ASSIGNMENT - 4

Logistic regression, Decision tree and random forest classifiers on Employee Attrition dataset

Data Preprocessing.

```
#Importing necessary libraries.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
#Importing the dataset.
df=pd.read_csv("Employee-Attrition.csv")
```

```
df.head()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeI
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	

5 rows × 35 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
```

```
Data columns (total 35 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Age                       1470 non-null   int64
 1   Attrition                 1470 non-null   object
 2   BusinessTravel            1470 non-null   object
 3   DailyRate                 1470 non-null   int64
 4   Department                1470 non-null   object
 5   DistanceFromHome          1470 non-null   int64
 6   Education                 1470 non-null   int64
 7   EducationField            1470 non-null   object
 8   EmployeeCount             1470 non-null   int64
 9   EmployeeNumber            1470 non-null   int64
 10  EnvironmentSatisfaction   1470 non-null   int64
 11  Gender                    1470 non-null   object
 12  HourlyRate                1470 non-null   int64
 13  JobInvolvement            1470 non-null   int64
 14  JobLevel                  1470 non-null   int64
 15  JobRole                   1470 non-null   object
 16  JobSatisfaction           1470 non-null   int64
 17  MaritalStatus             1470 non-null   object
 18  MonthlyIncome             1470 non-null   int64
 19  MonthlyRate               1470 non-null   int64
 20  NumCompaniesWorked        1470 non-null   int64
 21  Over18                    1470 non-null   object
 22  OverTime                  1470 non-null   object
 23  PercentSalaryHike         1470 non-null   int64
 24  PerformanceRating         1470 non-null   int64
 25  RelationshipSatisfaction  1470 non-null   int64
 26  StandardHours             1470 non-null   int64
 27  StockOptionLevel          1470 non-null   int64
 28  TotalWorkingYears         1470 non-null   int64
 29  TrainingTimesLastYear     1470 non-null   int64
 30  WorkLifeBalance           1470 non-null   int64
 31  YearsAtCompany            1470 non-null   int64
 32  YearsInCurrentRole        1470 non-null   int64
 33  YearsSinceLastPromotion   1470 non-null   int64
 34  YearsWithCurrManager      1470 non-null   int64
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
```

```
#Checking for Null Values.
df.isnull().any()
```

```
Age                         False
Attrition                   False
BusinessTravel              False
DailyRate                   False
Department                  False
```

```
DistanceFromHome           False
Education                  False
EducationField             False
EmployeeCount              False
EmployeeNumber             False
EnvironmentSatisfaction    False
Gender                     False
HourlyRate                 False
JobInvolvement             False
JobLevel                   False
JobRole                    False
JobSatisfaction            False
MaritalStatus              False
MonthlyIncome              False
MonthlyRate                False
NumCompaniesWorked         False
Over18                     False
OverTime                   False
PercentSalaryHike          False
PerformanceRating          False
RelationshipSatisfaction   False
StandardHours              False
StockOptionLevel           False
TotalWorkingYears          False
TrainingTimesLastYear      False
WorkLifeBalance            False
YearsAtCompany             False
YearsInCurrentRole         False
YearsSinceLastPromotion    False
YearsWithCurrManager       False
dtype: bool
```

```
df.isnull().sum()
```

```
Age                        0
Attrition                  0
BusinessTravel             0
DailyRate                  0
Department                 0
DistanceFromHome           0
Education                  0
EducationField             0
EmployeeCount              0
EmployeeNumber             0
EnvironmentSatisfaction    0
Gender                     0
HourlyRate                 0
JobInvolvement             0
JobLevel                   0
```

```
JobRole                   0
JobSatisfaction           0
MaritalStatus             0
MonthlyIncome             0
MonthlyRate               0
NumCompaniesWorked        0
Over18                    0
OverTime                  0
PercentSalaryHike         0
PerformanceRating         0
RelationshipSatisfaction  0
StandardHours             0
StockOptionLevel          0
TotalWorkingYears         0
TrainingTimesLastYear     0
WorkLifeBalance           0
YearsAtCompany            0
YearsInCurrentRole        0
YearsSinceLastPromotion   0
YearsWithCurrManager      0
dtype: int64
```

```
#Data Visualization.
sns.distplot(df["Age"])
```

