifestyle changes in high risk patients and in turn reduce thecomplications, which can be a great milestone in the field of medicine.

1.3 Objectives

The main objective of developing this project are:

1.To develop machine learning model to predict future possibility of heart disease byimplementing Logistic Regression.

2.To determine significant risk factors based on medical dataset which may lead to heartdisease

3To analyze feature selection methods and understand their working principle

CHAPTER 2: RELATED WORKS

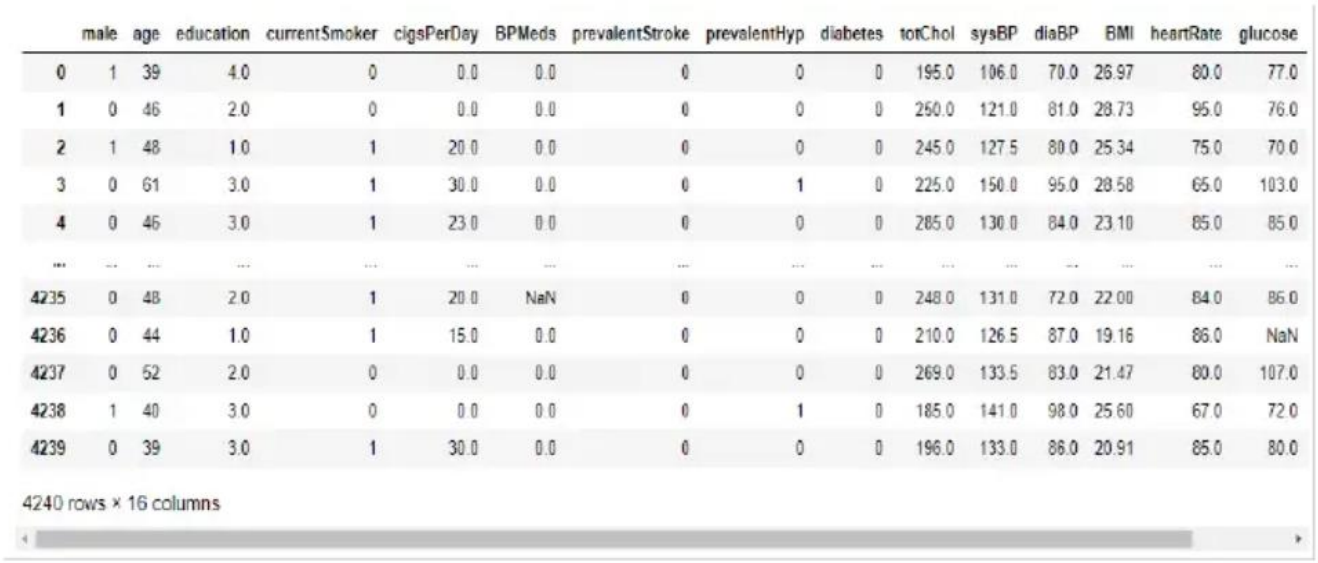
With growing development in the field of medical science alongside machine learning variousexperiments and researches has been carried out in these recent years releasing the relevantsignificant papers. The paper [1] propose heart disease prediction using KStar, J48, SMO, andBayes Net and Multilayer perceptron using WEKA software. Based on performance from differentfactor SMO (89% of accuracy) and Bayes Net (87% of accuracy) achieve optimum performancethan KStar, Multilayer perceptron and J48 techniques using k-fold cross validation. The accuracy performance achieved by those algorithms are still not satisfactory. So that if the performance ofaccuracy is improved more to give batter decision to diagnosis disease.

[2]In a research conducted using Cleveland dataset for heart diseases which contains 303 instancesand used 10-fold Cross Validation, considering 13 attributes, implementing 4 different algorithms,they concluded Gaussian Naïve Bayes and Random Forest gave the maximum accuracy of 91.2 percent

[3]Using the similar dataset of Framingham, Massachusetts, the experiments were carried outusing 4 models and were trained and tested with maximum accuracy K Neighbors Classifier: 87%,Support Vector Classifier: 83%, Decision Tree Classifier: 79% and Random Forest Classifier:84%.

