Topic:

Heart Disease Analysis Using Machine Learning Algorithms

Introduction

Data Preparation and Exploration: The notebook begins by importing essential libraries for data manipulation. It loads a dataset containing 1000 patients information , equally distributed between positive and negative sentiment. Exploratory Data Analysis (EDA) is performed, visualizing the distribution of positive and negative reviewsthrough a pie chart.

Data Preprocessing and Model Building: The text data undergoes preprocessing, including cleaning, stopword removal, and word stemming. The Bag of Words model is employed to convert the text data into numerical features suitable for machine learning. Several classification models, including Decision Trees, Logistic Regression, Random Forest, k-Nearest Neighbors, are trained and evaluated for sentiment classification. Logistic Regression emerge as the top-performing model in terms of accuracy.

Model Evaluation and Sentiment Prediction: Model performance is evaluated using confusion matrices to assess their effectiveness.

Importing Required Libraries:

Data Visualization and Analysis:

- **numpy** (as **np**): Used for numerical operations.
- **pandas** (as **pd**): Used for data manipulation and analysis.
- **matplotlib.pyplot** (as **plt**): Used for creating static data visualizations.
- **seaborn** (as **sns**): Built on top of Matplotlib, used for creating more aesthetically pleasing and informative statistical graphics.
- **plotly.express** (as **px**): Used for creating interactive visualizations.
- **plotly.graph_objects** (as **go**): Used for creating interactive visualizations with Plotly.

Machine Learning and Model Evaluation:

- **sklearn.feature_extraction.text.CountVectorizer**: Used for converting text data into numerical features (bag of words).
- **sklearn.model_selection.train_test_split**: Used for splitting data into training and testing sets.
- **sklearn.linear_model.LogisticRegression**: Logistic Regression classifier.
- **sklearn.tree.DecisionTreeClassifier**: Decision Tree classifier.
- **sklearn.ensemble.RandomForestClassifier**: Random Forest classifier.

- **sklearn.neighbors.KNeighborsClassifier**: K-Nearest Neighbors classifier.
- **sklearn.metrics.confusion_matrix**: Used for calculating the confusion matrix.
- **sklearn.metrics.accuracy_score**: Used for calculating accuracy.

Model Tuning:

- **sklearn.model_selection.GridSearchCV**: Used for hyperparameter tuning with grid search.

Warnings Handling:

- **warnings**: Used for managing warning messages in your code.

IMPORTING LIBRARIES

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from pandas.plotting import andrews_curves
```

WORKFLOW OF MODEL STEPS :

1. Selecting the Dataset
2. Data Preprocessing which includes loading the dataset and removing null and duplicate values
3. Feature Selection reduces irrelevant features and improve the performance of the algorithms
4. Classification and Modelling
5. Performance evaluation

Loading the Dataset:

This will load the dataset Restaurant_Reviews.tsv into a Pandas DataFrame called df. The delimiterparameter specifies the separator between the columns, which is tab in this case. The quoting=3 parameter tells Pandas to remove quotes from the text in the Review column.

DATA PREPROCESSING

- Load the data using panda read function
- print dataset info
- print statistics about data using describe function
- check for null values, if any then remove it
- check for duplicate values

```
[3]  df = pd.read_csv("heart.csv")
```

```
[4]  df.head()
```

	age	sex	cp	trestbps	chol	fbs	restecg	th
0	63	1	3	145	233	1	0	
1	37	1	2	130	250	0	1	
2	41	0	1	130	204	0	0	
3	56	1	1	120	236	0	1	
4	57	0	0	120	354	0	1	

```
[5]  df.describe()
```

	age	sex	cp	trestbps	chol	fbs
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000

DATA CLEANING

```
[ ]  print('Data Sum of Null Values \n')
     df.isnull().sum()
```

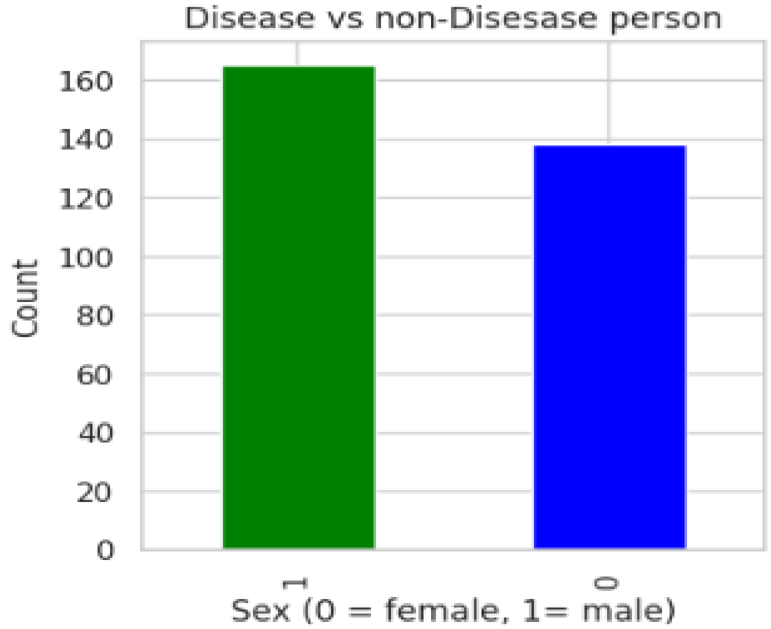
```
Data Sum of Null Values

age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

```
[88]  df.drop_duplicates(subset =None, keep = 'first', inplace = True)
```

