Import libraries

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

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
a=pd.read_csv("/content/drive/MyDrive/DATASETS/WA_Fn-UseC_-HR-Employee-Attrition.csv")
```

```
a
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNu
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	
...	...	...	...	...	...	...	...	...	...	
1465	36	No	Travel_Frequently	884	Research & Development	23	2	Medical	1	2
1466	39	No	Travel_Rarely	613	Research & Development	6	1	Medical	1	2
1467	27	No	Travel_Rarely	155	Research & Development	4	3	Life Sciences	1	2
1468	49	No	Travel_Frequently	1023	Sales	2	3	Medical	1	2
1469	34	No	Travel_Rarely	628	Research & Development	8	3	Medical	1	2

1470 rows × 35 columns

Read the data types

```
a.dtypes
```

```
Age                        int64
Attrition                 object
BusinessTravel            object
DailyRate                  int64
Department                object
DistanceFromHome           int64
Education                  int64
EducationField            object
EmployeeCount              int64
EmployeeNumber             int64
EnvironmentSatisfaction    int64
Gender                    object
HourlyRate                 int64
JobInvolvement             int64
JobLevel                   int64
JobRole                   object
JobSatisfaction            int64
MaritalStatus             object
MonthlyIncome              int64
MonthlyRate                int64
NumCompaniesWorked         int64
Over18                    object
OverTime                  object
PercentSalaryHike          int64
PerformanceRating          int64
```

```
RelationshipSatisfaction     int64
StandardHours                int64
StockOptionLevel             int64
TotalWorkingYears            int64
TrainingTimesLastYear        int64
WorkLifeBalance              int64
YearsAtCompany               int64
YearsInCurrentRole           int64
YearsSinceLastPromotion      int64
YearsWithCurrManager         int64
dtype: object
```

Shape of the dataset

```
a.shape
```

```
(1470, 35)
```

Information about the dataset

```
a.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
```

Statistics about the dataset

```
a.describe()
```

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	J
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	
min	18.000000	102.000000	1.000000	1.000000	1.0	1.000000	1.000000	30.000000	

Null values identification

```
a.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
```

```
a.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
```

```
# there are no null values
```

Data Visualization

```
d=a.corr()
d
```

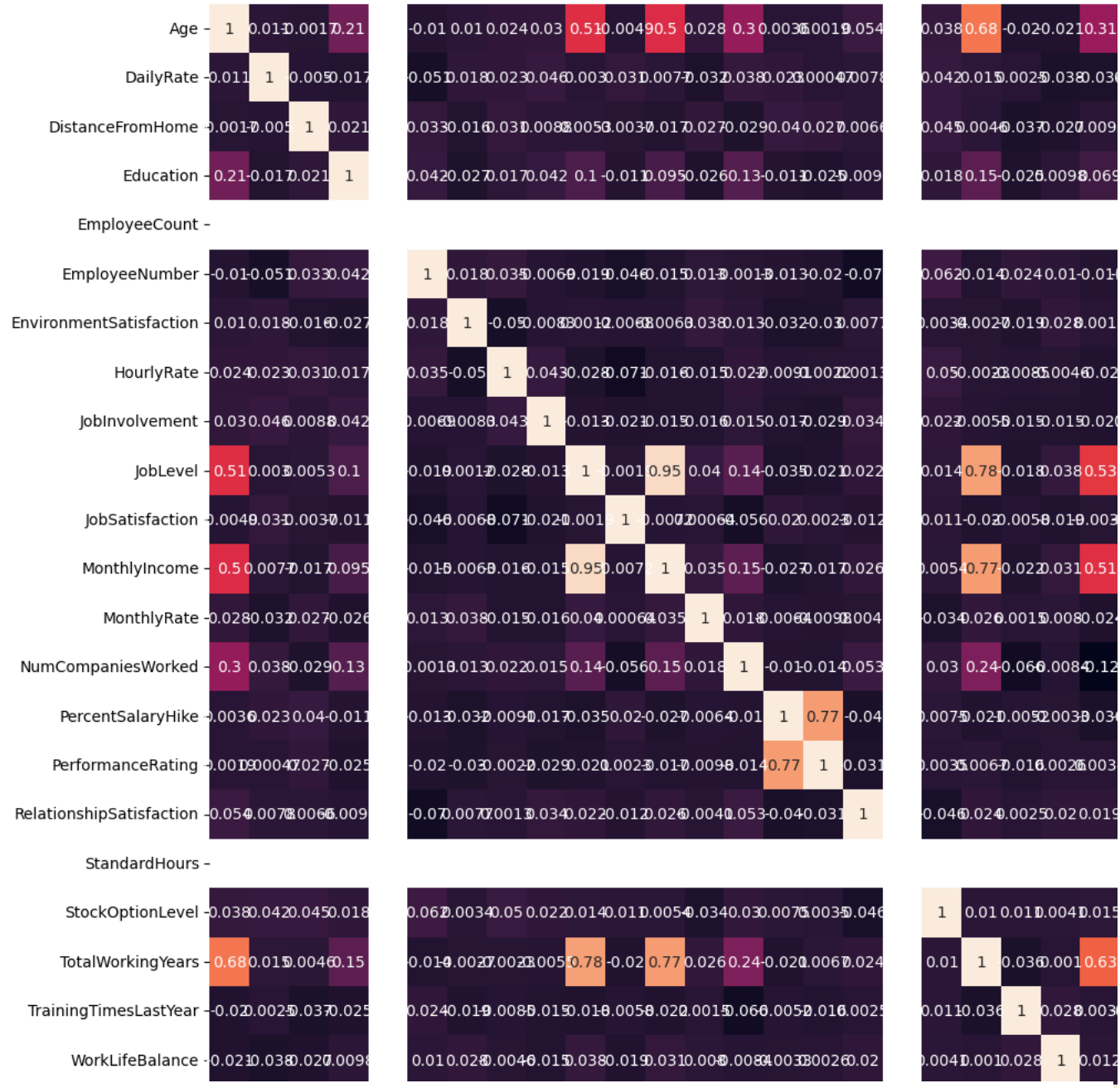
```
<ipython-input-12-385900cf86c7>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future ver
  d=a.corr()
```