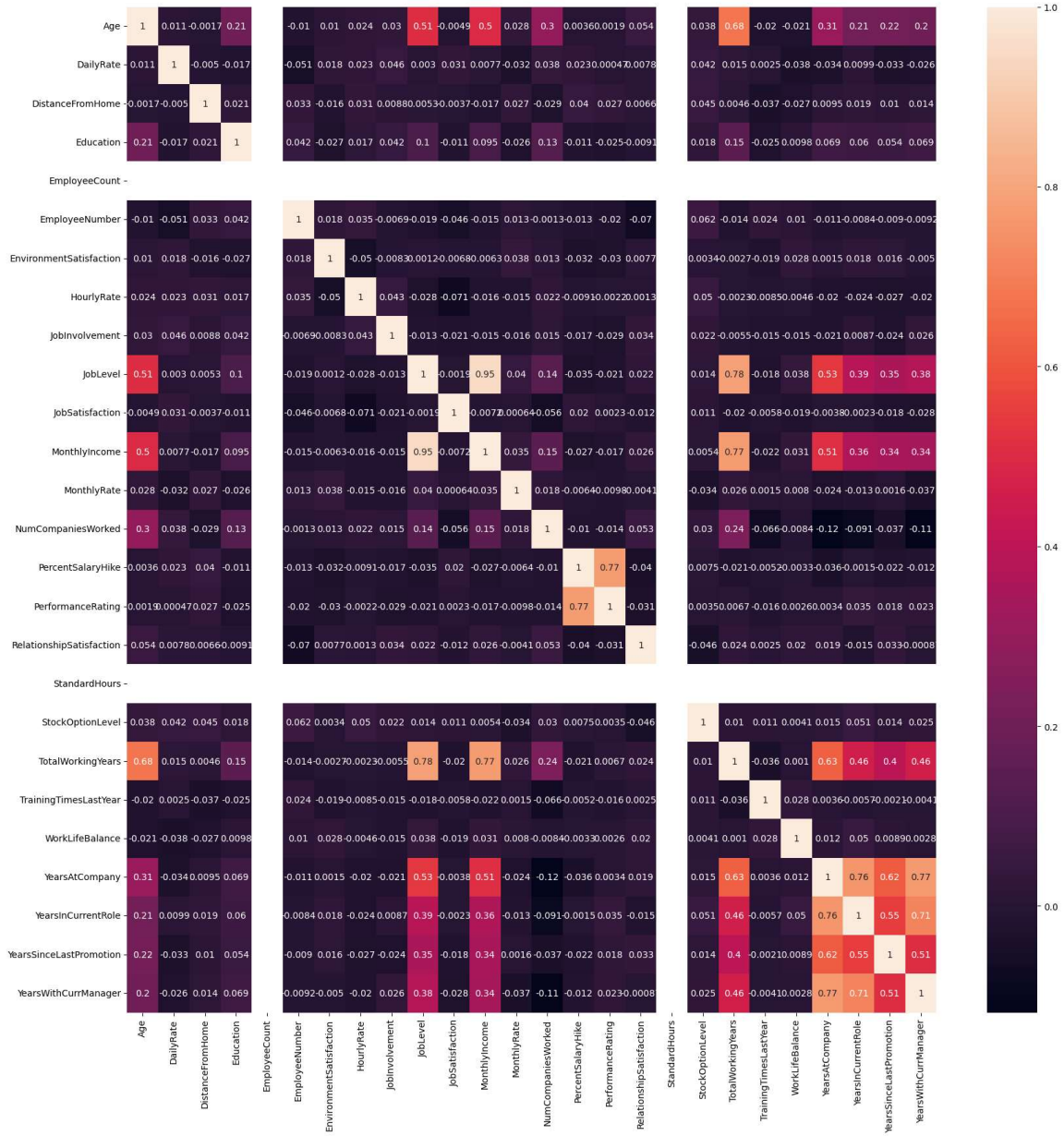
```
<ipython-input-9-25fc8198007f>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df["Age"])
<Axes: xlabel='Age', ylabel='Density'>
```

```
attrition_count = pd.DataFrame(df['Attrition'].value_counts())
plt.pie(attrition_count['Attrition'], labels = ['No', 'Yes'], explode = (0.2,0))
```

