

```
In [ ]: Name: J.Ganesh
Reg.no: 21BCE7325
```

```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [2]: data=pd.read_csv("Employee-Attrition.csv")
```

```
In [3]: data.head()
```

Out[3]:

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

5 rows x 35 columns

```
In [4]: data.tail()
```

Out[4]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNum
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

5 rows x 35 columns

```
In [5]: data.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
```

```
In [6]: data.describe()
```

Out[6]:

	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 x 26 columns

## Handling the null values

```
In [7]: data.isnull().any()
```

```
Out[7]: 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
```

```
In [8]: data.isnull().sum()
```

```
Out[8]: 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
```

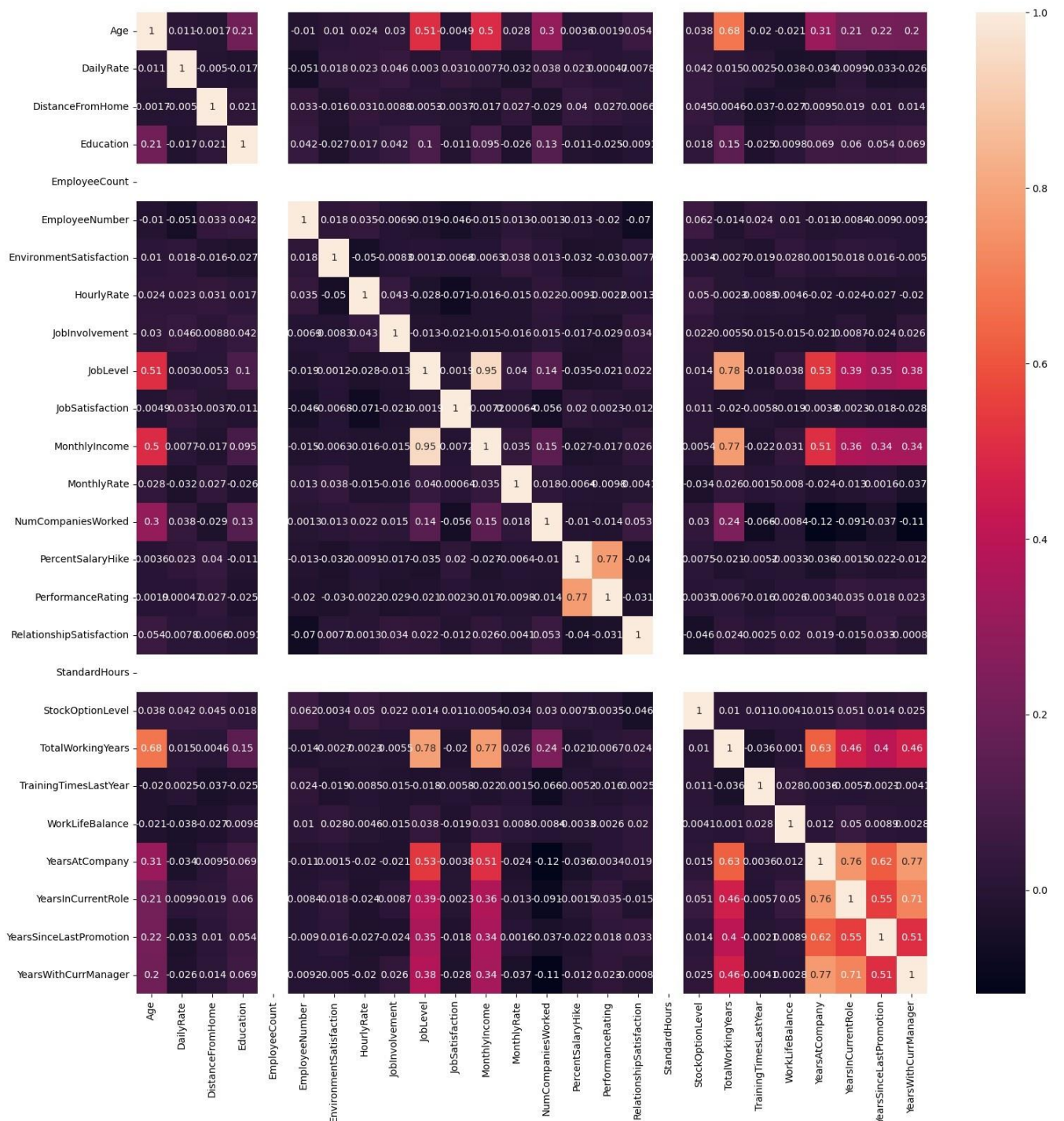
```
In [9]: cor=data.corr()
```

C:\Users\Prasanth Nimma\AppData\Local\Temp\ipykernel\_8884\1426905697.py:1: FutureWarning: The default value of numeric\_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric\_only to silence this warning.

```
cor=data.corr()
```

```
In [10]: fig=plt.figure(figsize=(18,18))
sns.heatmap(cor,annot=True)
```