DATA ANALYSIS

```python
plt.figure(figsize=(4, 4))
sns.set(style='whitegrid')
df.target.value_counts().plot(kind="bar", color=["green", "blue"])
plt.title("Disease vs non-Disesase person")
plt.xlabel("Sex (0 = female, 1= male)")
plt.ylabel("Count")
```

```
Text(0, 0.5, 'Count')
```



Percentage of Patients

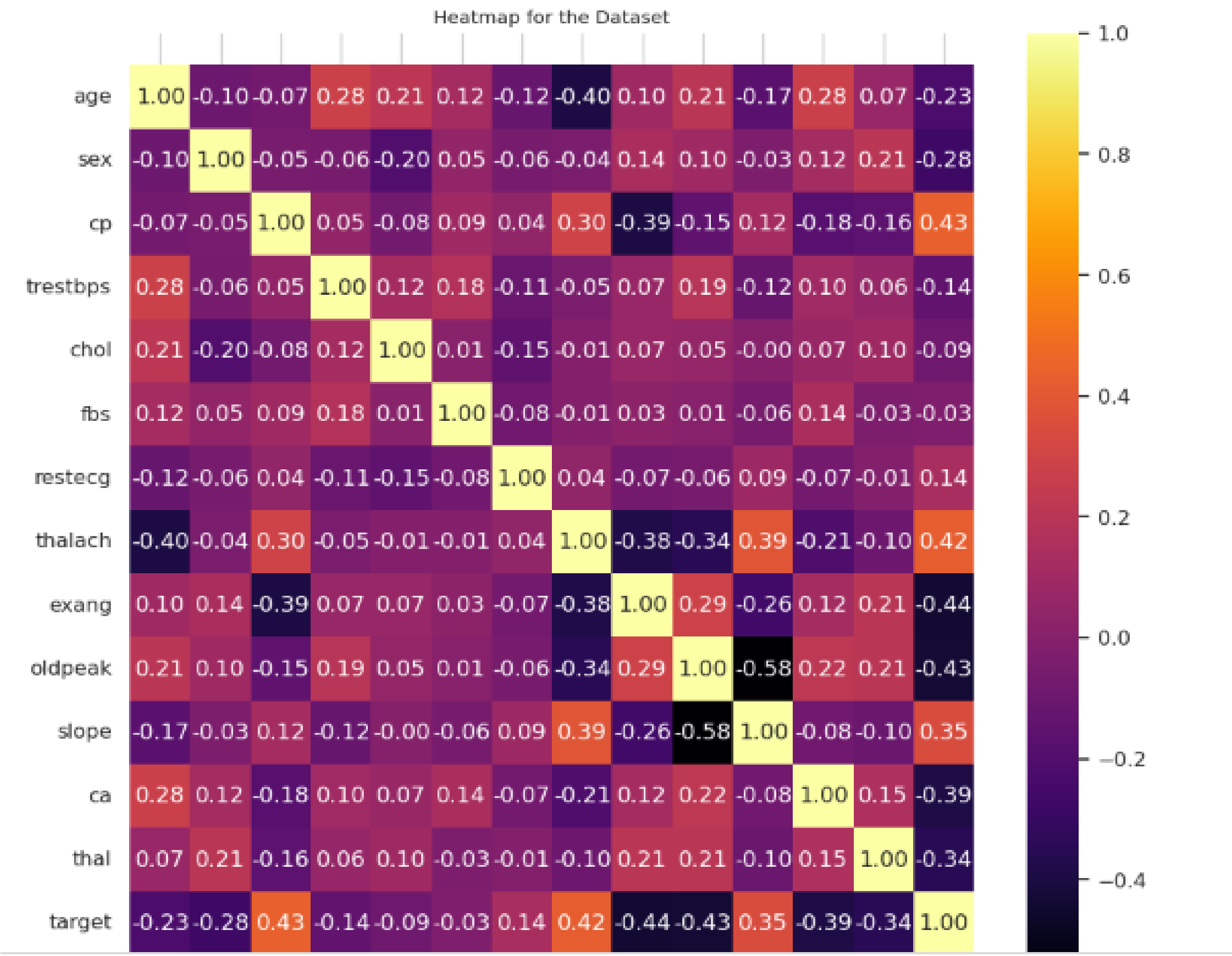
```python
countFemale = len(df[df.sex == 0])
countMale = len(df[df.sex == 1])
print("Percentage of Female Patients: {:.2f}%".format((countFemale / (len(df.sex))*100)))
print("Percentage of Male Patients: {:.2f}%".format((countMale / (len(df.sex))*100)))
```

```
Percentage of Female Patients: 31.68%
Percentage of Male Patients: 68.32%
```

