

# Capstone Project

## Cardiovascular Risk Prediction

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# Steps Performed

- 1. Defining the problem statement**
- 2. Data Summary**
- 3. EDA and Preparation of dataset**
- 4. Applying the Model**
- 5. Model Evaluation and Selection**
- 6. Conclusion**

# Problem Statement

**The dataset is from an ongoing cardiovascular study on residents of the town of Framingham, Massachusetts. The classification goal is to predict whether the patient has a 10-year risk of future coronary heart disease (CHD). Let's see how this can be accomplished in the coming sections.**

# Data Summary

## ➤ Demographic

- Sex
- Age
- Education

## ➤ Medical (history)

- BP Meds
- Prevalent Stroke
- Prevalent Hyp
- Diabetes

## ➤ Dependent or Predicted variable

- TenYearCHD

## ➤ Behavioral

- Is\_smoking
- Cigs per day

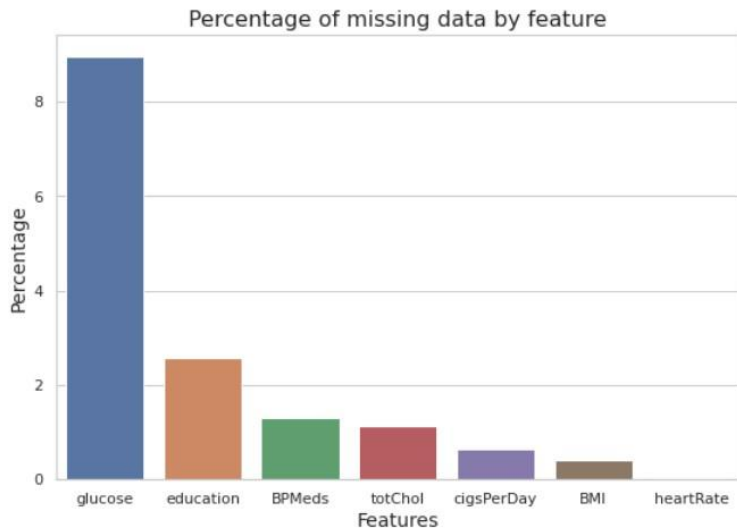
## ➤ Medical (current)

- Tot Chol
- Sys BP
- Dia BP
- BMI
- Heart rate
- Glucose

**Our dataset has 3390 rows and 17 columns to begin with.**

# Spread of Missing values

	Total	Percentage
glucose	304	8.967552
education	87	2.566372
BPMeds	44	1.297935
totChol	38	1.120944
cigsPerDay	22	0.648968
BMI	14	0.412979
heartRate	1	0.029499

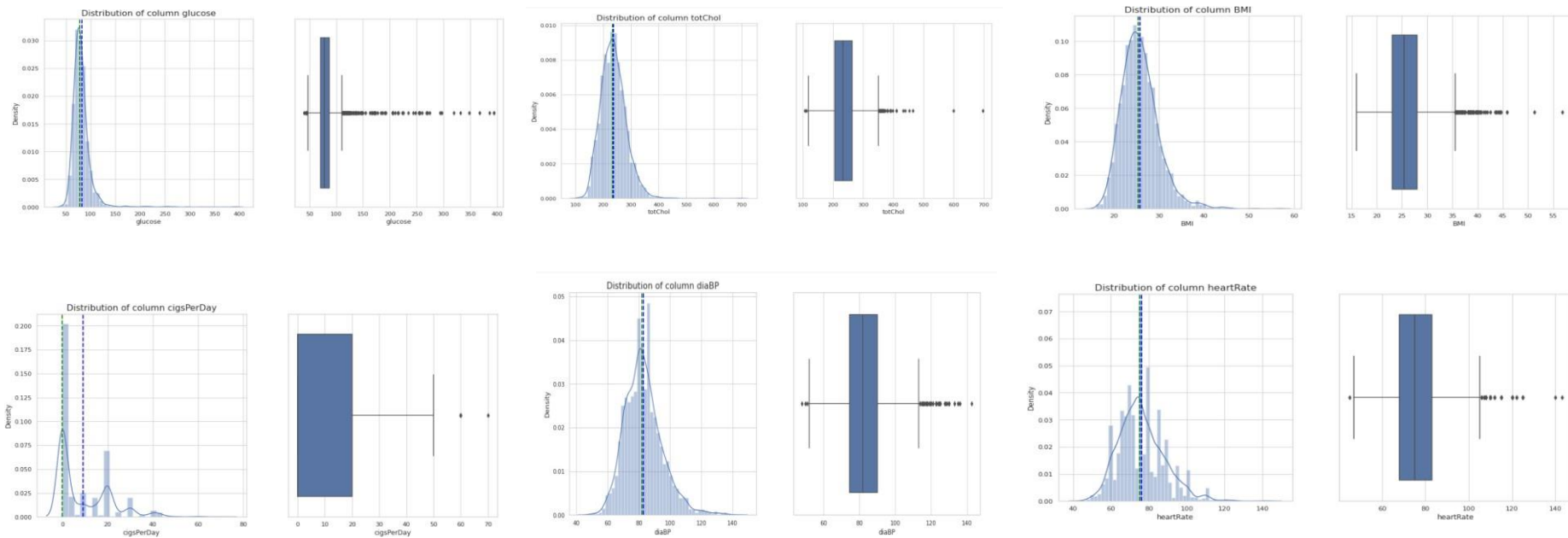


We have around **15% of missing values**.

- Since **Education** qualification of person won't be having any dependency in heart disease, dropped them
- Imputed missing value of **Glucose** with a median glucose value based on the record that has diabetes or not.
- Imputed missing **BPMeds** with a prevantHyp value. Because, if the person is suffering from hypertension, he/she will be under medication for the same.
- Missing value of **cigsPerDay** will be imputed with mean cigsPerDay.
- Since the distribution is close to normal imputing missing value of **totChol** with median totChol, **BMI** with median BMI and **heartrate** with median heartrate.

