CHAPTER 1: INTRODUCTION

According to the World Health Organization, every year 12 million deaths occur worldwide due to Heart Disease. The load of cardiovascular disease is rapidly increasing all over the world from the past few years. Many researches have been conducted in attempt to pinpoint the most influential factors of heart disease as well as accurately predict the overall risk. Heart Disease is even 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 in high-risk patients and in turn reduce the complications. This project aims to predict future Heart Disease by analyzing data of patients which classifies whether they have heart disease or not using machine-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 heart disease in human. Early detection of cardiac diseases can decrease the mortality rate and overall complications. However, it is not possible to monitor patients every day in all cases accurately and consultation of a patient for 24 hours by a doctor is not available since it requires more sapience, time and expertise. 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 be used for health diagnosis in medicinal data.

1.2 Motivation

Machine learning techniques have been around us and has been compared and used for analysis for 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 the training models in the machine learning. With first hand models and libraries, the challenge we face today is data where beside their abundance, and our cooked models, the accuracy we see during training, testing and actual validation has a higher variance. Hence this project is carried out with the motivation to explore behind the models, and further implement Support Vector Machine model to train the obtained data. Furthermore, as the whole machine learning is motivated to develop an appropriate computer-based system and decision support that can aid to early detection of heart disease, in this project we have developed a model which classifies if patient will have heart disease in ten years or not based on various features (i.e. potential risk factors that can cause heart disease) using logistic regression. Hence, the early prognosis of cardiovascular diseases can aid in making 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.

1.3 Objectives

The main objective of developing this project are:

- To develop machine learning model to predict future possibility of heart disease by implementing Support Vector Machine(SVM).
- To determine significant risk factors based on medical dateset which may lead to heart disease.
- To 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 various experiments and researches has been carried out in these recent years releasing the relevant significant papers. The paper [1] propose heart disease prediction using KStar, J48, SMO, and Bayes Net and Multi layer perceptron using WEKA software. Based on performance from different factor SMO (89% of accuracy) and Bayes Net (87% of accuracy) achieve optimum performance than KStar, Multi layer 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 of accuracy is improved more to give batter decision to diagnosis disease.

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

[3] Using the similar data set of Framingham, Massachusetts, the experiments were carried out using 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 data set is publicly available on the Kaggle Website at [4] which is from an ongoing cardiovascular study on residents of the town of Framingham, Massachusetts. It provides patient information which includes over 4000 records and 14 attributes. The attributes include: age, sex, chest pain type, resting blood pressure, serum cholesterol, fasting, sugar blood, resting electrocardiograph 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 which is further prepared to data frame as supported by pandas library in python.

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
298	57	0	0	140	241	0	1	123	1	0.2	1	0	3	0
299	45	1	3	110	264	0	1	132	0	1.2	1	0	3	0
300	68	1	0	144	193	1	1	141	0	3.4	1	2	3	0
301	57	1	0	130	131	0	1	115	1	1.2	1	1	3	0
302	57	0	1	130	236	0	0	174	0	0.0	1	1	2	0

303 rows × 14 columns

Figure 1: Original data snapshot

3.2 Features and Predictors

1. age (#)
2. sex : 1= Male, 0= Female (Binary)
3. (cp)chest pain type (4 values -Ordinal):Value 1: typical angina ,Value 2: atypical angina, Value 3: non-anginal pain , Value 4: asymptomatic (
4. (trestbps) resting blood pressure (#)
5. (chol) serum cholestoral in mg/dl (#)
6. (fbs)fasting blood sugar > 120 mg/dl(Binary)(1 = true; 0 = false)
7. (restecg) resting electrocardiographic results(values 0,1,2)
8. (thalach) maximum heart rate achieved (#)
9. (exang) exercise induced angina (binary) (1 = yes; 0 = no)
10. (oldpeak) = ST depression induced by exercise relative to rest (#)

11. (slope) of the peak exercise ST segment (Ordinal) (Value 1: upsloping , Value 2: flat , Value 3: downsloping)
12. (ca) number of major vessels (0-3, Ordinal) colored by fluoroscopy
13. (thal) maximum heart rate achieved - (Ordinal): 3 = normal; 6 = fixed defect; 7 = reversable defect

