Project – Heart Disease

Problem Statement:

You are the data scientist at a medical research facility. The facility wants you to build a machine learning model to classify if the given data of a patient should tell if the patient is at the risk of a heart attack.

Domain:

Healthcare

Tasks To Be Performed:

In [211…

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
from sklearn.metrics import *
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.ensemble import RandomForestClassifier
import graphviz
from sklearn.tree import export_graphviz
from IPython.display import Image
```

1. Data Analysis:

- a. Import the dataset
- b. Get information about the dataset (mean, max, min, quartiles etc.)
- c. Find the correlation between all fields

In [212…

```
# a. Import the dataset
df = pd.read_csv('dataset.csv')
df
```

Out[212…

	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

In [213…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       303 non-null    int64
 1   sex       303 non-null    int64
 2   cp        303 non-null    int64
 3   trestbps  303 non-null    int64
 4   chol      303 non-null    int64
 5   fbs       303 non-null    int64
 6   restecg   303 non-null    int64
 7   thalach   303 non-null    int64
 8   exang     303 non-null    int64
 9   oldpeak   303 non-null    float64
 10  slope     303 non-null    int64
 11  ca        303 non-null    int64
 12  thal      303 non-null    int64
 13  target    303 non-null    int64
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

In [214…

```
# b. Get information about the dataset (mean, max, min, quartiles etc.)
df.describe()
```

Out[214…

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	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	0.528053	149.646865	0.326733	1.039604	1.399340	0.729373	2.313531	0.544554
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.905161	0.469794	1.161075	0.616226	1.022606	0.612277	0.498835
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000	0.000000	1.000000	0.000000	2.000000	0.000000
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.000000	0.000000	0.800000	1.000000	0.000000	2.000000	1.000000
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.000000	1.000000	1.600000	2.000000	1.000000	3.000000	1.000000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.200000	2.000000	4.000000	3.000000	1.000000

In [215…