CHAPTER 3: DATASETS

The dataset is publicly available on the Kaggle Website at [4] which is from an ongoingcardiovascular study on residents of the town of Framingham, Massachusetts. It provides patientinformation which includes over 4000 records and 14 attributes. The attributes include: age, sex,chest pain type, resting blood pressure, serum cholesterol, fasting, sugar blood, restingelectrocardiographic results, maximum heart rate, exercise induced angina, ST depression induced by exercise, slope of the peak exercise, number of major vessels, and target ranging from 0 to 2,where 0 is absence of heart disease. The data set is in csv (Comma Separated Value) format whichis further prepared to data frame as supported by pandas library in python



	male	age	education	currentSmoker	cigsPerDay	BPMeds	prevalentStroke	prevalentHyp	diabetes	totChol	sysBP	diaBP	BMI	heartRate	glucose
0	1	39	4.0	0	0.0	0.0	0	0	0	195.0	106.0	70.0	26.97	80.0	77.0
1	0	46	2.0	0	0.0	0.0	0	0	0	250.0	121.0	81.0	28.73	95.0	76.0
2	1	48	1.0	1	20.0	0.0	0	0	0	245.0	127.5	80.0	25.34	75.0	70.0
3	0	61	3.0	1	30.0	0.0	0	1	0	225.0	150.0	95.0	28.58	65.0	103.0
4	0	46	3.0	1	23.0	0.0	0	0	0	285.0	130.0	84.0	23.10	85.0	85.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
4235	0	48	2.0	1	20.0	NaN	0	0	0	248.0	131.0	72.0	22.00	84.0	86.0
4236	0	44	1.0	1	15.0	0.0	0	0	0	210.0	126.5	87.0	19.16	86.0	NaN
4237	0	52	2.0	0	0.0	0.0	0	0	0	269.0	133.5	83.0	21.47	80.0	107.0
4238	1	40	3.0	0	0.0	0.0	0	1	0	185.0	141.0	98.0	25.60	67.0	72.0
4239	0	39	3.0	1	30.0	0.0	0	0	0	196.0	133.0	86.0	20.91	85.0	80.0

4240 rows × 16 columns

Figure 1: Original Dataset Snapshot

The education data is irrelevant to the heart disease of an individual, so it is dropped. Further withthis dataset pre-processing and experiments are then carried out

CHAPTER 4: METHODS AND ALGORITHMS USED

The main purpose of designing this system is to predict the ten-year risk of future heart disease.We have used Logistic regression as a machine-learning algorithm to train our system and variousfeature selection algorithms like Backward elimination and Recursive feature elimination. Thesealgorithms are discussed below in detail.

4.1 Logistic Regression

Logistic Regression is a supervised classification algorithm. It is a predictive analysis algorithm based on the concept of probability. It measures the relationship between the dependent variable(TenyearCHD) and the one or more independent variables (risk factors) by estimating probabilitiesusing underlying logistic function (sigmoid function). Sigmoid function is used as a cost functionto limit the hypothesis of logistic regression between 0 and 1 (squashing) .

$$Cost(\mathrm{h}\theta(\mathrm{x}),\mathrm{y}) = \begin{cases} -\log\big(h\theta(x)\big) & if\ y = 1 \\ -\log\big(1-h\theta(x)\big) & if\ y = 0 \end{cases}$$

Logistic Regression relies highly on the proper presentation of data. So, to make the model more powerful, important features from the available data set are selected using Backward eliminationand recursive elimination techniques.

4.2 Backward Elimination Method:

While building a machine learning model only the features which have a significant influence onthe target variable should be selected. In the backward elimination method for feature selection,the first step is selecting a significance level or P-value. For our model, we have chosen a 5%significance level or P-value of 0.05. The feature with high P-value is identified, and if its P-valueis greater than the significance level it is removed from the dataset. The model is fit again with anew dataset, and the process is repeated till all remaining features in dataset is less than thesignificance level. In this model, factors male, age, cigsPerDay, prevalentStroke, diabetes, andsysBP were chosen as significant ones after using the backward elimination algorithm.

4.3 Recursive Feature Elimination using Cross-Validation (RFECV)

RFECV is greedy optimization algorithm which aims to find the best performing feature subset.Recursive Feature Elimination (RFE) fits a model repeatedly and removes the weakest featureuntil specified number of features is reached. The optimal number of features is used with RFE toscore different feature subsets and select the best scoring collection of features which is RFECV.The main issue of this algorithm is that it can be expensive to run. So, it is better to reduce thenumber of features beforehand. Since correlated features provide the same information, suchfeatures can be eliminated prior to RFECV. To address this, correlation matrix is plotted and thecorrelated features are removed.
The arguments for instance of RFECV are:
a.estimator - model instance (RandomForestClassifier)
b.step - number of features removed on each iteration (1)
c.cv – Cross-Validation (StratifiedKFold)
d.scoring – scoring metric (accuracy)
Once RFECV is run and execution is finished, the features that are least important can be extractedand dropped from the dataset. Top 10 features ranked by the RFECV technique in our model listed below from least importance to highest importance.