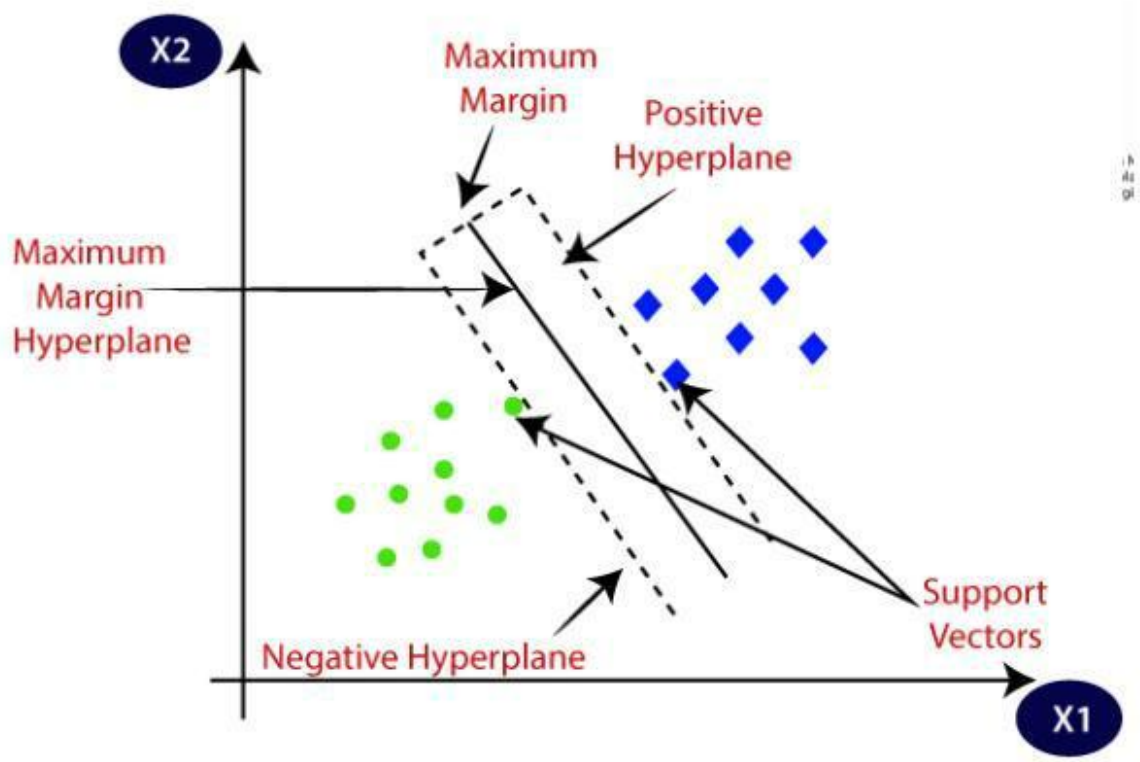
CHAPTER 4: METHODS AND ALGORITHMS USED

The main purpose of designing this system is to predict the risk of future heart disease. We have use Support Vector Machine(SVM) as a machine-learning algorithm to train our system and feature selection. The algorithm is discussed below-

4.1 Support Vector Machine

The goal of support vector machine is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