```
df.isna().sum()
```

Out[215…

```
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
```

In [216…

```
# c. Find the correlation between all fields
df.corr()
```

Out[216…

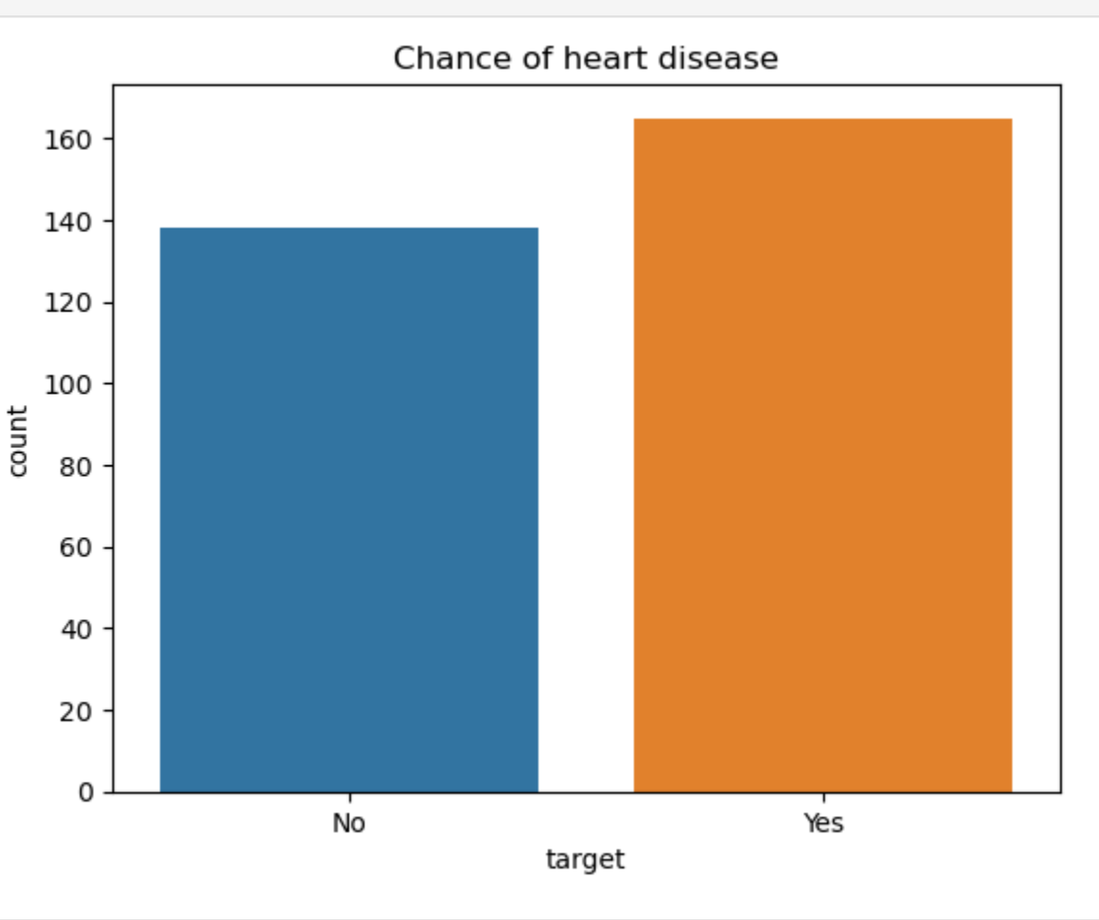
	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
age	1.000000	-0.098447	-0.068653	0.279351	0.213678	0.121308	-0.116211	-0.398522	0.096801	0.210013	-0.168814	0.276326	0.068001	-0.225439
sex	-0.098447	1.000000	-0.049353	-0.056769	-0.197912	0.045032	-0.058196	-0.044020	0.141664	0.096093	-0.030711	0.118261	0.210041	-0.280937
cp	-0.068653	-0.049353	1.000000	0.047608	-0.076904	0.094444	0.044421	0.295762	-0.394280	-0.149230	0.119717	-0.181053	-0.161736	0.433798
trestbps	0.279351	-0.056769	0.047608	1.000000	0.123174	0.177531	-0.114103	-0.046698	0.067616	0.193216	-0.121475	0.101389	0.062210	-0.144931
chol	0.213678	-0.197912	-0.076904	0.123174	1.000000	0.013294	-0.151040	-0.009940	0.067023	0.053952	-0.004038	0.070511	0.098803	-0.085239
fbs	0.121308	0.045032	0.094444	0.177531	0.013294	1.000000	-0.084189	-0.008567	0.025665	0.005747	-0.059894	0.137979	-0.032019	-0.028046
restecg	-0.116211	-0.058196	0.044421	-0.114103	-0.151040	-0.084189	1.000000	0.044123	-0.070733	-0.058770	0.093045	-0.072042	-0.011981	0.137230