HEATMAP

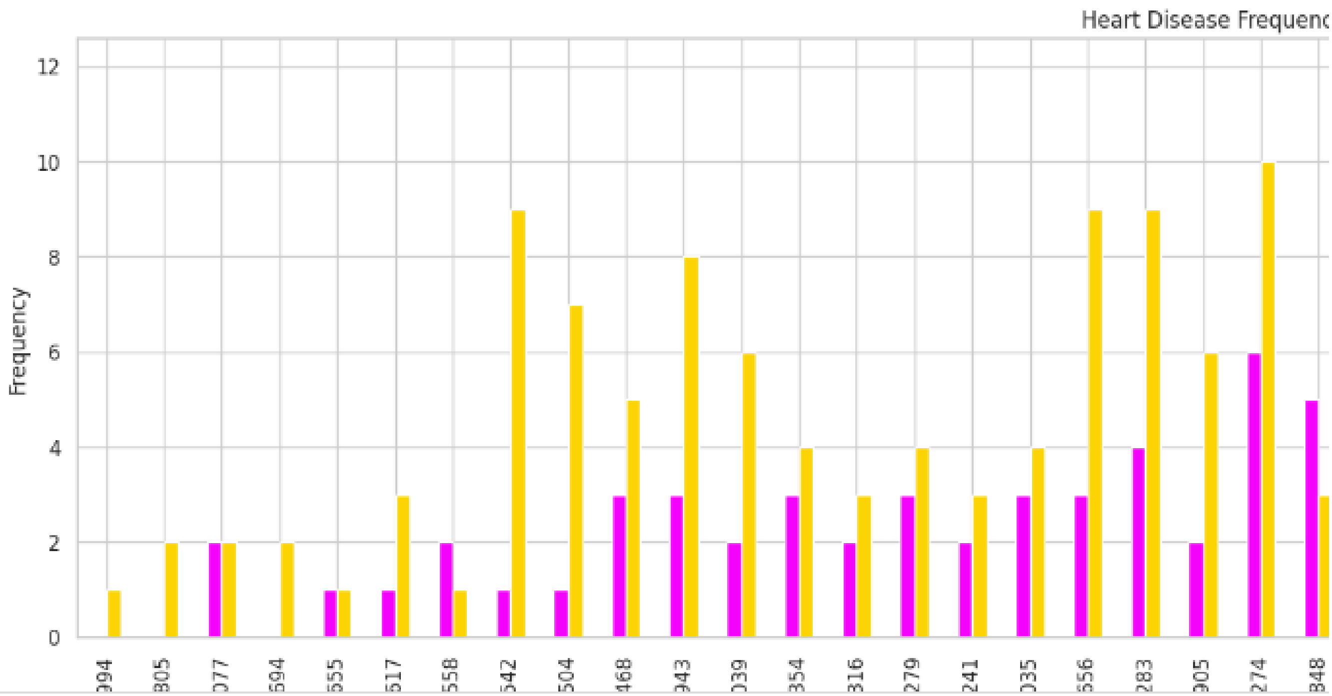
```python
corr_matrix = df.corr()
fig, ax = plt.subplots(figsize=(10, 10))
ax = sns.heatmap(corr_matrix,
                 annot=True,
                 fmt=".2f",
                 cmap="inferno");
plt.title('Heatmap for the Dataset', fontsize = 10)
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

```
(14.5, -0.5)
```



ANALYSIS USING AGE

```
pd.crosstab(df.age,df.target).plot(kind="bar",figsize=(24,6),color=['#f403fc', '#fcd303'])
plt.title('Heart Disease Frequency for Ages')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```

