Capstone Project - 3

Cardiovascular Risk Prediction

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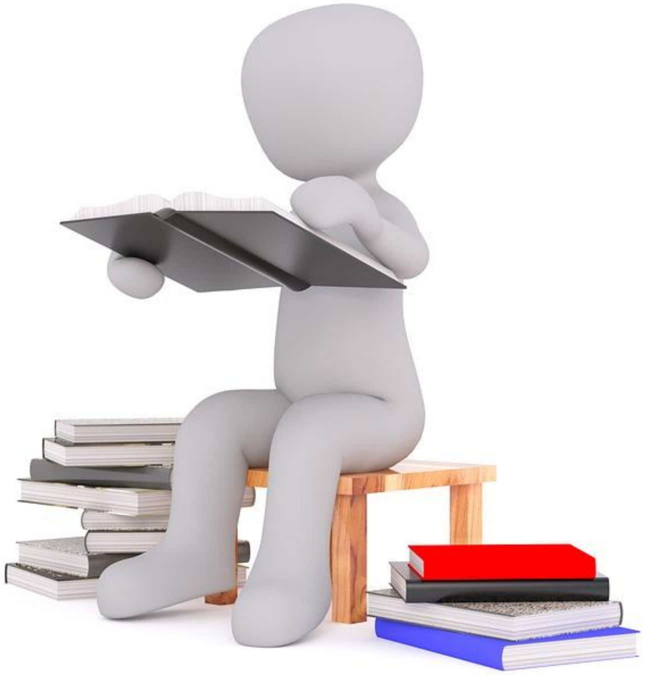
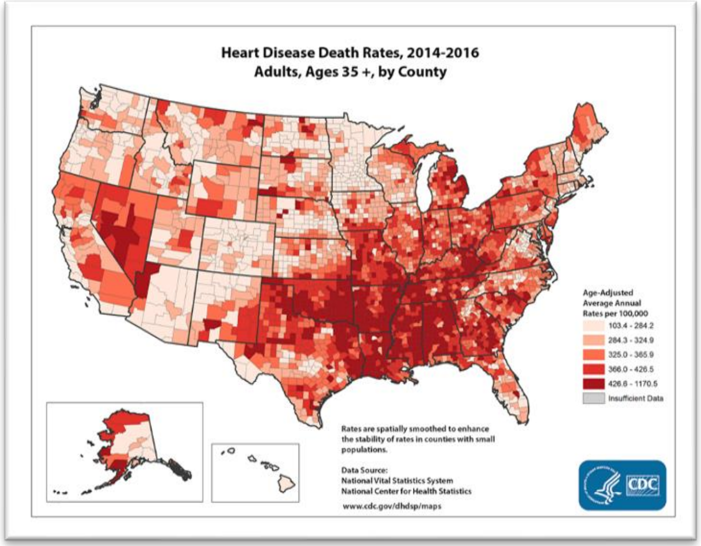


AI

Abstract

- Cardiovascular diseases (CVDs) are the major cause of mortality worldwide.
- According to WHO, **17.9 million** people died from CVDs in 2019, accounting for **32%** of all global fatalities.
- Though CVDs cannot be treated, predicting the risk of the disease and taking the necessary precautions and medications can help to avoid severe symptoms and, in some cases, even death.



Problem Statement

- The goal of this project is to develop a classification model that can predict whether a patient is at risk of **coronary heart disease (CHD)** over the period of 10 years, based on demographic, lifestyle, and medical history.
- The data was gathered from **3390** adults participating in a cardiovascular study in Framingham, Massachusetts.

Data Summary

- **Demographic**
  - Sex
  - Age
  - Education

- **Behavioral**
  - Is smoking
  - Cigarettes per day

- **Current Medical Status**
  - Total cholesterol
  - Systolic BP
  - Diastolic BP
  - BMI
  - Heart rate
  - Glucose

- **Medical History**
  - BP medication
  - Prevalent stroke
  - Prevalent hypertension
  - Diabetes

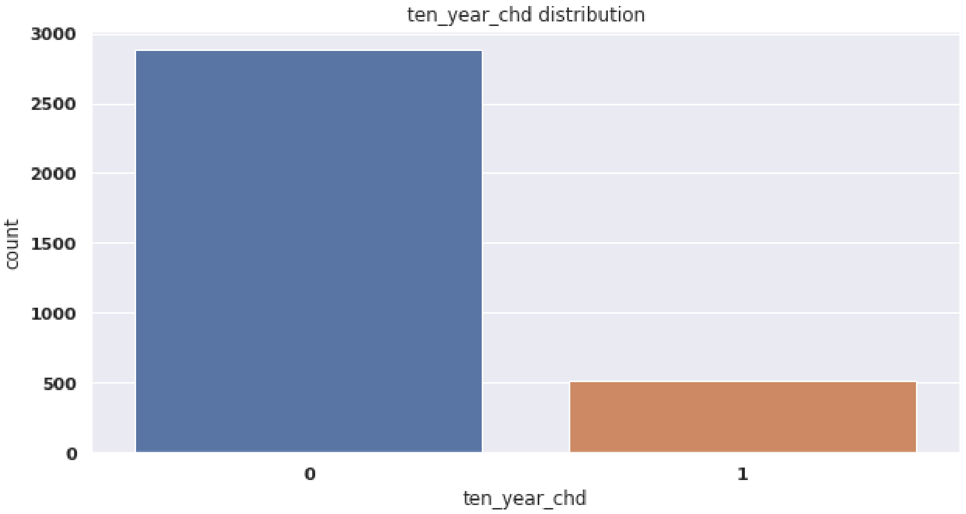
  - Ten year risk of CHD → DV

Handling Missing Values

- There were a total of **510** missing values in the dataset.
- Total missing values and how they were handled are as follows:
  - Education(87) , BP Medication(44) – **mode** imputation
  - Cigarettes per day(22) – imputed with **median** cigarettes per day for **smokers**
  - Total cholesterol(38), BMI(14), Heart rate(1) – **median** imputation
  - Glucose(304) – **KNN** imputation with k = 10

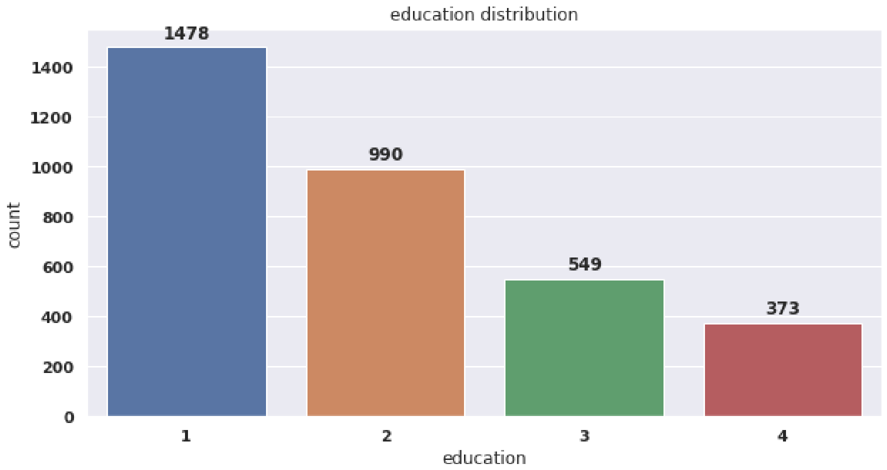
Exploratory Data Analysis (EDA)