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	Ho
Age	1.000000	0.010661	-0.001686	0.208034	NaN	-0.010145	0.010146	
DailyRate	0.010661	1.000000	-0.004985	-0.016806	NaN	-0.050990	0.018355	
DistanceFromHome	-0.001686	-0.004985	1.000000	0.021042	NaN	0.032916	-0.016075	
Education	0.208034	-0.016806	0.021042	1.000000	NaN	0.042070	-0.027128	
EmployeeCount	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
EmployeeNumber	-0.010145	-0.050990	0.032916	0.042070	NaN	1.000000	0.017621	
EnvironmentSatisfaction	0.010146	0.018355	-0.016075	-0.027128	NaN	0.017621	1.000000	
HourlyRate	0.024287	0.023381	0.031131	0.016775	NaN	0.035179	-0.049857	
JobInvolvement	0.029820	0.046135	0.008783	0.042438	NaN	-0.006888	-0.008278	
JobLevel	0.509604	0.002966	0.005303	0.101589	NaN	-0.018519	0.001212	
JobSatisfaction	-0.004892	0.030571	-0.003669	-0.011296	NaN	-0.046247	-0.006784	
MonthlyIncome	0.497855	0.007707	-0.017014	0.094961	NaN	-0.014829	-0.006259	
MonthlyRate	0.028051	-0.032182	0.027473	-0.026084	NaN	0.012648	0.037600	
NumCompaniesWorked	0.299635	0.038153	-0.029251	0.126317	NaN	-0.001251	0.012594	
PercentSalaryHike	0.003634	0.022704	0.040235	-0.011111	NaN	-0.012944	-0.031701	
PerformanceRating	0.001904	0.000473	0.027110	-0.024539	NaN	-0.020359	-0.029548	
RelationshipSatisfaction	0.053535	0.007846	0.006557	-0.009118	NaN	-0.069861	0.007665	
StandardHours	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
StockOptionLevel	0.037510	0.042143	0.044872	0.018422	NaN	0.062227	0.003432	
TotalWorkingYears	0.680381	0.014515	0.004628	0.148280	NaN	-0.014365	-0.002693	
TrainingTimesLastYear	-0.019621	0.002453	-0.036942	-0.025100	NaN	0.023603	-0.019359	
WorkLifeBalance	-0.021490	-0.037848	-0.026556	0.009819	NaN	0.010309	0.027627	
YearsAtCompany	0.311309	-0.034055	0.009508	0.069114	NaN	-0.011240	0.001458	
YearsInCurrentRole	0.212901	0.009932	0.018845	0.060236	NaN	-0.008416	0.018007	
YearsSinceLastPromotion	0.216513	-0.033229	0.010029	0.054254	NaN	-0.009019	0.016194	
YearsWithCurrManager	0.202089	-0.026363	0.014406	0.069065	NaN	-0.009197	-0.004999	

26 rows × 26 columns

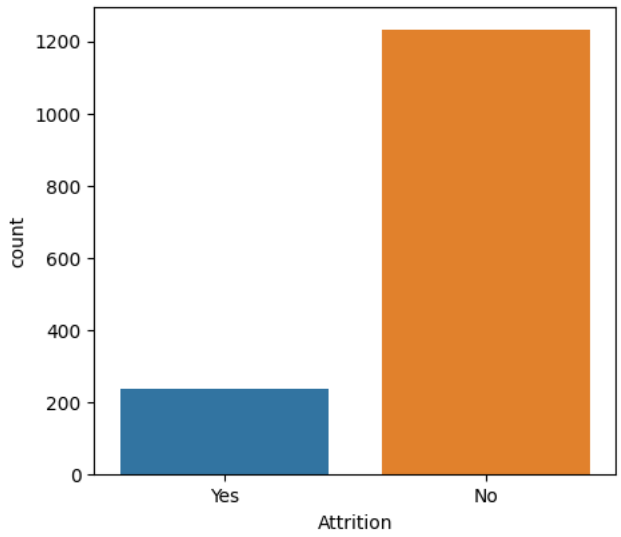
```
plt.subplots(figsize=(15,15))
sns.heatmap(d,annot=True)
```