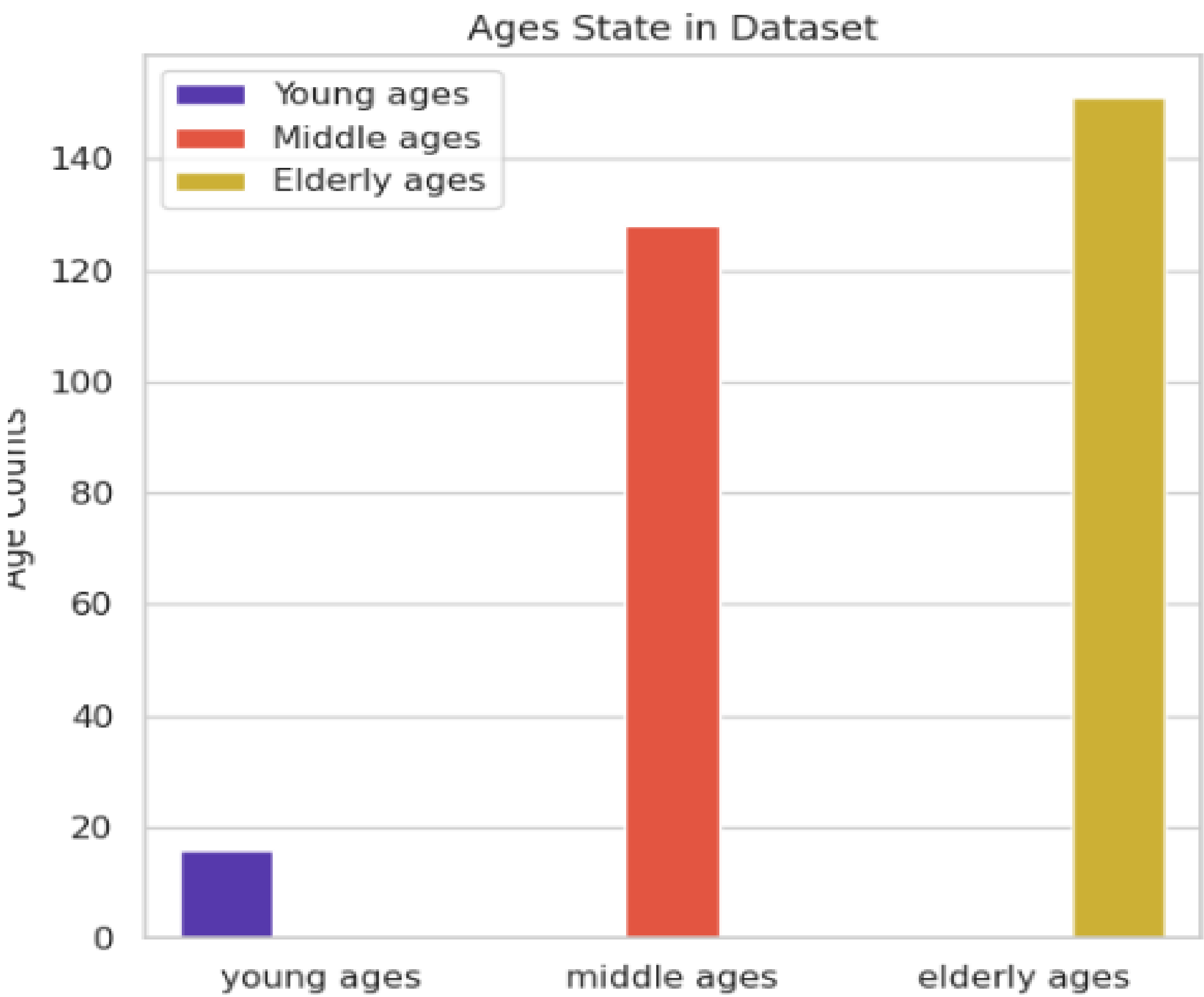


- Here I use 29-39 as Young age
- 40-54 as Middle age and
- older than 55 as Eardly age

```
[12]
young_ages=df[(df.age>=29)&(df.age<40)]
middle_ages=df[(df.age>=40)&(df.age<55)]
elderly_ages=df[(df.age>55)]
print('Young Ages :',len(young_ages))
print('Middle Ages :',len(middle_ages))
print('Elderly Ages :',len(elderly_ages))
```

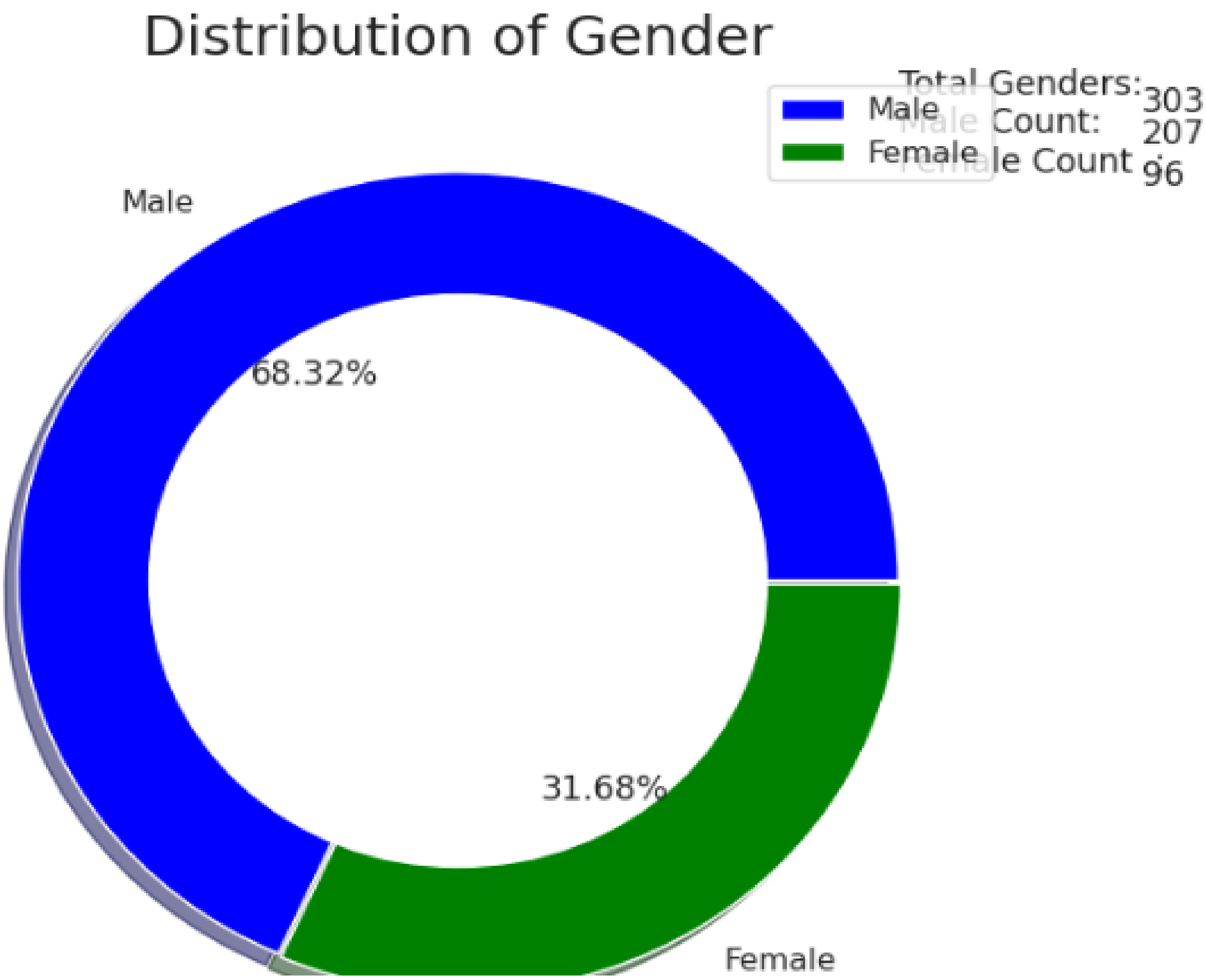
```
Young Ages : 16
Middle Ages : 128
Elderly Ages : 151
```

```
plt.figure(figsize=(6, 6))
sns.barplot(x=['young ages','middle ages','elderly ages'],y=[len(young_ages
plt.xlabel('Age Range')
plt.ylabel('Age Counts')
plt.title('Ages State in Dataset')
plt.show()
```

