NAME – AMAR DEEP SINGH

REG NUMBER – 21BCT0051

** Data Preprocesing **

#Import the 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.csv")

df.head()

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Educati
0	41	Yes	Travel_Rarely	1102	Sales	1	
1	49	No	Travel_Frequently	279	Research & Development	8	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	
4	27	No	Travel_Rarely	591	Research & Development	2	

5 rows × 35 columns

df.shape

(1470, 35)

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

df.describe()

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470.000000	1470.000000	1470.000000
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024.865306	2.721769	65.891156
std	9.135373	403.509100	8.106864	1.024165	0.0	602.024335	1.093082	20.329428
min	18.000000	102.000000	1.000000	1.000000	1.0	1.000000	1.000000	30.000000
25%	30.000000	465.000000	2.000000	2.000000	1.0	491.250000	2.000000	48.000000
50%	36.000000	802.000000	7.000000	3.000000	1.0	1020.500000	3.000000	66.000000
75%	43.000000	1157.000000	14.000000	4.000000	1.0	1555.750000	4.000000	83.750000
max	60.000000	1499.000000	29.000000	5.000000	1.0	2068.000000	4.000000	100.000000

8 rows × 26 columns

#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
```

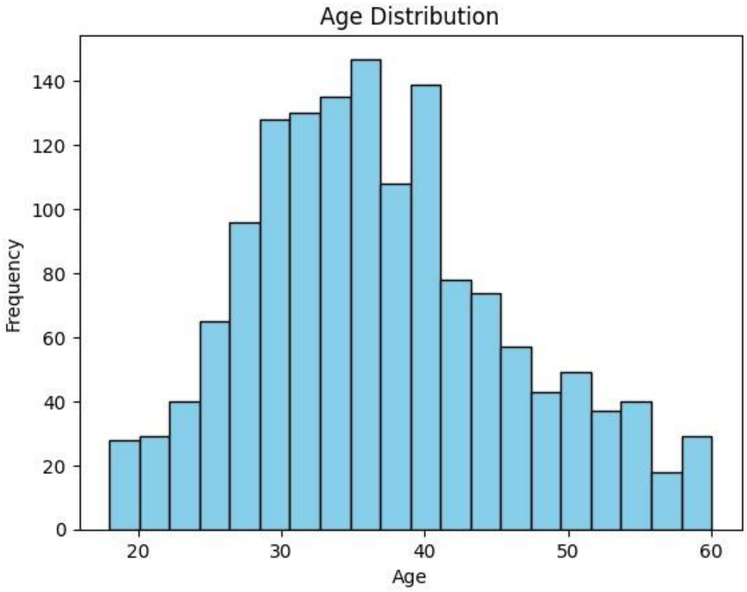
df.isnull().sum()

```
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
```

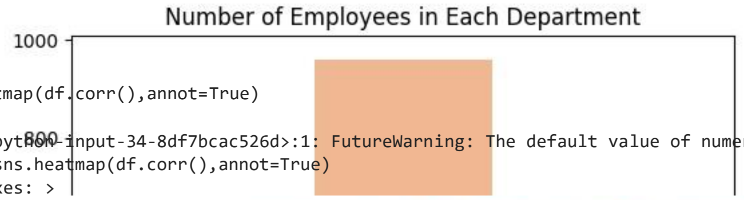
```
JobRole                     0
JobSatisfaction             0
MaritalStatus               0
MonthlyIncome               0
MonthlyRate                 0
NumCompaniesWorked          0
Over18                      0
OverTime                    0
PercentSalaryHike           0
PerformanceRating         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

DATA VISUALISATION

```
#histogram of Age plt.hist(df['Age'], bins=20, color='skyblue', edgecolor='black')
plt.xlabel('Age') plt.ylabel('Frequency') plt.title('Age Distribution') plt.show()
```

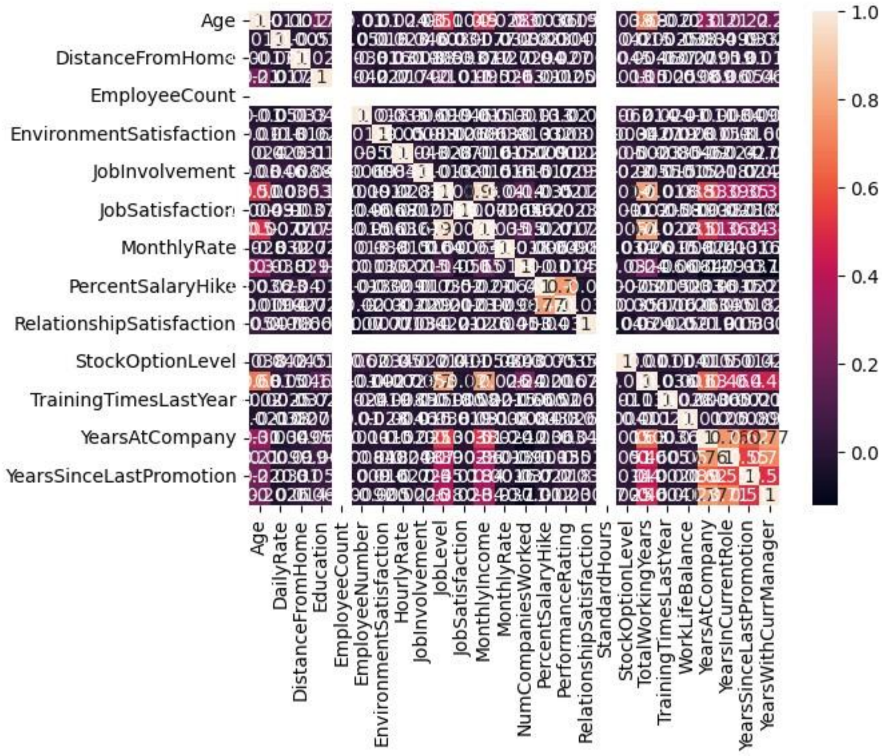



```
# countplot
sns.countplot(x='Department', data=df, palette='pastel')
plt.xlabel('Department') plt.ylabel('Count')
plt.title('Number of Employees in Each Department') plt.show()
```




```
sns.heatmap(df.corr(),annot=True)
```

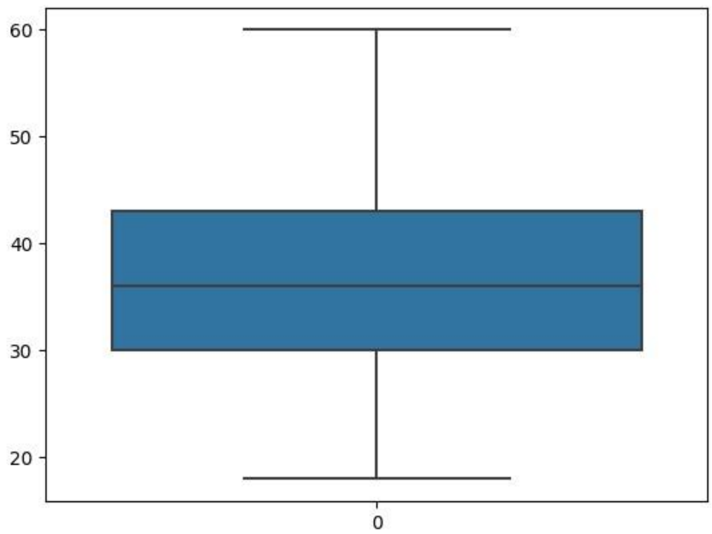
```
<ipython-input-34-8df7bcac526d>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future ve
  sns.heatmap(df.corr(),annot=True)
<Axes: >
```



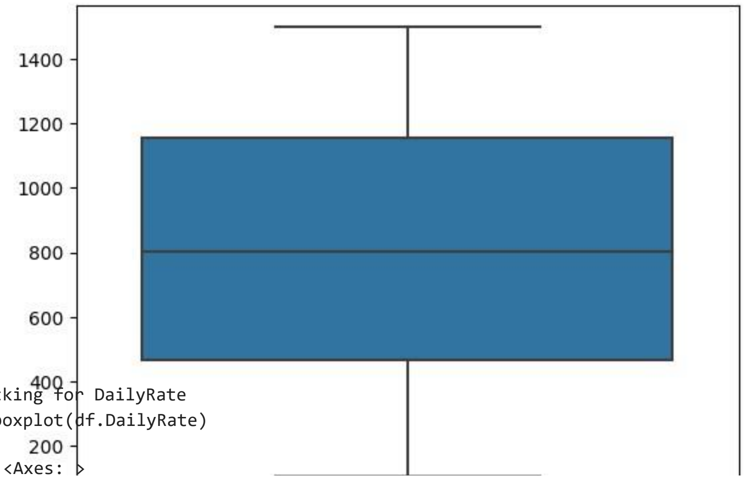
OUTLIERS **DETECTION**

#checking for age column sns.boxplot(df.Age)

<Axes: >

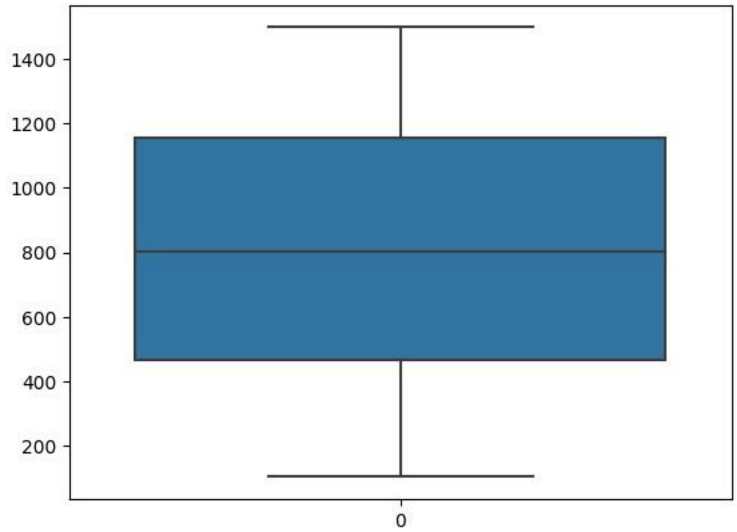


#Checking for Daily rate sns.boxplot(df.DailyRate) <Axes: >




```
#checking for DailyRate
sns.boxplot(df.DailyRate)
```

<Axes: >



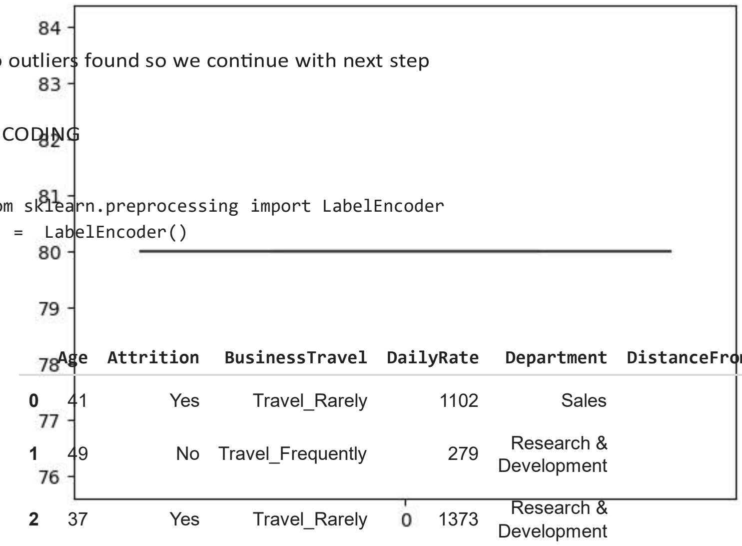

```
df.head(3)
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumb
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 rows × 35 columns

```
#checking for standardhours sns.boxplot(df.StandardHours) df.head
```

<Axes: >



No outliers found so we continue with next step

ENCODING

```
from sklearn.preprocessing import LabelEncoder
le  =  LabelEncoder()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumbe
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

```
#perfomring label encoding some satisfied columns columns = ['BusinessTravel', 'Department',
'Gender', 'Over18', 'OverTime'] df[columns]=df[columns].apply(le.fit_transform)
```

```
#performing one hot encoding on some satisfied columns one_hot_columns = ['JobRole',
'EducationField', 'MaritalStatus'] df = pd.get_dummies(df, columns=one_hot_columns,
drop_first=True)
```

```
df.head()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSat
0	41	Yes	2	1102	2	1	2	1	1	
1	49	No	1	279	1	8	1	1	2	
2	37	Yes	2	1373	1	2	2	1	4	
3	33	No	1	1392	1	3	4	1	5	
4	27	No	2	591	1	2	1	1	7	

5 rows × 47 columns

```
df.columns
```

```
Index(['Age', 'Attrition', 'BusinessTravel', 'DailyRate', 'Department',
    'DistanceFromHome', 'Education', 'EmployeeCount', 'EmployeeNumber',
    'EnvironmentSatisfaction', 'Gender', 'HourlyRate', 'JobInvolvement',
    'JobLevel', 'JobSatisfaction', 'MonthlyIncome', 'MonthlyRate',
    'NumCompaniesWorked', 'Over18', 'OverTime', 'PercentSalaryHike',
    'PerformanceRating', 'RelationshipSatisfaction', 'StandardHours',
    'StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear',
    'WorkLifeBalance', 'YearsAtCompany', 'YearsInCurrentRole',
    'YearsSinceLastPromotion', 'YearsWithCurrManager',
    'JobRole_Human Resources', 'JobRole_Laboratory Technician',
    'JobRole_Manager', 'JobRole_Manufacturing Director',
    'JobRole_Research Director', 'JobRole_Research Scientist',
    'JobRole_Sales Executive', 'JobRole_Sales Representative',
    'EducationField_Life Sciences', 'EducationField_Marketing',
    'EducationField_Medical', 'EducationField_Other',    'EducationField_Technical Degree',
'MaritalStatus_Married',
    'MaritalStatus_Single'],    dtype='object')
```

SPLITTING IN TO DEPENDENT AND INDEPENDENT

```
# Independent variables (features)
x = df[['Age', 'DailyRate', 'DistanceFromHome', 'Education', 'EmployeeCount', 'EmployeeNumber',
       'EnvironmentSatisfaction', 'HourlyRate', 'JobInvolvement', 'JobLevel', 'JobSatisfaction',
       'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorked', 'PercentSalaryHike',
       'PerformanceRating', 'RelationshipSatisfaction', 'StandardHours', 'StockOptionLevel',
       'TotalWorkingYears', 'TrainingTimesLastYear', 'WorkLifeBalance', 'YearsAtCompany',
       'YearsInCurrentRole', 'YearsSinceLastPromotion', 'YearsWithCurrManager',
       'BusinessTravel', 'Department', 'Gender', 'Over18', 'OverTime',
       'JobRole_Human Resources', 'JobRole_Laboratory Technician', 'JobRole_Manager',
       'JobRole_Manufacturing Director', 'JobRole_Research Director', 'JobRole_Research Scientist',
       'JobRole_Sales Executive', 'JobRole_Sales Representative',
       'EducationField_Life Sciences', 'EducationField_Marketing', 'EducationField_Medical',
       'EducationField_Other', 'EducationField_Technical Degree',
       'MaritalStatus_Married', 'MaritalStatus_Single']]

# Dependent variable (target) y =
df['Attrition']
```

FEATURE SACLING

```
#feature scaling from sklearn.preprocessing import
MinMaxScaler ms=MinMaxScaler()
x_scaled=pd.DataFrame(ms.fit_transform(x),columns=x.columns)
```

SPLITTING DATA INTO TRAIN AND SET

```
#TRAIN TEST AND SPLIT
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x_scaled,y,test_size =0.2,random_state =42)
```

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

((1176, 46), (294, 46), (1176,), (294,)) MODEL BUILDING

o Import the model building Libraries o

Initializing the model o Training and

testing the model o Evaluation of Model

o Save the Model

1.LOGISTIC REGRESION

2. DECISION TREE 3. RANDOM FOREST

```
#LOGISTIC REGRESSION
from sklearn.linear_model import LogisticRegression L_model=LogisticRegression()
```

```
L_model.fit(x_train,y_train)
```

▾ LogisticRegression
LogisticRegression()

```
pred_L=L_model.predict(x_test)
```

EVALUATION OF THE CLASSIFICATION MODEL

```
#Accuracy score
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report,roc_auc_score,roc_curve
```

```
accuracy_score(y_test,pred)
```

0.8877551020408163

```
confusion_matrix(y_test,pred)
```

```
array([[248,   7],
       [ 26,  13]])
```

pd.crosstab(y_test,pred)

col_0	No	Yes
Attrition		
No	248	7
Yes	26	13

DECISION TREE MODEL

from sklearn.tree import DecisionTreeClassifier dtc=DecisionTreeClassifier()

dtc.fit(x_train,y_train)

▾ DecisionTreeClassifier
DecisionTreeClassifier()

D_pred=dtc.predict(x_test)

Evaluation of classi cation model

#Accuracy score from sklearn.metrics import accuracy_score,confusion_matrix,classification_report,roc_auc_score,roc_curve

accuracy_score(y_test,D_pred)

0.7789115646258503

confusion_matrix(y_test,D_pred)

```
array([[222,  33],
       [ 32,   7]])
```

pd.crosstab(y_test,D_pred)

col_0	No	Yes
Attrition		
No	222	33
Yes	32	7

print(classification_report(y_test,D_pred)) precision recall f1-score

support

No 0.87 0.87 0.87 255 Yes 0.17 0.18 0.18
39

accuracy 0.78 294 macro avg 0.52 0.53 0.52
294 weighted avg 0.78 0.78 0.78 294

HYPER PARAMETER TUNING

```
from sklearn import tree plt.figure(figsize=(25,15))
tree.plot_tree(dtc,filled=True) from sklearn.model_selection import
GridSearchCV parameter={
 'criterion':['gini','entropy'],
  'splitter':['best','random'],
  'max_depth':[1,2,3,4,5],
  'max_features':['auto', 'sqrt', 'log2']

}
```

grid_search=GridSearchCV(estimator=dtc,param_grid=parameter,cv=5,scoring="accuracy")

grid_search.fit(x_train,y_train)

grid_search.best_params_

{'criterion': 'gini',

'max_depth': 5,
'max_features': 'sqrt', 'splitter': 'best'}

dtc_cv=DecisionTreeClassifier(criterion= 'gini', max_depth=5, max_features='sqrt', splitter='best') dtc_cv.fit(x_train,y_train)

▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=5, max_features='sqrt')

pred=dtc_cv.predict(x_test)

print(classification_report(y_test,D_pred)) precision recall f1-score

support

No 0.87 0.87 0.87 255 Yes 0.17 0.18 0.18
39

accuracy 0.78 294 macro avg 0.52 0.53 0.52
294 weighted avg 0.78 0.78 0.78 294

RANDOM FOREST

from sklearn.ensemble import RandomForestClassifier from sklearn.model_selection import train_test_split from sklearn.metrics import accuracy_score, classification_report

Initialize the Random Forest Classifier rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)

Train the classifier on the training data rf_classifier.fit(x_train, y_train)

# Predict on the test data
R_pred = rf_classifier.predict(x_test)

# Evaluate the model accuracy = accuracy_score(y_test, R_pred)
report = classification_report(y_test, R_pred)

print(f"Accuracy: {accuracy}") print("\nClassification Report:")
print(report)

Accuracy: 0.8775510204081632

Classification Report: precision recall f1-score support

No 0.88 1.00 0.93 255 Yes 0.80 0.10 0.18
39

accuracy 0.88 294 macro avg 0.84 0.55 0.56
294 weighted avg 0.87 0.88 0.83 294