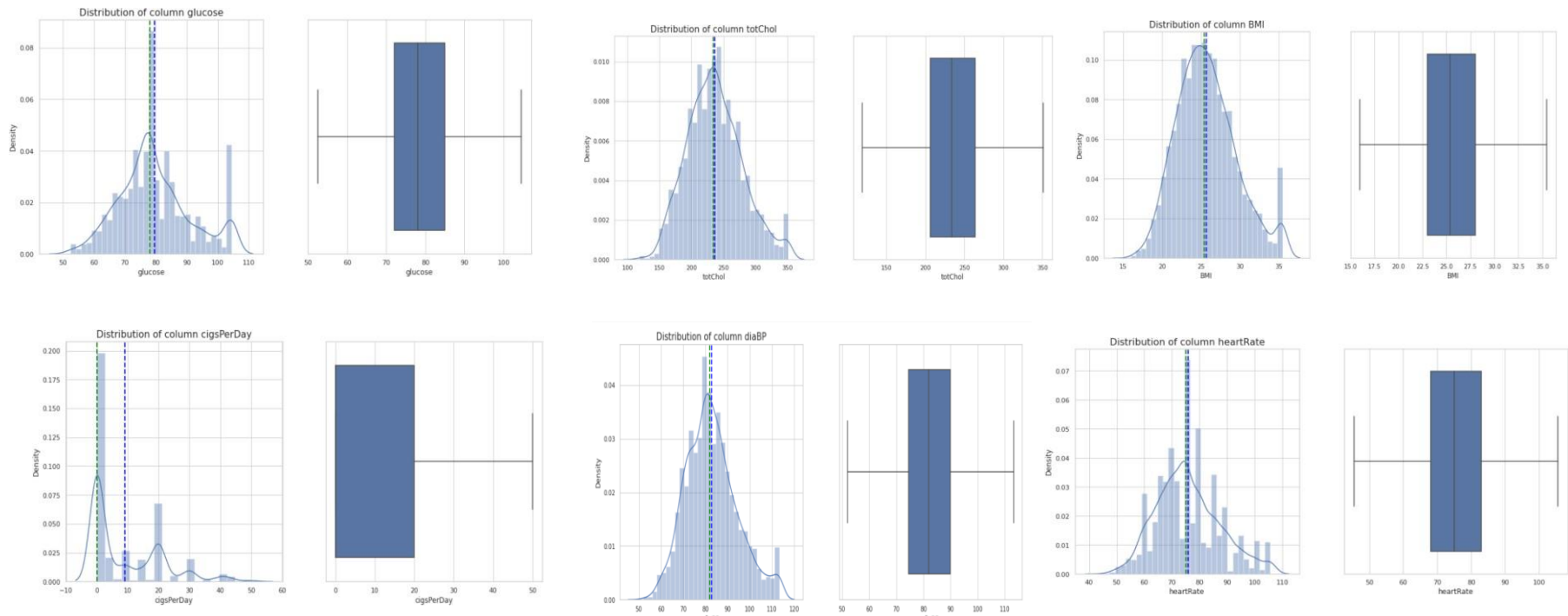
# Outlier Treatment

## Observation of outliers before treatment

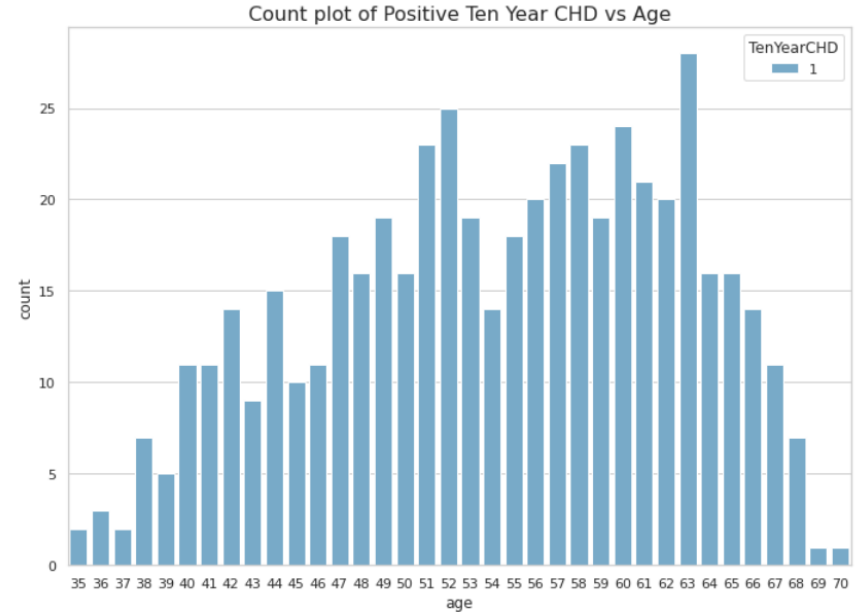
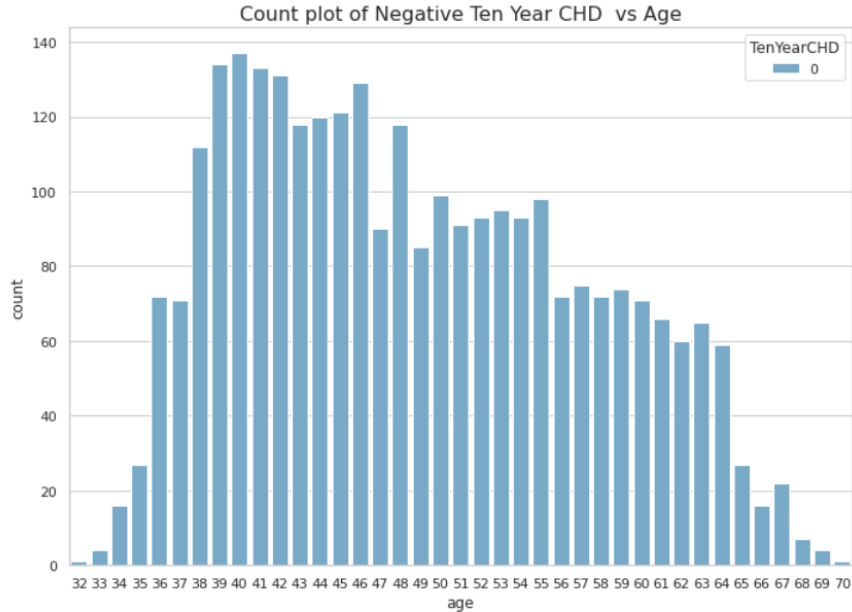