1. prevalentStroke

2.diabetes

3.BPMeds

4.currentSmoker

5. prevalentHyp

6.male

7.cigsPerDay

8.heartrate

9.glucose

10.diaBP

CHAPTER 5: EXPERIMENTS

5.1 Data Preparation

Since the dataset consists of 4240 observations with 388 missing data and 644 observations to be risked for heart disease, two different experiments were performed for data preparation. First, we checked by dropping the missing data, leaving with only 3751 data and only 572 observations risked for heart disease.

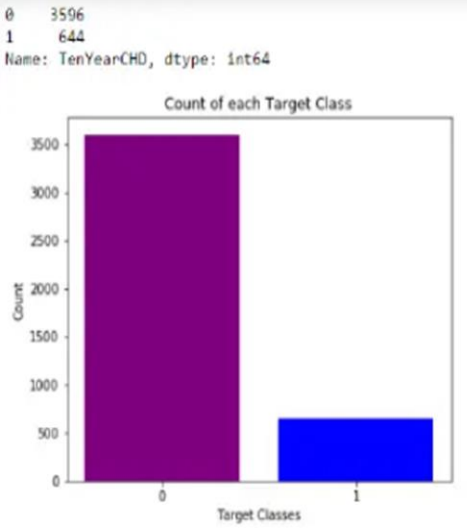


Figure 3: Bar Graph of the Target Classes Before Dropping

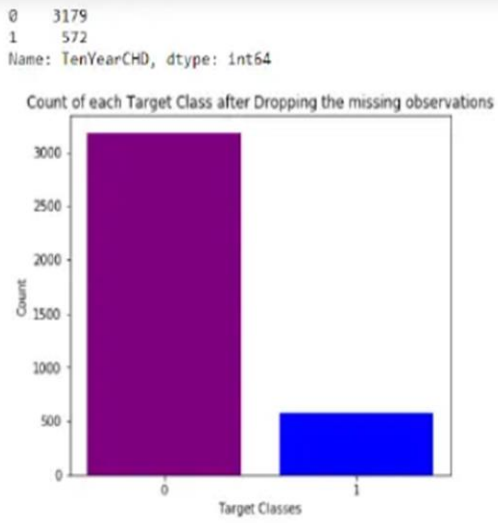


Figure 2: Bar Graph of the Target Classes After Dropping

This leads to reduced number of the observations providing irrelevant training to our model. So, we progressed with imputation of data with the mean value of the observations and scaling them using SimpleImputer and StandardScaler modules of Sklearn.

	male	age	currentSmoker	cigsPerDay	BPMeds	prevalentStroke	prevalentHyp	diabetes	totChol	sysBP	diaBP	BMI	heart
0	1.153113	-1.234283	-0.988276	-0.758062	-1.768000e-01	-0.077014	-0.871241	-0.152437	-0.948825	-1.198287	-1.083027	0.287258	0.34
1	-0.867217	-0.417564	-0.988276	-0.758062	-1.768000e-01	-0.077014	-0.871241	-0.152437	0.300085	-0.515306	-0.159365	0.710668	1.50
2	1.153113	-0.184345	1.011863	0.626419	-1.768000e-01	-0.077014	-0.871241	-0.152437	0.187275	-0.220956	-0.249326	-0.113213	-0.01
3	-0.867217	1.332233	1.011863	1.787148	-1.768000e-01	-0.077014	1.489778	-0.152437	-0.293965	0.830946	1.018227	0.682815	-0.90
4	-0.867217	-0.417564	1.011863	1.177931	-1.768000e-01	-0.077014	-0.871241	-0.152437	1.089760	-0.106878	0.002565	-0.093564	0.76
...	...	...	...	...	...	...	...	...	...	...	...	...	...
4235	-0.867217	-0.184345	1.011863	0.626419	2.059493e-17	-0.077014	-0.871241	-0.152437	0.264861	-0.051487	-0.915087	-0.933810	0.67
4236	-0.867217	-0.650984	1.011863	0.504542	-1.768000e-01	-0.077014	-0.871241	-0.152437	-0.902395	-0.285747	0.344468	-1.631564	0.84
4237	-0.867217	0.282295	-0.988276	-0.758062	-1.768000e-01	-0.077014	-0.871241	-0.152437	0.726764	0.051901	0.008585	-1.094026	0.34
4238	1.153113	-1.117523	-0.988276	-0.758062	-1.768000e-01	-0.077014	1.489778	-0.152437	-1.166445	0.382428	1.268138	-0.049334	-0.73
4239	-0.867217	-1.234283	1.011863	1.787148	-1.768000e-01	-0.077014	-0.871241	-0.152437	-0.918263	0.029296	0.289468	-1.291816	0.75