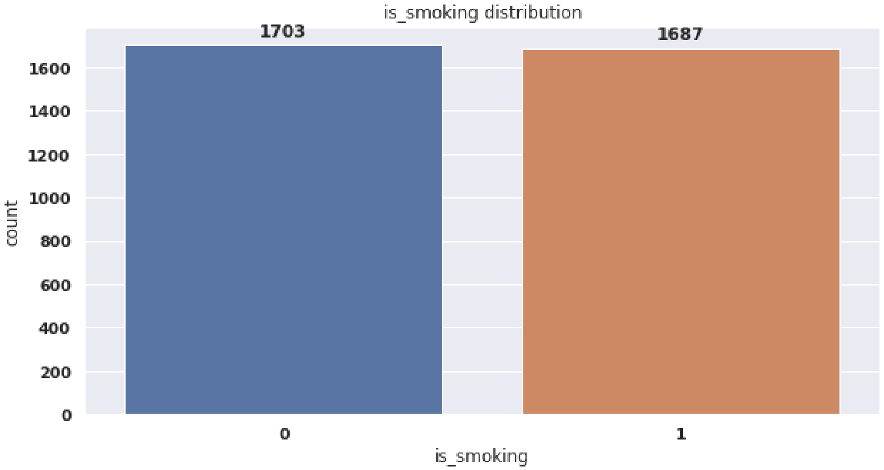
- The dependent variable is imbalanced, with just **~15%** of patients testing positive for CHD.
- All continuous independent variables are **positively skewed** except age, which is almost normally distributed.

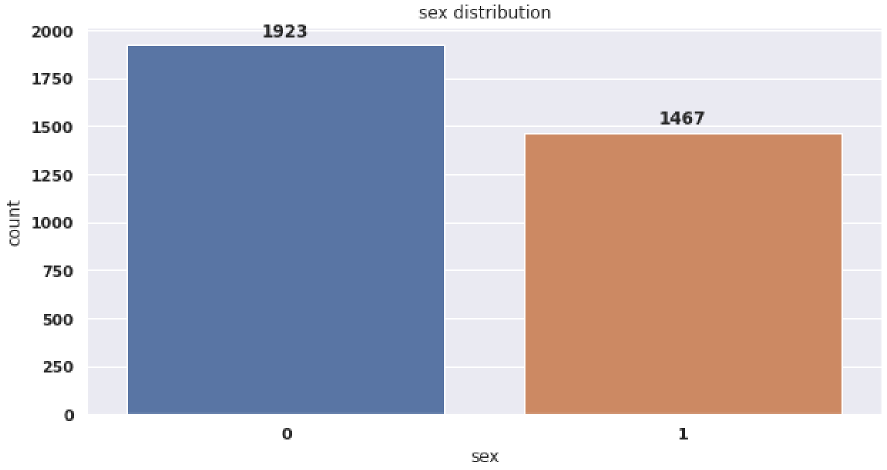


EDA (Contd.)

- **Half** the patients are smokers
- There are **more female** patients than male
- Most patients have education **level 1**

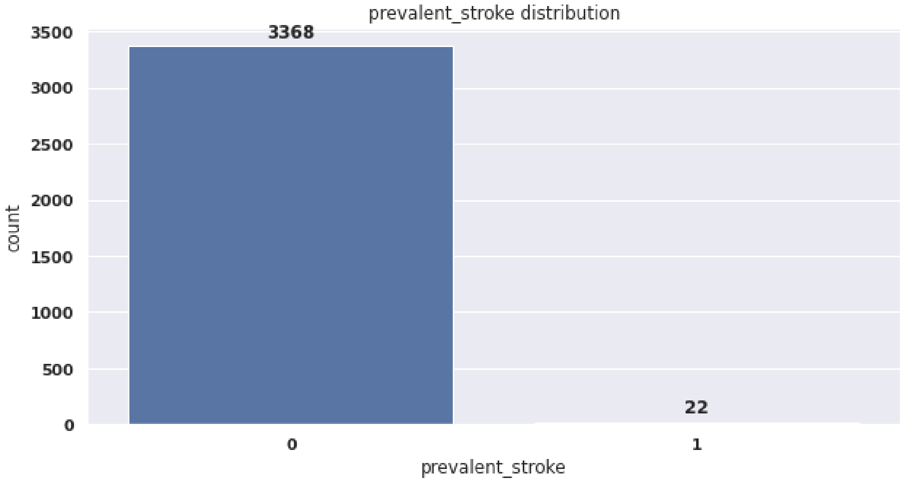


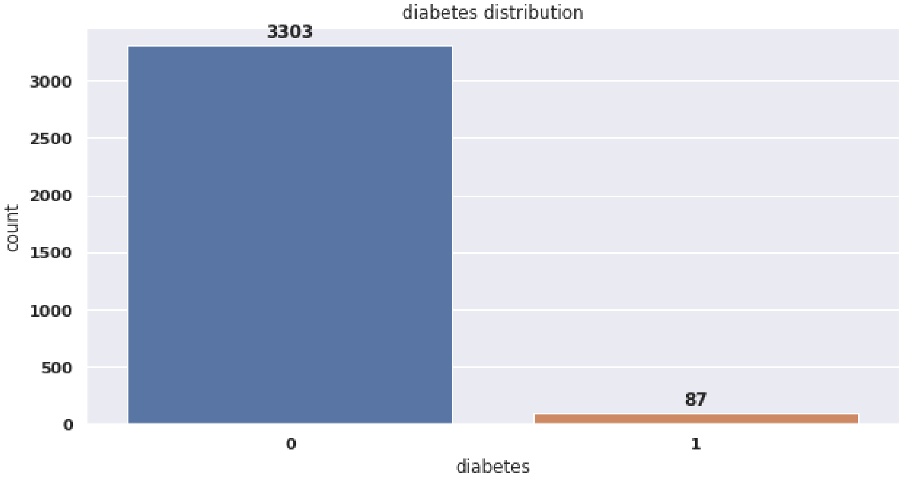


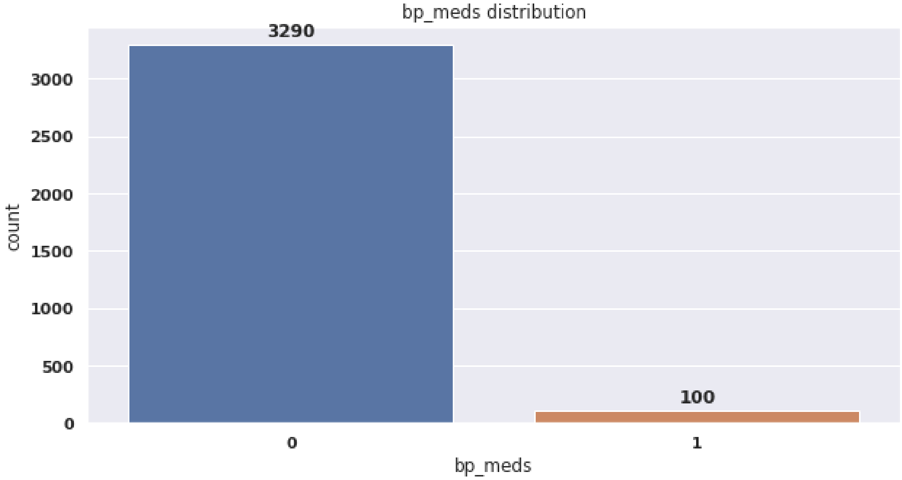


EDA (Contd.)