# Outlier Treatment (contd.)

## Outliers handled



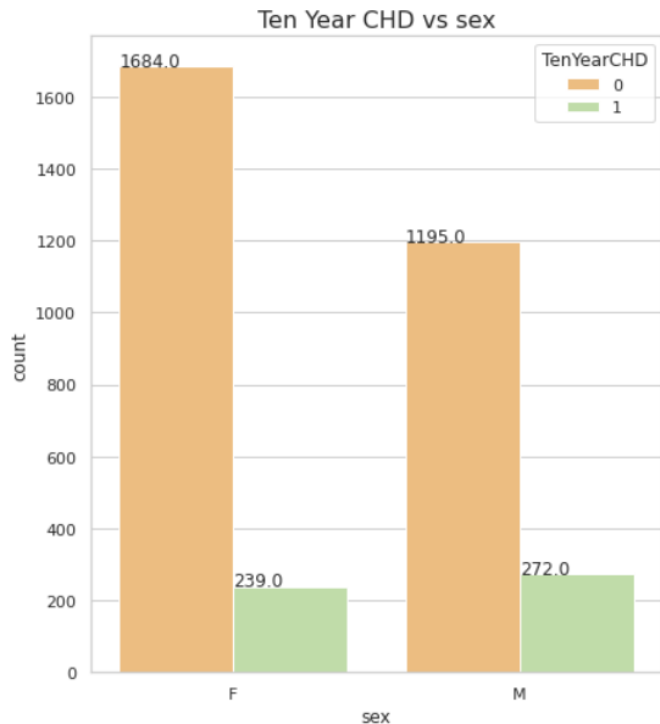
# Exploratory Data Analysis



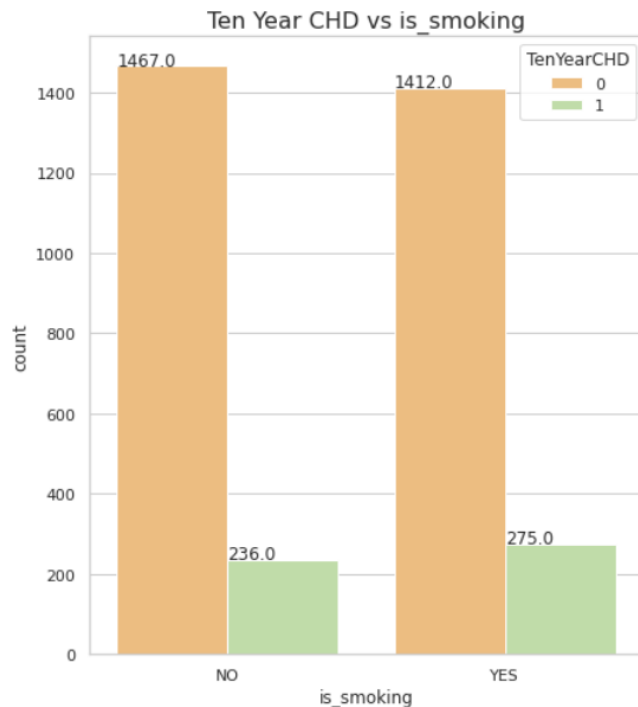
**The chances of Getting Coronary Heart Disease is less for the lower age groups.**



# Exploratory Data Analysis (contd.)



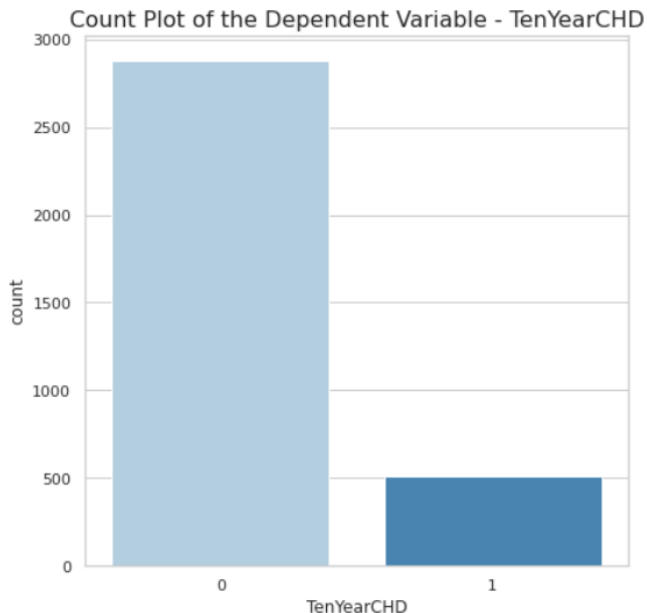
**Chances of CHD in 10 years is more among Males.**