thalach	-0.398522	-0.044020	0.295762	-0.046698	-0.009940	-0.008567	0.044123	1.000000	-0.378812	-0.344187	0.386784	-0.213177	-0.096439	0.421741
exang	0.096801	0.141664	-0.394280	0.067616	0.067023	0.025665	-0.070733	-0.378812	1.000000	0.288223	-0.257748	0.115739	0.206754	-0.436757
oldpeak	0.210013	0.096093	-0.149230	0.193216	0.053952	0.005747	-0.058770	-0.344187	0.288223	1.000000	-0.577537	0.222682	0.210244	-0.430696
slope	-0.168814	-0.030711	0.119717	-0.121475	-0.004038	-0.059894	0.093045	0.386784	-0.257748	-0.577537	1.000000	-0.080155	-0.104764	0.345877
ca	0.276326	0.118261	-0.181053	0.101389	0.070511	0.137979	-0.072042	-0.213177	0.115739	0.222682	-0.080155	1.000000	0.151832	-0.391724
thal	0.068001	0.210041	-0.161736	0.062210	0.098803	-0.032019	-0.011981	-0.096439	0.206754	0.210244	-0.104764	0.151832	1.000000	-0.344029
target	-0.225439	-0.280937	0.433798	-0.144931	-0.085239	-0.028046	0.137230	0.421741	-0.436757	-0.430696	0.345877	-0.391724	-0.344029	1.000000

2. Data Visualization:

- a. Visualize the number of patients having a heart disease and not having a heart disease
- b. Visualize the age and whether a patient has disease or not
- c. Visualize correlation between all features using a heat map

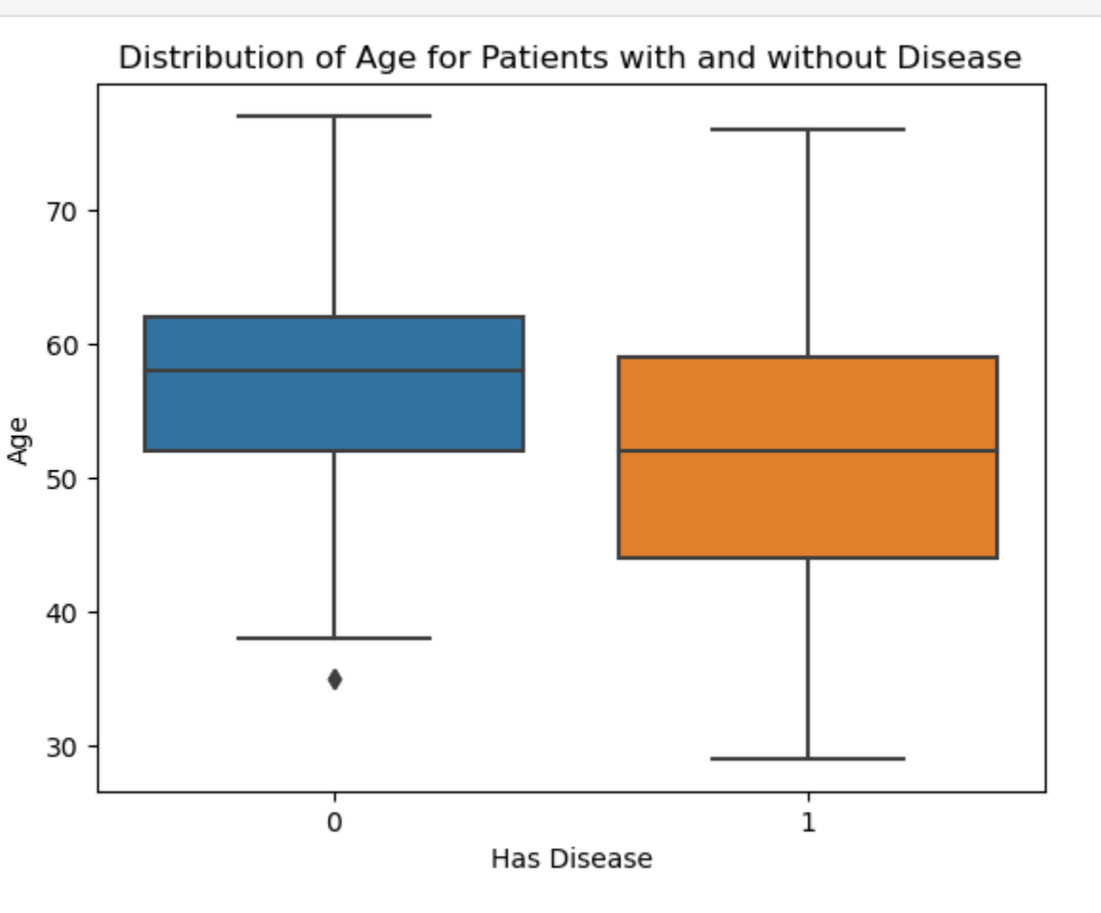
In [217…