4240 rows × 14 columns

Figure 4: Dataset after Scaling and Imputing

5.2 Exploratory Analysis:

Correlation Matrix visualization Before Feature Selection shows

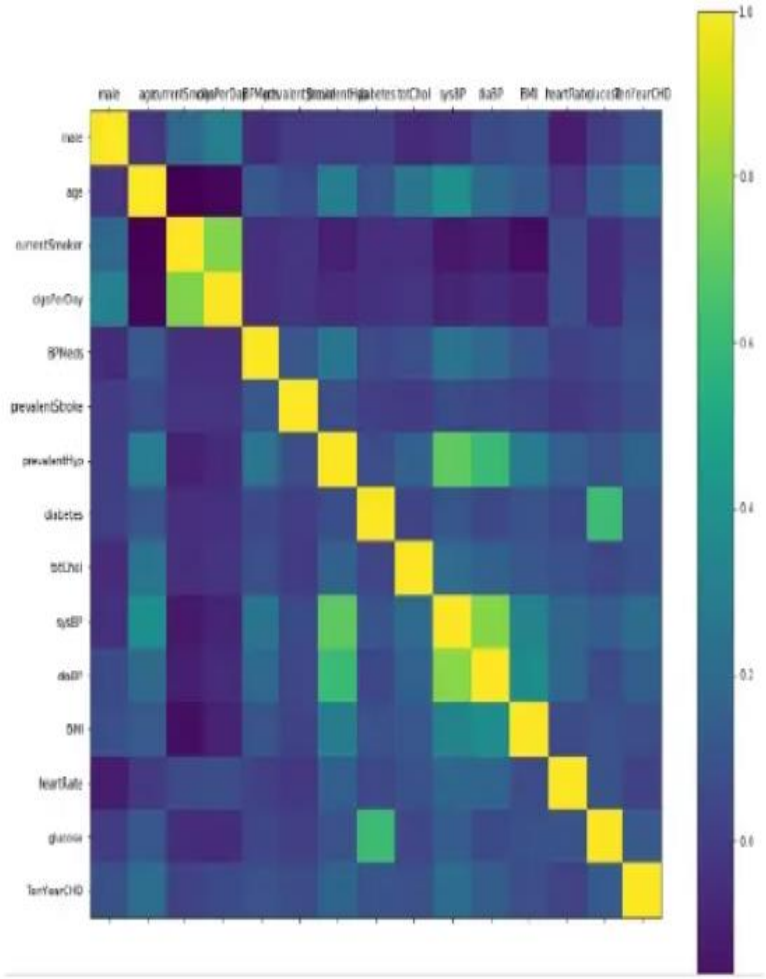


Figure 5: Correlation Matrix Visualization

It shows that there is no single feature that has a very high correlation with our target value. Also, some of the features have a negative correlation with the target value and some have positive. The data was also visualized through plots and bar graphs.

5.3 Feature Selection

Feature Selection using Backward Elimination (P-value) algorithm:

Further the data was passed through the backward elimination function to select the mostrelevant features which gave following result

Logit Regression Results

Dep. Variable:	TenYearCHD	No. Observations:	4240
Model:	Logit	Df Residuals:	4234
Method:	MLE	Df Model:	5
Date:	Mon, 09 Mar 2020	Pseudo R-squ.:	0.5700
Time:	08:42:03	Log-Likelihood:	-2835.5
converged:	True	LL-Null:	-1806.1
Covariance Type:	nonrobust	LLR p-value:	1.000

	coef	std err	z	P>|z|	[0.025	0.975]
male	0.1053	0.033	3.178	0.001	0.040	0.170
age	0.2626	0.035	7.505	0.000	0.194	0.331
cigsPerDay	0.1294	0.034	3.812	0.000	0.063	0.196
prevalentStroke	0.0813	0.038	2.124	0.034	0.006	0.156
diabetes	0.1056	0.035	3.046	0.002	0.038	0.173
sysBP	0.2244	0.035	6.370	0.000	0.155	0.293

Figure 6: Result from Feature Selection using Backward Elimination Method

According the result above the columns were dropped.

	male	age	cigsPerDay	prevalentStroke	diabetes	sysBP
0	1.153113	-1.234283	-0.758062	-0.077014	-0.162437	-1.196267
1	-0.867217	-0.417664	-0.758062	-0.077014	-0.162437	-0.515399
2	1.153113	-0.184345	0.925410	-0.077014	-0.162437	-0.220356
3	-0.867217	1.332233	1.767146	-0.077014	-0.162437	0.800946
4	-0.867217	-0.417664	1.177931	-0.077014	-0.162437	-0.106878
...	...	...	...	...	...	...
4235	-0.867217	-0.184345	0.925410	-0.077014	-0.162437	-0.061487
4236	-0.867217	-0.650984	0.504542	-0.077014	-0.162437	-0.265747
4237	-0.867217	0.282295	-0.758062	-0.077014	-0.162437	0.051991
4238	1.153113	-1.117623	-0.758062	-0.077014	-0.162437	0.392425
4239	-0.867217	-1.234283	1.767146	-0.077014	-0.162437	0.029296

4240 rows × 6 columns

Figure 7: Dataset After Dropping Columns after Feature Selection

Feature Selection using Recursive Feature Elimination and Cross-Validated selectionmethod:

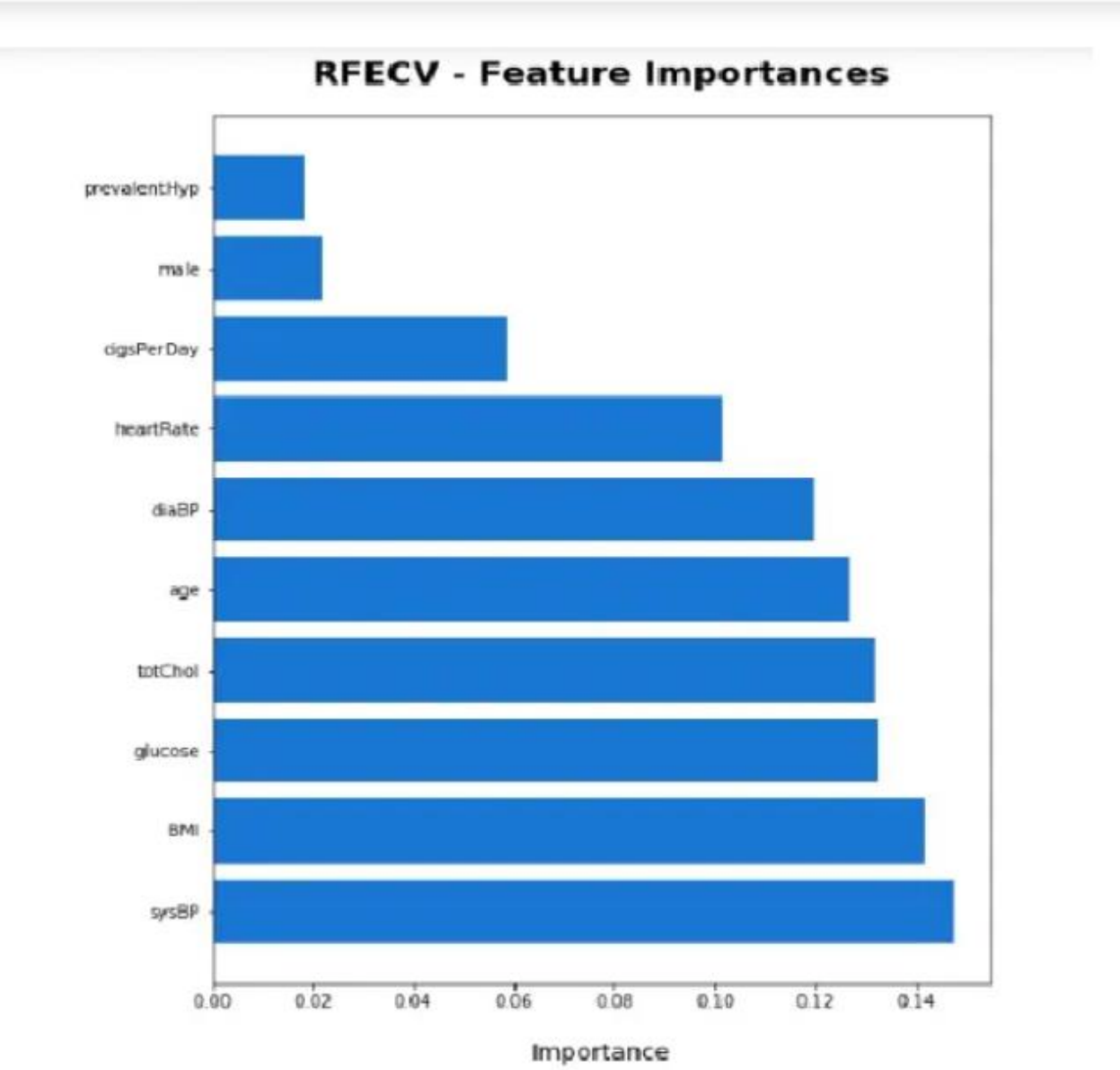


Figure 8: Top 10 important features supported by RFECV

5.4training and testing

Finally, this resulting data split into 80% train and 20% test data, which was further passed to theLogisticRegression model to fit, predict and score the model.

CHAPTER 6: EVALUATION METRICS

For the evaluation of our output from our training the data, the accuracy was analyzed "Confusion matrix".

6.1 Confusion Matrix

A confusion matrix, also known as an error matrix, is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. It allows the visualization of the performance of an algorithm. It allows easy identification of confusion between classes e.g. one class is commonly mislabeled as the other. The key to the confusion matrix is the number of correct and incorrect predictions are summarized with count values and broken down by each class not just the number of errors made.

TP=3569	FP=27
FN=599	TN=45

Table 1: Confusion Matrix Obtained after training the data (feature selection by backward elimination)

TP=3582	FP=14
FN=600	TN=44

Table 2: Confusion Matrix Obtained after training the data (feature selection by RFECV method)

Accuracy
The accuracy is calculated as:
Accuracy =TP+TN/TP+TN+FP+FN

Where,
•True Positive (TP) =Observation is positive, and is predicted to be positive.

•False Negative (FN) = Observation is positive, but is predicted negative.

•True Negative (TN) = Observation is negative, and is predicted to be negative.

•False Positive (FP) =Observation is negative, but is predicted positive

The obtained accuracy during training the data after feature selection using backward elimination was 86 % and during testing was 83%.

The obtained accuracy during training the data after feature selection using REFCV method was86 % and during testing was 85%

6.3 Recall

Recall can be defined as the ratio of the total number of correctly classified positive examplesdivide to the total number of positive examples. High Recall indicates the class is correctlyrecognized (a small number of FN). Recall is calculated as:

Recall =TP/TP+FN

The obtained recall during training the data after feature selection using backward elimination wasand during testing was 0.99.The obtained recall during training the data after feature selection using REFCV method was 1.00and during testing was 0.99.

6.4 Precision

To get the value of precision we divide the total number of correctly classified positive examples by the total number of predicted positive examples. High Precision indicates an example labelledas positive is indeed positive (a small number of FP). Precision is calculated as:

Precision =TP/TP+FP

The obtained precision during training the data after feature selection using backward eliminationwas 0.86 and during testing was 0.84

.The obtained precision during training the data after feature selection using REFCV method andduring testing was 0.86.

CHAPTER 6: DISCUSSION ON RESULTS

When performing various methods of feature selection, testing it was found that backwardelimination gave us the best results among others. The various methods tried were BackwardElimination with and without KFold, Recursive Feature Elimination with Cross Validation. Theaccuracy that was seen in them ranged around 85% with 85.5% being maximum. Though bothmethods gave similar accuracy but it was seen that in Backward Elimination we found that thenumber of misclassifications of True Negative was more and it was observed that the accuracy hadmore variance compared to RFEV. The precision of Backward Elimination and RFEV are 84%and 86% respectively. And the recalls are 0.99 and 1 respectively. The precision and recall alsoshows that the number of misclassifications is less in RFECV than in Backward Elimination

Evaluation Metrics	Backward Elimination	RFECV
Accuracy	83%	85%
Recall	0.99	0.99
Precision	0.84	0.86

Table 3: Comparison between the feature selection models after training and testing through LogisticRegression model

CHAPTER 7: CONTRIBUTIONS

MEMBERS / TASK	Vandana Rai	Ritika Roy
Data Imputation and Scaling		
Data Cleaning		
Exploratory Analysis		
Feature Selection		
Building Models		
Result Analysis And Accuracy Test		
Documentation		