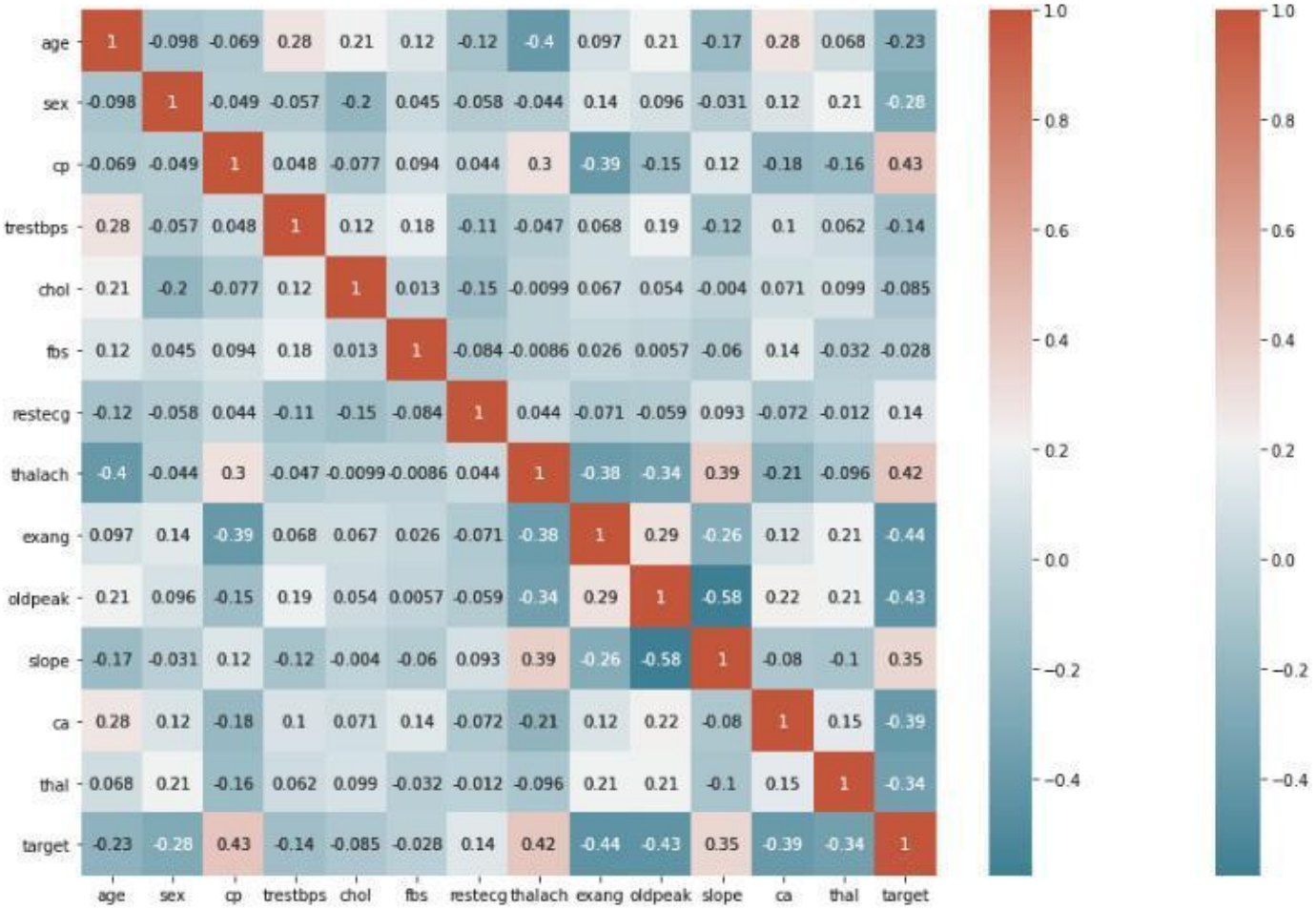
SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:



CHAPTER 5: EXPLORATORY DATA

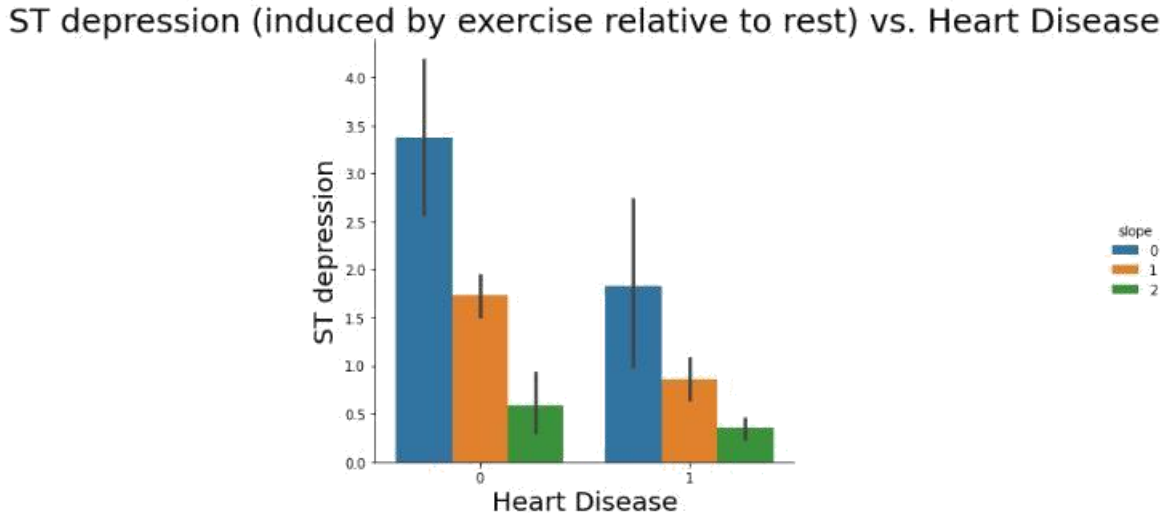
ANALYSIS 5.1 Correlations

A correlation matrix is simply a table which displays the correlation coefficients for different variables. The matrix depicts the correlation between all the possible pairs of values in a table. It is a powerful tool to summarize a large data set and to identify and visualize patterns in the given data.



We can see there is a positive correlation between chest pain (cp) & target (our predictor). This makes sense since, The greater amount of chest pain results in a greater chance of having heart disease. Cp (chest pain), is a ordinal feature with 4 values: Value 1: typical angina ,Value 2: atypical angina, Value 3: non-anginal pain , Value 4: asymptomatic.

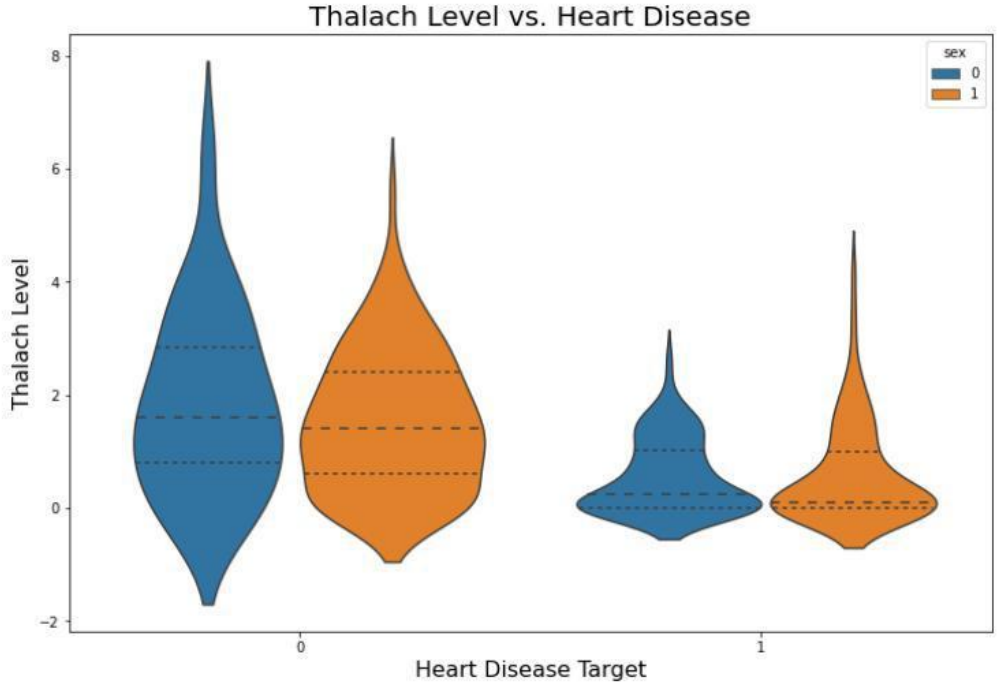
In addition, we see a negative correlation between exercise induced angina (exang) & our predictor. This makes sense because when you exercise, your heart requires more blood, but narrowed arteries slow down blood flow.
Pair plots are also a great way to immediately see the correlations between all variables. But you will see me make it with only continuous columns from our data, because with so many features, it can be difficult to see each one. So instead I will make a pair plot with only our continuous features.