```
# a. Visualize the number of patients having a heart disease and not having a heart disease
sns.countplot(data=df, x='target')
plt.title("Chance of heart disease")
plt.xticks(ticks=[0, 1], labels=['No', 'Yes'])
plt.show()
```



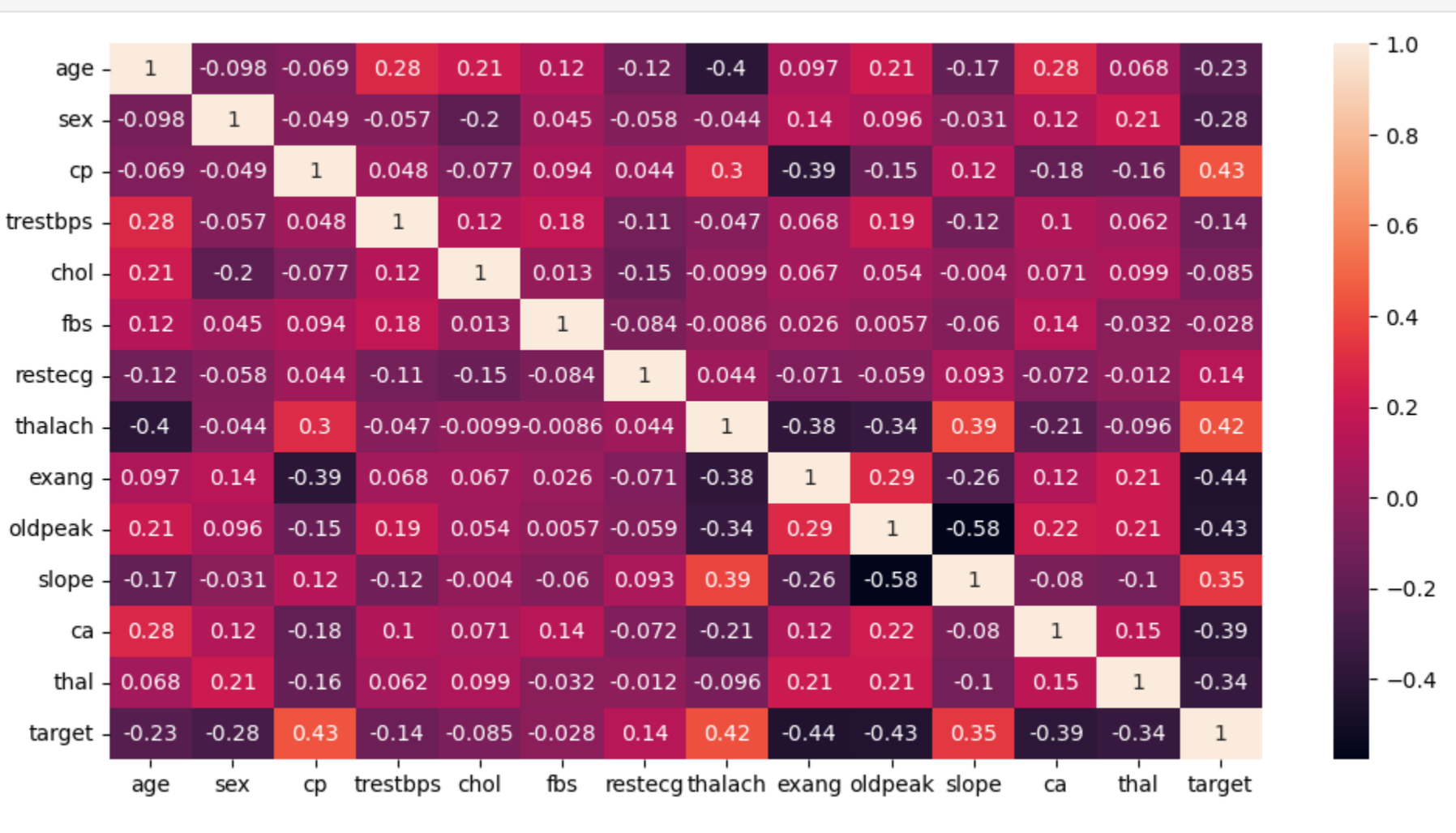
In [218…