- There are relatively **few** individuals who have had a stroke, have diabetes, or are using blood pressure medicine.

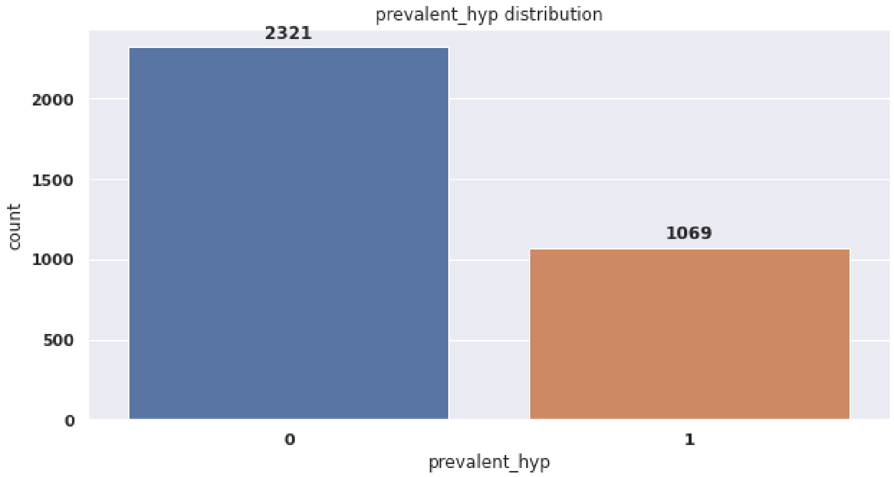


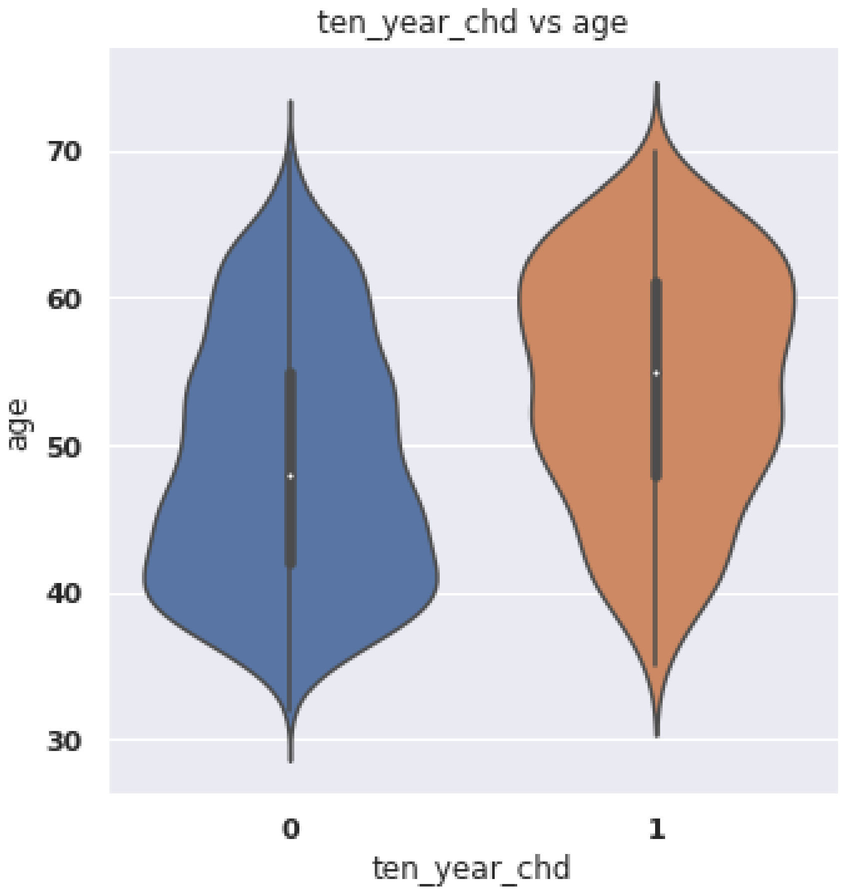




EDA (Contd.)

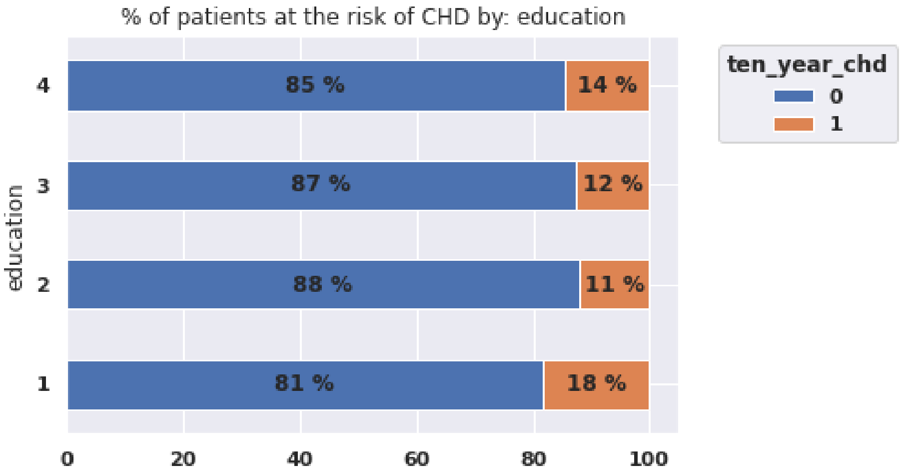
- 1069 patients have **hypertension**
- The risk of CHD **increases with age**