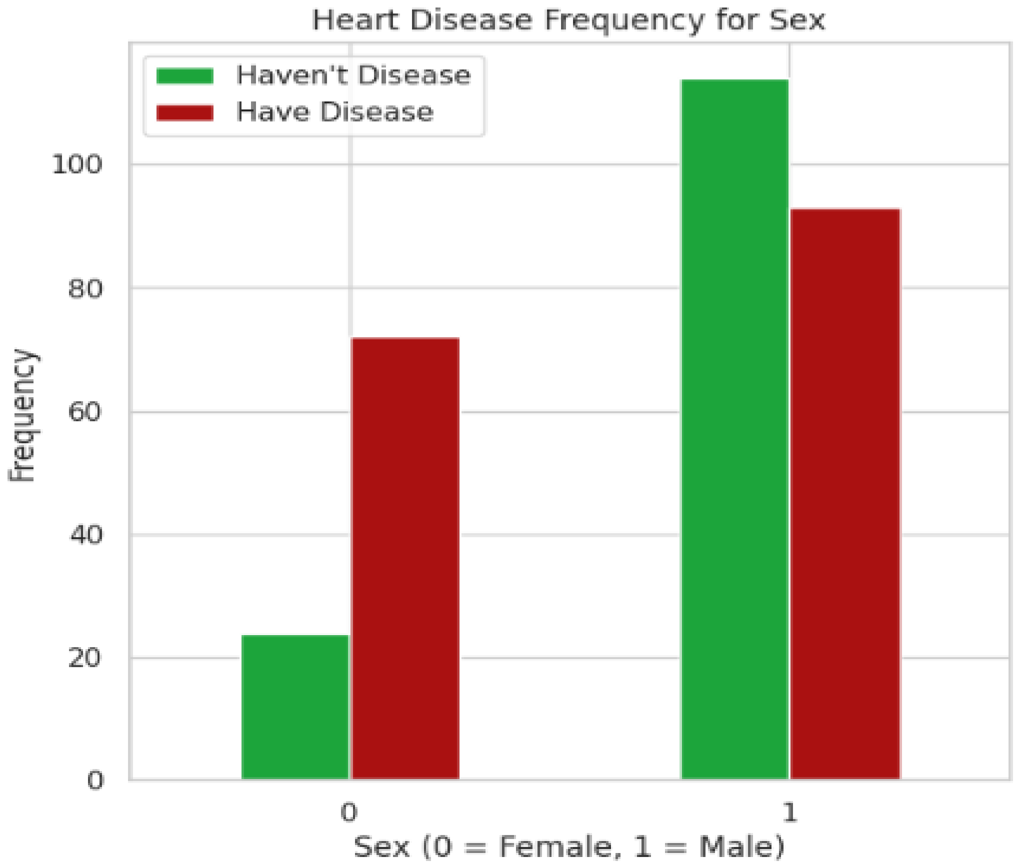


ANALYSIS USING GENDER

```python
size = df['sex'].value_counts()
colors = ['blue', 'green']
labels = "Male", "Female"
explode = [0, 0.01]

my_circle = plt.Circle((0, 0), 0.7, color = 'white')

plt.rcParams['figure.figsize'] = (7, 7)
plt.pie(size, colors = colors, labels = labels, shadow = True, explode = explode, autopct = '%.2f%%')
plt.title('Distribution of Gender', fontsize = 20)
p = plt.gcf()
p.gca().add_artist(my_circle)
plt.legend()

total_genders_count=len(df.sex)
male_count=len(df[df['sex']==1])
female_count=len(df[df['sex']==0])
plt.text(1, 1,'Total Genders:\nMale Count:\nFemale Count  :')
plt.text(1.55, 1.15,total_genders_count)
plt.text(1.55, 1.07,male_count)
plt.text(1.55, .97,female_count)

plt.show()
```



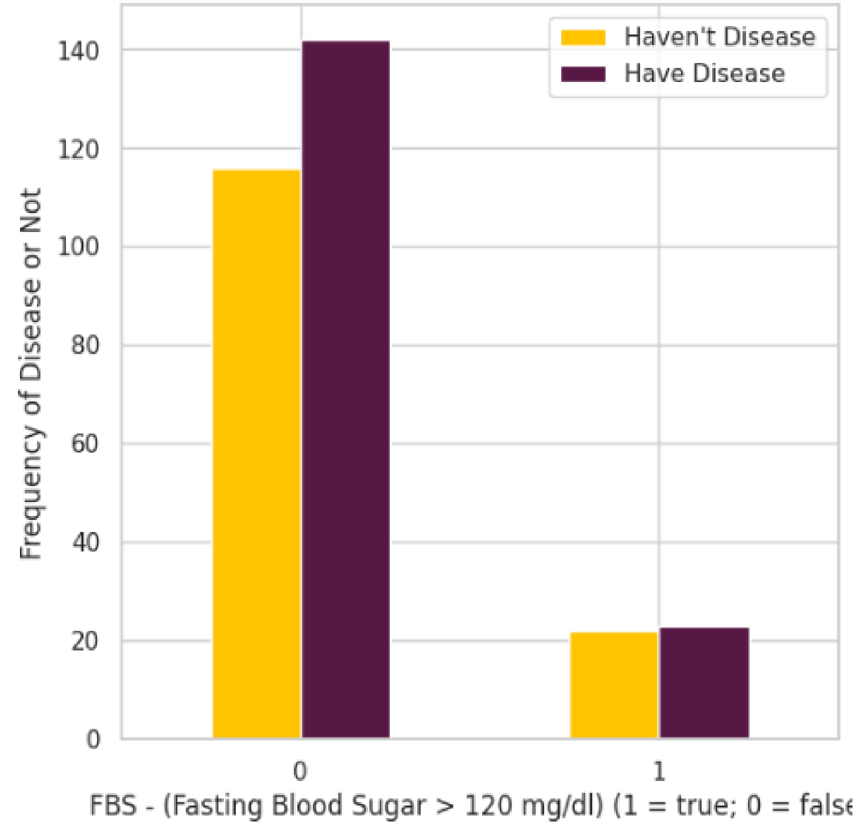

```
pd.crosstab(df.sex,df.target).plot(kind="bar",figsize=(6,6),color=['#1CA53B','#AA1111' ])
plt.title('Heart Disease Frequency for Sex')
plt.xlabel('Sex (0 = Female, 1 = Male)')
plt.xticks(rotation=0)
plt.legend(["Haven't Disease", "Have Disease"])
plt.ylabel('Frequency')
plt.show()
```



ANALYSIS USING FBS

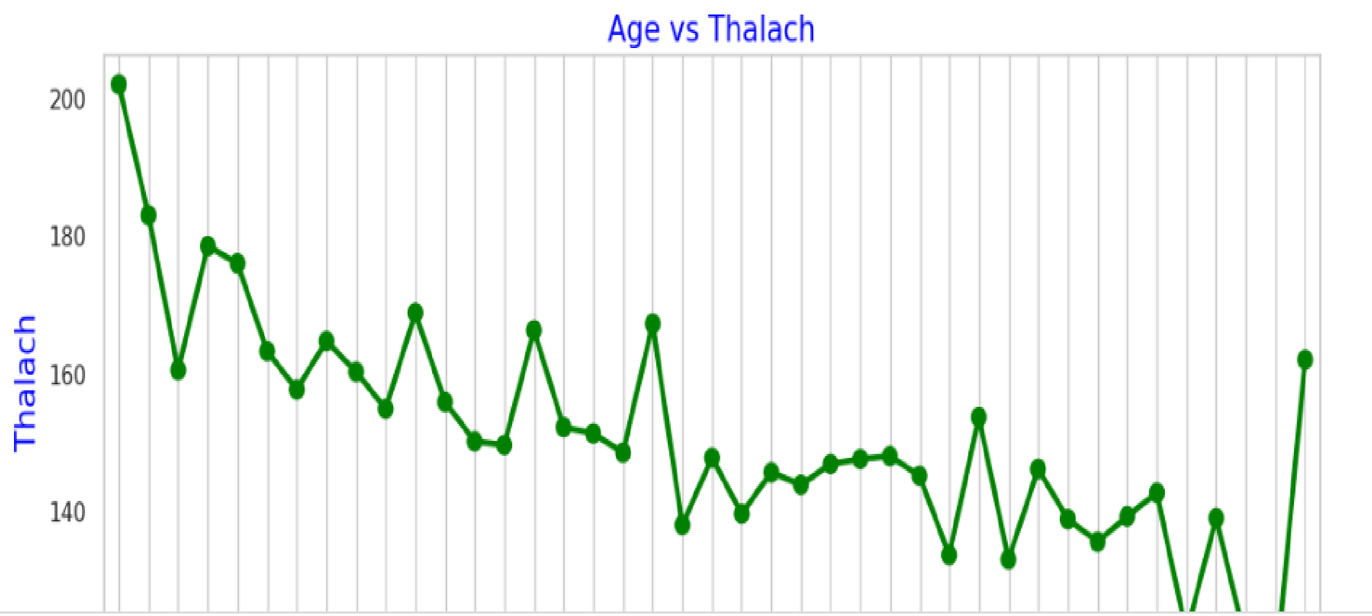
The person's fasting blood sugar > 120 mg/dl. (1 = true; 0 = false)

```
pd.crosstab(df.fbs,df.target).plot(kind="bar",figsize=(6,6),color=['#FFC300','#581845' ])
plt.title('Heart Disease Frequency According To FBS')
plt.xlabel('FBS - (Fasting Blood Sugar > 120 mg/dl) (1 = true; 0 = false)')
plt.xticks(rotation = 0)
plt.legend(["Haven't Disease", "Have Disease"])
plt.ylabel('Frequency of Disease or Not')
plt.show()
```



[28]

```
#data_sorted=data.sort_values(by='Age',ascending=True)
plt.figure(figsize=(12,5))
sns.pointplot(x=age_unique,y=mean_thalach,color='green')
plt.xlabel('Age',fontsize = 15,color='blue')
plt.xticks(rotation=45)
plt.ylabel('Thalach',fontsize = 15,color='blue')
plt.title('Age vs Thalach',fontsize = 15,color='blue')
plt.grid()
plt.show()
```