```
# b. Visualize the age and whether a patient has disease or not
sns.boxplot(x='target', y='age', data=df)
plt.xlabel('Has Disease')
plt.ylabel('Age')
plt.title('Distribution of Age for Patients with and without Disease')
plt.show()
```



In [219…

```
# c. Visualize correlation between all features using a heat map
plt.subplots(figsize=(12,6))
sns.heatmap(data=df.corr(), annot=True)
plt.show()
```



Creating models

VIF

In [220…

```
col_list = []
for col in df.columns:
    if((df[col].dtype!='object')&(col!='target')):
        col_list.append(col)

X = df[col_list]
vif_data = pd.DataFrame()
vif_data['feature'] = X.columns
vif_data['VIF'] = [variance_inflation_factor(X.values, i) for i in range(len(X.columns))]
print(vif_data)
```

```
     feature        VIF
0        age  38.998305
1        sex   3.523211
2         cp   2.414403
3   trestbps  58.557335
4       chol  26.267365
5        fbs   1.268205
6    restecg   2.058206
7    thalach  42.742178
8      exang   2.022527
9    oldpeak   3.062890
10     slope  10.072734
11        ca   1.808925
12      thal  17.165303
```

In [221…

```
df.drop(columns=['trestbps'], inplace=True)
```

In [222…

```
col_list = []
for col in df.columns:
    if((df[col].dtype!='object')&(col!='target')):
        col_list.append(col)

X = df[col_list]
vif_data = pd.DataFrame()
vif_data['feature'] = X.columns
vif_data['VIF'] = [variance_inflation_factor(X.values, i) for i in range(len(X.columns))]
print(vif_data)
```

```
    feature        VIF
0       age  28.599796
1       sex   3.522376
2        cp   2.403644
3      chol  25.923434
4       fbs   1.250256
5   restecg   2.058206
6   thalach  34.026519
7     exang   1.990878
8   oldpeak   2.973430
9     slope  10.067190
10       ca   1.808102
11     thal  17.005949
```

In [223…

```
df.drop(columns=['thalach'], inplace=True)
```

In [224…

```
col_list = []
for col in df.columns:
    if((df[col].dtype!='object')&(col!='target')):
        col_list.append(col)

X = df[col_list]
vif_data = pd.DataFrame()
vif_data['feature'] = X.columns
vif_data['VIF'] = [variance_inflation_factor(X.values, i) for i in range(len(X.columns))]
print(vif_data)
```

```
    feature        VIF
0       age  27.213596
1       sex   3.412645
2        cp   2.264790
3      chol  22.374105
4       fbs   1.248307
5   restecg   2.022210
6     exang   1.955987
7   oldpeak   2.965697
8     slope   8.372679
9        ca   1.760648
10     thal  15.963052
```

In [225…

```
df.drop(columns=['age'], inplace=True)
```

In [226…

```
col_list = []
for col in df.columns:
    if((df[col].dtype!='object')&(col!='target')):
        col_list.append(col)

X = df[col_list]
vif_data = pd.DataFrame()
vif_data['feature'] = X.columns
vif_data['VIF'] = [variance_inflation_factor(X.values, i) for i in range(len(X.columns))]
print(vif_data)
```

```
   feature        VIF
0      sex   3.404301
1       cp   2.211674
2     chol  14.917083
3      fbs   1.232428
4  restecg   2.006017
5    exang   1.947640
6  oldpeak   2.827322
7    slope   7.983150
8       ca   1.710828
9     thal  14.860553
```

In [227…

```
df.drop(columns=['chol'], inplace=True)
```

In [228…

```
col_list = []
for col in df.columns:
    if((df[col].dtype!='object')&(col!='target')):
        col_list.append(col)

X = df[col_list]
vif_data = pd.DataFrame()
vif_data['feature'] = X.columns
vif_data['VIF'] = [variance_inflation_factor(X.values, i) for i in range(len(X.columns))]
print(vif_data)
```

```
   feature        VIF
0      sex   3.348022
1       cp   2.154649
2      fbs   1.223893
3  restecg   2.005247
4    exang   1.915642
5  oldpeak   2.628953
6    slope   6.201591
7       ca   1.707658
8     thal  10.478889
```

In [229…

```
df.drop(columns=['thal'], inplace=True)
```

In [230…

```
col_list = []
for col in df.columns:
    if((df[col].dtype!='object')&(col!='target')):
        col_list.append(col)

X = df[col_list]
vif_data = pd.DataFrame()
vif_data['feature'] = X.columns
vif_data['VIF'] = [variance_inflation_factor(X.values, i) for i in range(len(X.columns))]
print(vif_data)
```

```
   feature       VIF
0      sex  3.038525
1       cp  2.112149
2      fbs  1.222870
3  restecg  1.957971
4    exang  1.795800
5  oldpeak  2.062440
6    slope  3.756703
7       ca  1.686170
```

3. Logistic Regression:

a. Build a simple logistic regression model:

- i. Divide the dataset in 70:30 ratio
- ii. Build the model on train set and predict the values on test set
- iii. Build the confusion matrix and get the accuracy score

In [231…