**Chances of CHD in 10 years is more among Smokers.**

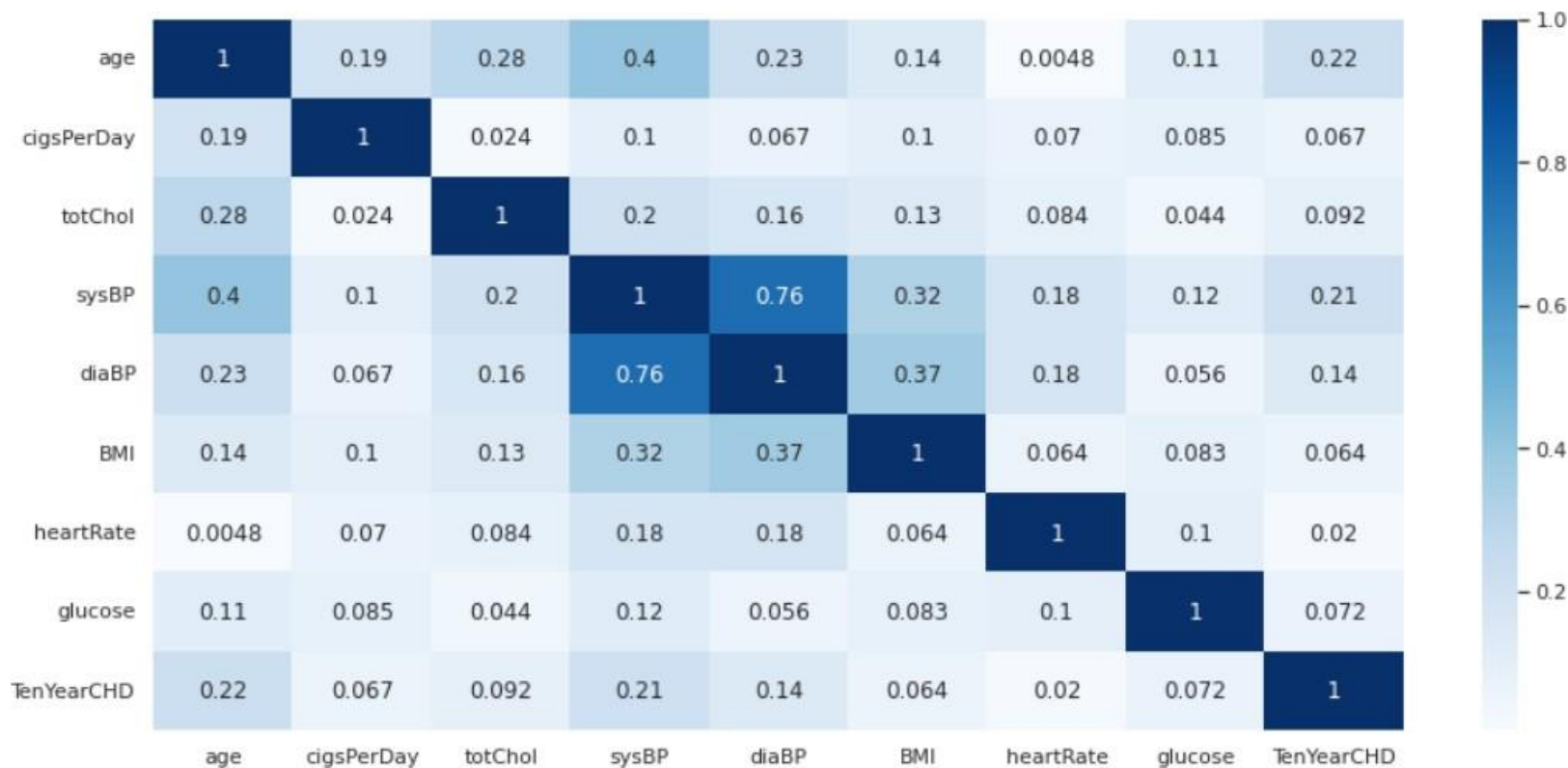
# Dependent Variable Analysis

**TenYearCHD is our dependent variable. This gives us the information whether that person will have a risk of getting coronary heart disease (CHD) in 10years. It is a categorical variable.**



**We can observe a huge imbalance in the dependent variable. So, we will be using SMOTE technique to solve this imbalance issue.**