CHAPTER 9: CODE

The coding portion were carried out to prepare the data, visualize it, pre-process it, building the model and then evaluating it. The code has been written in Python programming language using Jupyter Notebook as IDE. The experiments and all the models building are done based on python libraries. The code is available in the Git repository given in following link:

In [2]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import scipy.stats as st
import statsmodels.api as sm
from matplotlib import rcParams
from matplotlib.pyplot import matshow
```

Loading the data and preparing the DataFrame from the csv file

In [3]:
```
data_frame = pd.read_csv('framingham.csv')
df = pd.DataFrame(data_frame)
df_pre=pd.DataFrame(data_frame)
df
```

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
male               0
age                0
education        105
currentSmoker      0
cigsPerDay        29
BPMeds            53
prevalentStroke    0
prevalentHyp       0
diabetes           0
totChol           50
sysBP              0
diaBP              0
BMI               19
heartRate          1
glucose          388
TenYearCHD         0
dtype: int64
```

In [9]:
```
df.sum()
```

Out[9]:
```
male               1820.00
age              210220.00
education          8185.00
currentSmoker      2095.00
cigsPerDay        37924.00
BPMeds              124.00
prevalentStroke      25.00
prevalentHyp       1317.00
diabetes            109.00
totChol          991771.00
sysBP            561183.50
diaBP            351486.50
BMI              108905.18
heartRate        321651.00
glucose          315724.00
TenYearCHD          644.00
dtype: float64
```

In [10]:
```
df.drop(['education'], axis = 1, inplace = True)
```

In [14]:
```
df.isnull().sum()
```

Out[14]:
```
male                0
age                 0
currentSmoker       0
cigsPerDay         29
BPMeds             53
prevalentStroke     0
prevalentHyp        0
diabetes            0
totChol            50
sysBP               0
diaBP               0
BMI                19
heartRate           1
glucose           388
TenYearCHD          0
dtype: int64
```

In [15]:
```
rcParams['figure.figsize'] = 6,5
plt.bar(df.TenYearCHD.unique(), df.TenYearCHD.value_counts(), color = ['purple', 'blue'])
plt.xticks([0, 1])
plt.xlabel('Target Classes')
plt.ylabel('Count')
plt.title('Count of each Target Class')
print(df.TenYearCHD.value_counts())
```

```
0    3596
1     644
Name: TenYearCHD, dtype: int64
```

A total of 4240 data with 15 columns, 644 observations to be risked to heart disease, and 388 data are missing or invalid.

Data Preparation

Dropping the missing data

In [16]:
```
df_test=df
df_test.dropna(axis=0,inplace=True)
df_test.shape

rcParams['figure.figsize'] = 6,5
plt.bar(df_test.TenYearCHD.unique(), df_test.TenYearCHD.value_counts(), color = ['purple', 'blue'])
plt.xticks([0, 1])
plt.xlabel('Target Classes')
plt.ylabel('Count')
plt.title('Count of each Target Class after Dropping the missing observations')
print(df_test.TenYearCHD.value_counts())
```

```
0    3179
1     572
Name: TenYearCHD, dtype: int64
```

Imputation and Scaling using Pipeline

In [17]:
```
data_frame = pd.read_csv('framingham.csv')
df = pd.DataFrame(data_frame)
df.drop(['education'], axis = 1, inplace = True)
```

In [18]:
```
df.shape
```

Out[18]: (4240, 15)

In [19]:
```
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
```

In [20]:
```
cols=["male","age","currentSmoker","cigsPerDay","BPMeds","prevalentStroke","prevalentHyp","diabetes","totChol","sysBP","diaBP","BMI","heartRate","gluco
```

In [21]:
```
X_components=df.columns[:-1]
ddf=df[X_components]
ddf
```

4240 rows × 14 columns

In [22]:
```
pipe1=Pipeline([("imputer",SimpleImputer(strategy="mean")),("scaler",StandardScaler())])
df1=pipe1.fit_transform(ddf)
df_mean=pd.DataFrame(data=df1[0:,0:],  columns=cols)

pipe2=Pipeline([("imputer",SimpleImputer(strategy="median")),("scaler",StandardScaler())])
df2=pipe1.fit_transform(ddf)
df_median=pd.DataFrame(data=df2[0:,0:],  columns=cols)

pipe3=Pipeline([("imputer",SimpleImputer(strategy="most_frequent")),("scaler",StandardScaler())])
df3=pipe1.fit_transform(ddf)
df_most=pd.DataFrame(data=df3[0:,0:],  columns=cols)

#imp1=SimpleImputer(strategy="mean")
#imp2=SimpleImputer(strategy="median")
#imp3=SimpleImputer(strategy="most_frequent")
```