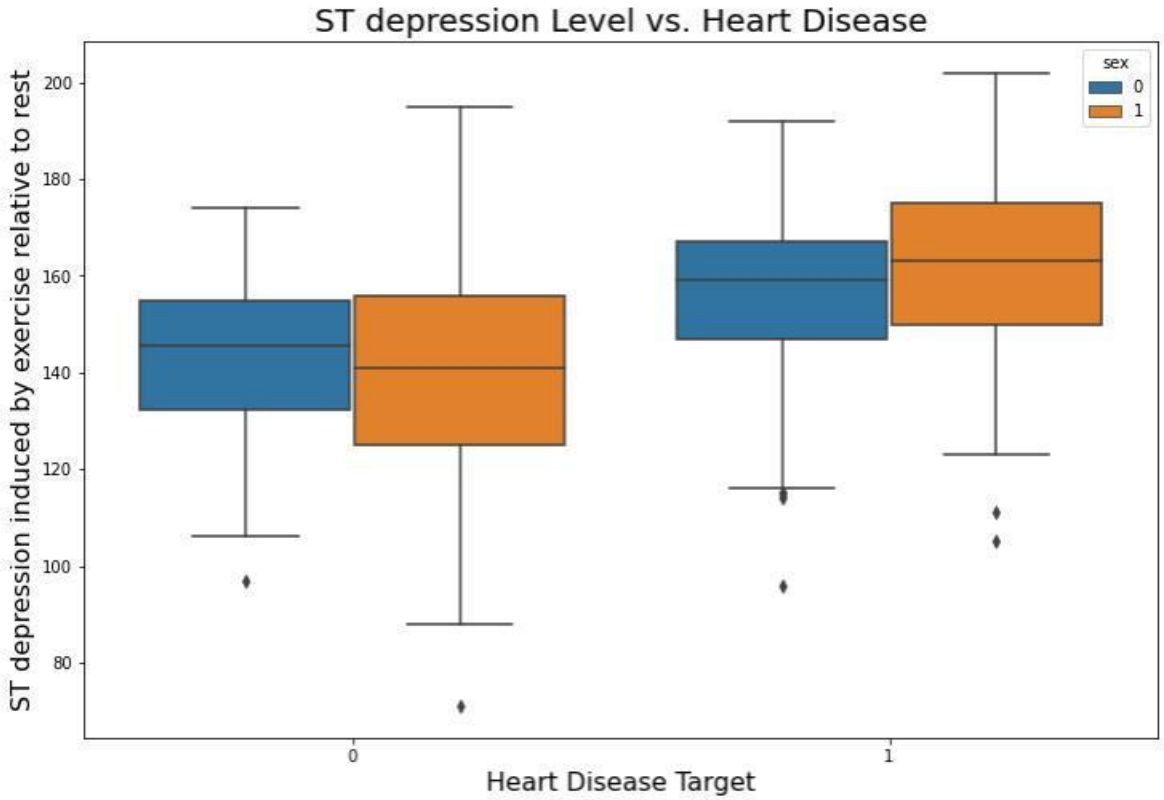
ST segment depression occurs because when the ventricle is at rest and therefore re-polarized. If the trace in the ST segment is abnormally low below the baseline, this can lead to this Heart Disease. This is supports the plot above because low ST Depression yields people at greater risk for heart disease. While a high ST depression is considered normal & healthy. The "slope" hue, refers to the peak exercise ST segment, with values: 0: upsloping , 1: flat , 2: down-sloping). Both positive & negative heart disease patients exhibit equal distributions of the 3 slope categories.

5.2 Violin and Box-plots

The advantages of showing the Box & Violin plots is that it shows the basic statistics of the data, as well as its distribution. These plots are often used to compare the distribution of a given variable across some categories. It shows the median, IQR, & Turkey's fence. (minimum, first quartile (Q1), median, third quartile (Q3), and maximum). In addition it can provide us with outliers in our data.



We can see that the overall shape & distribution for negative & positive patients differ vastly. Positive patients exhibit a lower median for ST depression level & thus a great distribution of their data is between 0 & 2, while negative patients are between 1 & 3. In addition, we don't see many differences between male & female target outcomes.



Positive patients exhibit a heightened median for ST depression level, while negative patients have lower levels. In addition, we don't see many differences between male & female target outcomes, expect for the fact that males have slightly larger ranges of ST Depression.

CHAPTER 6: MACHINE LEARNING AND PREDICTIVE ANALYSIS