# Multivariate Analysis



# Preparation of Dataset

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3390 entries, 0 to 3389
Data columns (total 5 columns):
#   Column      Non-Null Count  Dtype
---  -
0   age         3390 non-null   int64
1   cigsPerDay  3390 non-null   float64
2   sysBP       3390 non-null   float64
3   glucose     3390 non-null   float64
4   sex         3390 non-null   int64
dtypes: float64(3), int64(2)
memory usage: 132.5 KB
```

**Task** – Classification

**Train dataset** – (2712, 5)

**Test dataset** – (678, 5)

**Response** – Categorical variable  
(prediction of 10 year risk of CHD)

# Handling Class Imbalance

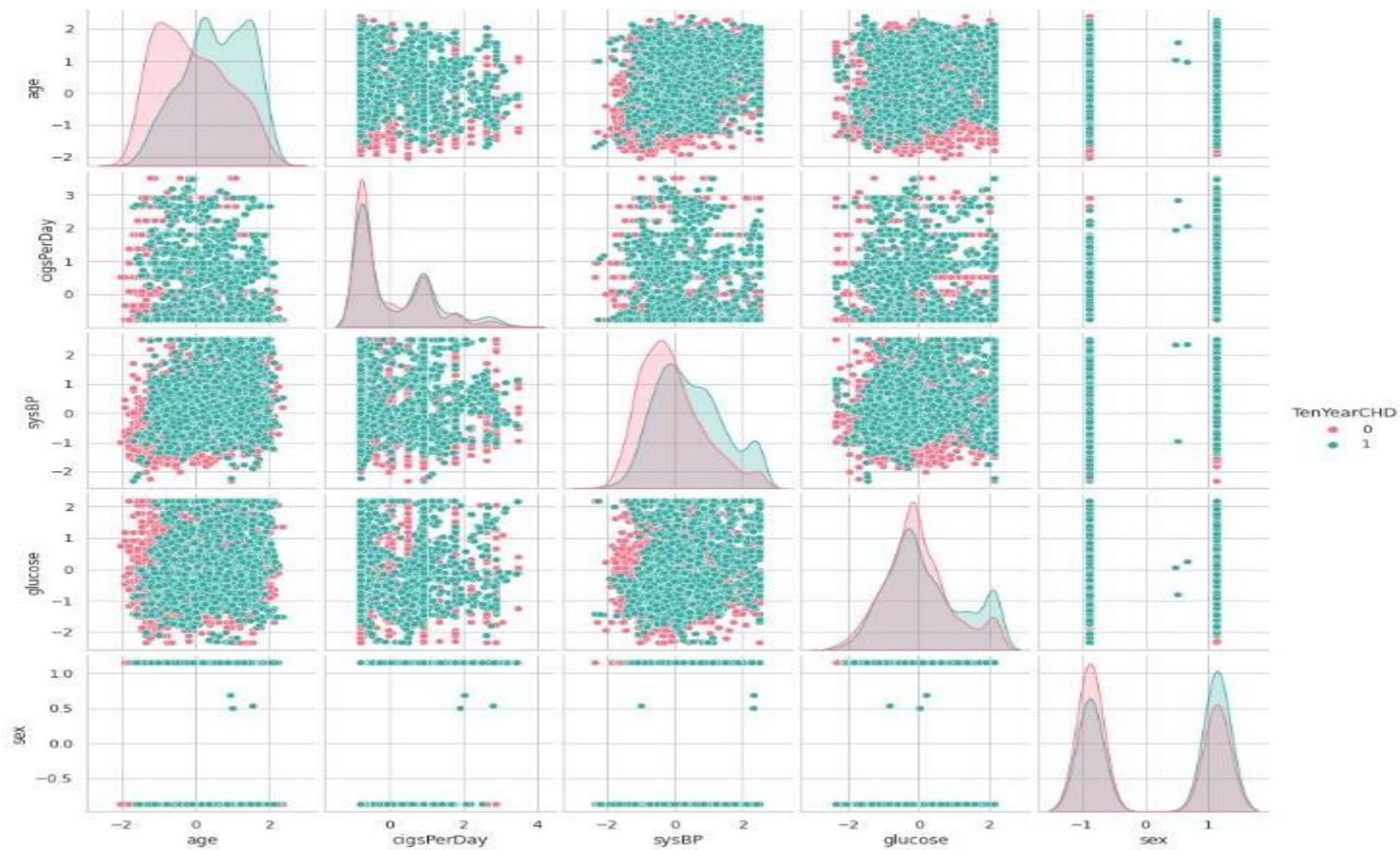
➤



**Apply SMOTE  
TOMEK for training  
dataset**



## Pair plot of features after SMOTE



# Evaluation Metrics

	Predicted 0	Predicted 1
Actual 0	TN	FP
Actual 1	FN	TP

$$precision = \frac{TP}{TP + FP}$$

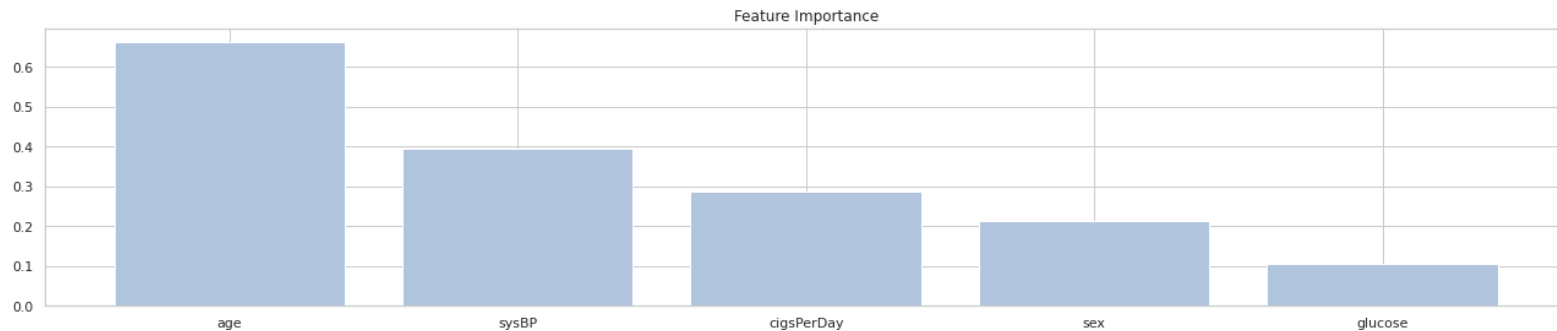
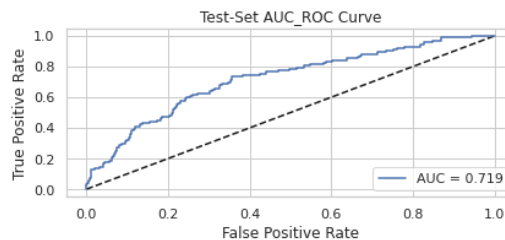
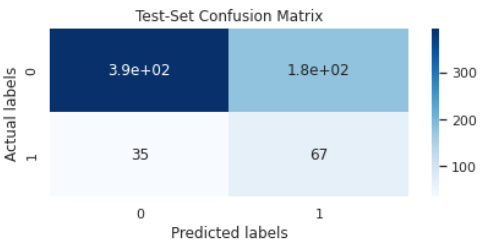
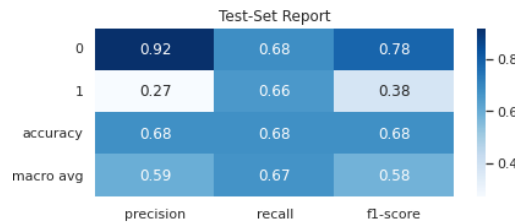
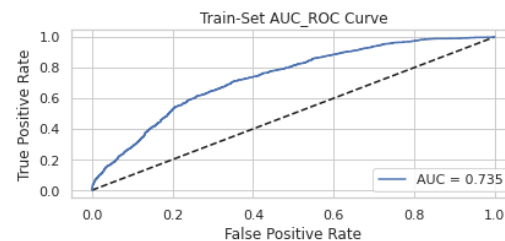
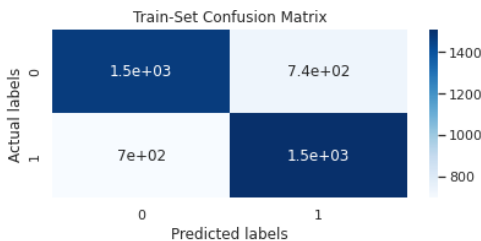
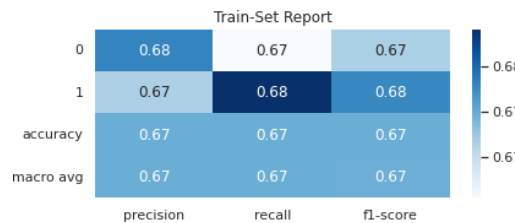
$$recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall}$$

$$accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

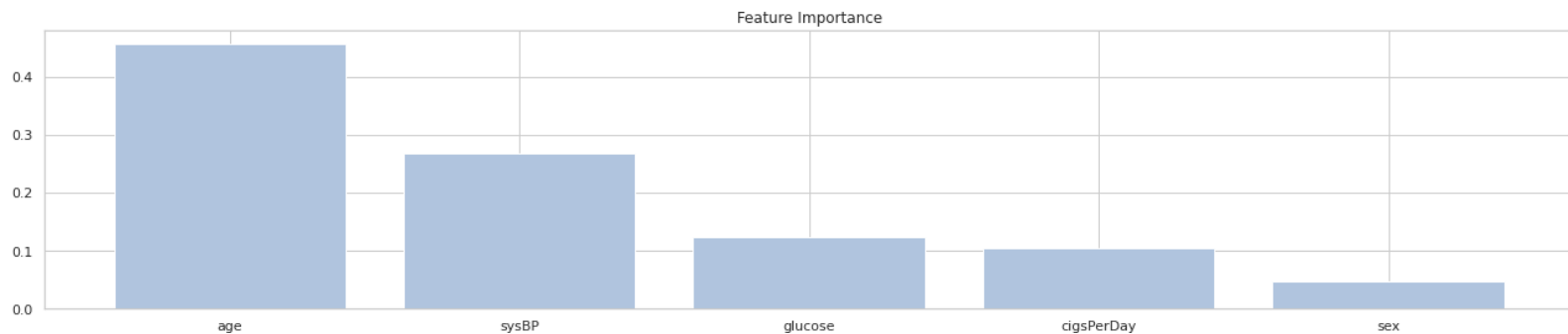
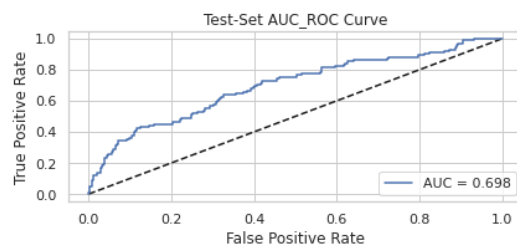
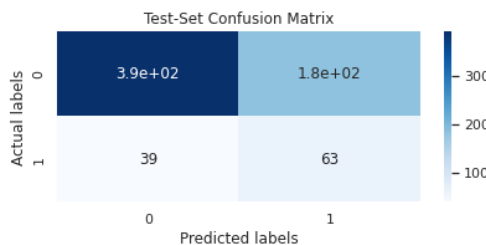
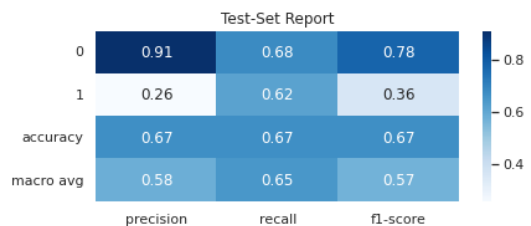
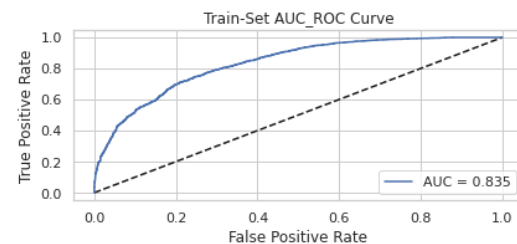
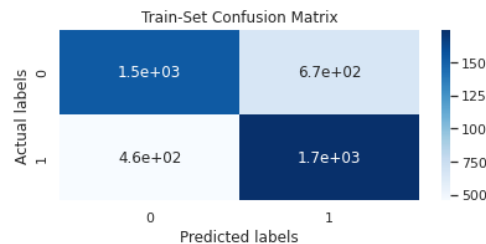
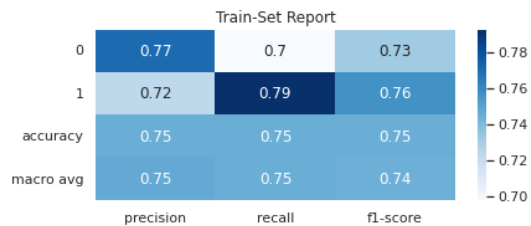
$$specificity = \frac{TN}{TN + FP}$$

# Logistic Regression





# Random Forest Classifier



# Random Forest Classifier (contd.)

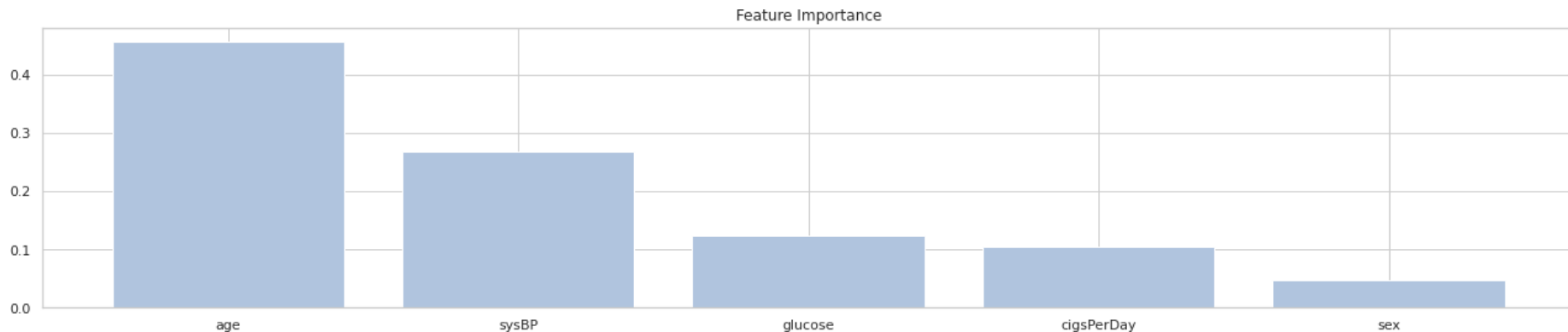
## **BEST FIT PARAMETERS:**

Max\_depth - 8

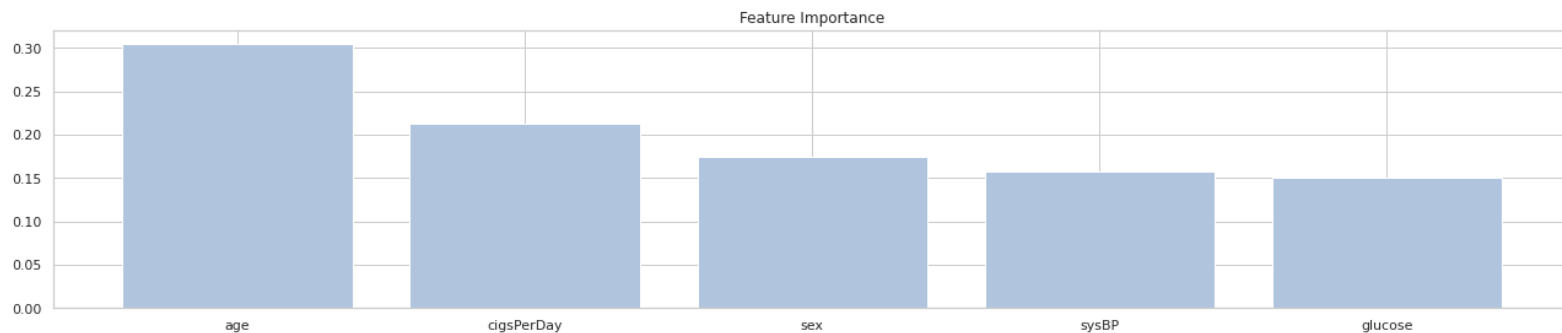
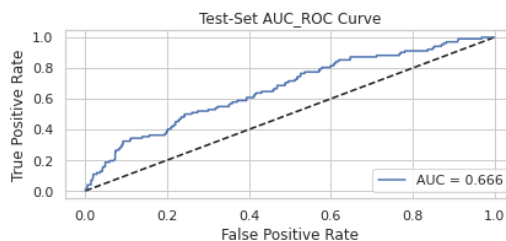
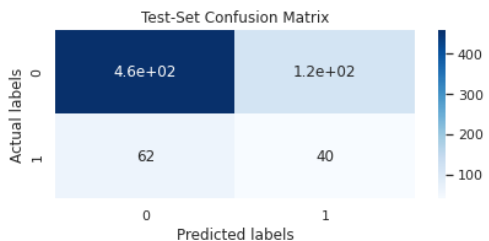
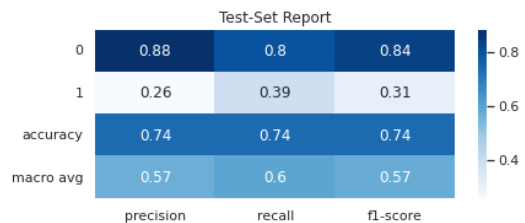
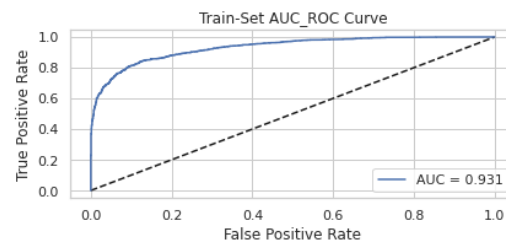
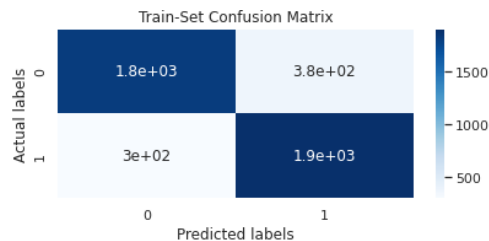
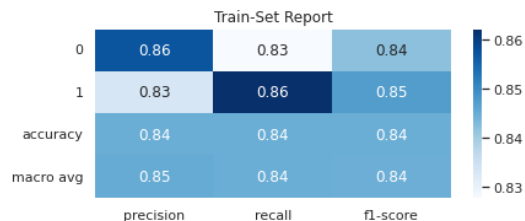
Min\_samples\_leaf - 40

Min\_samples\_split - 100

N\_estimators - 50



# Extreme Gradient Boost (XGB)



# Extreme Gradient Boost (XGB) (contd.)

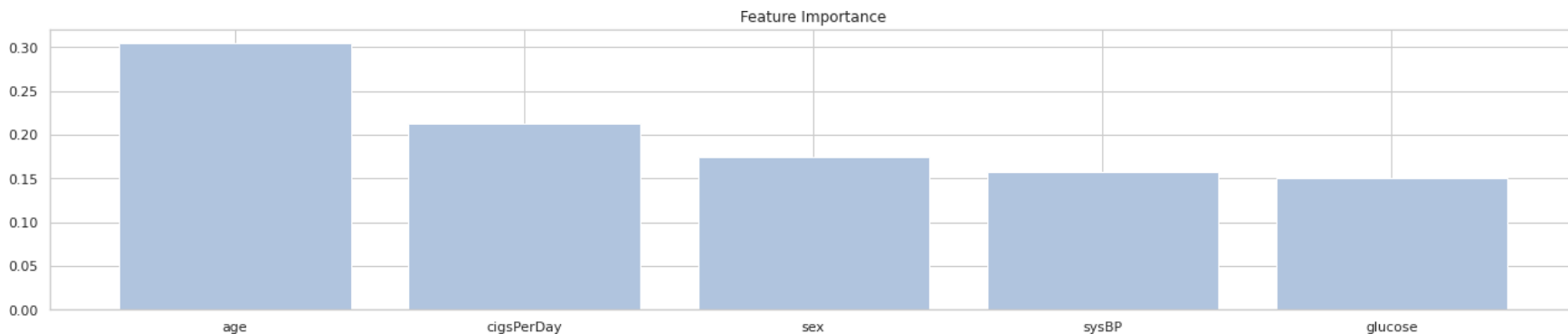
## **BEST FIT PARAMETERS:**

Learning\_rate – 0.1

Min\_samples\_leaf – 30

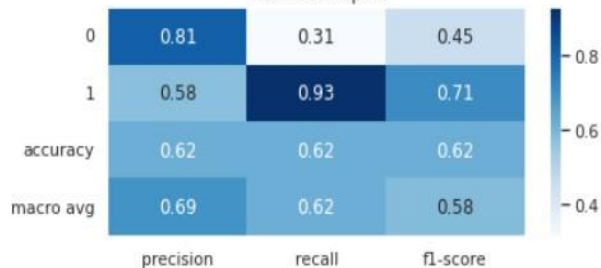
Min\_samples\_split – 20

N\_estimators – 140

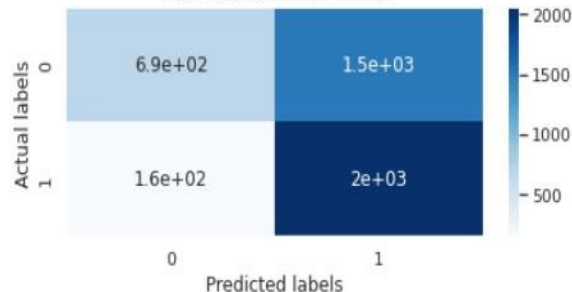


# Support Vector Machine (SVM)

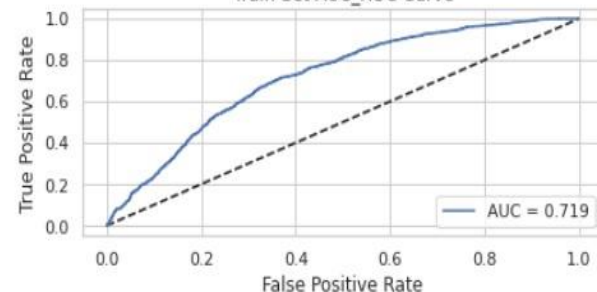
Train-Set Report



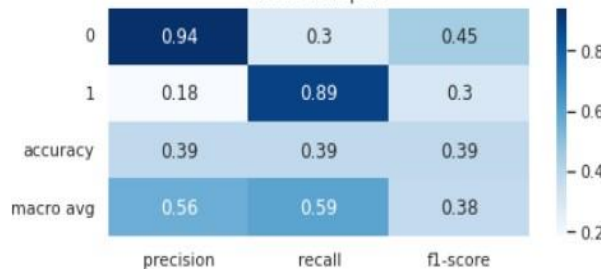
Train-Set Confusion Matrix



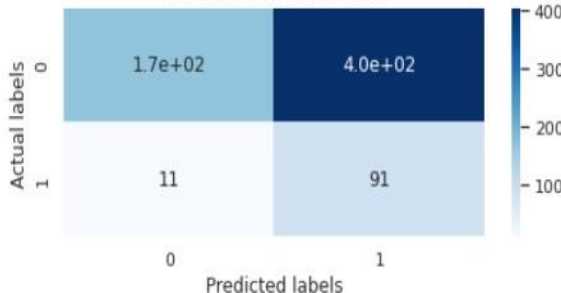
Train-Set AUC\_ROC Curve



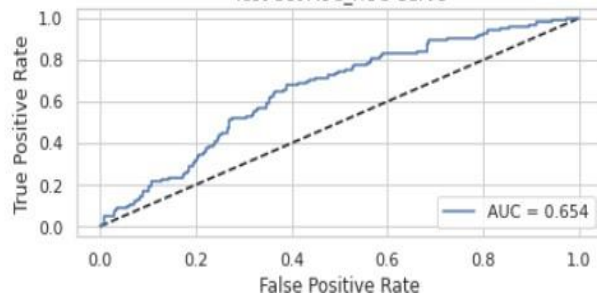
Test-Set Report



Test-Set Confusion Matrix



Test-Set AUC\_ROC Curve



# Conclusion

- **We have successfully built predictive model that can predict a patients risk for CHD based on their demography, lifestyle and medical history.**
- **Considered Recall score has the best metric to measure.**
- **Logistic Regression and other tree based algorithms were not quite good in classifying our data with accuracy.**
- **SVM worked has best classification model with recall score of 93% in training data and 89% in test data.**

# Challenges

- **Computation time**

**Multiple iterations are run on a single model to tune the hyperparameters.**

- **Less amount of data**

**Efforts must be put in gathering more data so that we can improve the model and can save more lives.**

**Q & A**



**Thank You**