```
X = df.drop('target', axis=1)
y = df['target']
```

In [232…

```
# i. Divide the dataset in 70:30 ratio
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=0)
```

In [233…

```
# ii. Build the model on train set and predict the values on test set
LR = LogisticRegression()
LR.fit(X_train, y_train)
```

Out[233…

```
▾ LogisticRegression
LogisticRegression()
```

In [234…

```
y_pred_lr = LR.predict(X_test)
```

In [235…

```
# iii. Build the confusion matrix and get the accuracy score
print('Confusion Matrix:\n',confusion_matrix(y_test, y_pred_lr))
print('Accuracy Score ', accuracy_score(y_test, y_pred_lr))
```

```
Confusion Matrix:
 [[30 14]
 [ 7 40]]
Accuracy Score  0.7692307692307693
```

5. Random Forest:

a. Build a Random Forest model:

- i. Divide the dataset in 70:30 ratio
- ii. Build the model on train set and predict the values on test set
- iii. Build the confusion matrix and calculate the accuracy
- iv. Visualize the model using the Graphviz package

In [236…

```
# i. Divide the dataset in 70:30 ratio
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=0)
```

In [237…

```
# ii. Build the model on train set and predict the values on test set
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
```

Out[237…

```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [238…

```
y_pred_rf = rf.predict(X_test)
```

In [239…

```
# iii. Build the confusion matrix and calculate the accuracy
print('Confusion Matrix:\n',confusion_matrix(y_test, y_pred_rf))
print('Accuracy Score ', accuracy_score(y_test, y_pred_rf))
```

```
Confusion Matrix:
 [[31 13]
 [ 6 41]]
Accuracy Score  0.7912087912087912
```

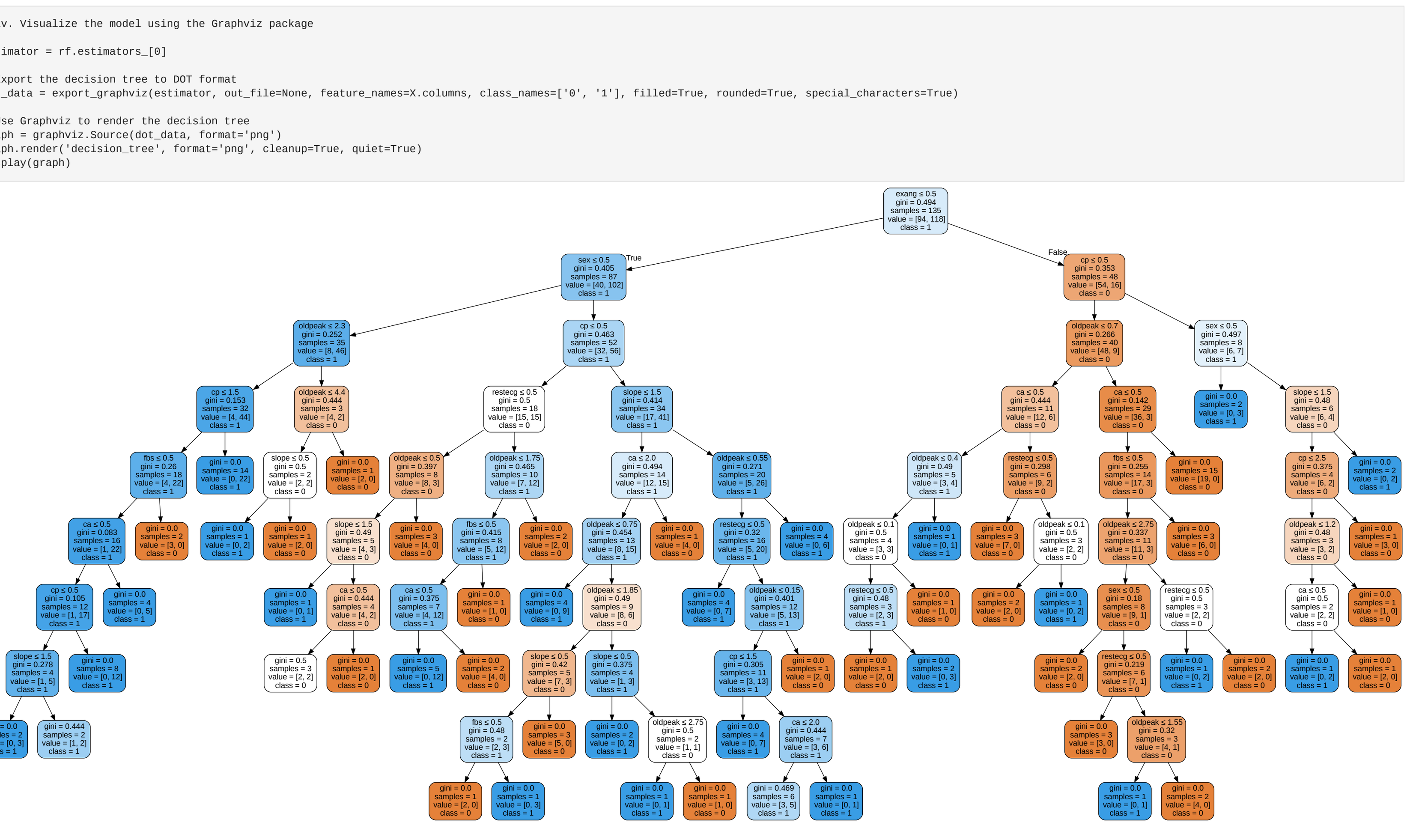
In [250…

```
# iv. Visualize the model using the Graphviz package

estimator = rf.estimators_[0]

# Export the decision tree to DOT format
dot_data = export_graphviz(estimator, out_file=None, feature_names=X.columns, class_names=['0', '1'], filled=True, rounded=True, special_characters=True)

# Use Graphviz to render the decision tree
graph = graphviz.Source(dot_data, format='png')
graph.render('decision_tree', format='png', cleanup=True, quiet=True)
display(graph)
```