MACHINE LEARNING MODELLING

[37]
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
StandardScaler = StandardScaler()
columns_to_scale = ['age','sex','cp','trestbps','chol','fbs','restecg','thalach','exang','oldpeak','slope','ca','thal']
df[columns_to_scale] = StandardScaler.fit_transform(df[columns_to_scale])
```

[38]
```
X= df.drop(['target'], axis=1) #,'trestbps','chol','fbs','restecg'
y= df['target']

#devide Dataset into test and train
X_train, X_test,y_train, y_test=train_test_split(X,y,test_size=0.3,random_state=40)
```

[39]
```
#check those dataset
print('X_train-', X_train.size)
print('X_test-',X_test.size)
print('y_train-', y_train.size)
print('y_test-', y_test.size)
```

```
X_train- 2756
X_test- 1183
y_train- 212
y_test- 91
```

LOGISTIC REGRESSION

[40]
```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression(random_state=999, C =  1, tol = 5)
model1 = lr.fit(X_train,y_train)
prediction1 = model1.predict(X_test)

y_pred_quant1 = model1.predict_proba(X_test)[:, 1]
```

[41]
```
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test,prediction1)
cm
```

```
array([[36,  4],
       [ 3, 48]])
```

```
[44]
from sklearn.metrics import accuracy_score

accuracies = {}

acc = accuracy_score(y_test,prediction1)*100
accuracies['Logistic Regration'] = acc
acc
```

```
92.3076923076923
```

```
[71]
from sklearn.metrics import classification_report
print(classification_report(y_test,prediction1))
```

```
              precision    recall  f1-score   support

           0       0.92      0.90      0.91        40
           1       0.92      0.94      0.93        51

    accuracy                           0.92        91
   macro avg       0.92      0.92      0.92        91
weighted avg       0.92      0.92      0.92        91
```

DECISION TREE

[45]
```
from sklearn.tree import DecisionTreeClassifier

dtc = DecisionTreeClassifier(random_state=999)
model2 = dtc.fit(X_train,y_train)
prediction2 = model2.predict(X_test)

y_pred_quant2 = model2.predict_proba(X_test)[:, 1]
```

[46]
```
cm2 = confusion_matrix(y_test,prediction2)
cm2
```

```
array([[32,  8],
       [13, 38]])
```

[47]
```
acc = accuracy_score(y_test,prediction2)*100
accuracies['Decision Tree'] = acc
acc
```

```
76.92307692307693
```

RANDOM FOREST

```
from sklearn.ensemble import RandomForestClassifier

rfc=RandomForestClassifier(random_state=20)
model3 = rfc.fit(X_train, y_train)
prediction3 = model3.predict(X_test)

y_pred_quant3 = model3.predict_proba(X_test)[:, 1]

cm3 = confusion_matrix(y_test, prediction3)
cm3
```

```
array([[33,  7],
       [ 7, 44]])
```

[49]

```
acc = accuracy_score(y_test, prediction3)*100
accuracies['Random Forest'] = acc
acc
```

```
84.61538461538461
```

K NEAREST NEIGHBOUR

[75]

```
from sklearn.neighbors import KNeighborsClassifier

KNN = KNeighborsClassifier(n_neighbors = 5)
model4 = KNN.fit(X_train, y_train)
prediction4 = model4.predict(X_test)

y_pred_quant4 = model4.predict_proba(X_test)[:, 1]

cm4= confusion_matrix(y_test, prediction4)
cm4
```

```
array([[34,  6],
       [ 7, 44]])
```

[76]

```
acc = accuracy_score(y_test, prediction4)*100
accuracies['K nearest neighbour'] = acc
acc
```

```
85.71428571428571
```

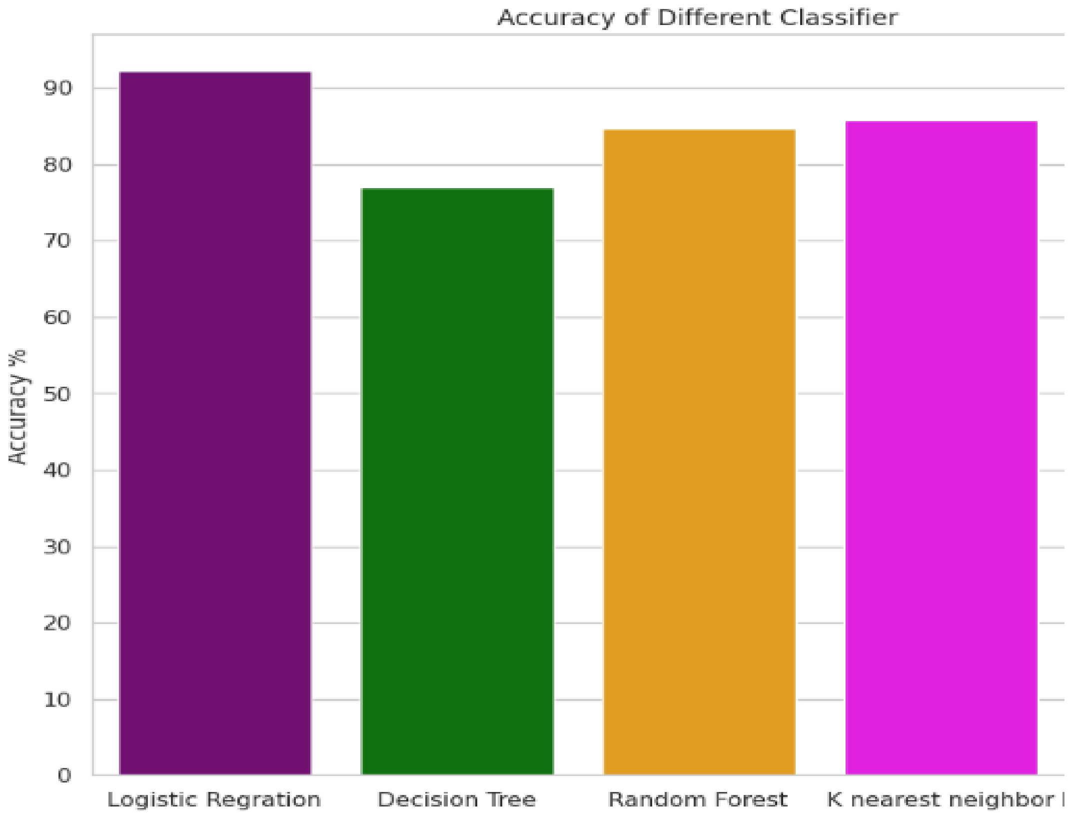
COMPARING THE MODELS

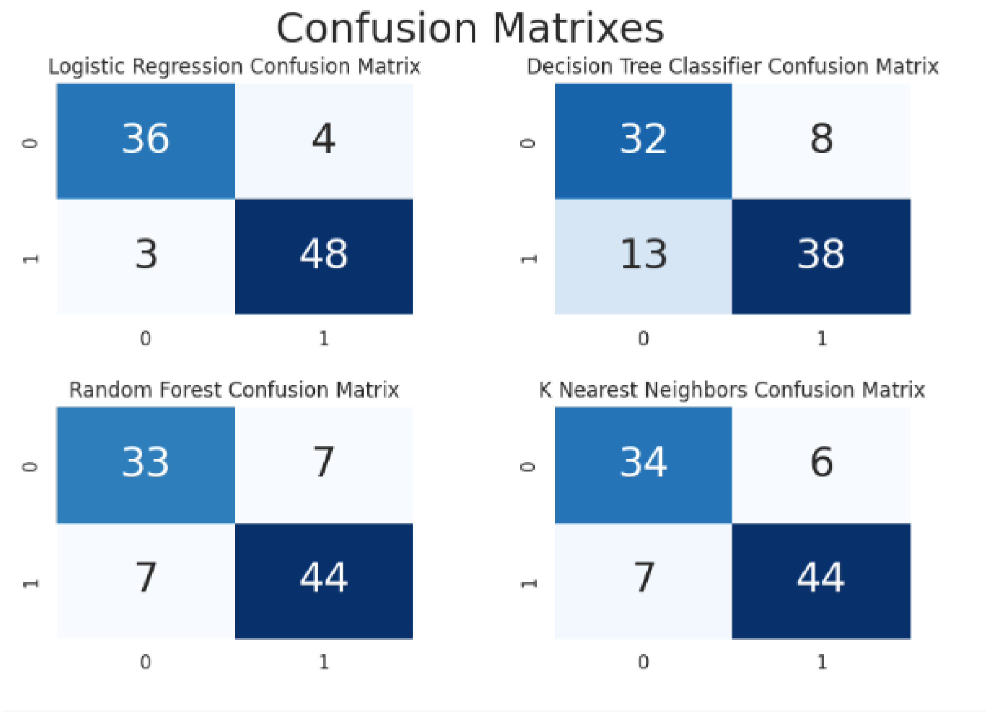
[78]

```
print('Logistic Regression - lr :', accuracy_score(y_test, prediction1) * 100)
print('Decision Tree - dtc :', accuracy_score(y_test, prediction2) * 100)
print('Random Forest - rfc :', accuracy_score(y_test, prediction3) * 100)
print('K Nearest - KNN :', accuracy_score(y_test, prediction4) * 100)
```

```
Logistic Regression - lr : 92.3076923076923
Decision Tree - dtc : 76.92307692307693
Random Forest - rfc : 84.61538461538461
K Nearest - KNN : 85.71428571428571
```

```python
colors = ["purple", "green", "orange", "magenta"]

sns.set_style("whitegrid")
plt.figure(figsize=(10,8))
plt.yticks(np.arange(0,100,10))
plt.ylabel("Accuracy %")
plt.xlabel("Algorithms")
plt.title("Accuracy of Different Classifier")
sns.barplot(x=list(accuracies.keys()), y=list(accuracies.values()), palette=colors)
plt.show()
```





The code first defines a function called confusion_matrix(). This function takes the true labels and predicted labels as input and returns a confusion matrix.
The code then creates a confusion matrix for the test set predictions. The confusion matrix shows that the model correctly classified 85 positive instances and 32 negative instances. The model incorrectly classified 15 positive instances as negative and 30 negative instances as positive.
The code then uses the Seaborn library to plot the confusion matrix. The plot shows the confusion matrix as a heatmap, with the true labels on the x-axis and the predicted labels on the y-axis. The cells of the heatmap are colored according to the number of instances in each cell.
The code also prints the accuracy, precision, recall, and F1 score of the model. The accuracy is 0.92, which means that the model correctly classified 92% of the instances in the test set by using the Machine Learning Algorithm Logistic Regression.