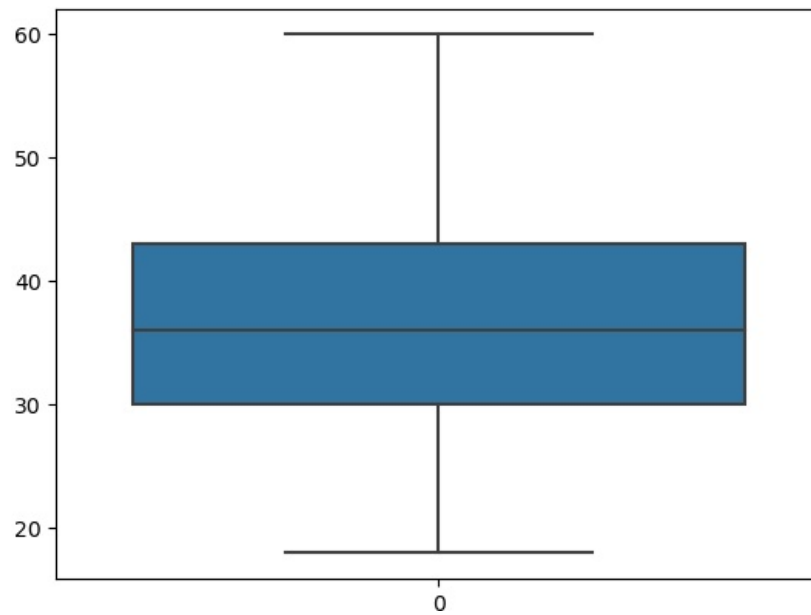
```
Out[10]: <Axes: >
```



## Outliers

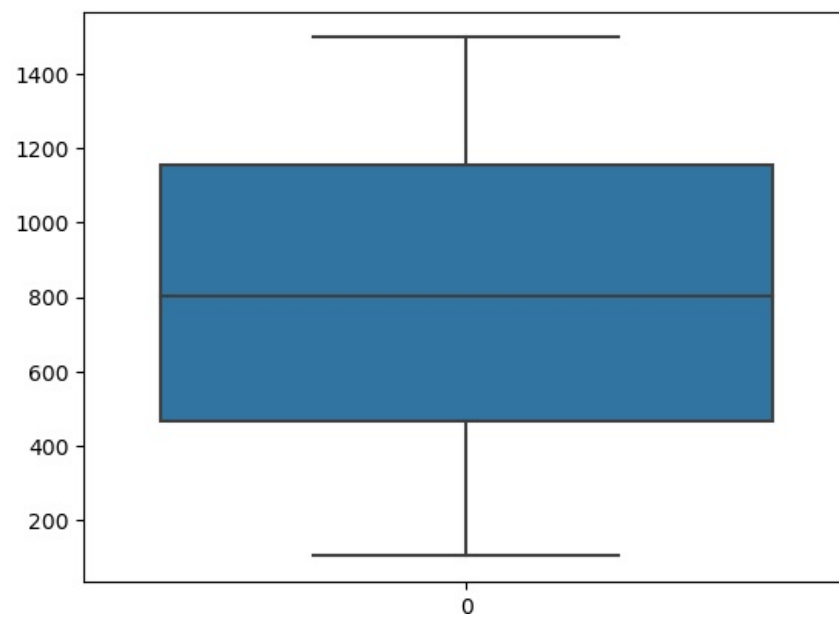
```
In [11]: sns.boxplot(data["Age"])
```

```
Out[11]: <Axes: >
```



```
In [12]: sns.boxplot(data["DailyRate"])
```

```
Out[12]: <Axes: >
```



```
In [29]: data.describe()
```

Out[29]:

	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

In [30]:

data.head()

Out[30]:

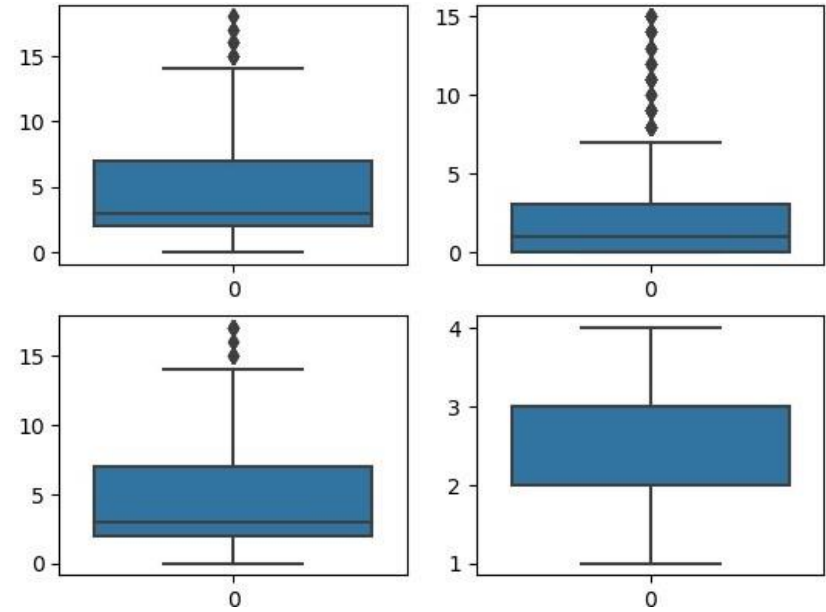
	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction
0	41	Travel_Rarely	1102	Sales		1	2	1	2
1	49	Travel_Frequently	279	Research & Development		8	1	1	2
2	37	Travel_Rarely	1373	Research & Development		2	2	1	4
3	33	Travel_Frequently	1392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

5 rows × 33 columns

In [14]:

```
fig, axes = plt.subplots(2,2)
sns.boxplot(data=data["YearsInCurrentRole"],ax=axes[0,0])
sns.boxplot(data=data["YearsSinceLastPromotion"],ax=axes[0,1])
sns.boxplot(data=data["YearsWithCurrManager"],ax=axes[1,0])
sns.boxplot(data=data["WorkLifeBalance"],ax=axes[1,1])
```

<Axes: >

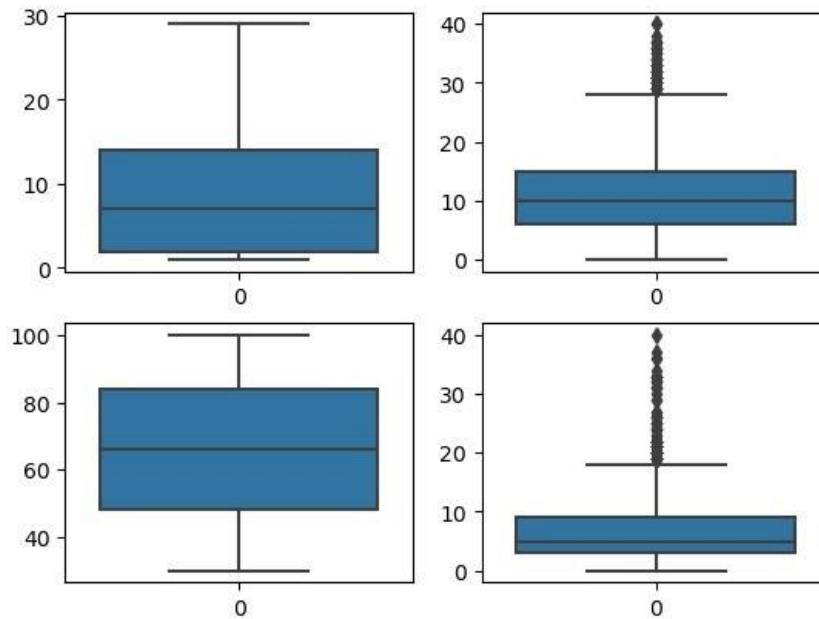


In [15]:

```
fig, axes = plt.subplots(2,2)
sns.boxplot(data=data["DistanceFromHome"],ax=axes[0,0])
sns.boxplot(data=data["TotalWorkingYears"],ax=axes[0,1])
sns.boxplot(data=data["HourlyRate"],ax=axes[1,0])
sns.boxplot(data=data["YearsAtCompany"],ax=axes[1,1])
```

<Axes: >

Out[15]:



## Handling the outliers

```
In [16]: YearsInCurrentRole_q1 = data.YearsInCurrentRole.quantile(0.25)
YearsInCurrentRole_q3 = data.YearsInCurrentRole.quantile(0.75)
IQR_YearsInCurrentRole=YearsInCurrentRole_q3-YearsInCurrentRole_q1
upper_limit_YearsInCurrentRole=YearsInCurrentRole_q3+1.5*IQR_YearsInCurrentRole
lower_limit_YearsInCurrentRole =YearsInCurrentRole_q1-1.5*IQR_YearsInCurrentRole
median_YearsInCurrentRole=data["YearsInCurrentRole"].median()
data["YearsInCurrentRole"] = np.where(
    (data["YearsInCurrentRole"] > upper_limit_YearsInCurrentRole),
    median_YearsInCurrentRole,
    data["YearsInCurrentRole"]
)
```

```
In [17]: YearsSinceLastPromotion_q1 = data.YearsSinceLastPromotion.quantile(0.25)
YearsSinceLastPromotion_q3 = data.YearsSinceLastPromotion.quantile(0.75)
IQR_YearsSinceLastPromotion=YearsSinceLastPromotion_q3-YearsSinceLastPromotion_q1
upper_limit_YearsSinceLastPromotion=YearsSinceLastPromotion_q3+1.5*IQR_YearsSinceLastPromotion
lower_limit_YearsSinceLastPromotion =YearsSinceLastPromotion_q1-1.5*IQR_YearsSinceLastPromotion
median_YearsSinceLastPromotion=data["YearsSinceLastPromotion"].median()
data["YearsSinceLastPromotion"] = np.where(
    (data["YearsSinceLastPromotion"] > upper_limit_YearsSinceLastPromotion),
    median_YearsSinceLastPromotion,
    data["YearsSinceLastPromotion"]
)
```

```
In [18]: YearsWithCurrManager_q1 = data.YearsWithCurrManager.quantile(0.25)
YearsWithCurrManager_q3 = data.YearsWithCurrManager.quantile(0.75)
IQR_YearsWithCurrManager=YearsWithCurrManager_q3-YearsWithCurrManager_q1
upper_limit_YearsWithCurrManager=YearsWithCurrManager_q3+1.5*IQR_YearsWithCurrManager
lower_limit_YearsWithCurrManager =YearsWithCurrManager_q1-1.5*IQR_YearsWithCurrManager
median_YearsWithCurrManager=data["YearsWithCurrManager"].median()
data["YearsWithCurrManager"] = np.where(
    (data["YearsWithCurrManager"] > upper_limit_YearsWithCurrManager),
    median_YearsWithCurrManager,
    data["YearsWithCurrManager"]
)
```

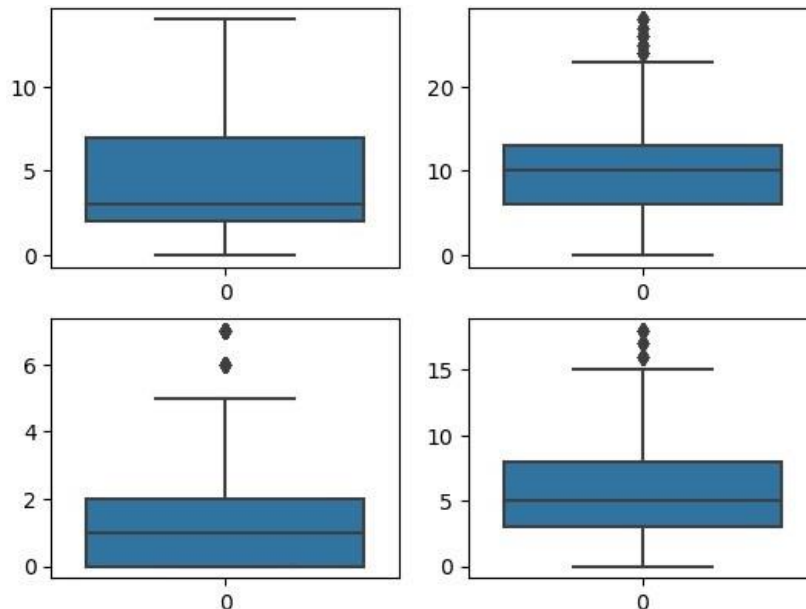
```
In [19]: TotalWorkingYears_q1 = data.TotalWorkingYears.quantile(0.25)
TotalWorkingYears_q3 = data.TotalWorkingYears.quantile(0.75)
IQR_TotalWorkingYears=TotalWorkingYears_q3-TotalWorkingYears_q1
upper_limit_TotalWorkingYears=TotalWorkingYears_q3+1.5*IQR_TotalWorkingYears
lower_limit_TotalWorkingYears=TotalWorkingYears_q1-1.5*IQR_TotalWorkingYears
median_TotalWorkingYears=data["TotalWorkingYears"].median()
data["TotalWorkingYears"] = np.where(
    (data["TotalWorkingYears"] > upper_limit_TotalWorkingYears),
    median_TotalWorkingYears,
    data["TotalWorkingYears"]
)
```

```
In [20]: YearsAtCompany_q1 = data.YearsAtCompany.quantile(0.25)
```

```
YearsAtCompany_q3 = data.YearsAtCompany.quantile(0.75)
IQR_YearsAtCompany=YearsAtCompany_q3-YearsAtCompany_q1
upper_limit_YearsAtCompany=YearsAtCompany_q3+1.5*IQR_YearsAtCompany
lower_limit_YearsAtCompany=YearsAtCompany_q1-1.5*IQR_YearsAtCompany
median_YearsAtCompany=data["YearsAtCompany"].median()
data["YearsAtCompany"] = np.where(
    (data["YearsAtCompany"] > upper_limit_YearsAtCompany),
    median_YearsAtCompany,
    data["YearsAtCompany"]
)
```

```
In [21]: fig, axes = plt.subplots(2,2)
sns.boxplot(data=data["YearsWithCurrManager"],ax=axes[0,0])
sns.boxplot(data=data["TotalWorkingYears"],ax=axes[0,1])
sns.boxplot(data=data["YearsSinceLastPromotion"],ax=axes[1,0])
sns.boxplot(data=data["YearsAtCompany"],ax=axes[1,1])
```

Out[21]: <Axes: >



```
In [31]: data.head()
```

```
Out[31]:
```

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

5 rows x 33 columns

```
In [22]: data.drop("EducationField",axis=1,inplace=True)
```

```
In [23]: data.head(2)
```

```
Out[23]:
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSa
0	41	Yes	Travel_Rarely	1102	Sales		1	2	1	1
1	49	No	Travel_Frequently	279	Research & Development		8	1	1	2

2 rows x 34 columns

```
In [24]: data["BusinessTravel"].unique()
```

```
Out[24]: array(['Travel_Rarely', 'Travel_Frequently', 'Non-Travel'], dtype=object)
```

## Splitting the data

```
In [25]: y=data["Attrition"]
```



```
Out [25]:
```

```
In [26]: y.head()
```

```
Out[26]:
```

0	Yes
1	No
2	Yes
3	No
4	No

Name: Attrition, dtype: object

```
In [27]: data.drop("Attrition",axis=1,inplace=True)
```

```
In [28]: data.head()
```

```
Out[28]:
```

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

5 rows × 33 columns

## Encoding

```
In [32]: from sklearn.preprocessing import LabelEncoder
```

```
In [33]: le=LabelEncoder()
```

```
In [34]: data["BusinessTravel"]=le.fit_transform(data["BusinessTravel"])
```

```
In [35]: data["Department"]=le.fit_transform(data["Department"])
```

```
In [36]: data["Gender"]=le.fit_transform(data["Gender"])
```

```
In [37]: y=le.fit_transform(y)
```

```
In [38]: y
```

```
Out[38]: array([1, 0, 1, ..., 0, 0, 0])
```

```
In [39]: data["JobRole"]=le.fit_transform(data["JobRole"])
```

```
In [40]: data["Over18"]=le.fit_transform(data["Over18"])
```

```
In [41]: data["MaritalStatus"]=le.fit_transform(data["MaritalStatus"])
```

```
In [42]: data["OverTime"]=le.fit_transform(data["OverTime"])
```

```
In [43]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 33 columns):
#   Column                                Non-Null Count  Dtype
---  -
0    Age                                   1470 non-null   int64
1    BusinessTravel                       1470 non-null   int32
2    DailyRate                           1470 non-null   int64
3    Department                          1470 non-null   int32
4    DistanceFromHome                    1470 non-null   int64
5    Education                           1470 non-null   int64
6    EmployeeCount                       1470 non-null   int64
7    EmployeeNumber                      1470 non-null   int64
8    EnvironmentSatisfaction             1470 non-null   int64
9    Gender                              1470 non-null   int32
10   HourlyRate                          1470 non-null   int64
11   JobInvolvement                      1470 non-null   int64
12   JobLevel                            1470 non-null   int64
13   JobRole                            1470 non-null   int32
14   JobSatisfaction                     1470 non-null   int64
15   MaritalStatus                      1470 non-null   int32
16   MonthlyIncome                      1470 non-null   int64
17   MonthlyRate                        1470 non-null   int64
18   NumCompaniesWorked                 1470 non-null   int64
19   Over18                             1470 non-null   int32
20   OverTime                           1470 non-null   int32
21   PercentSalaryHike                  1470 non-null   int64
22   PerformanceRating                  1470 non-null   int64
23   RelationshipSatisfaction            1470 non-null   int64
24   StandardHours                      1470 non-null   int64
25   StockOptionLevel                   1470 non-null   int64
26   TotalWorkingYears                  1470 non-null   float64
27   TrainingTimesLastYear              1470 non-null   int64
28   WorkLifeBalance                    1470 non-null   int64
29   YearsAtCompany                     1470 non-null   float64
30   YearsInCurrentRole                 1470 non-null   float64
31   YearsSinceLastPromotion             1470 non-null   float64
32   YearsWithCurrManager                1470 non-null   float64
dtypes: float64(5), int32(7), int64(21)
memory usage: 338.9 KB
```

## train test split

```
In [44]: from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(data,y,test_size=0.3,random_state=0)
```

```
In [45]: x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

```
Out[45]: ((1029, 33), (441, 33), (1029,), (441,))
```

## Feature Scaling

```
In [46]: from sklearn.preprocessing import StandardScaler
```

```
In [47]: sc=StandardScaler()
```

```
In [48]: x_train=sc.fit_transform(x_train)
```

```
In [49]: x_test=sc.fit_transform(x_test)
```

## Building the model

### Multi-Linear Regression

```
In [50]: from sklearn.linear_model import LinearRegression
```

```
In [51]: lr = LinearRegression()
```

```
In [52]: lr.fit(x_train,y_train)
```

```
Out[52]: LinearRegression
LinearRegression()
```

```
In [53]: lr.coef_ #slope (m)
```

```
Out[53]: array([-3.54940447e-02, 7.88352347e-05, -1.70825038e-02, 3.46389690e-02,
        2.44612841e-02, 3.65668214e-03, 4.16333634e-17, -9.46820520e-03,
        -4.11203734e-02, 1.06338881e-02, -2.97662154e-03, -3.84864283e-02,
        -1.52927977e-02, -1.57839139e-02, -3.67252862e-02, 3.35765928e-02,
        -5.90043558e-03, 5.81099165e-03, 3.78471890e-02, -6.93889390e-18,
        9.55263279e-02, -2.55800078e-02, 2.01844797e-02, -2.64773510e-02,
        -1.21430643e-17, -1.79286106e-02, -3.30529386e-02, -1.09247807e-02,
        -3.10631611e-02, -2.47887717e-02, -1.10177742e-02, 2.11897289e-02,
        -6.60823991e-03])
```

```
In [54]: lr.intercept_ # (c)
```

```
Out[54]: 0.16229348882410102
```

```
In [55]: y_pred = lr.predict(x_test)
```

```
In [56]: y_pred
```

```
Out[56]: array([ 1.30302477e-01, 2.17626230e-01, 3.46282415e-01, 5.41382549e-03,
        4.99292896e-01, 1.01628868e-01, 3.44742777e-01, 1.23994945e-01,
        -1.60694945e-01, 4.02435622e-01, 1.44159172e-01, 2.67416840e-01,
        -4.62559536e-02, 5.58671849e-01, 2.81858700e-01, 1.53537792e-02,
        1.78573363e-01, 2.77532834e-01, 9.37121052e-02, 2.17571624e-01,
        2.65936178e-01, 1.41499184e-02, 8.36251186e-02, 9.58849826e-02,
        5.09869963e-01, 2.94764240e-01, 7.85819529e-02, 1.26647773e-01,
        5.05518902e-01, 8.48456917e-02, -7.97229275e-02, 2.15516993e-02,
        1.08079105e-01, 3.65998400e-01, 1.24517362e-01, 5.13682786e-02,
        1.06749689e-01, 6.07640778e-02, 6.66425313e-02, 4.81312859e-02,
        -1.16761425e-02, -2.97852924e-02, 5.25135582e-02, -1.59076817e-02,
        -1.71522795e-02, 4.17777714e-01, 3.67341564e-01, -2.14569245e-01,
        5.47964121e-01, 4.40723777e-01, 1.96701754e-01, 4.42415223e-01,
        1.45760263e-01, 3.75821843e-01, 4.92762622e-01, 2.95885645e-01,
        -4.62363391e-02, 3.16337190e-01, -7.90813313e-03, 2.52644685e-01,
        -3.18239329e-02, 2.83907645e-01, 9.03615010e-02, 1.26934391e-01,
        3.58670014e-01, 2.40923530e-02, 3.55890111e-01, 1.95961225e-01,
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```

```
In [57]: y_test
```

Out[57]:

```
In [58]: from sklearn.linear_model import LogisticRegression
```

```
In [60]: lg.fit(x_train,y_train)
```

```
Out[60]: ▾ LogisticRegression
LogisticRegression()
```

```
In [62]: y_pred
```

```
Out[62]: array([ 1.30302477e-01,  2.17626230e-01,  3.46282415e-01,  5.41382549e-03,  
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               -1.60694945e-01,  4.02435622e-01,  1.44159172e-01,  2.67416840e-01,  
               -4.62559536e-02,  5.58671849e-01,  2.81858700e-01,  1.53537792e-02])
```

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-8.21467550e-02])
```

```
In [63]: y_test
```

```
Out[63]: array([0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0,
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0])
```

```
In [64]: score = lg.score(x_test, y_test)
print(score)
```

```
0.8820861678004536
```

## Confusion matrix

```
In [65]: from sklearn import metrics
cm = metrics.confusion_matrix(y_test, y_pred_lg)
print(cm)
```

```
[[366  5]
 [ 47 23]]
```

## Ridge and Lasso

```
In [66]: from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV
```

```
In [67]: rg=Ridge()
```

```
In [68]: paramteres={"alpha":[1,2,3,5,10,20,30,40,60,70,80,90]}
ridgecv=GridSearchCV(rg,paramteres,scoring="neg_mean_squared_error",cv=5)
ridgecv.fit(x_train,y_train)
```

```
Out[68]: ▸ GridSearchCV
▸ estimator: Ridge
▸ Ridge
```

```
In [69]: print(ridgecv.best_params_)
```

```
{'alpha': 90}
```

```
In [70]: print(ridgecv.best_score_)
```

```
-0.11390621139234183
```

```
In [71]: y_pred_rg=ridgecv.predict(x_test)
```

```
In [72]: y_pred_rg
```

```
Out[72]: array([ 1.34413485e-01, 2.22561818e-01, 3.41692977e-01, 3.88209867e-03,
 4.84617338e-01, 1.16361483e-01, 3.30449743e-01, 1.27358807e-01,
-1.34442619e-01, 3.77692888e-01, 1.33001445e-01, 2.69898751e-01,
-2.54707392e-02, 5.25771894e-01, 2.67543514e-01, 2.78725024e-02,
1.82233111e-01, 2.78896415e-01, 9.12689699e-02, 2.11494641e-01,
2.70103341e-01, 8.44922044e-03, 8.74746722e-02, 1.05348798e-01,
4.87749940e-01, 2.83080512e-01, 8.80556209e-02, 1.23817268e-01,
4.82185624e-01, 9.34824523e-02, -7.16448509e-02, 4.07003104e-02,
1.08437994e-01, 3.42151399e-01, 1.22270929e-01, 6.85889862e-02,
1.06690533e-01, 7.08689637e-02, 7.51570276e-02, 6.05829413e-02,
1.08782897e-02, -6.91368661e-03, 5.83191600e-02, -1.54680056e-02,
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1.40754410e-01, 3.52173952e-01, 4.70372694e-01, 2.89240343e-01,
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3.48994545e-01, 3.41026778e-02, 3.40548051e-01, 1.95847356e-01,
1.30040885e-01, 1.32259137e-01, -2.34680143e-02, 3.04595468e-01,
1.12452197e-01, 1.30525275e-01, 2.19329505e-01, 9.44722098e-02,
9.98185782e-02, 2.60042486e-01, 2.51475715e-01, 4.59039018e-02,
-7.94007856e-02, -7.05812314e-03, 2.04344419e-01, -3.97180151e-03,
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4.07117263e-01, 1.48860323e-01, 3.88471838e-02, 3.79029267e-02,
1.09895981e-01, -4.30946471e-02, 3.30298512e-01, 1.07254284e-01,
-1.13032643e-02, -3.69192632e-02, 2.87732288e-01, 9.91961213e-02,
2.12225886e-01, 3.88660531e-01, 3.15623317e-01, 1.80996998e-01,
2.69970366e-01, 2.81850174e-01, 2.49972461e-01, -2.33065542e-03,
2.34240860e-01, 1.51536128e-01, 6.56810225e-02, 1.35221573e-02,
3.03956323e-02, 9.22075626e-02, 1.28297232e-01, 2.04669352e-01,
2.26917512e-01, -1.62627965e-01, 2.95984225e-01, 1.80934145e-01,
-6.34810776e-02, 4.36092057e-02, 1.39814157e-01, 1.72029014e-01,
1.65538329e-01, 2.24411690e-01, 2.15315070e-01, 1.16342630e-01,
-6.24745967e-02))
```

In [73]: `y_test`

Out[73]: `array([0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
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0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
0])`

In [74]: `from sklearn import metrics
print(metrics.r2_score(y_test,y_pred_rg))
print(metrics.r2_score(y_train,ridgecv.predict(x_train)))`

0.21073458438815906  
0.2061567210285109

## Lasso

In [75]: `from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV`

In [76]: `la=Ridge()`

In [77]: `parameters={"alpha":[1,2,3,5,10,20,30,40,60,70,80,90]}
ridgecv=GridSearchCV(la,parameters,scoring="neg_mean_squared_error",cv=5)
ridgecv.fit(x_train,y_train)`

Out[77]: `GridSearchCV
estimator: Ridge
Ridge`

In [78]: `print(ridgecv.best_params_)`

{'alpha': 90}

In [79]: `print(ridgecv.best_score_)`

-0.11390621139234183

In [80]: `y_pred_la=ridgecv.predict(x_test)`

In [81]: `y_pred_la`

Out[81]: `array([ 1.34413485e-01, 2.22561818e-01, 3.41692977e-01, 3.88209867e-03,
4.84617338e-01, 1.16361483e-01, 3.30449743e-01, 1.27358807e-01,`



-1.34442619e-01, 3.77692888e-01, 1.33001445e-01, 2.69898751e-01,  
-2.54707392e-02, 5.25771894e-01, 2.67543514e-01, 2.78725024e-02,  
1.82233111e-01, 2.78896415e-01, 9.12689699e-02, 2.11494641e-01,  
2.70103341e-01, 8.44922044e-03, 8.74746722e-02, 1.05348798e-01,  
4.87749940e-01, 2.83080512e-01, 8.80556209e-02, 1.23817268e-01,  
4.82185624e-01, 9.34824523e-02, -7.16448509e-02, 4.07003104e-02,  
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-7.94007856e-02, -7.05812314e-03, 2.04344419e-01, -3.97180151e-03,  
-5.91286905e-03, 1.26797761e-01, 8.02495203e-02, 2.55422079e-02,  
4.65384158e-02, 2.32985240e-01, 3.16063931e-01, 2.02833301e-01,  
3.14235904e-01, 2.33427101e-01, -1.42446708e-02, 2.24789285e-01,  
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-3.30262214e-02, 1.44305312e-01, -8.99199978e-02, -3.74712872e-02,  
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2.05300799e-01, 8.08917915e-02, -2.89389327e-02, 3.88975789e-02,  
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2.72386022e-01, -4.84039332e-02, 1.90411095e-01, 1.89810174e-01,  
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2.24222741e-01, 1.35207932e-01, 1.91240682e-01, 3.87158365e-02,  
1.17416027e-01, 1.20780070e-01, 2.19845528e-01, 3.11363894e-01,  
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1.11492990e-01, 2.94090069e-02, 2.30676290e-01, 1.19192017e-01,  
1.49461455e-02, 2.42284371e-01, 7.22361156e-02, 3.33852369e-01,  
1.61213354e-01, 9.69685794e-02, 2.32264965e-01, -6.93181380e-02,  
1.86467739e-01, 2.03098589e-01, -1.10349710e-02, 2.63095846e-01,  
-2.48406147e-01, -3.25418955e-02, 1.74487006e-01, 2.62780720e-02,

```
[82]: from sklearn import metrics
print(metrics.r2_score(y_test,y_pred_la))
print(metrics.r2_score(y_train,ridgecv.predict(x_train)))
```

## Decision Tree

```
In [84]: dtc.fit(x_train,y_train)
```

```
In [85]: pred=dtc.predict(x_test)
```

```
In [86]: pred
```

y\_test

```
Out[87]: array([0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
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0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1,
0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
0])
```

```
In [88]: #Accuracy score
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, roc_auc_score, roc_curve
```

```
In [89]: accuracy_score(y_test, pred)
```

```
Out[89]: 0.7664399092970522
```

```
In [90]: confusion_matrix(y_test, pred)
```

```
Out[90]: array([[316, 55],
[ 48, 22]], dtype=int64)
```

```
In [91]: pd.crosstab(y_test, pred)
col_0  0  1
```

```
Out[91]: row_0
0  316  55
1   48  22
```

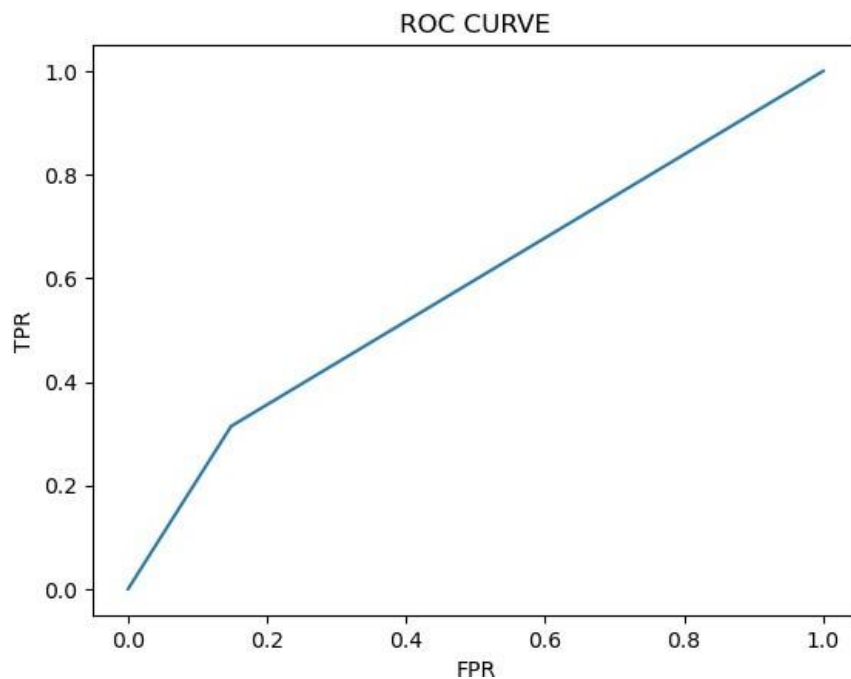
```
In [92]: print(classification_report(y_test, pred))
```

	precision	recall	f1-score	support
0	0.87	0.85	0.86	371
1	0.29	0.31	0.30	70
accuracy			0.77	441
macro avg	0.58	0.58	0.58	441
weighted avg	0.78	0.77	0.77	441

```
In [93]: probability=dtc.predict_proba(x_test)[: ,1]
```

```
In [94]: # roc_curve
fpr,tpr,threshsholds = roc_curve(y_test,probability)
```

```
In [95]: plt.plot(fpr,tpr)
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ROC CURVE")
plt.show()
```



## Random Forest

```
In [96]: from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier()
```

```
In [97]: forest_params = [{"max_depth": list(range(10, 15)), "max_features": list(range(0,14))}]
```

```
In [98]: from sklearn.model_selection import GridSearchCV
```

```
In [99]: rfc_cv= GridSearchCV(rfc,param_grid=forest_params,cv=10,scoring="accuracy")
```

```
In [100]: rfc_cv.fit(x_train,y_train)
```

C:\Users\Prasanth Nimmala\anaconda3\lib\site-packages\sklearn\model\_selection\\_validation.py:378: FitFailedWarning:

50 fits failed out of a total of 700.

The score on these train-test partitions for these parameters will be set to nan.

If these failures are not expected, you can try to debug them by setting error\_score='raise'.

Below are more details about the failures:

50 fits failed with the following error:

Traceback (most recent call last):

File "C:\Users\Prasanth Nimmala\anaconda3\lib\site-packages\sklearn\model\_selection\\_validation.py", line 686, in \_fit\_and\_score

estimator.fit(X\_train, y\_train, \*\*fit\_params)

File "C:\Users\Prasanth Nimmala\anaconda3\lib\site-packages\sklearn\ensemble\\_forest.py", line 340, in fit  
self.\_validate\_params()

File "C:\Users\Prasanth Nimmala\anaconda3\lib\site-packages\sklearn\base.py", line 581, in \_validate\_params  
validate\_parameter\_constraints()

File "C:\Users\Prasanth Nimmala\anaconda3\lib\site-packages\sklearn\utils\\_param\_validation.py", line 97, in validate\_parameter\_constraints  
raise InvalidParameterError(

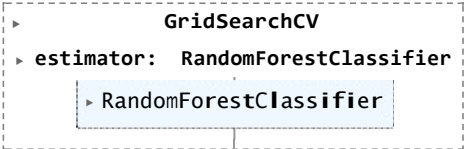
sklearn.utils.\_param\_validation.InvalidParameterError: The "max\_features" parameter of RandomForestClassifier must be an int in the range [1, inf), a float in the range (0.0, 1.0], a str among {"log2", "sqrt", "auto" (deprecated)} or None. Got 0 instead.

warnings.warn(some\_fits\_failed\_message, FitFailedWarning)

C:\Users\Prasanth Nimmala\anaconda3\lib\site-packages\sklearn\model\_selection\\_search.py:952: UserWarning: One or more of the test scores are non-finite: [ nan 0.84353703 0.84840091 0.8483914 0.85325528 0.85033314 0.85421664 0.85033314 0.85422616 0.84644013 0.85517799 0.85519703 0.85033314 0.84449838 nan 0.8445079 0.84935275 0.85031411 0.85421664 0.84936227 0.85516848 0.85032362 0.84934323 0.8512945 0.84935275 0.84934323 0.85322673 0.85032362 nan 0.8445079 0.84936227 0.85324576 0.85033314 0.85033314 0.85324576 0.85810013 0.85711974 0.84935275 0.85225585 0.8483914 0.85131354 0.85324576 nan 0.84546926 0.84937179 0.84936227 0.85325528 0.85324576 0.85615839 0.85324576 0.85520655 0.85615839 0.85517799 0.85324576 0.8512945 0.85030459 nan 0.84547877 0.84644965 0.84546926 0.85518751 0.84353703 0.84937179 0.85615839 0.85031411 0.8561679 0.85713878 0.84838188 0.85227489 0.84643061]

warnings.warn(

Out[100]:



```
In [101]: pred=rfc_cv.predict(x_test)
```

```
In [102]: print(classification_report(y_test,pred))
```

	precision	recall	f1-score	support
0	0.87	0.99	0.93	371
1	0.84	0.23	0.36	70
accuracy			0.87	441
macro avg	0.86	0.61	0.64	441
weighted avg	0.87	0.87	0.84	441

```
In [103]: rfc_cv.best_params_
```

Out[103]: {'max\_depth': 12, 'max\_features': 7}

```
In [104]: rfc_cv.best_score_
```

Out[104]: 0.8581001332571864