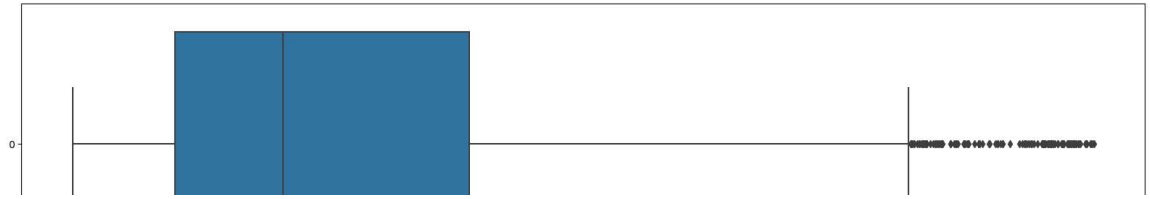
```
([<matplotlib.patches.Wedge at 0x7e32463492d0>,
  <matplotlib.patches.Wedge at 0x7e32463491e0>],
 [Text(-1.136781068348268, 0.6306574368426737, 'No'),
  Text(0.961891673217765, -0.5336332157899548, 'Yes')])
```


```
plt.figure(figsize=[20,20])
sns.heatmap(df.corr(),annot=True)
```

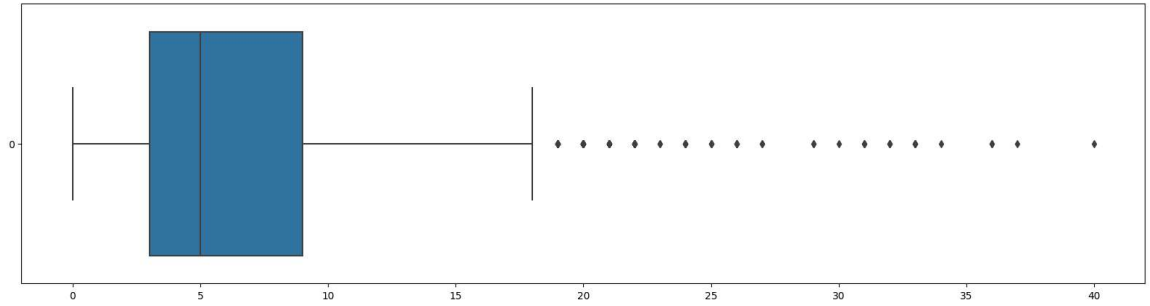
```
<ipython-input-11-23b86f049ad3>:2: FutureWarning: The default value of numeric_only in DataF
  sns.heatmap(df.corr(),annot=True)
<Axes: >
```



```
#Outlier detection
plt.figure(figsize=[20,5])
sns.boxplot(df['MonthlyIncome'],orient='h')
plt.show()
```



```
plt.figure(figsize=[20,5])
sns.boxplot(df['YearsAtCompany'],orient='h')
plt.show()
```




```
# Label Encoding
categories = ['BusinessTravel','Department','Education','EducationField','Gender','MaritalStatus','OverTime',
              'EnvironmentSatisfaction','JobInvolvement','JobLevel','JobRole','JobSatisfaction','NumCompaniesWorked',
              'PerformanceRating','RelationshipSatisfaction','StockOptionLevel','TrainingTimesLastYear','WorkLifeBalance']
categorical = df[categories].astype('object')
categorical = pd.get_dummies(df[categories], drop_first = True)


# Splitting Dependent and Independent variables
independent = ['Attrition','Over18','EmployeeCount','StandardHours','EmployeeNumber']
continuous = df.drop(columns= categories)
continuous = continuous.drop(columns= independent)


# X - Features, Y- Target variables
X = pd.concat([categorical,continuous],axis=1)
```

```
Y = df['Attrition'].replace({'Yes': 1, 'No': 0}).values.reshape(-1,1)


# Feature scaling
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

continuous_variables = list(continuous.columns)

X = X.reset_index()
del X['index']
X[continuous_variables] = pd.DataFrame(scaler.fit_transform(X[continuous_variables]), columns = continuous_variables)


#Splitting Data into Train and Test.
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(X,Y,test_size=0.2,random_state=0)


x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

```
((1176, 44), (294, 44), (1176, 1), (294, 1))
```

Logistic Regression model

```
#Importing necessary libraries
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score,precision_score, recall_score, f1_score,confusion_matrix,classification_report,roc_auc_score,roc_curve


#Initializing the model
lr = LogisticRegression()


#Training the model
lr.fit(x_train,y_train)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:1143: DataConversionWarn
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWa
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
```

```
#Testing the model
y_pred = lr.predict(x_test)
```

```
LogisticRegression
```

```
# Evaluation of model
# Accuracy score
print("Accuracy of Logistic regression model:",accuracy_score(y_test,y_pred))
```

```
Accuracy of Logistic regression model: 0.8843537414965986
```

```
# Precision score
precision_yes = precision_score(y_test, y_pred, pos_label=1)
print("Precision (Yes): " + str(round(precision_yes, 2)))
precision_no = precision_score(y_test, y_pred, pos_label=0)
print("Precision (No): " + str(round(precision_no, 2)))
```

```
Precision (Yes): 0.76
Precision (No): 0.9
```

```
# Recall score
recall_yes = recall_score(y_test, y_pred, pos_label=1)
print("Recall (Yes): " + str(round(recall_yes, 2)))
recall_no = recall_score(y_test, y_pred, pos_label=0)
print("Recall (No): " + str(round(recall_no, 2)))
```

```
Recall (Yes): 0.45
Recall (No): 0.97
```

```
# F1 score
f1_score_yes = f1_score(y_test, y_pred, pos_label=1)
print("F1 Score (Yes): " + str(round(f1_score_yes, 2)))
f1_score_no = f1_score(y_test, y_pred, pos_label=0)
print("F1 Score (No): " + str(round(f1_score_no, 2)))
```

```
F1 Score (Yes): 0.56
F1 Score (No): 0.93
```

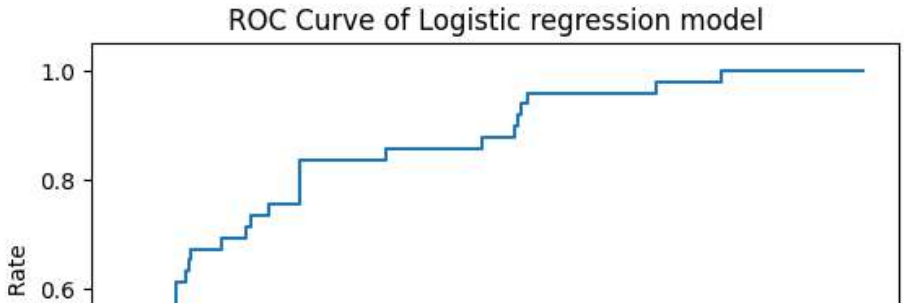
```
# Confusion matrix
print("Confusion matrix:\n\n",confusion_matrix(y_test,y_pred))
```

```
Confusion matrix:

 [[238   7]
 [ 27  22]]
```

```
# Classification Report
print("Classification report of Logistic Regression model:\n\n",classification_report(y_test,y_pred))
```

```
Classification report of Logistic Regression model:

                precision    recall  f1-score   support

           0       0.90      0.97      0.93       245
           1       0.76      0.45      0.56        49

    accuracy                           0.88       294
   macro avg       0.83      0.71      0.75       294
weighted avg       0.87      0.88      0.87       294
```

```
# ROC curve
probability = lr.predict_proba(x_test)[:,1]
fpr,tpr,threshsholds = roc_curve(y_test,probability)
plt.plot(fpr,tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve of Logistic regression model')
plt.show()
```



Decision Tree Classifier

```
# Importing necesary packages
from sklearn.tree import DecisionTreeClassifier
```

```
# Initializing the model
dtc = DecisionTreeClassifier(random_state=30)
```

```
# Training the model
dtc.fit(x_train, y_train)
```

```
DecisionTreeClassifier(random_state=30)
```

```
# Testing the model
y_pred1 = dtc.predict(x_test)
```

```
# Evaluation metrics
# Accuracy score
accuracy = accuracy_score(y_test, y_pred1)
print("Accuracy of Decision tree model: ",accuracy)
```

```
Accuracy of Decision tree model:  0.7517006802721088
```

```
# Precision score
precision_yes = precision_score(y_test, y_pred1, pos_label=1)
print("Precision (Yes): " , str(round(precision_yes,2)))
precision_no = precision_score(y_test, y_pred1, pos_label=0)
print("Precision (No): " + str(round(precision_no, 2)))
```

```
Precision (Yes):  0.27
Precision (No): 0.86
```

```
# Recall score
recall_yes = recall_score(y_test, y_pred1, pos_label=1)
print("Recall (Yes): " + str(round(recall_yes, 2)))
recall_no = recall_score(y_test, y_pred1, pos_label=0)
print("Recall (No): " + str(round(recall_no, 2)))
```

```
Recall (Yes): 0.29
Recall (No): 0.84
```

```
# F1 score
f1_score_yes = f1_score(y_test, y_pred1, pos_label=1)
print("F1 Score (Yes): " + str(round(f1_score_yes, 2)))
f1_score_no = f1_score(y_test, y_pred1, pos_label=0)
print("F1 Score (No): " + str(round(f1_score_no, 2)))
```

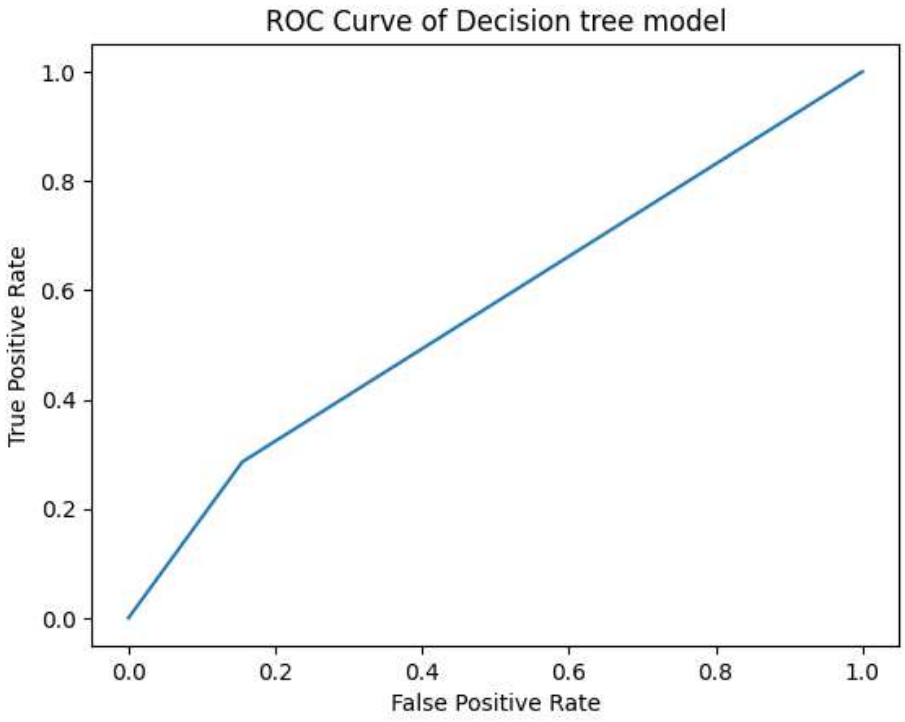
```
F1 Score (Yes): 0.28
F1 Score (No): 0.85
```

```
# Classification report
print("Classification report of Decision tree model:\n\n",classification_report(y_test,y_pred1))
```

```
Classification report of Decision tree model:

                precision    recall  f1-score   support

           0       0.86      0.84      0.85       245
           1       0.27      0.29      0.28        49

    accuracy                           0.75       294
   macro avg       0.56      0.57      0.56       294
weighted avg       0.76      0.75      0.75       294
```

```
# ROC curve
probability = dtc.predict_proba(x_test)[:,1]
fpr,tpr,threshsholds = roc_curve(y_test,probability)
```

```
plt.plot(fpr,tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve of Decision tree model')
plt.show()
```



Random Forest Classifier

```
# Importing necessary packages
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score


# Initializing the model
rf = RandomForestClassifier(n_estimators=10, criterion='entropy', random_state=30)


# Training the model
rf.fit(x_train, y_train)
```

```
<ipython-input-43-c45868107741>:2: DataConversionWarning: A column-vector y was passed when
  rf.fit(x_train, y_train)
```

```
RandomForestClassifier(criterion='entropy', n_estimators=10, random_state=30)
```

```
rf.score(x_train, y_train)
```

```
0.983843537414966
```

```
# Testing the model
y_pred2 = rf.predict(x_test)
```

```
# Evaluation metrics
# Accuracy score
accuracy = accuracy_score(y_test, y_pred2)
print("Accuracy of Random forest model: ",accuracy)
```

```
Accuracy of Random forest model:  0.8435374149659864
```

```
# Precision score
precision_yes = precision_score(y_test, y_pred2, pos_label=1)
print("Precision (Yes): " , str(round(precision_yes,2)))
precision_no = precision_score(y_test, y_pred2, pos_label=0)
print("Precision (No): " + str(round(precision_no, 2)))
```

```
Precision (Yes):  0.71
Precision (No): 0.85
```

```
# Recall score
recall_yes = recall_score(y_test, y_pred2, pos_label=1)
print("Recall (Yes): " + str(round(recall_yes, 2)))
recall_no = recall_score(y_test, y_pred2, pos_label=0)
print("Recall (No): " + str(round(recall_no, 2)))
```

```
Recall (Yes): 0.1
Recall (No): 0.99
```

```
# F1 score
f1_score_yes = f1_score(y_test, y_pred2, pos_label=1)
print("F1 Score (Yes): " + str(round(f1_score_yes, 2)))
```

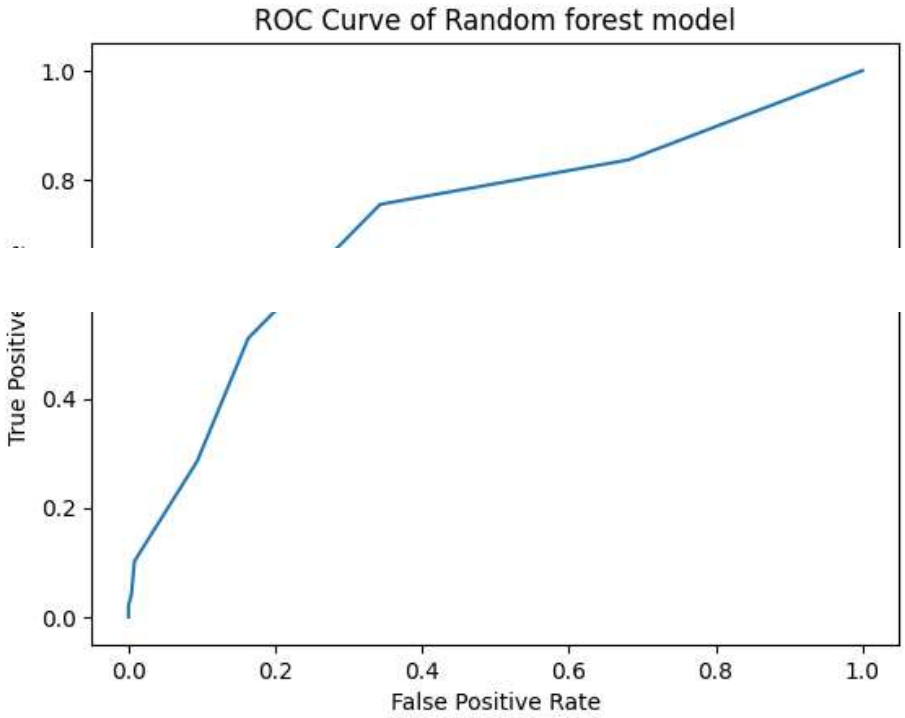
```
f1_score_no = f1_score(y_test, y_pred2, pos_label=0)
print("F1 Score (No): " + str(round(f1_score_no, 2)))
```

```
F1 Score (Yes): 0.18
F1 Score (No): 0.91
```

```
# Classification Report
print("Classification report of Random Forest model:\n\n",classification_report(y_test,y_pred2))
```

```
Classification report of Random Forest model:

                precision    recall  f1-score   support

            0       0.85      0.99      0.91       245
            1       0.71      0.10      0.18        49

     accuracy                           0.84       294
    macro avg       0.78      0.55      0.55       294
 weighted avg       0.82      0.84      0.79       294
```

```
# ROC curve
probability = rf.predict_proba(x_test)[:,1]
fpr,tpr,threshsholds = roc_curve(y_test,probability)
plt.plot(fpr,tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve of Random forest model')
plt.show()
```


ROC Curve of Random forest model
True Positive
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0