6. Select the best model

- a. Print the confusion matrix of all classifiers
- b. Print the classification report of all classifiers
- c. Calculate Recall Precision and F1 score of all the models
- d. Visualize confusion matrix using heatmaps
- e. Select the best model based on the best accuracies

In [241…

```
# a. Print the confusion matrix of all classifiers
print('Confusion Matrix of Logistic Regression:\n',confusion_matrix(y_test, y_pred_lr))
print('Confusion Matrix of Random Forest:\n',confusion_matrix(y_test, y_pred_rf))
```

```
Confusion Matrix of Logistic Regression:
 [[30 14]
 [ 7 40]]
Confusion Matrix of Random Forest:
 [[31 13]
 [ 6 41]]
```

In [242…

```
# b. Print the classification report of all classifiers
print('Classification Report of Logistic Regression:\n', classification_report(y_test, y_pred_lr))
print('Classification Report of Random Forest:\n', classification_report(y_test, y_pred_rf))
```

```
Classification Report of Logistic Regression:
               precision    recall  f1-score   support

           0       0.81      0.68      0.74        44
           1       0.74      0.85      0.79        47

    accuracy                           0.77        91
   macro avg       0.78      0.77      0.77        91
weighted avg       0.77      0.77      0.77        91

Classification Report of Random Forest:
               precision    recall  f1-score   support

           0       0.84      0.70      0.77        44
           1       0.76      0.87      0.81        47

    accuracy                           0.79        91
   macro avg       0.80      0.79      0.79        91
weighted avg       0.80      0.79      0.79        91
```

In [243…

```
# c. Calculate Recall Precision and F1 score of all the models
print('Recall Score of Logistic Regression:', recall_score(y_test, y_pred_lr))
print('F1 Score of Logistic Regression:', f1_score(y_test, y_pred_lr))
print()
print('Recall Score of Random Forest:', recall_score(y_test, y_pred_rf))
print('F1 Score of Random Forest:', f1_score(y_test, y_pred_rf))
```