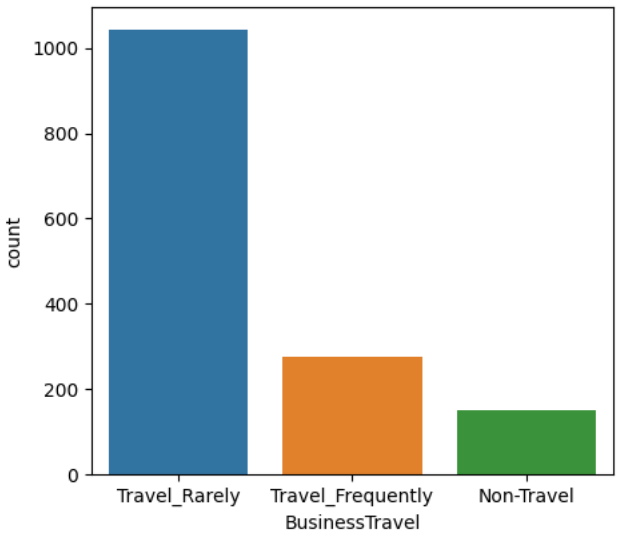
```
<Axes: >
```

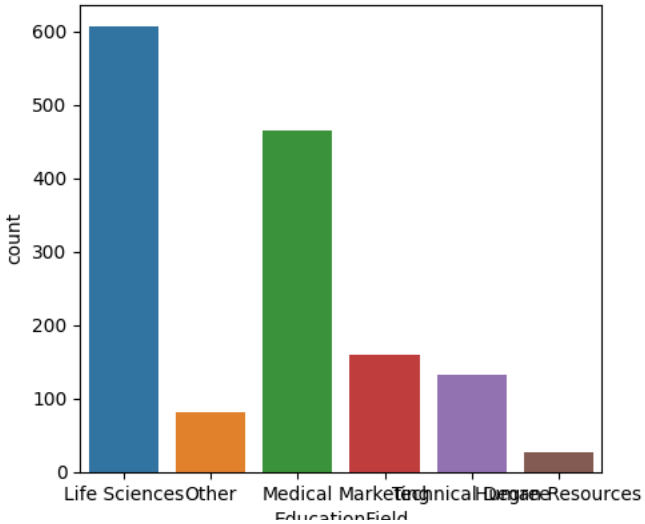


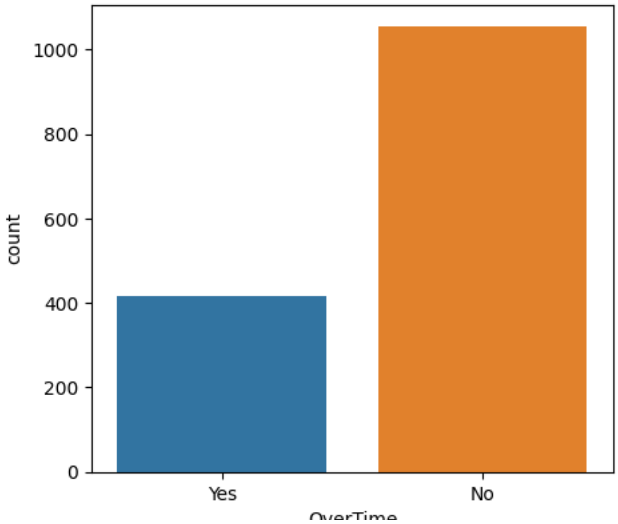

```
f = plt.figure()
f.set_figwidth(15)
f.set_figheight(12)

# Subplot 1
plt.subplot(3, 3, 1)
sns.countplot(x="Attrition", data=a)

# Subplot 2
plt.subplot(3, 3, 2)
sns.countplot(x="BusinessTravel", data=a)

# Subplot 5
plt.subplot(3, 3, 3)
sns.countplot(x="Department", data=a)

# Subplot 8
plt.subplot(3, 3, 4)
sns.countplot(x="EducationField", data=a)

# Subplot 9
plt.subplot(3, 3, 5)
sns.countplot(x="OverTime", data=a)

# Adjust layout
plt.tight_layout()
```

```
# Show the plots
plt.show()
```





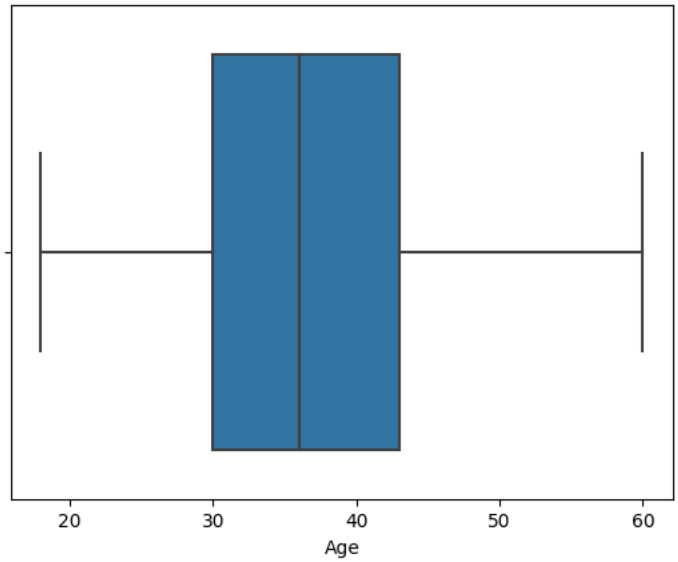




Outlier Detection

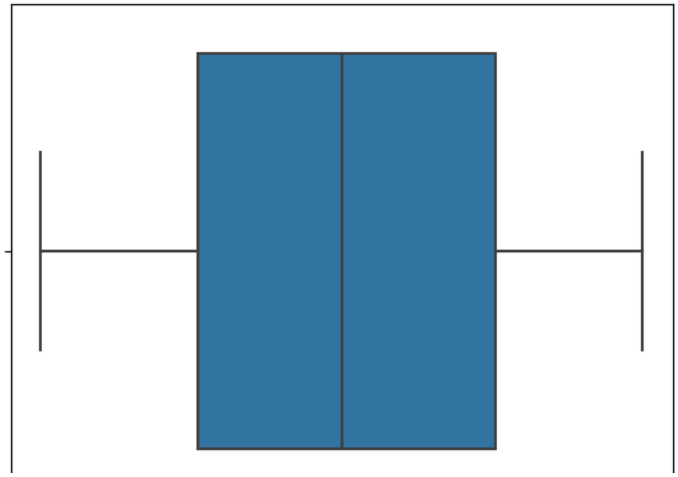
```
sns.boxplot(x="Age",data=a)
```

```
<Axes: xlabel='Age'>
```



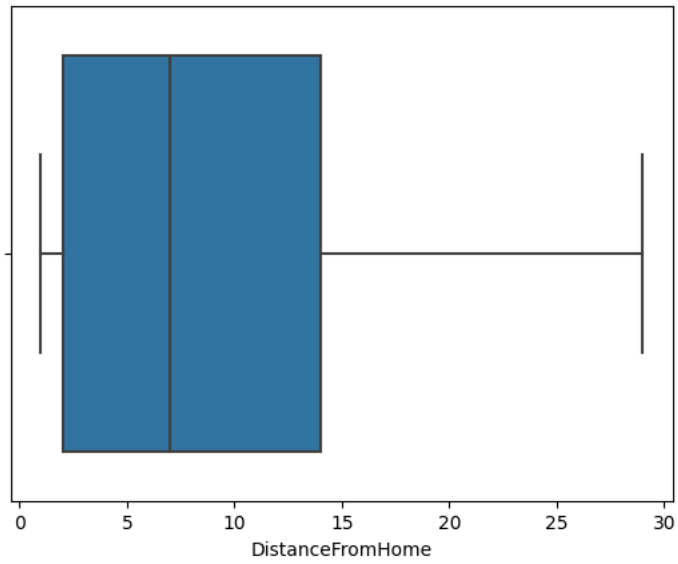

```
sns.boxplot(x="DailyRate",data=a)
```

```
<Axes: xlabel='DailyRate'>
```



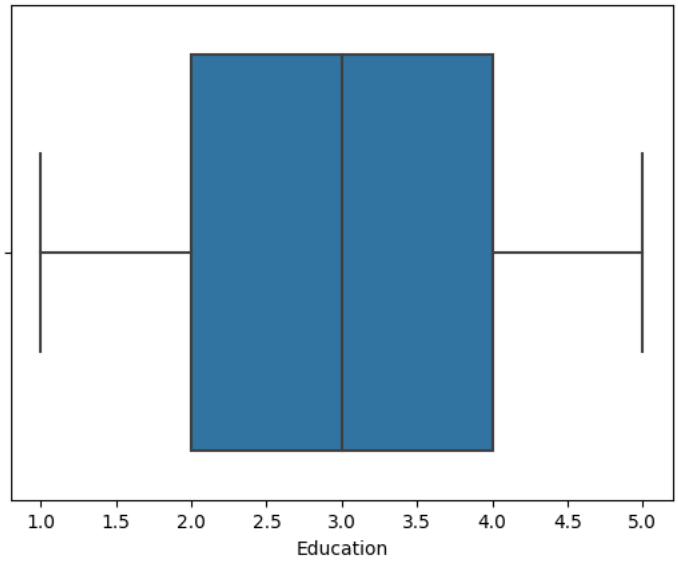
```
sns.boxplot(x="DistanceFromHome",data=a)
```

```
<Axes: xlabel='DistanceFromHome'>
```



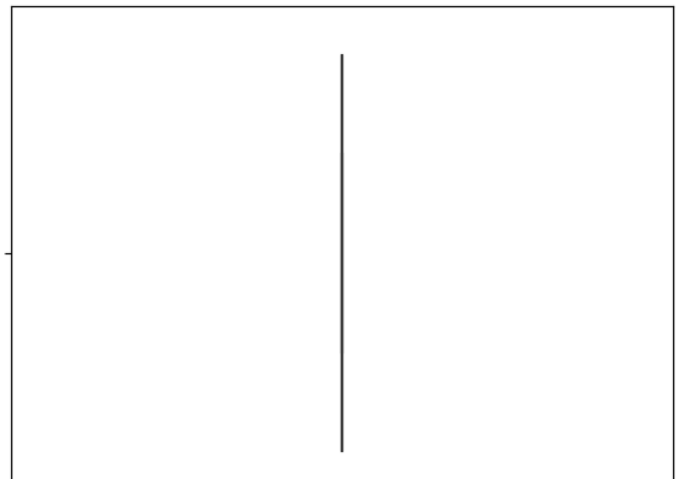

```
sns.boxplot(x="Education",data=a)
```

```
<Axes: xlabel='Education'>
```



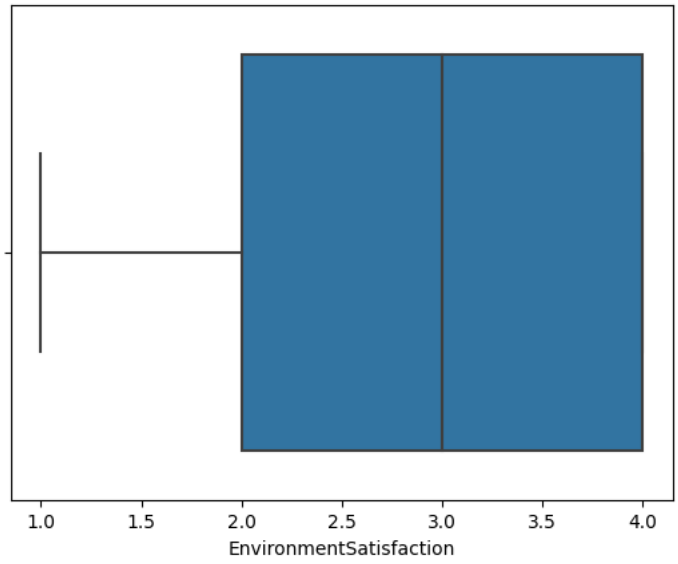

```
sns.boxplot(x="EmployeeCount",data=a)
```

```
<Axes: xlabel='EmployeeCount'>
```



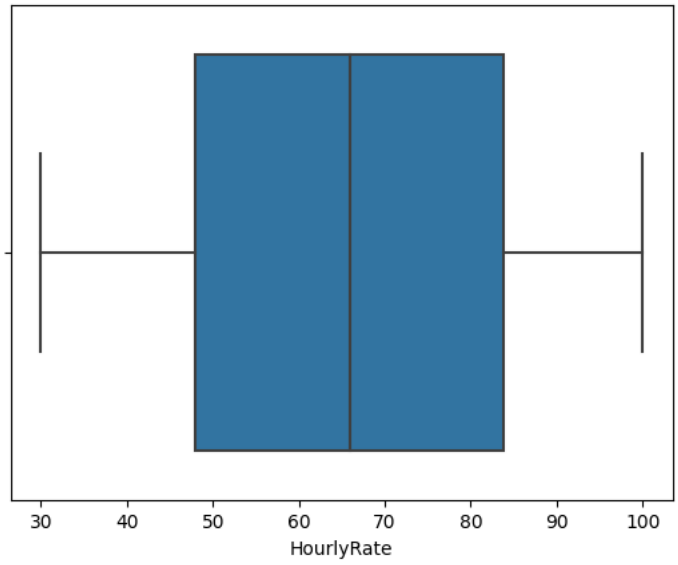
```
sns.boxplot(x="EnvironmentSatisfaction",data=a)
```

```
<Axes: xlabel='EnvironmentSatisfaction'>
```




```
sns.boxplot(x="HourlyRate",data=a)
```

```
<Axes: xlabel='HourlyRate'>
```




```
# there are no outliers , the data is clean
```

Splitting dependent and independent variables

```
x=a.drop(columns=["Attrition"],axis=1)
x.head()
```

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	Environme
0	41	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1	
1	49	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	2	
2	37	Travel_Rarely	1373	Research & Development	2	2	Other	1	4	
3	33	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	5	
4	27	Travel_Rarely	591	Research & Development	2	1	Medical	1	7	

5 rows × 34 columns

```
x.shape
```

```
(1470, 34)
```

```
y=a["Attrition"]
y.head()
```

```
0    Yes
1     No
2    Yes
3     No
4     No
Name: Attrition, dtype: object
```

```
y.shape
```

```
(1470,)
```

Encoding

```
from sklearn.preprocessing import LabelEncoder
```

```
l=LabelEncoder()
```

```
x["Gender"]=l.fit_transform(x["Gender"])
x['Gender']
```

```
0       0
1       1
2       1
3       0
4       1
       ..
1465    1
1466    1
1467    1
1468    1
1469    1
Name: Gender, Length: 1470, dtype: int64
```

```
x['Gender'].value_counts()
```

```
1    882
0    588
Name: Gender, dtype: int64
```

```
x['Gender'].nunique()
```

```
2
```

```
x.head()
```

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	Environme
0	41	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1	
1	49	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	2	
2	37	Travel_Rarely	1373	Research & Development	2	2	Other	1	4	
3	33	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	5	

```
Dept = pd.get_dummies(a, columns=["Department"])
print(Dept)
```

```
1466                       4  ...                 9                     5
1467                       2  ...                 6                     0
1468                       4  ...                17                     3
1469                       2  ...                 6                     3

      WorkLifeBalance  YearsAtCompany YearsInCurrentRole  \
0                   1               6                  4
1                   3              10                  7
2                   3               0                  0
3                   3               8                  7
4                   3               2                  2
...               ...             ...                ...
1465                3               5                  2
1466                3               7                  7
1467                3               6                  2
1468                2               9                  6
1469                4               4                  3

      YearsSinceLastPromotion YearsWithCurrManager  \
0                           0                    5
1                           1                    7
2                           0                    0
3                           3                    0
4                           2                    2
...                       ...                  ...
1465                        0                    3
1466                        1                    7
1467                        0                    3
1468                        0                    8
1469                        1                    2

      Department_Human Resources  Department_Research & Development  \
0                              0                                  0
1                              0                                  1
2                              0                                  1
3                              0                                  1
4                              0                                  1
...                          ...                                ...
1465                           0                                  1
1466                           0                                  1
1467                           0                                  1
1468                           0                                  0
1469                           0                                  1

      Department_Sales
0                    1
1                    0
2                    0
3                    0
4                    0
...                ...
1465                 0
1466                 0
1467                 0
1468                 1
1469                 0

[1470 rows x 37 columns]
```

```
print(x)
```

```
1465           2061                  3  ...                       3
1466           2062                  4  ...                       1
1467           2064                  2  ...                       2
1468           2065                  4  ...                       4
1469           2068                  2  ...                       1

      StandardHours  StockOptionLevel  TotalWorkingYears  \
0                80                 0                  8
1                80                 1                 10
2                80                 0                  7
3                80                 0                  8
4                80                 1                  6
...             ...               ...                ...
1465             80                 1                 17
1466             80                 1                  9
1467             80                 1                  6
1468             80                 0                 17
1469             80                 0                  6

     TrainingTimesLastYear  WorkLifeBalance YearsAtCompany  \
0                        0                1              6
1                        3                3             10
2                        3                3              0
3                        3                3              8
4                        3                3              2
...                    ...              ...            ...
1465                     3                3              5
1466                     5                3              7
1467                     0                3              6
1468                     3                2              9
1469                     3                4              4

      YearsInCurrentRole  YearsSinceLastPromotion  YearsWithCurrManager
0                      4                        0                     5
1                      7                        1                     7
2                      0                        0                     0
3                      7                        3                     0
4                      2                        2                     2
...                  ...                      ...                   ...
1465                   2                        0                     3
1466                   7                        1                     7
1467                   2                        0                     3
1468                   6                        0                     8
1469                   3                        1                     2

[1470 rows x 34 columns]
```

```
a.head()
```

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

5 rows × 40 columns

```
x.head()
```

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	Environme
0	41	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1	
1	49	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	2	
2	37	Travel_Rarely	1373	Research & Development	2	2	Other	1	4	
3	33	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	5	
4	27	Travel_Rarely	591	Research & Development	2	1	Medical	1	7	

5 rows × 34 columns

```
Dept=pd.get_dummies(x["Department"],drop_first=True)
Dept
```

	Research & Development	Sales
0	0	1
1	1	0
2	1	0
3	1	0
4	1	0
...	...	...
1465	1	0
1466	1	0
1467	1	0
1468	0	1
1469	1	0

1470 rows × 2 columns

```
x=pd.concat([x,Dept],axis=1)
```

```
x.head()
```

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Educatic
0	41	Travel_Rarely	1102	Sales	1	2	Life S
1	49	Travel_Frequently	279	Research & Development	8	1	Life S
2	37	Travel_Rarely	1373	Research & Development	2	2	
3	33	Travel_Frequently	1392	Research & Development	3	4	Life S
4	27	Travel_Rarely	591	Research & Development	2	1	

5 rows × 36 columns

Feature Scaling

```
from sklearn.preprocessing import StandardScaler
```

```
scaler = StandardScaler()
```

```
X = a[['Age', 'MonthlyIncome', 'YearsAtCompany', 'JobSatisfaction', 'EnvironmentSatisfaction','YearsWithCurrManager','WorkLifeBalance']]
Y = a['Attrition']
```

```
X.head()
```

	Age	MonthlyIncome	YearsAtCompany	JobSatisfaction	EnvironmentSatisfaction	YearsWithCurrManager	WorkLifeBalance
0	41	5993	6	4	2	5	1
1	49	5130	10	2	3	7	3
2	37	2090	0	3	4	0	3
3	33	2909	8	3	4	0	3
4	27	3468	2	2	1	2	3

```
x.tail()
```

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	Envir
1465	36	Travel_Frequently	884	Research & Development	23	2	Medical	1	2061	
1466	39	Travel_Rarely	613	Research & Development	6	1	Medical	1	2062	
1467	27	Travel_Rarely	155	Research & Development	4	3	Life Sciences	1	2064	
1468	49	Travel_Frequently	1023	Sales	2	3	Medical	1	2065	
				Research &						

x

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	Envir
0	41	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1	
1	49	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	2	
2	37	Travel_Rarely	1373	Research & Development	2	2	Other	1	4	
3	33	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	5	
4	27	Travel_Rarely	591	Research & Development	2	1	Medical	1	7	
...	...	...	...	...	...	...	...	...	...	
1465	36	Travel_Frequently	884	Research & Development	23	2	Medical	1	2061	
1466	39	Travel_Rarely	613	Research & Development	6	1	Medical	1	2062	
1467	27	Travel_Rarely	155	Research & Development	4	3	Life Sciences	1	2064	
1468	49	Travel_Frequently	1023	Sales	2	3	Medical	1	2065	
1469	34	Travel_Rarely	628	Research & Development	8	3	Medical	1	2068	

1470 rows × 36 columns

Splitting data into test and train

```
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=42)
```

```
X_train,X_test,Y_train,Y_test.shape
```

```
(      Age  MonthlyIncome  YearsAtCompany  JobSatisfaction  \
 1097   24           2296               1                1
 727    18           1051               0                4
 254    29           6931               3                4
 1175   39           5295               5                2
 1341   31           4197              10                3
 ...   ...            ...             ...              ...
 1130   35           3407              10                3
 1294   41           6870               3                2
 860    22           2853               0                4
 1459   29           4025               4                2
 1126   50          19331               1                3

       EnvironmentSatisfaction  YearsWithCurrManager  WorkLifeBalance
 1097                        3                     0                3
 727                         2                     0                3
 254                         4                     2                3
 1175                        4                     0                3
 1341                        2                     2                3
 ...                       ...                   ...              ...
 1130                        2                     8                2
 1294                        2                     2                1
 860                         3                     0                3
 1459                        4                     3                3
 1126                        3                     0                3

 [1176 rows x 7 columns],
       Age  MonthlyIncome  YearsAtCompany  JobSatisfaction  \
```

```
1041   28           8463                5               1
184    53           4450                4               1
1222   24           1555                1               3
67     45           9724                1               1
220    36           5914               13               2
...   ...            ...              ...             ...
567    34           6274                6               4
560    34           5121                0               1
945    50          16880                3               1
522    37           4680                1               4
651    47           4537                7               4

      EnvironmentSatisfaction  YearsWithCurrManager  WorkLifeBalance
1041                        4                     3                3
184                         4                     3                3
1222                        4                     0                3
67                          2                     0                3
220                         4                     7                4
...                       ...                   ...              ...
567                         4                     4                3
560                         2                     0                3
945                         4                     2                3
522                         4                     0                3
651                         3                     7                3

[294 rows x 7 columns],
1097     No
727      No
254      No
1175     No
```

Logistic Regression

Model Building & Import the model building Libraries

```
from sklearn.linear_model import LogisticRegression
model=LogisticRegression()
```

```
model.fit(X_train, Y_train)
```

```
▾ LogisticRegression
LogisticRegression()
```

```
pred=model.predict(X_test)
```

```
pred
```

```
array(['No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No'], dtype=object)
```

```
Y_test
```

```
1041     No
184      No
1222    Yes
67       No
220      No
        ...
```

```
567      No
560      No
945      No
522      No
651      No
Name: Attrition, Length: 294, dtype: object
```

a

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	Environment
0	41	Yes	Travel_Rarely	1102	Sales	1	2	1	1	
1	49	No	Travel_Frequently	279	Research & Development	8	1	1	2	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	1	4	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	1	5	
4	27	No	Travel_Rarely	591	Research & Development	2	1	1	7	
...	...	...	...	...	...	...	...	...	...	
1465	36	No	Travel_Frequently	884	Research & Development	23	2	1	2061	
1466	39	No	Travel_Rarely	613	Research & Development	6	1	1	2062	
1467	27	No	Travel_Rarely	155	Research & Development	4	3	1	2064	
1468	49	No	Travel_Frequently	1023	Sales	2	3	1	2065	
1469	34	No	Travel_Rarely	628	Research & Development	8	3	1	2068	

1470 rows × 40 columns

Evaluation of classification model

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

```
accuracy = accuracy_score(Y_test, pred)
```

```
report = classification_report(Y_test, pred, zero_division=1)
```

```
print(f'Accuracy: {accuracy}')
print(f'Classification Report:\n{report}')
```

```
Accuracy: 0.8673469387755102
Classification Report:
              precision    recall  f1-score   support

          No       0.87      1.00      0.93       255
         Yes       1.00      0.00      0.00        39

    accuracy                           0.87       294
   macro avg       0.93      0.50      0.46       294
weighted avg       0.88      0.87      0.81       294
```

```
confusion_matrix(Y_test,pred)
```

```
array([[255,   0],
       [ 39,   0]])
```

```
pd.crosstab(Y_test,pred)
```

Roc-AUC curve

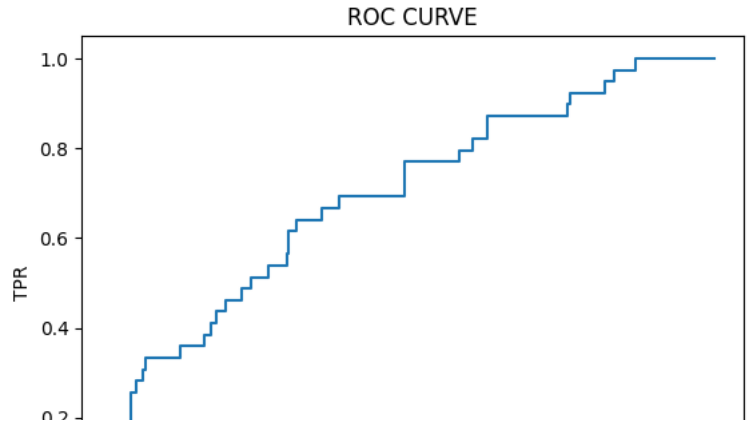
```
probability=model.predict_proba(X_test)[:,1]
```

Yes 39

```
probability
```

```
array([0.14873939, 0.17373604, 0.25084589, 0.1865791 , 0.11911736,
       0.14963007, 0.15969356, 0.20644099, 0.08193936, 0.18537088,
       0.16096129, 0.02189805, 0.15660552, 0.11782876, 0.18248771,
       0.13287268, 0.14334387, 0.0892007 , 0.06858367, 0.05708061,
       0.1753651 , 0.14395111, 0.10012064, 0.15057687, 0.2329628 ,
       0.03338823, 0.27116899, 0.15771847, 0.18762417, 0.10029771,
       0.10548668, 0.15048832, 0.12644386, 0.14778903, 0.2030313 ,
       0.06737083, 0.04935137, 0.35253675, 0.19926437, 0.23846212,
       0.08198467, 0.28864726, 0.23955634, 0.19282515, 0.22246873,
       0.11288909, 0.17545014, 0.24051176, 0.14059822, 0.32377579,
       0.08977525, 0.15148043, 0.01896052, 0.14635136, 0.20158982,
       0.10191406, 0.10573264, 0.08537077, 0.1631479 , 0.12443613,
       0.10510977, 0.33623452, 0.11027653, 0.05493965, 0.28005007,
       0.18450873, 0.12499531, 0.17197795, 0.17873294, 0.06110176,
       0.18127058, 0.08791989, 0.15005295, 0.15959692, 0.19866202,
       0.07388538, 0.19341696, 0.19100387, 0.08712656, 0.08033949,
       0.02928375, 0.13253218, 0.05956382, 0.16844953, 0.08753921,
       0.17957672, 0.12899389, 0.16872069, 0.16947305, 0.12397644,
       0.1099147 , 0.24576674, 0.07821105, 0.2716565 , 0.12140547,
       0.06524951, 0.1337184 , 0.14536957, 0.18726004, 0.10915274,
       0.04570312, 0.10169758, 0.07390408, 0.22704117, 0.07208355,
       0.08035364, 0.18593691, 0.16647288, 0.10818369, 0.05315879,
       0.17696614, 0.18973955, 0.22476227, 0.17342537, 0.21403334,
       0.16943373, 0.16771766, 0.09747364, 0.11387728, 0.2559594 ,
       0.32393512, 0.08431327, 0.13118746, 0.10751731, 0.09837008,
       0.25991497, 0.18954525, 0.11954205, 0.10534474, 0.09694665,
       0.07268098, 0.30507638, 0.06501248, 0.14080365, 0.1255734 ,
       0.11537899, 0.23299235, 0.17264787, 0.24765337, 0.06927027,
       0.21512755, 0.09901074, 0.16646941, 0.08047622, 0.03233445,
       0.15363939, 0.14131117, 0.25851265, 0.26761484, 0.1665985 ,
       0.10685997, 0.11549038, 0.19827264, 0.19076354, 0.13247131,
       0.26173972, 0.17180386, 0.21324175, 0.04115976, 0.15054569,
       0.16012435, 0.09434315, 0.09921354, 0.22000675, 0.06421677,
       0.16643204, 0.12016002, 0.14827189, 0.08450615, 0.05725373,
       0.12102272, 0.02681568, 0.18300015, 0.21076054, 0.11715199,
       0.16127828, 0.18483891, 0.09043029, 0.14086669, 0.20253644,
       0.0594472 , 0.10383826, 0.01617733, 0.15428555, 0.08595314,
       0.22434066, 0.11577713, 0.07998958, 0.07811109, 0.12006351,
       0.12845942, 0.14824842, 0.10405812, 0.19816497, 0.1162661 ,
       0.21477996, 0.24395257, 0.04972863, 0.2156586 , 0.16831872,
       0.17867722, 0.15398516, 0.21871738, 0.03416769, 0.07072713,
       0.22242289, 0.10244091, 0.10919764, 0.12517809, 0.0706504 ,
       0.07399615, 0.24438034, 0.17159597, 0.17617076, 0.10663942,
       0.13898632, 0.15178097, 0.10545546, 0.2723432 , 0.07462743,
       0.23465253, 0.26405405, 0.10124306, 0.3028089 , 0.12410107,
       0.1909214 , 0.20302625, 0.13276688, 0.0401135 , 0.18943046,
       0.23129363, 0.25951761, 0.08630086, 0.21347439, 0.20469075,
       0.13330949, 0.08581729, 0.10996842, 0.06690194, 0.04616928,
       0.18853288, 0.11542819, 0.21231547, 0.03597583, 0.07176025,
       0.17130681, 0.11593175, 0.23407496, 0.1533375 , 0.09696206,
       0.16256038, 0.06366454, 0.04689748, 0.0855508 , 0.23703024,
       0.07106702, 0.18067446, 0.2069784 , 0.22648723, 0.02715875,
       0.17170263, 0.14167865, 0.276632  , 0.10463943, 0.12037205,
       0.21133882, 0.02933273, 0.0973697 , 0.23466029, 0.23184945,
       0.1882965 , 0.04906958, 0.19036583, 0.1399965 , 0.11412922,
       0.22223015, 0.12517666, 0.24824295, 0.07113102, 0.07508479,
       0.14609486, 0.15491467, 0.18318556, 0.09382192, 0.04811606,
       0.20893659, 0.20088061, 0.23217748, 0.10747859, 0.11268901,
```

```
from sklearn.preprocessing import LabelBinarizer
lb = LabelBinarizer()
Y_test_bin = lb.fit_transform(Y_test)
fpr, tpr, thresholds = roc_curve(Y_test_bin, probability)


plt.plot(fpr,tpr)
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('ROC CURVE')
plt.show()
```



Decision Tree

```
ki from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report
```

```
dt_model = DecisionTreeClassifier(random_state=50)
```

```
dt_model.fit(X_train, Y_train)
```

```
DecisionTreeClassifier(random_state=50)
```

```
dt_predictions = dt_model.predict(X_test)
```

```
dt_accuracy = accuracy_score(Y_test, dt_predictions)
```

```
dt_report = classification_report(Y_test, dt_predictions)
```

```
print(f'Decision Tree Accuracy: {dt_accuracy}')
```

```
Decision Tree Accuracy: 0.7789115646258503
```

```
print(f'Decision Tree Classification Report:\n{dt_report}')
```

```
Decision Tree Classification Report:
              precision    recall  f1-score   support

          No       0.90      0.84      0.87       255
         Yes       0.28      0.41      0.33        39

    accuracy                           0.78       294
   macro avg       0.59      0.62      0.60       294
weighted avg       0.82      0.78      0.80       294
```

Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier
```

```
rf_model = RandomForestClassifier(random_state=50)
```

```
rf_model.fit(X_train, Y_train)
```

```
RandomForestClassifier(random_state=50)
```

```
rf_predictions = rf_model.predict(X_test)
```

```
rf_accuracy = accuracy_score(Y_test, rf_predictions)
```

```
rf_report = classification_report(Y_test, rf_predictions)
```

```
print(f'Random Forest Accuracy: {rf_accuracy}')
```

```
Random Forest Accuracy: 0.8435374149659864
```

```
print(f'Random Forest Classification Report:\n{rf_report}')
```

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

          No       0.88      0.95      0.91       255
         Yes       0.33      0.18      0.23        39

    accuracy                           0.84       294
   macro avg       0.61      0.56      0.57       294
weighted avg       0.81      0.84      0.82       294
```