Exploratory Analysis

Histogram

In [30]:
```
from ipywidgets import widgets

feature_desc={'age':'Age of person',
              'cigsPerDay':'No of average ciggarete taken per day',
              'BPMeds':'BPMeds',
              'prevalentStroke':'prevalentStroke',
              'prevalentHype':'prevalentHype',
             'diabetes':'diabetes',
             'totChol':'Total Cholesterol Value Measured',
             'sysBP':'sysBP',
             'diaBP':'diaBP',
             'BMI':'Body Mass Index',
             'heartRate':'Heart Rate',
             'glucose':'Glucose',
             'TenYearCHD':'Ten Year CHD'}

def hist_feature(column):
    df[column].hist(bins=20,facecolor='midnightblue')
    plt.show()


dropdown_menu = {v:k for k,v in feature_desc.items()}

widgets.interact(hist_feature, column=dropdown_menu)
```

```
interactive(children=(Dropdown(description='column', options={'Age of person': 'age', 'No of average ciggarete…
```

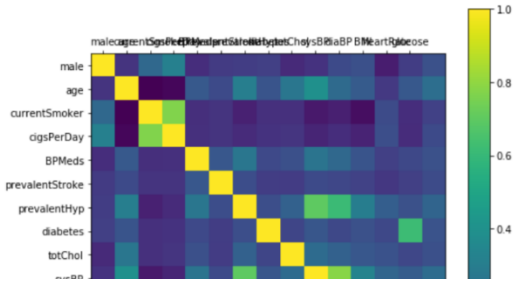
Out[30]:
```
<function __main__.hist_feature(column)>
```

Correlation Matrix Visualization

In [27]:
```
from matplotlib import rcParams
from matplotlib.pyplot import matshow

rcParams['figure.figsize'] = 3,8
plt.matshow(df.corr())
plt.yticks(np.arange(df_mean.shape[1]), df.columns)
plt.xticks(np.arange(df_mean.shape[1]), df.columns)
plt.colorbar()
```

Out[27]:
```
<matplotlib.colorbar.Colorbar at 0x2177b7d03c8>
```



Libraries used:

1. NumPy
2. SciPy
3. .Matplotlib (pyplot, rcparams, matshow)
4. Statsmodels
5. Pandas
6. Tkinter
7. Sklearn

Module Used	*Imported Class*
a.Sklearn.impute	Simple Imputor
b.Sklearn.preprocessing	StandardScalar
c.Sklearn.Pipeline	Pipeline
d. Sklearn.Feature_-selection	RFECV
e.Sklearn.ensemble	Randomforestclassifier
f.Sklearn.model-selection	Train_TestSplit
g.Sklearn.linear-model	LogisticRegression
h. Sklearn.utils	Shuffle
i.Sklearn.metrices	AccuracyScore,confusionmatrix

CHAPTER 10: CONCLUSION

The early prognosis of cardiovascular diseases can aid in making decisions on lifestyle changes inhigh risk patients and in turn reduce the complications, which can be a great milestone in the field of medicine. This project resolved the feature selection i.e. backward elimination and RFECV behind the models and successfully predict the heart disease, with 85% accuracy. The model usedwas Logistic Regression. Further for its enhancement, we can train on models and predict thetypes of cardiovascular diseases providing recommendations to the users, and also use moreenhanced models

REFERENCES

[1] A. H. M. S. U. Marjia Sultana, "Analysis of Data Mining Techniques for Heart DiseasePrediction," 2018.[2] M. I. K. ,. A. I. ,. S. Musfiq Ali, "Heart Disease Prediction Using Machine LearningAlgorithms".[3] K. Bhanot, "towarddatascience.com," 13 Feb 2019. [Online].

Available:https://towardsdatascience.com/predicting-presence-of-heart-diseases-using-machine-learning-36f00f3edb2c. [Accessed 2 March 2020].[4] [Online].

Available: https://www.kaggle.com/ronitf/heart-disease-uci#heart.csv..

[Accessed05 December 2019].[5] M. A. K. S. H. K. M. a. V. P. M Marimuthu, "A Review on Heart Disease Prediction usingMachine Learning and Data Analytics Approach"