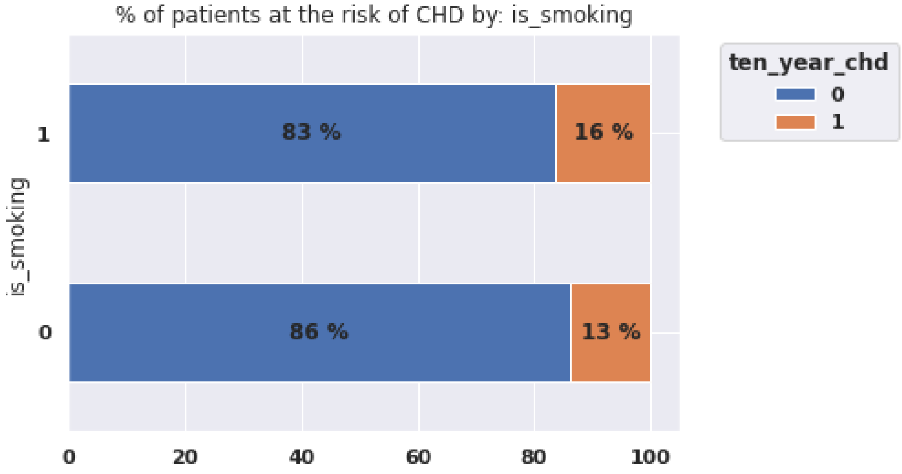


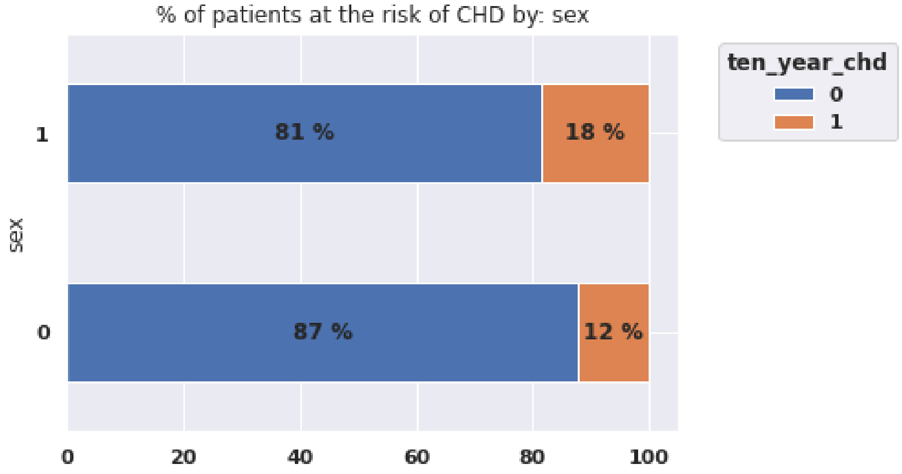


EDA (Contd.)

- The risk of CHD **varies** by educational level, gender, and whether or not the patient smokes.

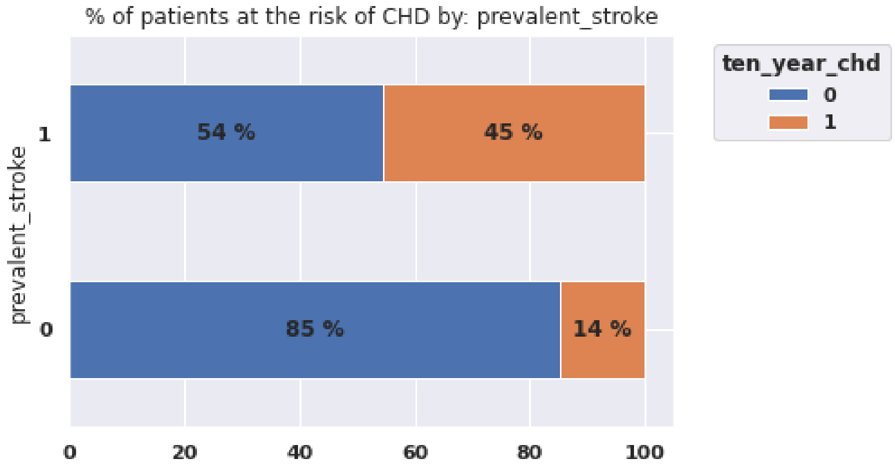


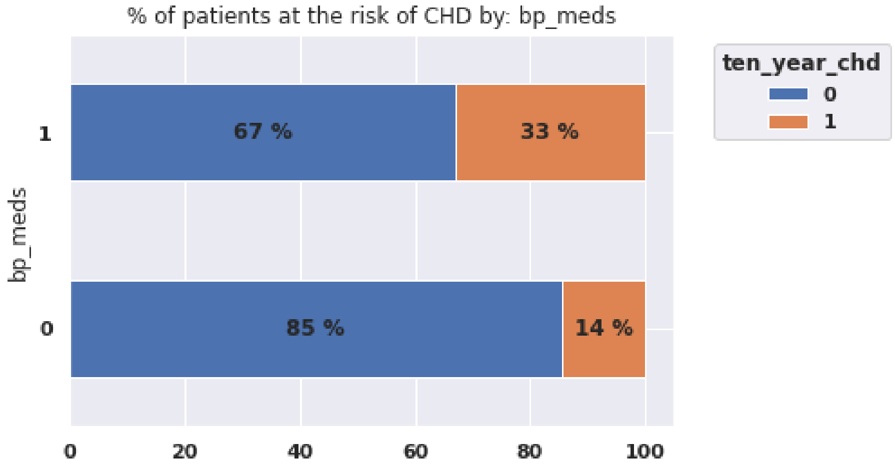




EDA (Contd.)

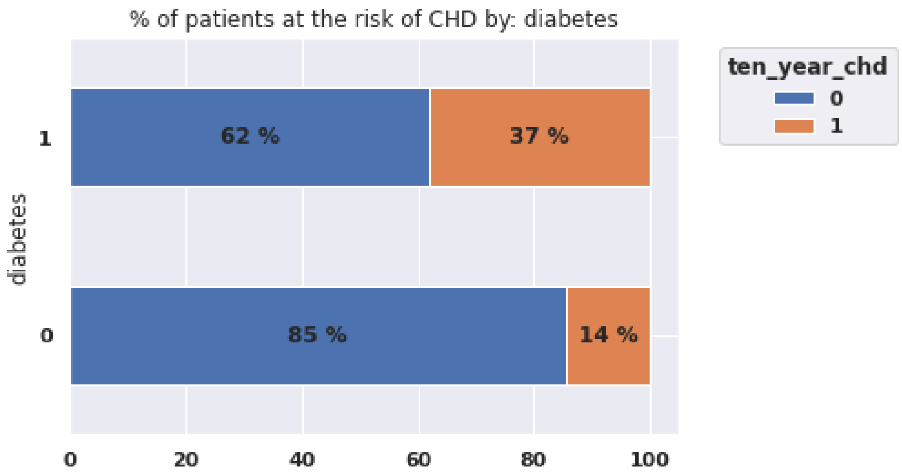
- Patients who have had a **stroke** or are presently on **blood pressure medication** are more likely to test positive for CHD.

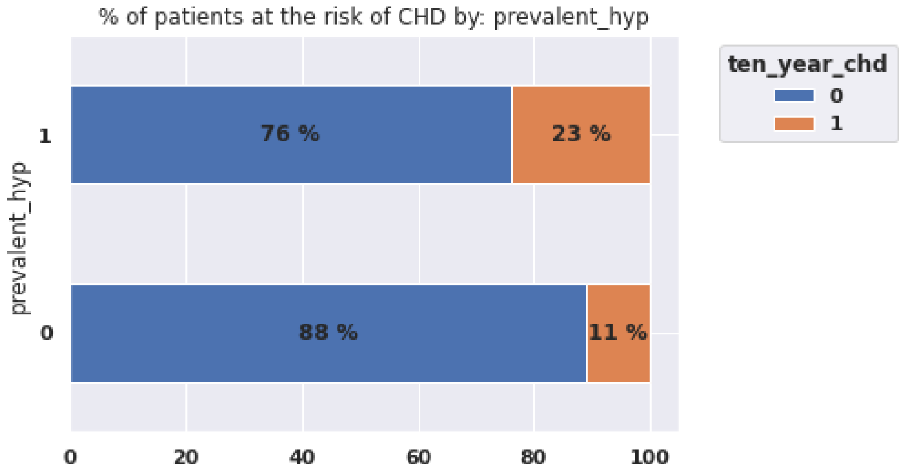




EDA (Contd.)

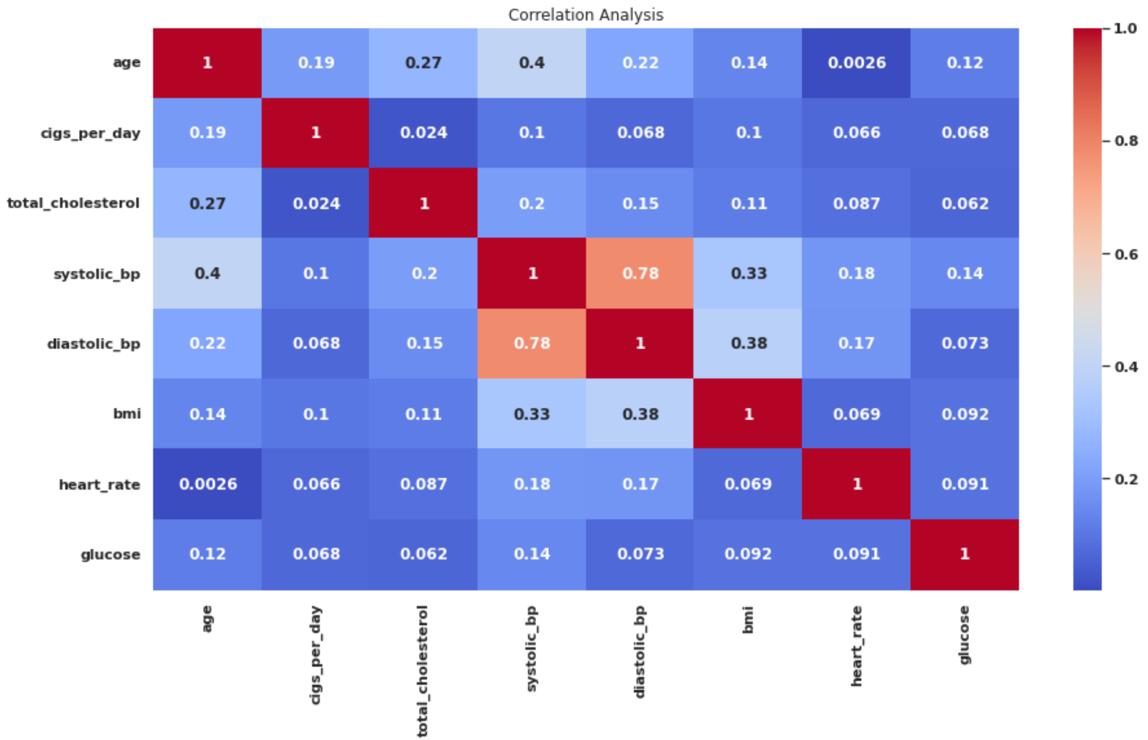
- Patients with **hypertension** or **diabetes** are more likely to be diagnosed with CHD.





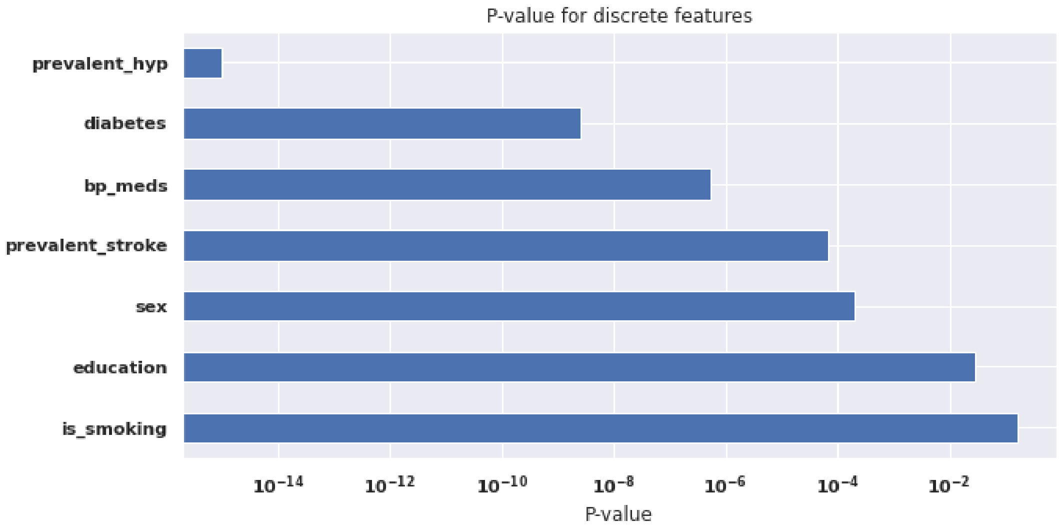
EDA (Contd.)

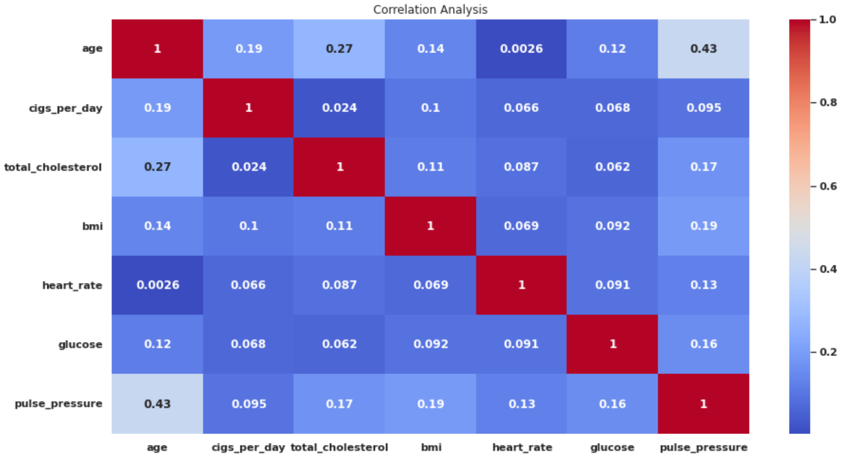
- Systolic BP and diastolic BP are **highly correlated**



Feature Engineering

- **Pulse Pressure = Systolic BP – Diastolic BP**
- The **Chi2 test** on discrete features indicates that the **'is_smoking'** column has the highest p-value and so is the **least relevant feature**. As a result, we **drop** it.





Handling Skew and Outliers

- The skew in numeric variables is reduced by performing **log transformation**.
- The outliers beyond **3 standard deviations** from the mean were **imputed** with the **median** value

Attribute	Original skew	Skew After Transformation
Age	0.225796	-0.015053
Cigarettes Per Day	1.204077	0.275072
Total Cholesterol	0.948170	0.011860
BMI	1.025551	0.370422
Heart Rate	0.676660	0.165898
Glucose	6.361911	2.310918
Pulse Pressure	1.412382	0.354174

Summary so far...

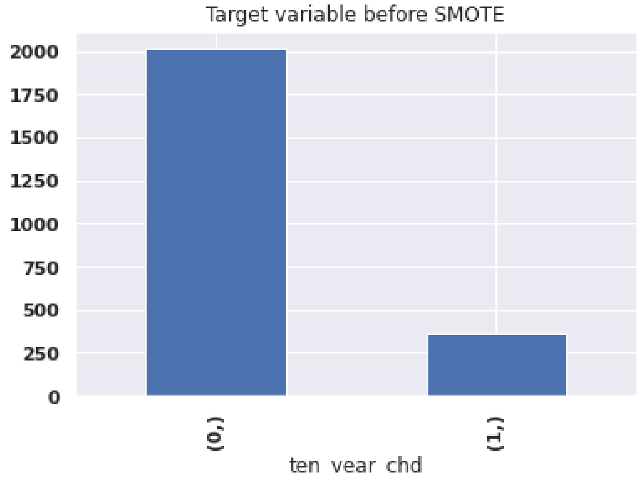
- We defined the problem statement
- Handled the missing values
- Created data visualizations
- Performed feature engineering and feature selection
- Transformed numeric variables to reduce skew.
- Handled outliers.

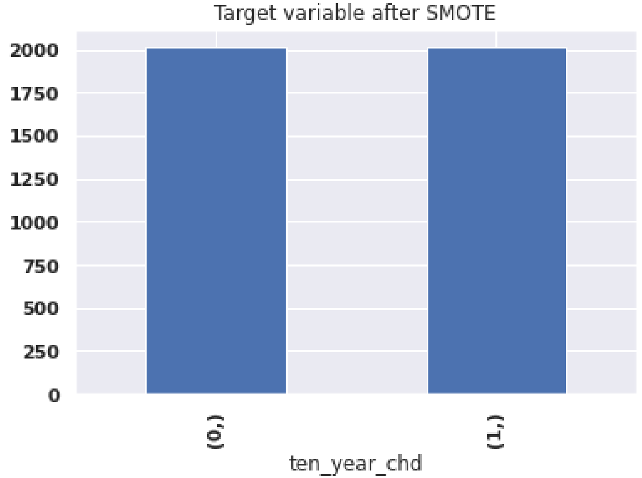
Modelling Approach

- Data points in test data set = 30%
- Choice of split: **Repeated stratified K fold**, k = 4
- Evaluation metric: **Recall**

$$\textbf{Recall} = \frac{\textit{True Positive}}{\textit{False Negative}+\textit{True Positive}}$$

- Hyperparameter tuning: **Grid search**
- Oversampling strategy: **SMOTE**
- Data points before SMOTE = **2373**
- Data points after SMOTE = **4030**
- Scaler used: **Standard Scaler**

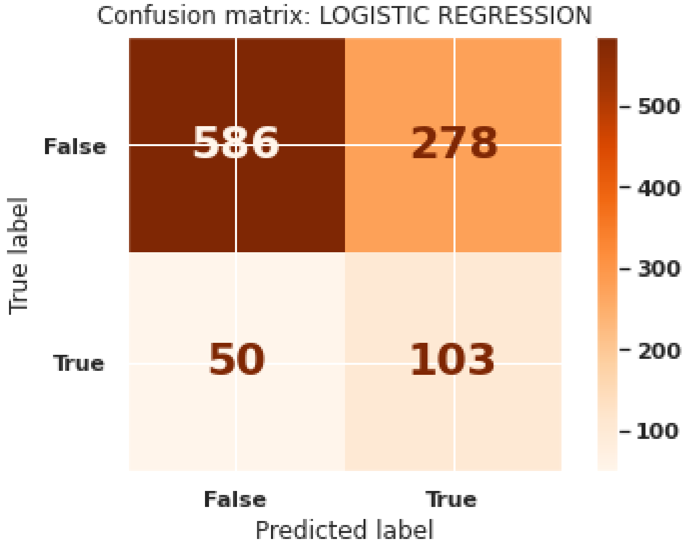




Logistic Regression

Evaluation metrics:

- Train Recall = 0.6987
- Test Recall = 0.6732
- Test Accuracy = 68%



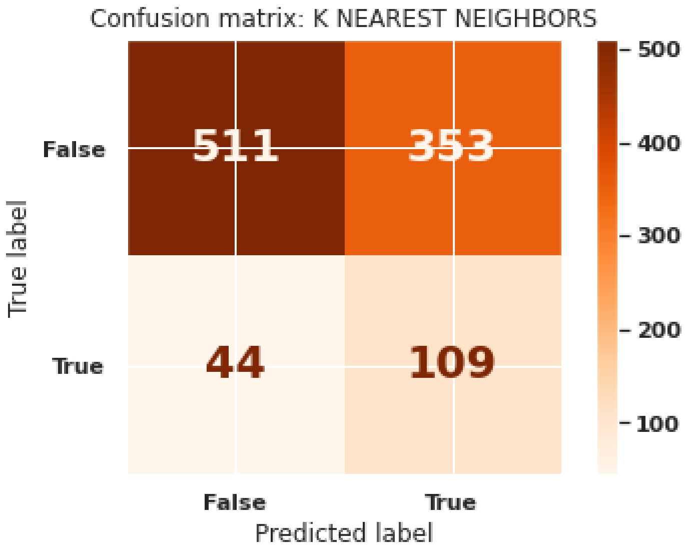
K-Nearest Neighbors

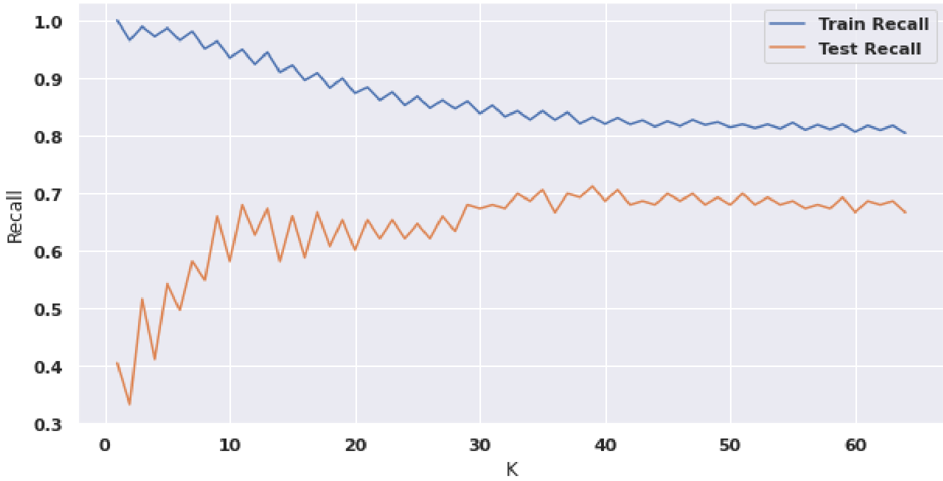
Parameters:

- K = 39

Evaluation metrics:

- Train Recall = 0.8317
- Test Recall = 0.7124
- Test Accuracy = 61%





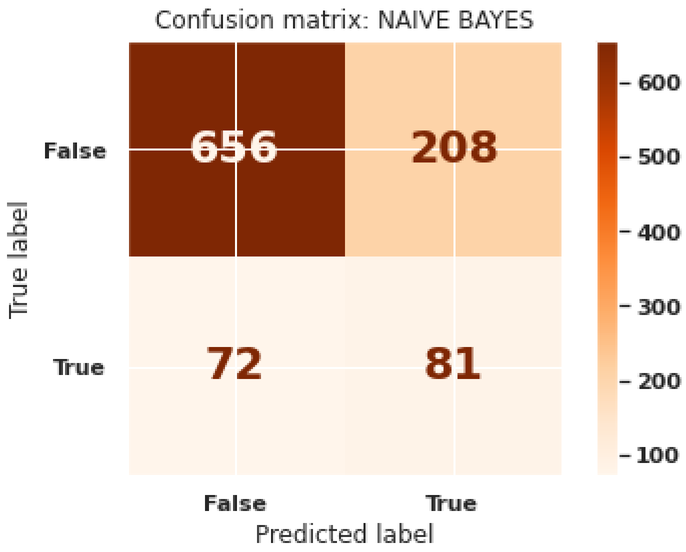
Naïve Bayes

Parameters:

- var_smoothing= 1.0

Evaluation metrics:

- Train Recall = 0.5811
- Test Recall = 0.5294
- Test Accuracy = 72%



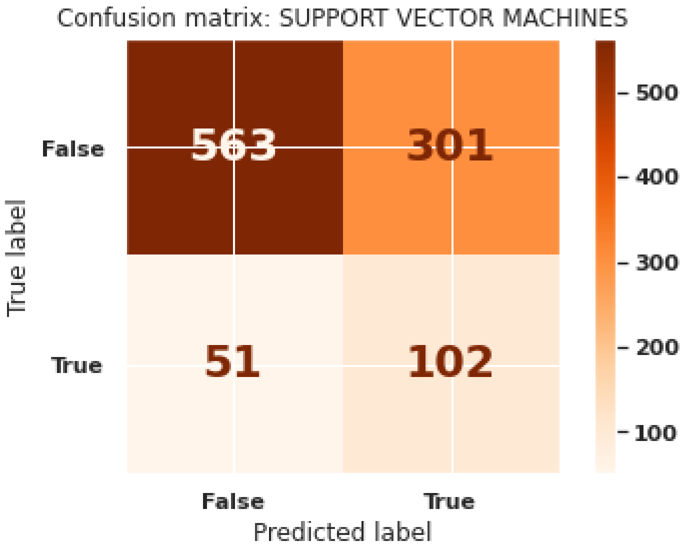
Support Vector Machines

Parameters:

- C = 1
- Gamma = 0.01
- Kernel = rbf

Evaluation metrics:

- Train Recall = 0.7652
- Test Recall = 0.6666
- Test Accuracy = 65%



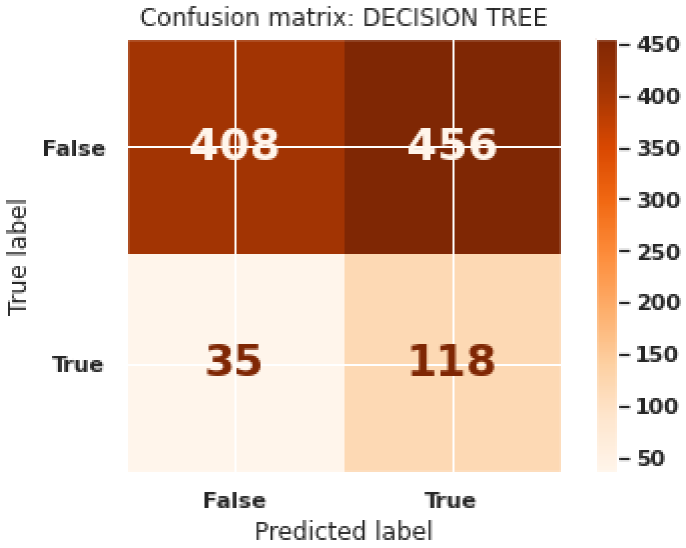
Decision Tree

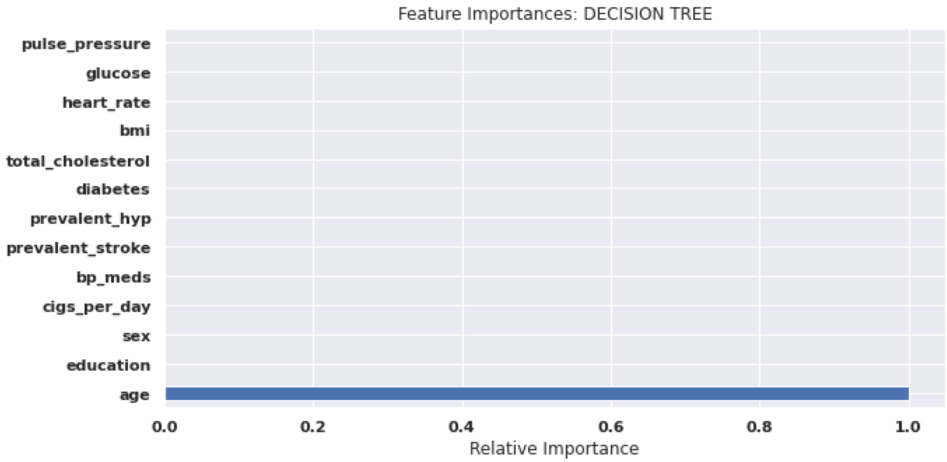
Parameters:

- max_depth = 1
- min_samples_leaf = 0.1
- min_samples_split = 0.1

Evaluation metrics:

- Train Recall = 0.8595
- Test Recall = 0.7712
- Test Accuracy = 52%





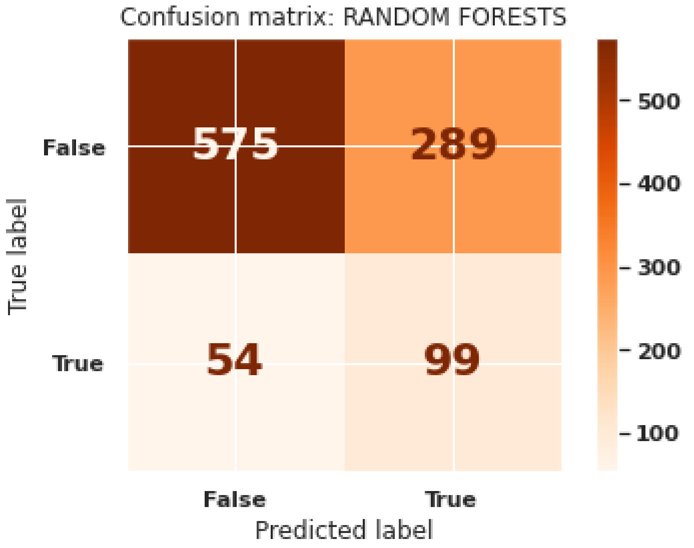
Random Forests

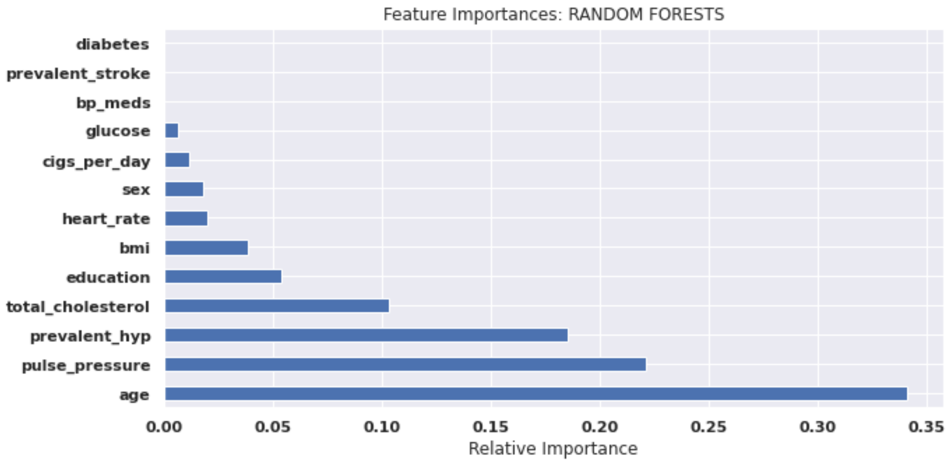
Parameters:

- max_depth = 2
- min_samples_leaf = 0.1
- min_samples_split = 0.1
- n_estimators = 500

Evaluation metrics:

- Train Recall = 0.6997
- Test Recall = 0.647
- Test Accuracy = 66%





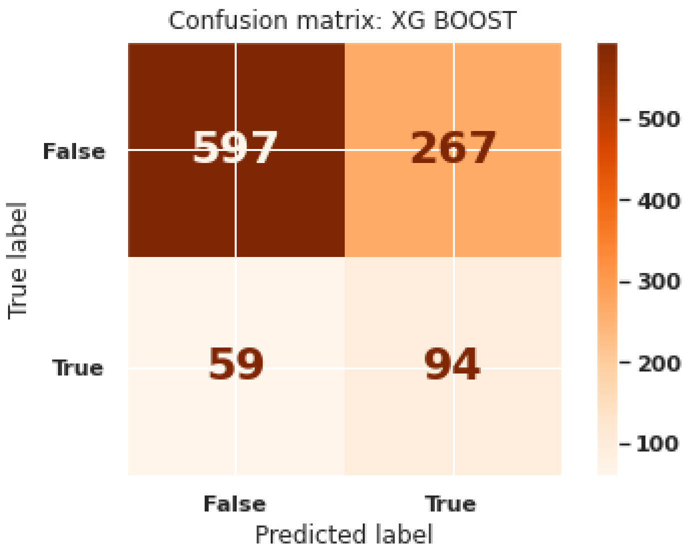
XG Boost

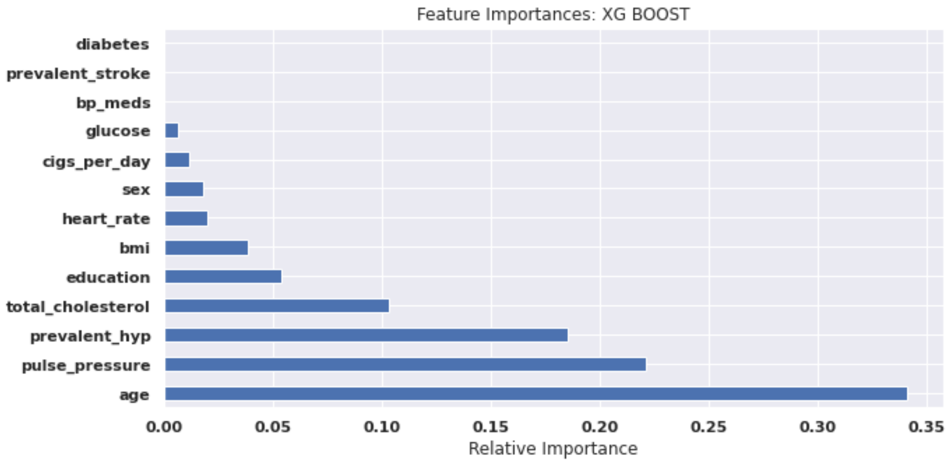
Parameters:

- max_depth = 1
- min_samples_leaf = 0.1
- min_samples_split = 0.1
- n_estimators = 500

Evaluation metrics:

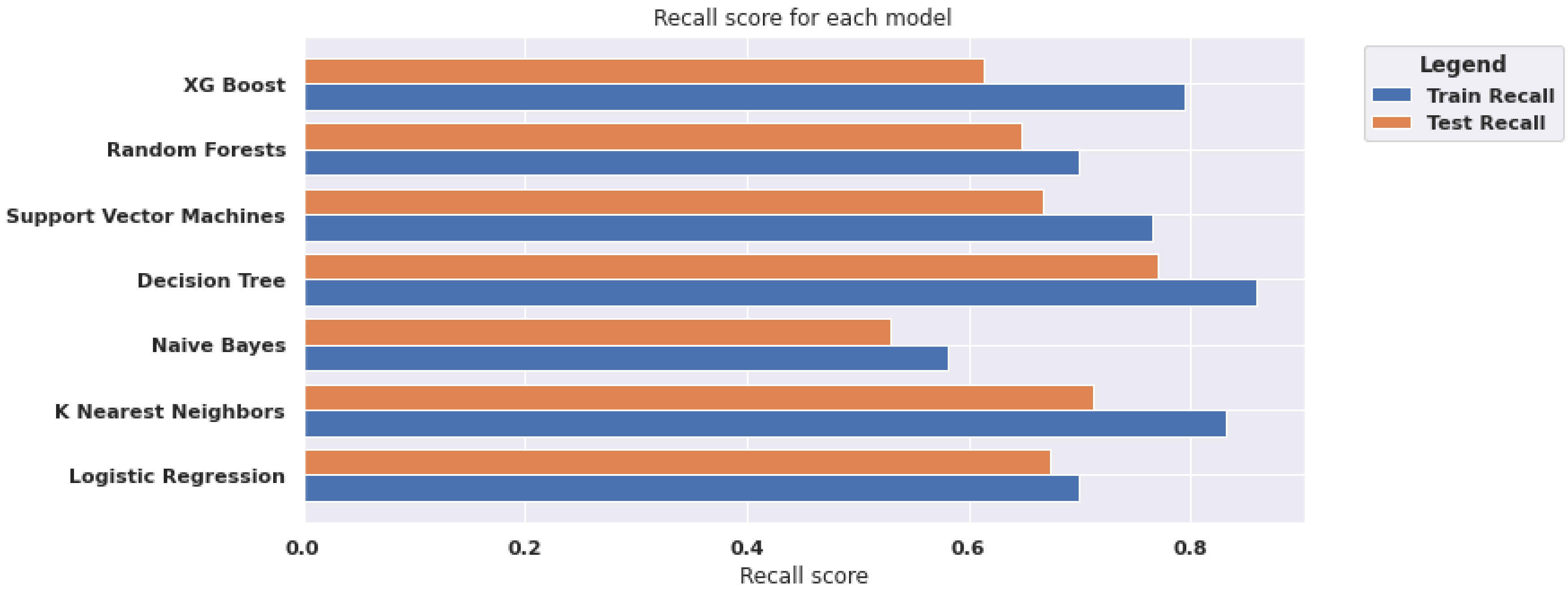
- Train Recall = 0.7945
- Test Recall = 0.6143
- Test Accuracy = 68%





Model Comparison

- The **Decision Tree** model has the **highest test Recall** compared to other models.



Challenges Faced

- Comprehending the problem statement, and understanding the business implications – understanding the importance of predicting the risk of this disease
- Handling missing values in the dataset, and working with limited availability of data
- Feature engineering – deciding on which features to be dropped / kept / transformed
- Choosing the best visualization to show the trends among different features clearly in the EDA phase
- Deciding on ways to handle skew and outliers
- Choosing the best hyperparameters, which prevents overfitting

Conclusion

- We have successfully built predictive models that can predict a patients risk for CHD based on their demography, lifestyle, and medical history.
- The predictive models built were evaluated using Recall, and it was found that decision tree (0.77) has the highest test recall compared to other models.
- Efforts must be put into gathering more data, and also include people who have undergone different medical conditions.
- Future developments must include a strategy to improve the model recall score, enabling us to save even more lives from this disease.

Thank You!