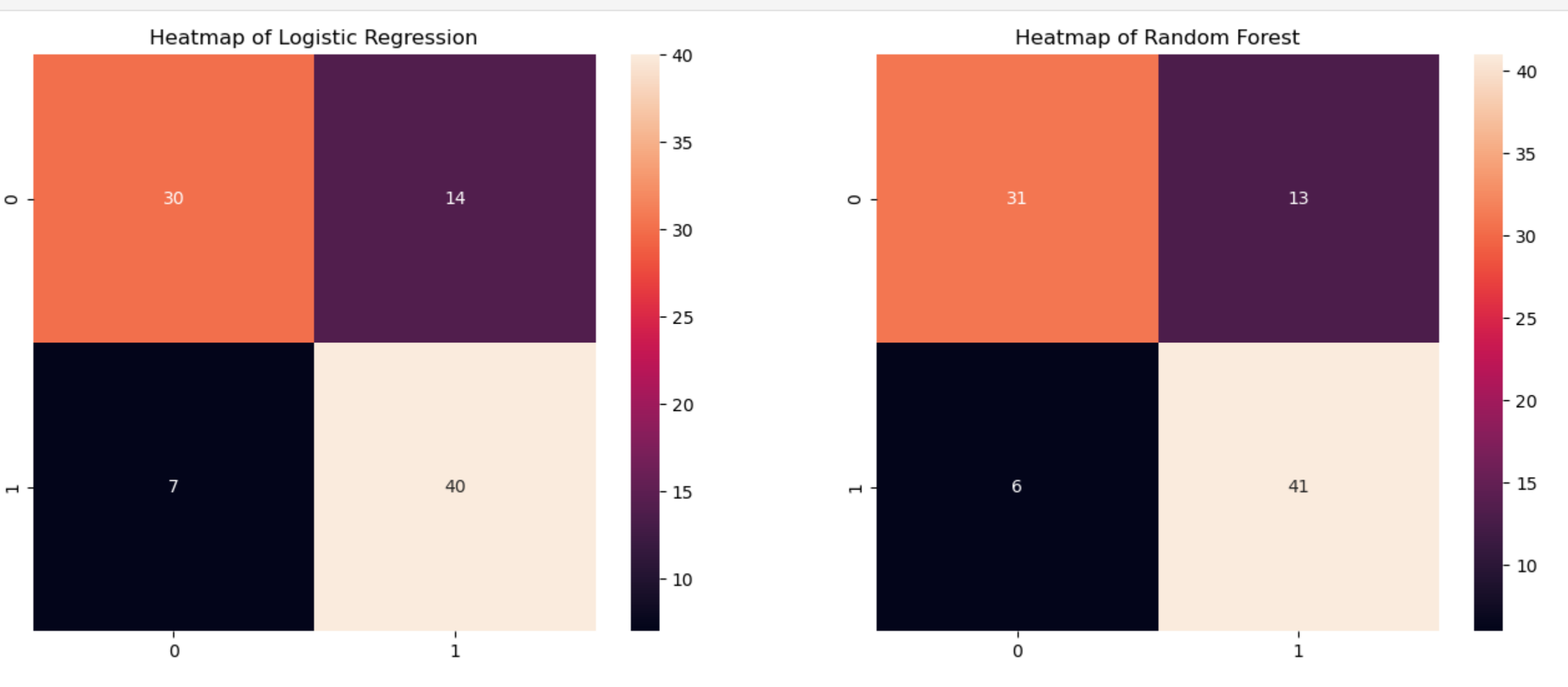
```
Recall Score of Logistic Regression: 0.851063829787234
F1 Score of Logistic Regression: 0.7920792079207921

Recall Score of Random Forest: 0.8723404255319149
F1 Score of Random Forest: 0.8118811881188118
```

In [244…

```
# d. Visualize confusion matrix using heatmaps
plt.figure(figsize=(16,6))
plt.subplot(1,2,1)
sns.heatmap(confusion_matrix(y_test, y_pred_lr), annot=True)
plt.title("Heatmap of Logistic Regression")

plt.subplot(1,2,2)
sns.heatmap(confusion_matrix(y_test, y_pred_rf), annot=True)
plt.title("Heatmap of Random Forest")
plt.show()
```



In [245…

```
# e. Select the best model based on the best accuracies
print('Accuracy Score of Logistic Regression:', accuracy_score(y_test, y_pred_lr))
print('Accuracy Score of Random Forest:', accuracy_score(y_test, y_pred_rf))
```

```
Accuracy Score of Logistic Regression: 0.7692307692307693
Accuracy Score of Random Forest: 0.7912087912087912
```

Conclusion

Random Forest is slightly more accurate than Logistic Regression

In [ ]: