• Data Preprocessing.

- o Import the Libraries.
- o Importing the dataset.
- o Checking for Null Values.
- o Data Visualization.
- o Outlier Detection
- o Splitting Dependent and Independent variables
- o- Encoding
- o Feature Scaling.
- o Splitting Data into Train and Test.

1.Import the Libraries.

In [4]:
```
import numpy as np
import pandas as  pd
import matplotlib.pyplot as plt
import seaborn as sns
```

2.Importing the dataset.

In [5]:
```
df=pd.read_csv("Employee-Attrition.csv")
```

In [6]:
```
df.head()
```

Out[6]:

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

5 rows × 35 columns

In [7]:
```
df.tail()
```

Out[7]:

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

5 rows × 35 columns

In [8]:
```
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
```

In [9]:
```
df.describe()
```

Out[9]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNur
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470.00
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024.86
std	9.135373	403.509100	8.106864	1.024165	0.0	602.02
min	18.000000	102.000000	1.000000	1.000000	1.0	1.00
25%	30.000000	465.000000	2.000000	2.000000	1.0	491.25
50%	36.000000	802.000000	7.000000	3.000000	1.0	1020.50
75%	43.000000	1157.000000	14.000000	4.000000	1.0	1555.75
max	60.000000	1499.000000	29.000000	5.000000	1.0	2068.00

8 rows × 26 columns

In [10]:
```
df.shape
```

Out[10]:
```
(1470, 35)
```

In [11]:
```
df.corr()
```

Out[11]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	E
Age	1.000000	0.010661	-0.001686	0.208034	NaN	
DailyRate	0.010661	1.000000	-0.004985	-0.016806	NaN	
DistanceFromHome	-0.001686	-0.004985	1.000000	0.021042	NaN	
Education	0.208034	-0.016806	0.021042	1.000000	NaN	
EmployeeCount	NaN	NaN	NaN	NaN	NaN	
EmployeeNumber	-0.010145	-0.050990	0.032916	0.042070	NaN	
EnvironmentSatisfaction	0.010146	0.018355	-0.016075	-0.027128	NaN	
HourlyRate	0.024287	0.023381	0.031131	0.016775	NaN	
JobInvolvement	0.029820	0.046135	0.008783	0.042438	NaN	
JobLevel	0.509604	0.002966	0.005303	0.101589	NaN	
JobSatisfaction	-0.004892	0.030571	-0.003669	-0.011296	NaN	
MonthlyIncome	0.497855	0.007707	-0.017014	0.094961	NaN	
MonthlyRate	0.028051	-0.032182	0.027473	-0.026084	NaN	
NumCompaniesWorked	0.299635	0.038153	-0.029251	0.126317	NaN	
PercentSalaryHike	0.003634	0.022704	0.040235	-0.011111	NaN	
PerformanceRating	0.001904	0.000473	0.027110	-0.024539	NaN	
RelationshipSatisfaction	0.053535	0.007846	0.006557	-0.009118	NaN	
StandardHours	NaN	NaN	NaN	NaN	NaN	
StockOptionLevel	0.037510	0.042143	0.044872	0.018422	NaN	
TotalWorkingYears	0.680381	0.014515	0.004628	0.148280	NaN	
TrainingTimesLastYear	-0.019621	0.002453	-0.036942	-0.025100	NaN	
WorkLifeBalance	-0.021490	-0.037848	-0.026556	0.009819	NaN	
YearsAtCompany	0.311309	-0.034055	0.009508	0.069114	NaN	
YearsInCurrentRole	0.212901	0.009932	0.018845	0.060236	NaN	
YearsSinceLastPromotion	0.216513	-0.033229	0.010029	0.054254	NaN	
YearsWithCurrManager	0.202089	-0.026363	0.014406	0.069065	NaN	

26 rows × 26 columns

3.Checking for Null Values.

In [12]:
```
df.isnull().any()
```

Out[12]:
```
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 [13]:
```
df.isnull().sum()
```

Out[13]:
```
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 [14]:
```
df["Department"].value_counts()
```

Out[14]:
```
Research & Development    961
Sales                     446
Human Resources            63
Name: Department, dtype: int64
```

In [15]:
```
df["BusinessTravel"].value_counts()
```

Out[15]:
```
Travel_Rarely        1043
Travel_Frequently     277
Non-Travel            150
Name: BusinessTravel, dtype: int64
```

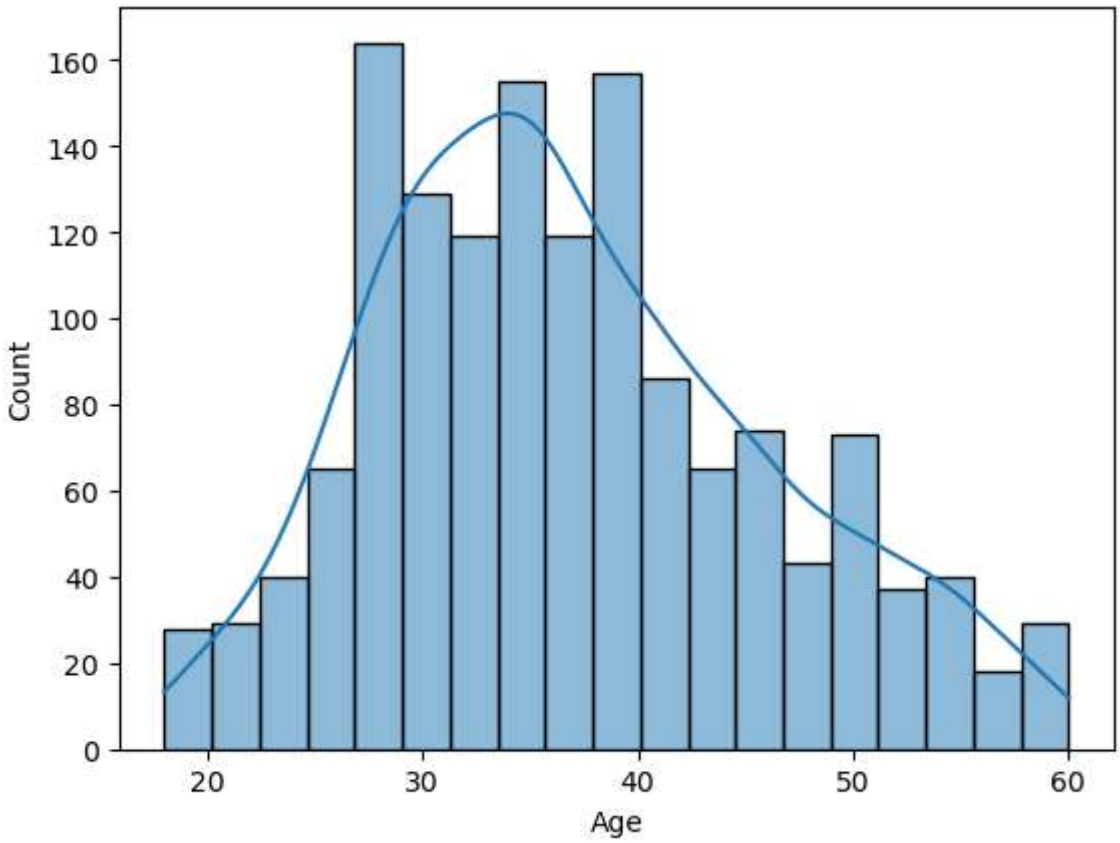
In [16]:
```
df["EducationField"].value_counts()
```

Out[16]:
```
Life Sciences       606
Medical             464
Marketing           159
Technical Degree    132
Other                82
Human Resources      27
Name: EducationField, dtype: int64
```

4.Data Visualization.

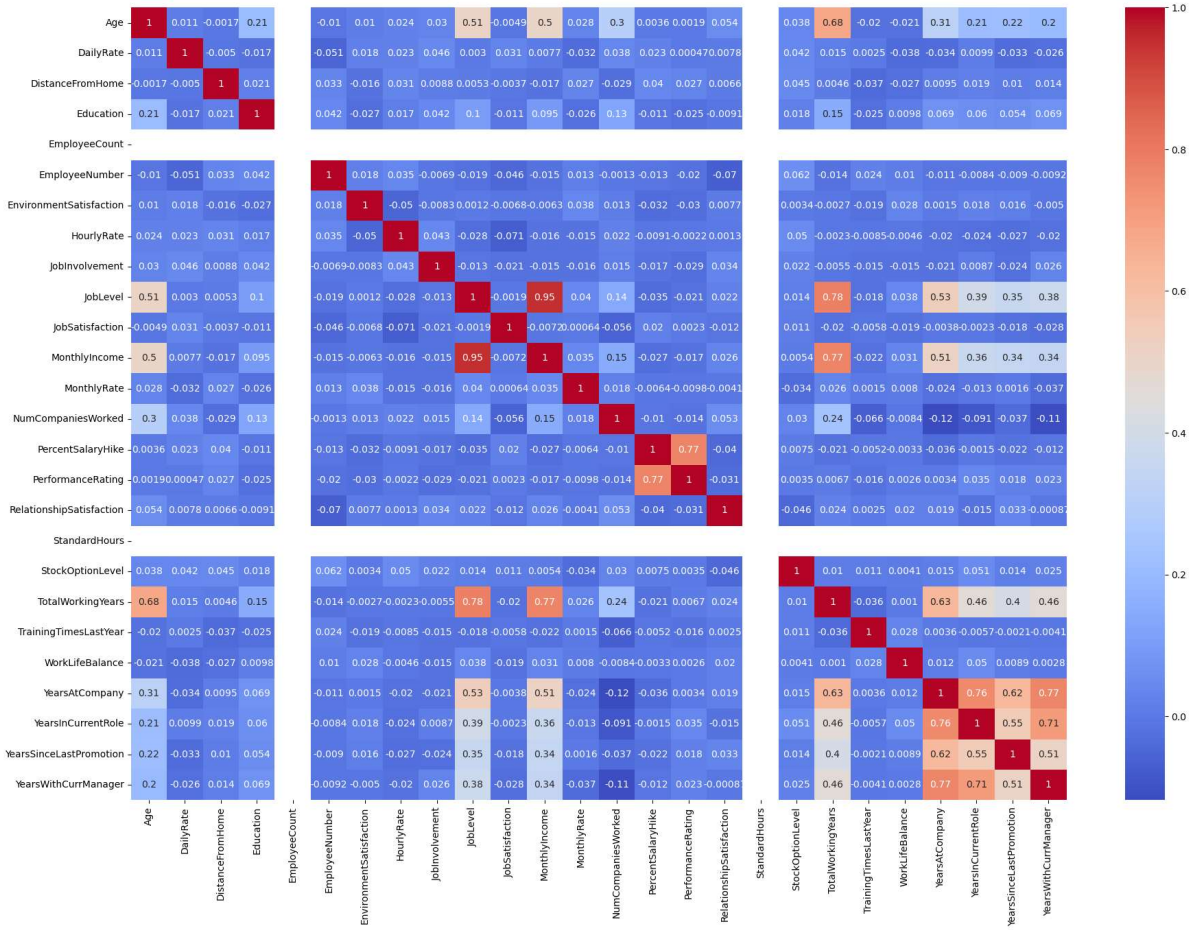
In [17]:
```
sns.histplot(x="Age",data=df,kde=True)
```

Out[17]:
```
<AxesSubplot:xlabel='Age', ylabel='Count'>
```



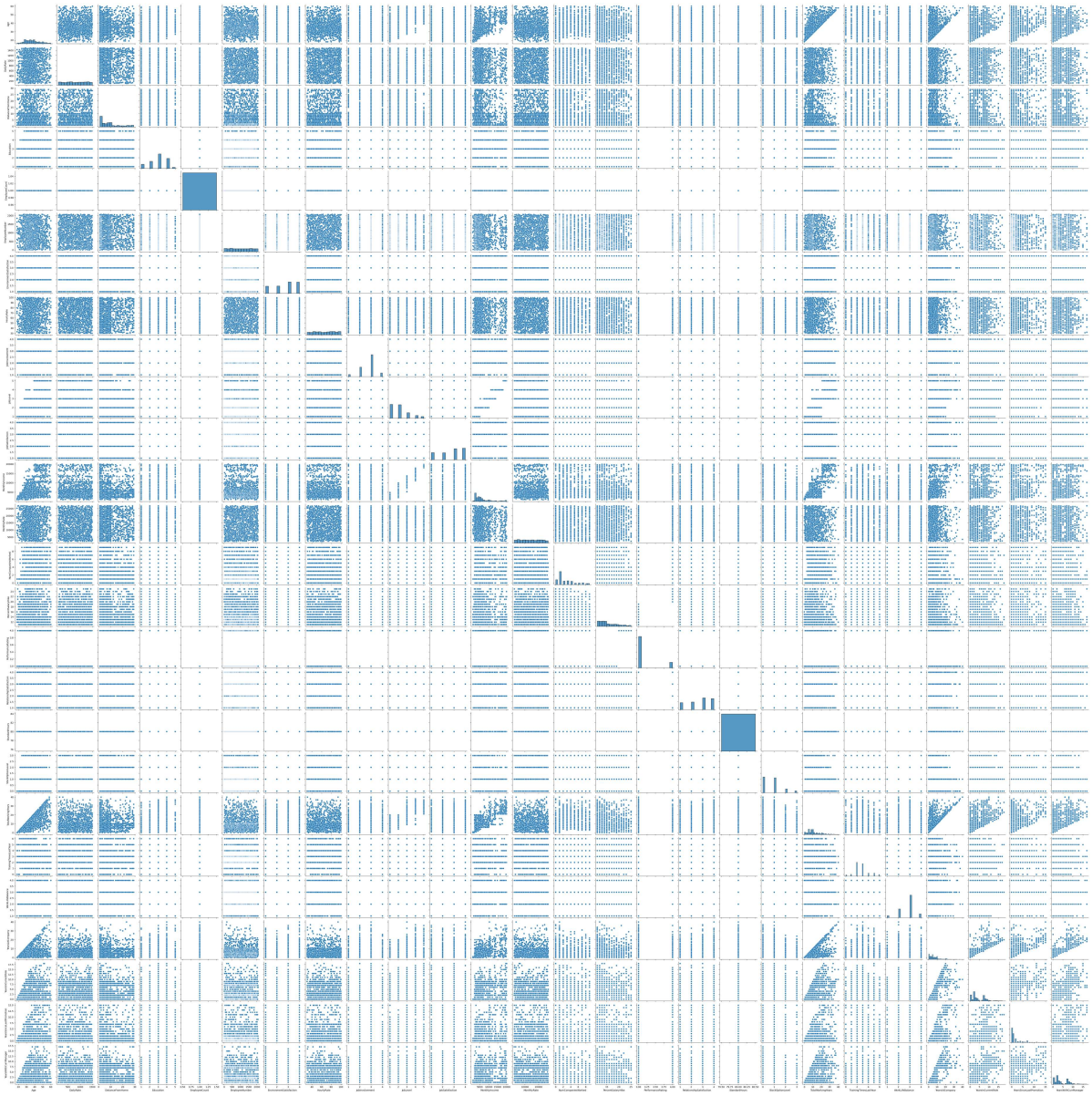
In [15]:
```
plt.subplots(figsize=(22,15))
sns.heatmap(df.corr(),annot=True,cmap="coolwarm")
```

Out[15]: <AxesSubplot:>



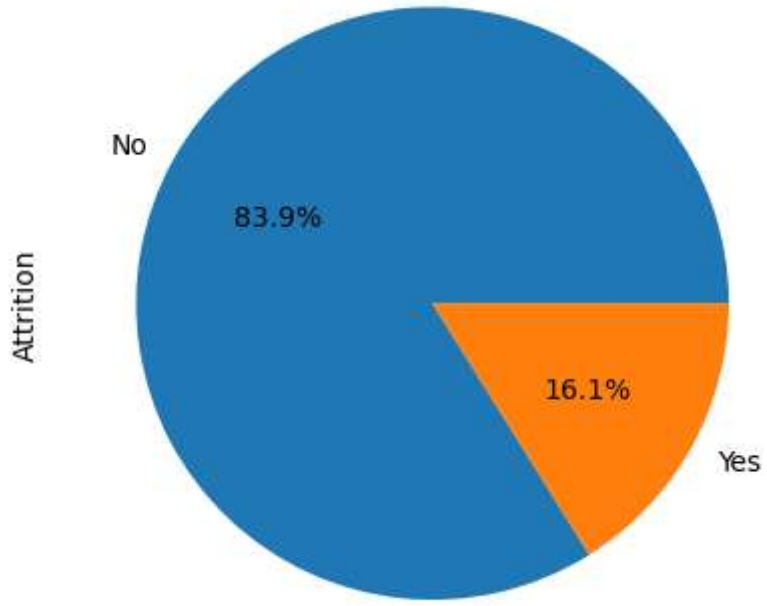
In [16]:
```
sns.pairplot(df)
```

Out[16]:
```
<seaborn.axisgrid.PairGrid at 0x1e9dd3441f0>
```



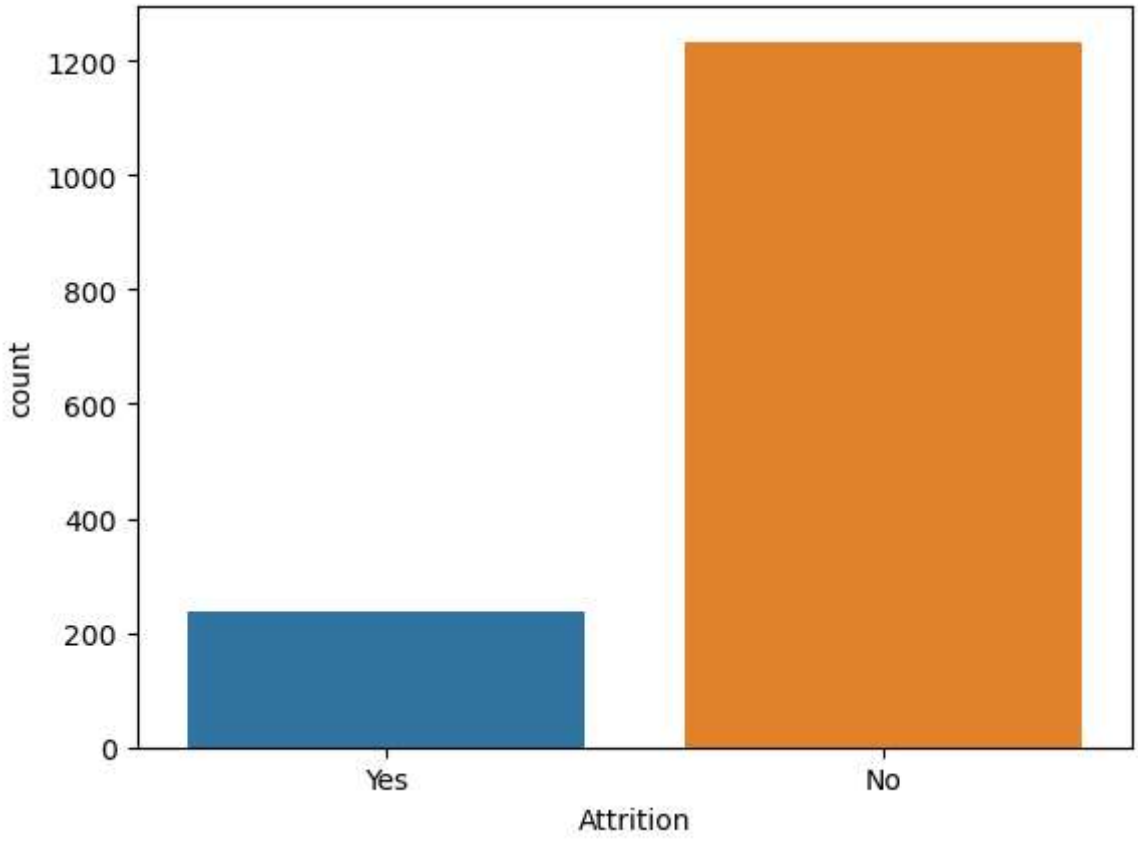
In [18]:
```
df.Attrition.value_counts().plot(kind="pie",autopct="%1.1f%%")
```

Out[18]:
```
<AxesSubplot:ylabel='Attrition'>
```



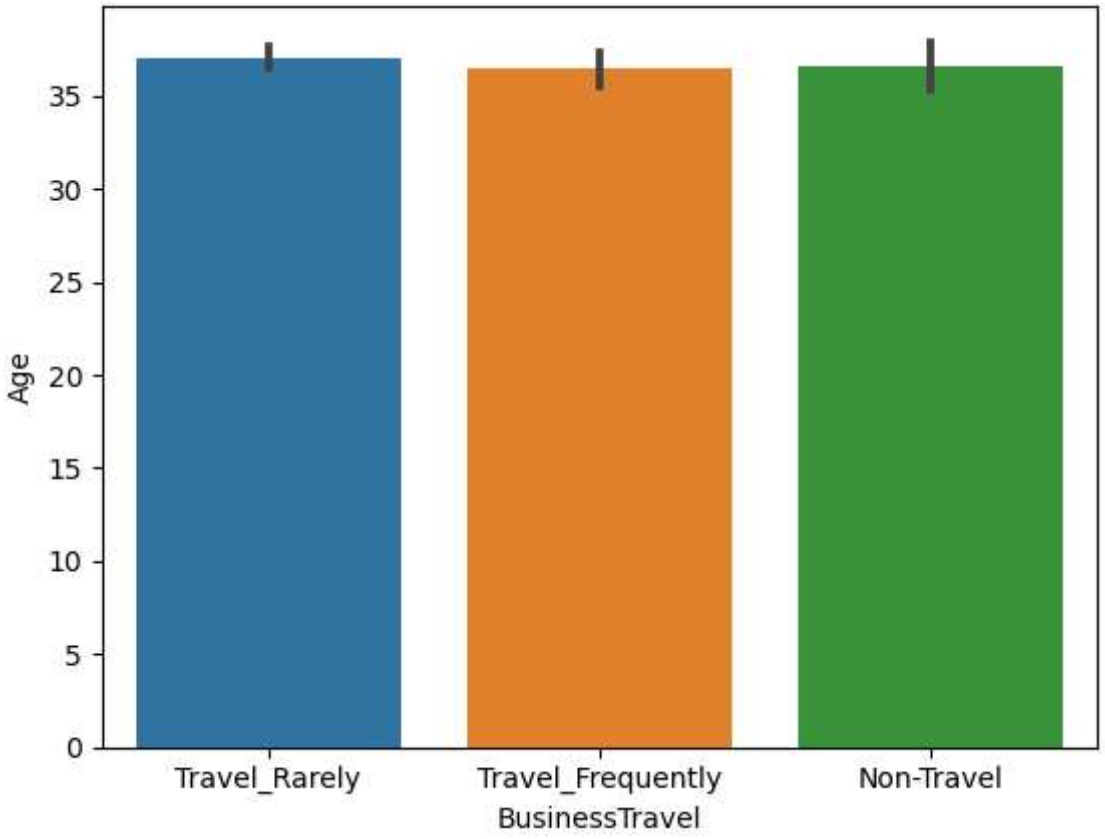
In [19]:
```
sns.countplot(x="Attrition",data=df)
```

Out[19]:
```
<AxesSubplot:xlabel='Attrition', ylabel='count'>
```



In [20]:
```
sns.barplot(x=df["BusinessTravel"],y=df["Age"])
```

Out[20]:
```
<AxesSubplot:xlabel='BusinessTravel', ylabel='Age'>
```



5.Outlier Detection

In [21]:
```
df.head()
```

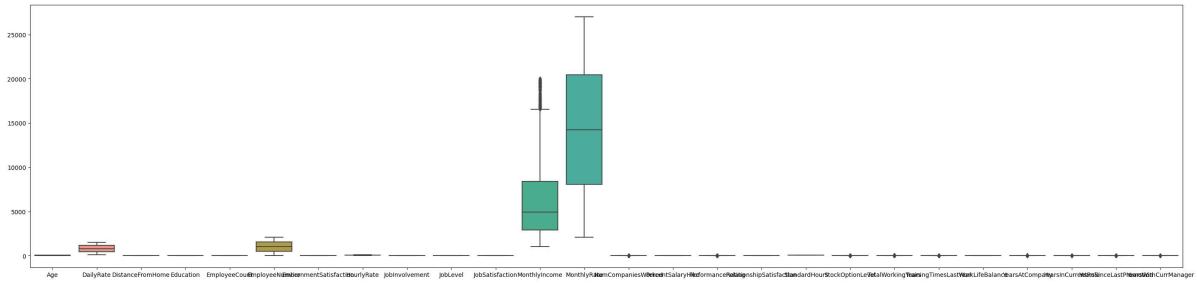
Out[21]:

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

5 rows × 35 columns

In [22]:
```
plt.figure(figsize=(35,8))
sns.boxplot(data=df)
```

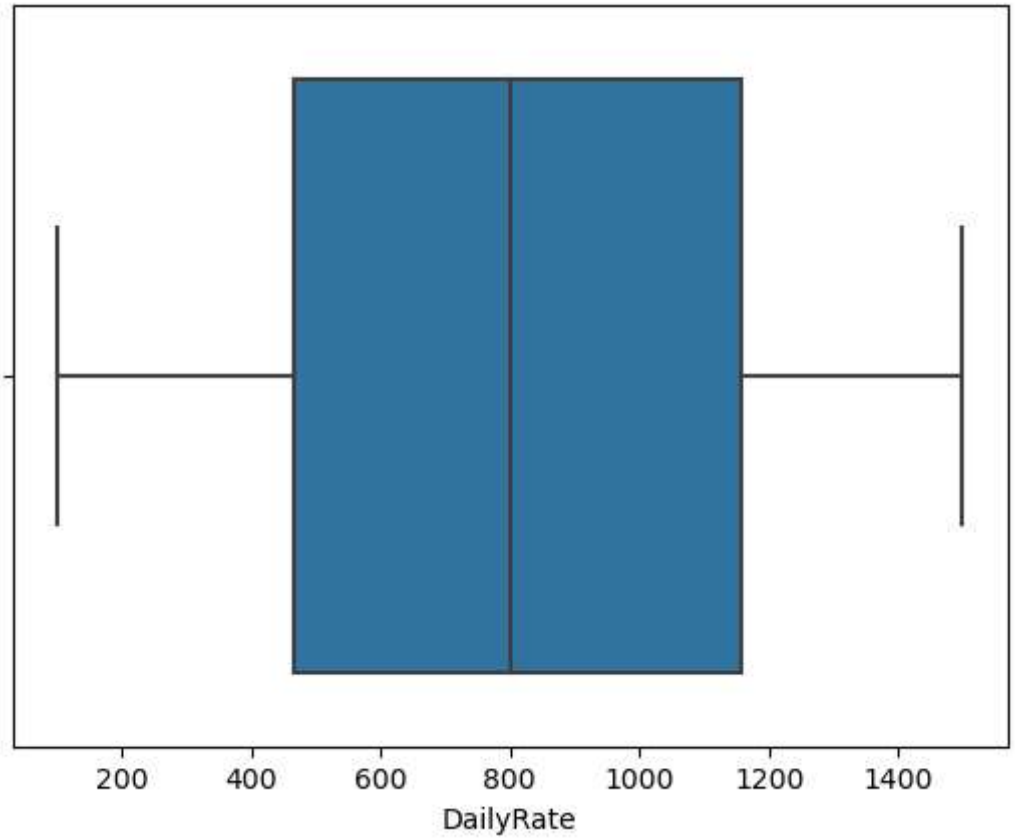
Out[22]: <AxesSubplot:>



In [23]:
```
sns.boxplot(df["DailyRate"])
```

```
C:\Users\admin\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureW
arning: Pass the following variable as a keyword arg: x. From version 0.12, t
he only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

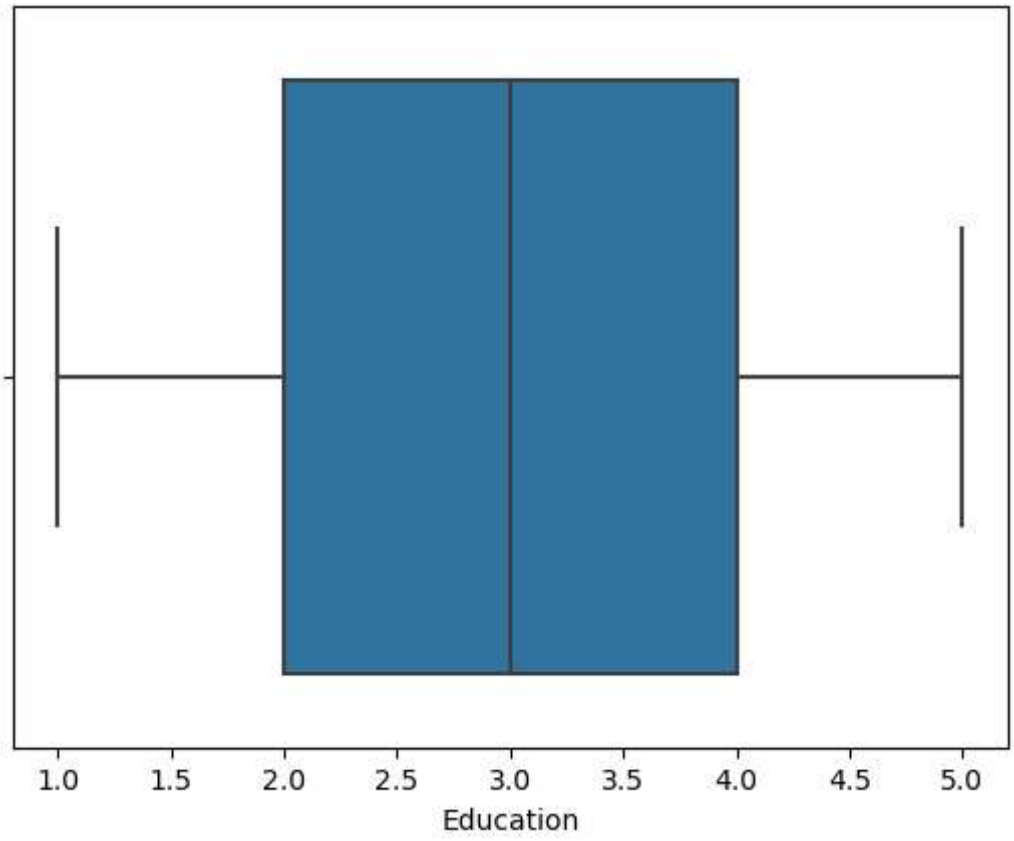
Out[23]: <AxesSubplot:xlabel='DailyRate'>



In [24]:
```
sns.boxplot(df["Education"])
```

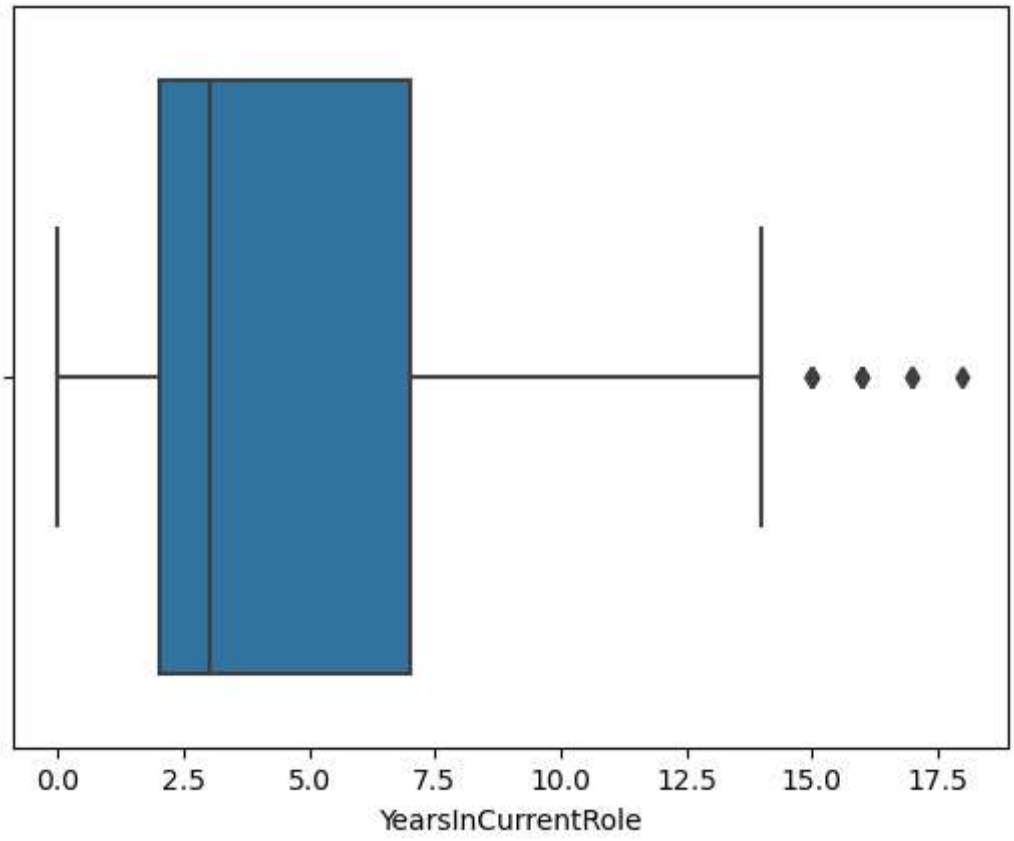
```
C:\Users\admin\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureW
arning: Pass the following variable as a keyword arg: x. From version 0.12, t
he only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[24]: <AxesSubplot:xlabel='Education'>



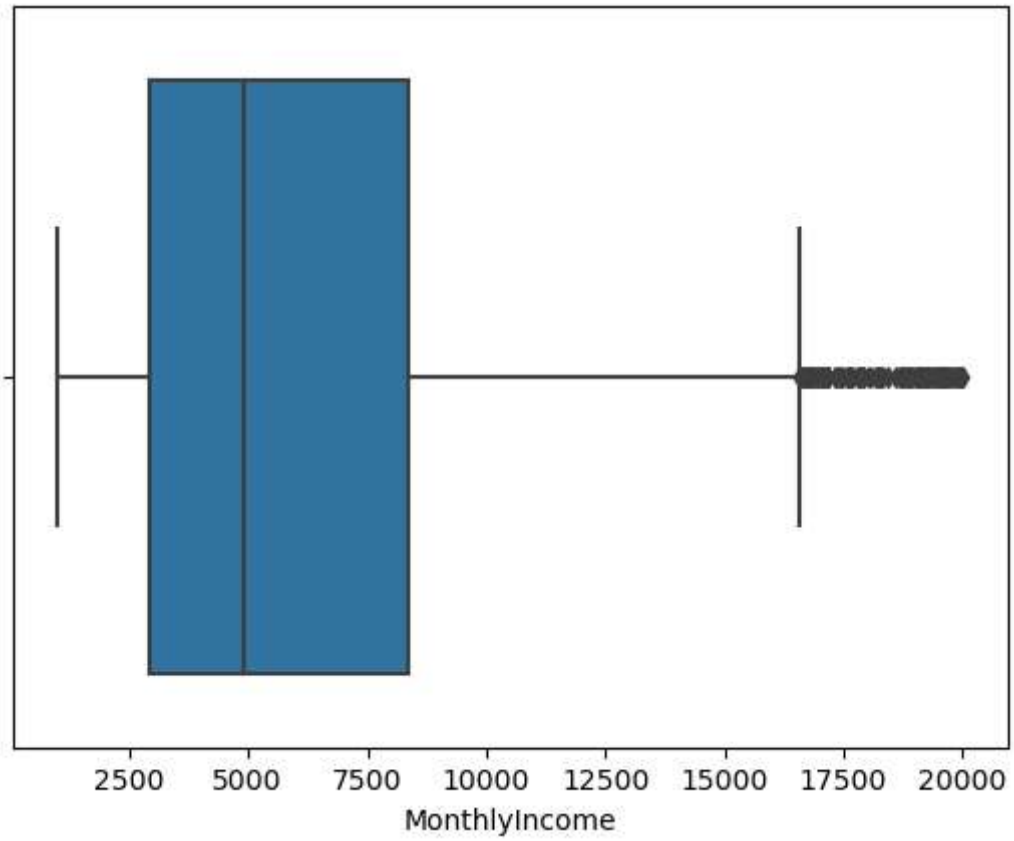
In [25]:
```
sns.boxplot(data=df, x='YearsInCurrentRole')
```

Out[25]:
```
<AxesSubplot:xlabel='YearsInCurrentRole'>
```



In [26]:
```
sns.boxplot(data=df, x='MonthlyIncome')
```

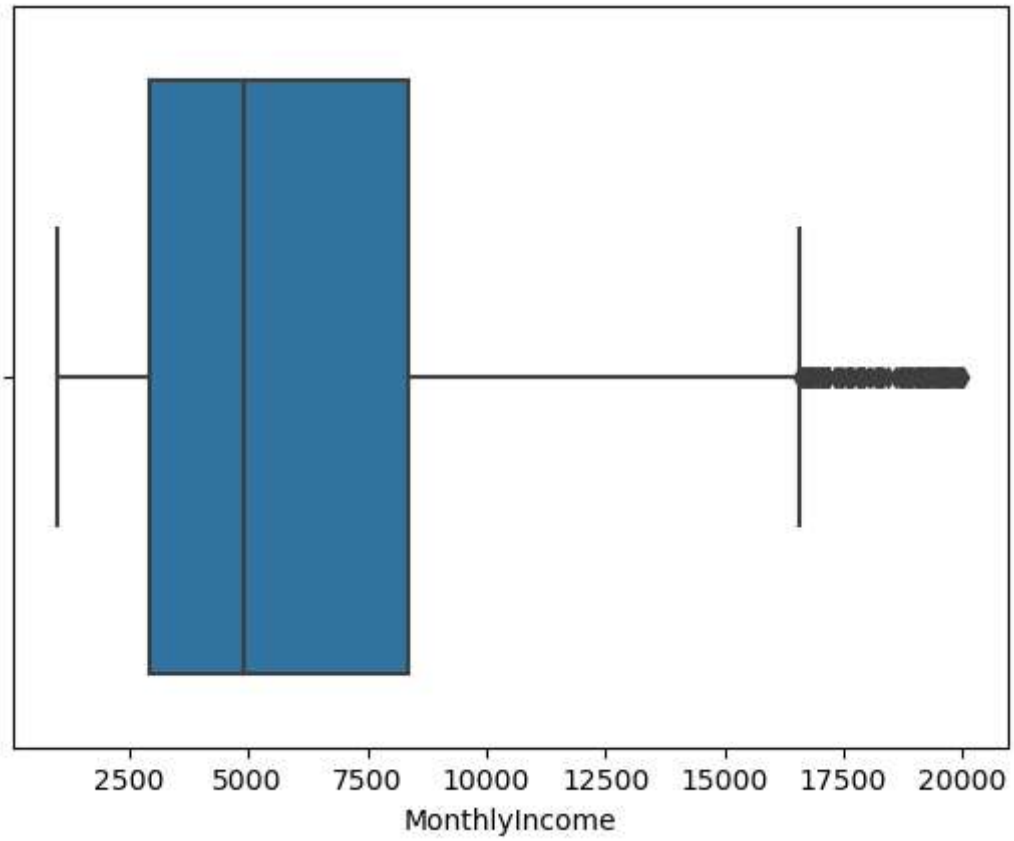
Out[26]:
```
<AxesSubplot:xlabel='MonthlyIncome'>
```



In [27]:
```
from scipy import stats
z_scores = stats.zscore(df['MonthlyIncome'])
df_cleaned = df[(np.abs(z_scores) <= 3)]
```

In [28]:
```
sns.boxplot(data=df_cleaned, x='MonthlyIncome')
```

Out[28]:
```
<AxesSubplot:xlabel='MonthlyIncome'>
```




```
So the outliers are in large quantity and they are inside the threshold, so
let us not remove the outliers
```

6.Splitting Dependent and Independent variables

In [29]:
```
x=df.drop(columns=["Attrition"],axis=1)
```

In [30]:
```
x.head()
```

Out[30]:

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

5 rows × 34 columns

In [31]:
```
type(x)
```

Out[31]:
```
pandas.core.frame.DataFrame
```

In [32]:
```
y=df["Attrition"]
```

In [33]:
```
y.head()
```

Out[33]:
```
0    Yes
1     No
2    Yes
3     No
4     No
Name: Attrition, dtype: object
```

In [34]:
```
type(y)
```

Out[34]:
```
pandas.core.series.Series
```

7.Encoding

In [35]:
```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
```

In [36]:
```
categorical_features = x.select_dtypes(include=['object']).columns.tolist()
x_encoded = pd.get_dummies(x, columns=categorical_features, drop_first=True)
```

In [37]:
```
x_encoded.head()
```

Out[37]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	Environmer
0	41	1102	1	2	1	1	
1	49	279	8	1	1	2	
2	37	1373	2	2	1	4	
3	33	1392	3	4	1	5	
4	27	591	2	1	1	7	

5 rows × 47 columns

8.Feature Scaling

In [38]:
```
from sklearn.preprocessing import StandardScaler
s=StandardScaler()
x_scaled=pd.DataFrame(s.fit_transform(x_encoded),columns=x_encoded.columns)
```

In [39]:
```
x_scaled.head()
```

Out[39]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	Envir
0	0.446350	0.742527	-1.010909	-0.891688	0.0	-1.701283	
1	1.322365	-1.297775	-0.147150	-1.868426	0.0	-1.699621	
2	0.008343	1.414363	-0.887515	-0.891688	0.0	-1.696298	
3	-0.429664	1.461466	-0.764121	1.061787	0.0	-1.694636	
4	-1.086676	-0.524295	-0.887515	-1.868426	0.0	-1.691313	

5 rows × 47 columns

9.Splitting Data into Train and Test.

In [40]:
```
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,ran
```

In [41]:
```
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

Out[41]:
```
((1176, 47), (294, 47), (1176,), (294,))
```

• Model Building

- Import the model building Libraries
- Initializing the model
- Training and testing the model
- Evaluation of Model
- Save the Model

Logistic Regression

1.Import the model building Libraries

In [42]:
```
from sklearn.linear_model import LogisticRegression
```

2.Initializing the model

In [43]:
```
lr=LogisticRegression()
```

3.Training and testing the model

In [44]:
```
lr.fit(x_train,y_train)
```

Out[44]:
```
LogisticRegression()
```

In [45]:
```
y_pred=lr.predict(x_test)
```

In [96]:
```
y_pred
```

Out[96]:
```
array(['No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', '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)
```

In [97]:
```
y_test
```

Out[97]:
```
442      No
1091     No
981     Yes
785      No
1332    Yes
       ...
1439     No
481      No
124     Yes
198      No
1229     No
Name: Attrition, Length: 294, dtype: object
```

In [48]:
```
df.head()
```

Out[48]:

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

5 rows × 35 columns

4.Evaluation of Model

In [49]:
```
from sklearn.metrics import accuracy_score,confusion_matrix,classification_rep
```

In [50]:
```
accuracy_score(y_test,y_pred)
```

Out[50]:
```
0.8775510204081632
```

In [51]:
```
confusion_matrix(y_test,y_pred)
```

Out[51]:
```
array([[238,   7],
       [ 29,  20]], dtype=int64)
```

In [52]:
```
pd.crosstab(y_test,y_pred)
```

Out[52]:

col_0	No	Yes
Attrition		
No	238	7
Yes	29	20

In [53]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

          No       0.89      0.97      0.93       245
         Yes       0.74      0.41      0.53        49

    accuracy                           0.88       294
   macro avg       0.82      0.69      0.73       294
weighted avg       0.87      0.88      0.86       294
```

In [54]:
```
probability=lr.predict_proba(x_test)[:,1]
```

In [55]:
```
probability
```

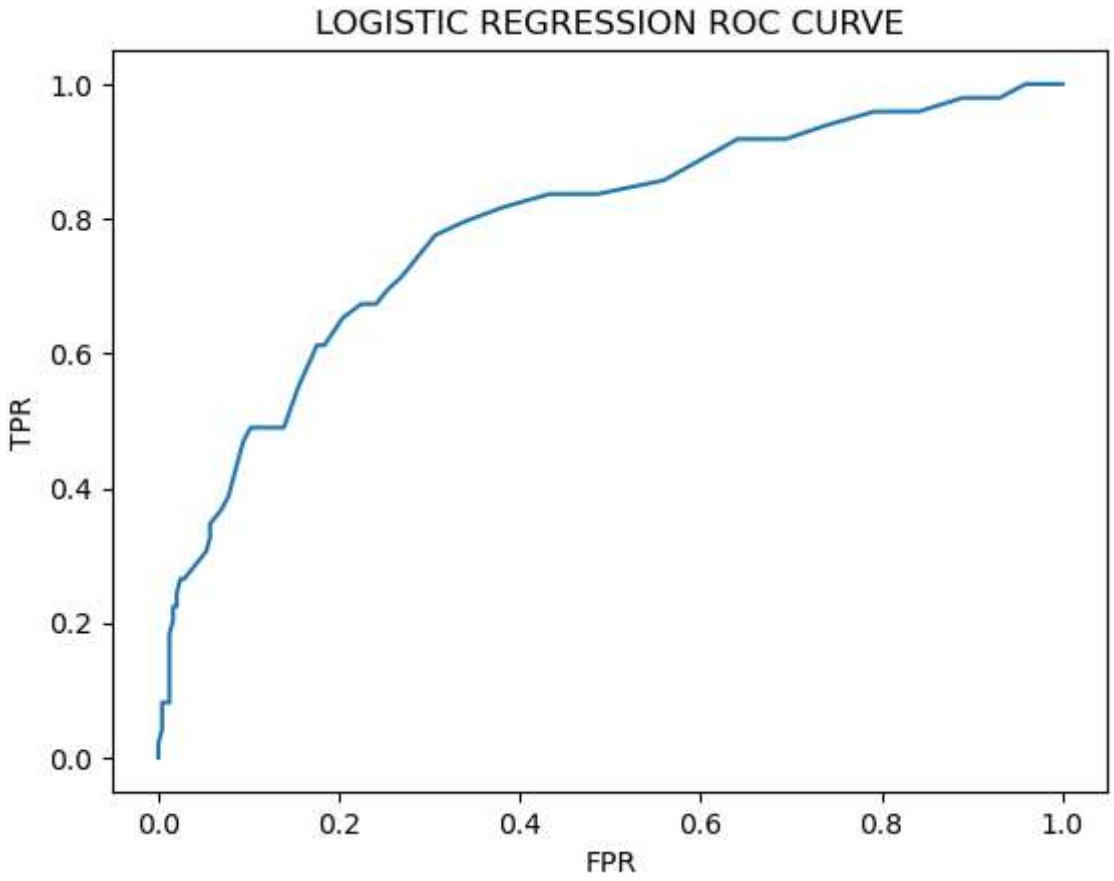
Out[55]:
```
array([6.61367680e-02, 8.06198087e-02, 5.95640954e-01, 1.42633628e-01,
       7.84184536e-01, 4.42409704e-02, 4.90141163e-01, 3.64319554e-02,
       8.44925839e-04, 4.30164151e-01, 3.70048030e-02, 1.96283567e-01,
       1.51964558e-02, 5.39471444e-01, 5.88816107e-02, 1.18804547e-02,
       1.13489514e-01, 3.82574810e-02, 2.32011787e-02, 2.66149260e-01,
       1.31568762e-01, 9.99913247e-03, 1.30286201e-02, 3.88975456e-02,
       7.51582081e-01, 4.58920880e-01, 6.43869830e-02, 2.97280577e-02,
       6.90209855e-01, 3.77607239e-02, 5.59306642e-03, 3.05902665e-01,
       3.65028773e-02, 3.90288488e-02, 2.27899092e-02, 5.90358760e-03,
       2.32731579e-01, 5.29386349e-02, 1.38241033e-02, 1.13353905e-01,
       3.42777217e-02, 8.33820691e-03, 1.07151981e-03, 5.52578825e-03,
       8.80282261e-03, 5.59254552e-01, 4.21978392e-01, 5.99712843e-04,
       4.00447399e-01, 3.68527002e-01, 3.55627577e-02, 8.16716675e-01,
       1.58976261e-02, 3.55101528e-01, 4.94410470e-01, 2.54453615e-01,
       1.03880530e-02, 4.22173742e-01, 2.22235299e-02, 2.95631863e-01,
       1.26998325e-02, 1.53660325e-01, 1.65718568e-01, 2.37981819e-02,
       1.13922041e-01, 2.33156457e-02, 3.48112915e-01, 1.78088100e-01,
       1.21220858e-01, 1.82213934e-01, 3.38118048e-02, 1.58551253e-01,
       9.58027931e-02, 3.08386596e-02, 7.44773642e-02, 4.13402445e-02,
       1.92788840e-02, 2.80415152e-02, 4.93838215e-01, 1.65502835e-02,
       3.08277540e-03, 1.74647710e-02, 2.61191408e-01, 1.97665118e-02,
       1.95892874e-02, 7.95183218e-02, 6.72183840e-04, 1.32195797e-02,
       1.24777389e-02, 6.32250258e-02, 5.79625808e-02, 7.28350500e-02,
       3.24892323e-01, 1.73612641e-01, 8.28152031e-04, 7.99639374e-02,
       4.97002372e-01, 6.41780395e-01, 5.52704989e-02, 7.62263342e-02,
       1.32740233e-01, 5.87050953e-01, 5.91342152e-01, 5.08443347e-03,
       1.06560968e-01, 6.69002781e-03, 6.09068154e-02, 2.11328359e-01,
       3.68701854e-02, 3.96643551e-01, 2.94309518e-02, 5.18292700e-02,
       3.44618460e-03, 2.96577876e-01, 2.24618906e-02, 2.45843670e-02,
       9.84944236e-03, 2.82977886e-02, 2.36629032e-03, 4.89083971e-03,
       1.06593614e-01, 3.22277227e-02, 8.43908260e-02, 8.89755562e-01,
       1.01655842e-02, 2.07510840e-03, 3.14944475e-03, 9.91294127e-02,
       1.39271996e-01, 1.05763678e-02, 4.62491869e-03, 3.29517891e-01,
       7.00654301e-01, 1.96667235e-01, 9.97786091e-03, 3.85631608e-01,
       6.96550561e-01, 2.28516613e-01, 1.82557187e-01, 4.88667496e-01,
       2.73199468e-02, 3.53431498e-02, 3.17068584e-02, 3.13677515e-01,
       4.71792593e-01, 3.75527841e-02, 2.67239299e-01, 3.83012181e-03,
       7.37038139e-02, 1.24740256e-01, 4.07667992e-03, 1.71768746e-01,
       7.20048951e-02, 1.75320014e-01, 7.13178095e-03, 2.39429405e-02,
       1.98658569e-01, 3.20547275e-01, 3.96927966e-03, 9.49330798e-03,
       7.45555587e-01, 3.12330244e-03, 3.32408074e-02, 9.19392780e-01,
       1.48852250e-02, 2.57190744e-01, 1.73014525e-01, 1.51785386e-01,
       1.86931379e-02, 8.28851842e-04, 2.54342547e-01, 4.56483830e-02,
       3.99204597e-02, 1.25490112e-01, 1.70919482e-02, 8.25299901e-02,
       4.38992386e-02, 4.31506741e-02, 3.39152219e-02, 5.12964217e-02,
       2.12219051e-02, 1.57474151e-01, 2.44952859e-03, 8.22895146e-01,
       5.98438753e-02, 8.69783952e-02, 5.40701108e-01, 8.54091278e-03,
       5.57078600e-01, 2.31232882e-01, 2.11246138e-01, 2.75461703e-01,
       1.33154014e-01, 1.82199815e-02, 3.32865074e-02, 1.09429647e-01,
       1.86460970e-02, 7.81476677e-03, 2.65574308e-01, 1.69272765e-02,
       3.86686532e-01, 2.20988923e-01, 8.08612471e-01, 2.03966645e-02,
       1.28650474e-01, 1.77680007e-02, 3.57289398e-01, 5.30474583e-04,
       1.67105418e-01, 1.00764993e-02, 8.58290380e-02, 3.05739812e-01,
       6.81826517e-02, 3.81711531e-01, 1.10859745e-01, 4.71842280e-03,
       1.86894274e-02, 5.45048658e-02, 4.72421338e-02, 9.34489342e-02,
       8.33653672e-02, 4.44029727e-01, 5.18663398e-01, 1.79271982e-01,
       2.87090882e-01, 2.67710024e-03, 1.09509162e-01, 2.65241921e-01,
```

```
7.65032998e-01, 4.64180665e-02, 1.97677279e-01, 2.06495230e-01,
3.00475823e-02, 4.28680929e-02, 9.01257179e-02, 1.16204269e-01,
2.66591825e-01, 9.07332777e-04, 7.47052094e-02, 1.49451887e-03,
1.41520152e-01, 2.92363790e-01, 5.07029822e-03, 1.26501783e-01,
3.79539275e-02, 1.77150306e-02, 1.54456455e-01, 3.43384106e-01,
4.27481928e-02, 3.44423944e-02, 2.93165700e-01, 7.16660273e-02,
5.38151329e-01, 1.63749013e-02, 1.23951727e-01, 6.52278702e-02,
2.45783680e-03, 6.25002778e-01, 6.25608255e-01, 3.74616723e-01,
1.41256456e-01, 2.84604841e-02, 2.91843045e-01, 5.95069780e-02,
3.21045151e-02, 6.99486994e-02, 1.15155181e-03, 4.47317458e-01,
5.39084197e-01, 2.55697184e-02, 2.85616158e-02, 8.43094503e-03,
6.55595901e-02, 2.48427612e-02, 9.60265542e-03, 5.93422188e-03,
8.58521685e-02, 3.64680251e-01, 1.20449475e-01, 1.84226608e-01,
6.91761349e-01, 3.24455148e-03, 4.85788438e-02, 7.34675868e-02,
5.35355633e-02, 7.58287245e-02, 2.30602991e-04, 1.53563842e-01,
1.43056931e-03, 9.15060156e-03, 1.08956580e-01, 6.50047900e-01,
2.36548949e-02, 7.52606168e-02])
```

In [98]:
```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
y_test = label_encoder.fit_transform(y_test)
```

In [99]:
```
fpr,tpr,threshsholds = roc_curve(y_test,probability)
```

In [100]:
```
plt.plot(fpr,tpr)
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('LOGISTIC REGRESSION ROC CURVE')
plt.show()
```



Decision Tree

In [57]:
```
from sklearn.tree import DecisionTreeClassifier
dtc=DecisionTreeClassifier()
```

In [58]:
```
dtc.fit(x_train,y_train)
```

Out[58]:
```
DecisionTreeClassifier()
```

In [59]:
```
y_pred1=dtc.predict(x_test)
```

In [101]:
```
y_pred1
```

Out[101]:
```
array(['No', 'No', 'Yes', 'No', 'No', 'Yes', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'Yes', 'Yes', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'Yes', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No',
       'Yes', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No',
       'No', 'Yes', 'No', 'No', 'No', 'Yes', 'No', 'No', 'Yes', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'No', 'No', 'No',
       'Yes', 'No', 'No', 'No', 'Yes', 'No', 'Yes', 'No', 'No', 'Yes',
       'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'Yes', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'Yes', 'No', 'No',
       'No', 'No', 'Yes', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'Yes', 'No',
       'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes',
       'No', 'Yes', 'No', 'No', 'Yes', 'No', 'No', 'Yes', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No'], dtype=object)
```

In [64]:
```
y_test
```

Out[64]:
```
442      No
1091     No
981     Yes
785      No
1332    Yes
       ...
1439     No
481      No
124     Yes
198      No
1229     No
Name: Attrition, Length: 294, dtype: object
```

In [65]:
```
#Accuracy score
from sklearn.metrics import accuracy_score,confusion_matrix,classification_rep
```

In [66]:
```
accuracy_score(y_test,y_pred1)
```

Out[66]:
```
0.7687074829931972
```

In [67]:
```
confusion_matrix(y_test,y_pred1)
```

Out[67]:
```
array([[210,  35],
       [ 33,  16]], dtype=int64)
```

In [68]:
```
pd.crosstab(y_test,y_pred1)
```

Out[68]:

col_0	No	Yes
Attrition		
No	210	35
Yes	33	16

In [69]:
```
print(classification_report(y_test,y_pred1))
```

```
              precision    recall  f1-score   support

          No       0.86      0.86      0.86       245
         Yes       0.31      0.33      0.32        49

    accuracy                           0.77       294
   macro avg       0.59      0.59      0.59       294
weighted avg       0.77      0.77      0.77       294
```

In [70]:
```
probability=dtc.predict_proba(x_test)[:,1]
```

In [71]:
```
probability
```

Out[71]:
```
array([0., 0., 1., 0., 0., 1., 1., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0.,
       0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 1.,
       1., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 1., 0., 1., 0., 0., 0.,
       0., 0., 0., 1., 0., 0., 0., 1., 1., 0., 0., 0., 0., 0., 0., 1., 0.,
       0., 1., 0., 0., 0., 1., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0.,
       1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 1., 1., 0., 0., 0., 0., 0., 0., 1., 1., 1., 1., 0.,
       0., 0., 1., 0., 0., 0., 1., 0., 1., 0., 0., 1., 0., 0., 0., 1., 0.,
       0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 1., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 1., 1., 0., 0., 0., 0., 1., 0., 0., 1.,
       0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0.,
       0., 1., 0., 0., 0., 0., 1., 0., 0., 0., 1., 0., 0., 0., 0., 0., 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., 0., 1., 0., 1., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 1., 0., 1., 0., 0., 1., 0., 0., 1., 0., 0., 0.,
       0., 0., 0., 0., 0.])
```

Hyper parameter Tuning

In [67]:
```
from sklearn import tree
plt.figure(figsize=(25,15))
tree.plot_tree(dtc,filled=True)
```

Out[67]:
```
[Text(0.32960321576763485, 0.96875, 'X[19] <= -1.257\ngini = 0.269\nsamples
= 1176\nvalue = [988, 188]'),
 Text(0.08298755186721991, 0.90625, 'X[45] <= 0.387\ngini = 0.5\nsamples =
78\nvalue = [39, 39]'),
 Text(0.04979253112033195, 0.84375, 'X[2] <= 0.902\ngini = 0.426\nsamples =
39\nvalue = [27, 12]'),
 Text(0.03319502074688797, 0.78125, 'X[26] <= 0.797\ngini = 0.312\nsamples
= 31\nvalue = [25, 6]'),
 Text(0.01991701244813278, 0.71875, 'X[10] <= -1.114\ngini = 0.198\nsamples
= 27\nvalue = [24, 3]'),
 Text(0.013278008298755186, 0.65625, 'X[46] <= 0.482\ngini = 0.5\nsamples =
6\nvalue = [3, 3]'),
 Text(0.006639004149377593, 0.59375, 'gini = 0.0\nsamples = 3\nvalue = [3,
0]'),
 Text(0.01991701244813278, 0.59375, 'gini = 0.0\nsamples = 3\nvalue = [0,
3]'),
 Text(0.026556016597510373, 0.65625, 'gini = 0.0\nsamples = 21\nvalue = [2
1, 0]'),
 Text(0.046473029045643155, 0.71875, 'X[6] <= 0.712\ngini = 0.375\nsamples
```

In [72]:
```
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']
}
```

In [73]:
```
grid_search=GridSearchCV(estimator=dtc,param_grid=parameter,cv=5,scoring="accu
```

In [74]:
```
grid_search.fit(x_train,y_train)
```

Out[74]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(),
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [1, 2, 3, 4, 5],
                         'max_features': ['auto', 'sqrt', 'log2'],
                         'splitter': ['best', 'random']},
             scoring='accuracy')
```

In [75]:
```
grid_search.best_params_
```

Out[75]:
```
{'criterion': 'entropy',
 'max_depth': 4,
 'max_features': 'auto',
 'splitter': 'best'}
```

In [76]:
```
dtc_cv=DecisionTreeClassifier(criterion= 'entropy',
 max_depth=3,
 max_features='sqrt',
 splitter='best')
dtc_cv.fit(x_train,y_train)
```

Out[76]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=3, max_features='sqrt')
```

In [77]:
```
y_pred=dtc_cv.predict(x_test)
```

In [78]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

          No       0.84      0.98      0.90       245
         Yes       0.33      0.04      0.07        49

    accuracy                           0.83       294
   macro avg       0.59      0.51      0.49       294
weighted avg       0.75      0.83      0.77       294
```

Random Forest

In [79]:
```
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier()
```

In [80]:
```
rfc.fit(x_train,y_train)
```

Out[80]:
```
RandomForestClassifier()
```

In [81]:
```
y_pred2=dtc.predict(x_test)
```

In [82]:
```
y_pred2
```

Out[82]:
```
array(['No', 'No', 'Yes', 'No', 'No', 'Yes', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'Yes', 'Yes', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'Yes', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No',
       'Yes', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No',
       'No', 'Yes', 'No', 'No', 'No', 'Yes', 'No', 'No', 'Yes', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'No', 'No', 'No',
       'Yes', 'No', 'No', 'No', 'Yes', 'No', 'Yes', 'No', 'No', 'Yes',
       'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'Yes', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'Yes', 'No', 'No',
       'No', 'No', 'Yes', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'Yes', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes',
       'No', 'Yes', 'No', 'No', 'Yes', 'No', 'No', 'Yes', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'No'], dtype=object)
```

In [83]:
```
y_test
```

Out[83]:
```
442      No
1091     No
981     Yes
785      No
1332    Yes
       ...
1439     No
481      No
124     Yes
198      No
1229     No
Name: Attrition, Length: 294, dtype: object
```

In [84]:
```
forest_params = [{'max_depth': list(range(10, 15)), 'max_features': list(range
```

In [85]:
```
rfc_cv=GridSearchCV(rfc,param_grid=forest_params,cv=10,scoring='accuracy')
```

In [86]:
```
rfc_cv.fit(x_train,y_train)
```

```
C:\Users\admin\anaconda3\lib\site-packages\sklearn\model_selection\_validatio
n.py:372: 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 erro
r_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
---
50 fits failed with the following error:
Traceback (most recent call last):
  File "C:\Users\admin\anaconda3\lib\site-packages\sklearn\model_selection\_v
alidation.py", line 680, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "C:\Users\admin\anaconda3\lib\site-packages\sklearn\ensemble\_forest.p
y", line 450, in fit
    trees = Parallel(
  File "C:\Users\admin\anaconda3\lib\site-packages\joblib\parallel.py", line
1863, in __call__
    return output if self.return_generator else list(output)
  File "C:\Users\admin\anaconda3\lib\site-packages\joblib\parallel.py", line
1792, in _get_sequential_output
    res = func(*args, **kwargs)
  File "C:\Users\admin\anaconda3\lib\site-packages\sklearn\utils\fixes.py", l
ine 216, in __call__
    return self.function(*args, **kwargs)
  File "C:\Users\admin\anaconda3\lib\site-packages\sklearn\ensemble\_forest.p
y", line 185, in _parallel_build_trees
    tree.fit(X, y, sample_weight=curr_sample_weight, check_input=False)
  File "C:\Users\admin\anaconda3\lib\site-packages\sklearn\tree\_classes.py",
line 937, in fit
    super().fit(
  File "C:\Users\admin\anaconda3\lib\site-packages\sklearn\tree\_classes.py",
line 308, in fit
    raise ValueError("max_features must be in (0, n_features]")
ValueError: max_features must be in (0, n_features]

  warnings.warn(some_fits_failed_message, FitFailedWarning)
C:\Users\admin\anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:969: UserWarning: One or more of the test scores are non-finite: [       na
n 0.84948573 0.84950022 0.85034043 0.85459945 0.85801101
 0.85628712 0.8605389  0.85885122 0.85798204 0.86052441 0.8596842
 0.86138635 0.85796031        nan 0.84693611 0.85290453 0.85714907
 0.85882949 0.85884398 0.85799652 0.85798204 0.85543242 0.8596842
 0.8596842  0.85883674 0.8613936  0.85542518        nan 0.84948573
 0.85204983 0.85630161 0.85798928 0.85628712 0.85543966 0.86222657
 0.85883674 0.86309576 0.86053165 0.86223381 0.86308127 0.85797479
        nan 0.84779806 0.85204983 0.85800377 0.85883674 0.86055338
 0.85800377 0.86052441 0.8605389  0.85712009 0.85797479 0.85798928
 0.86053165 0.86137187        nan 0.84863827 0.85545415 0.85629436
 0.85884398 0.85798928 0.85373751 0.85799652 0.85799652 0.85712734
 0.86140808 0.85712734 0.86222657 0.85967695]
  warnings.warn(
```

Out[86]:
```
GridSearchCV(cv=10, estimator=RandomForestClassifier(),
             param_grid=[{'max_depth': [10, 11, 12, 13, 14],
                          'max_features': [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10,
11,
                                           12, 13]}],
             scoring='accuracy')
```

In [87]:
```
y_pred=rfc_cv.predict(x_test)
```

In [88]:
```
from sklearn.metrics import accuracy_score,confusion_matrix,classification_rep
```

In [89]:
```
accuracy_score(y_test,y_pred2)
```

Out[89]:
```
0.7687074829931972
```

In [90]:
```
confusion_matrix(y_test,y_pred2)
```

Out[90]:
```
array([[210,  35],
       [ 33,  16]], dtype=int64)
```

In [91]:
```
pd.crosstab(y_test,y_pred2)
```

Out[91]:

col_0	No	Yes
Attrition		
No	210	35
Yes	33	16

In [92]:
```
print(classification_report(y_test,y_pred2))
```

```
              precision    recall  f1-score   support

          No       0.86      0.86      0.86       245
         Yes       0.31      0.33      0.32        49

    accuracy                           0.77       294
   macro avg       0.59      0.59      0.59       294
weighted avg       0.77      0.77      0.77       294
```

In [93]:
```
rfc_cv.best_params_
```

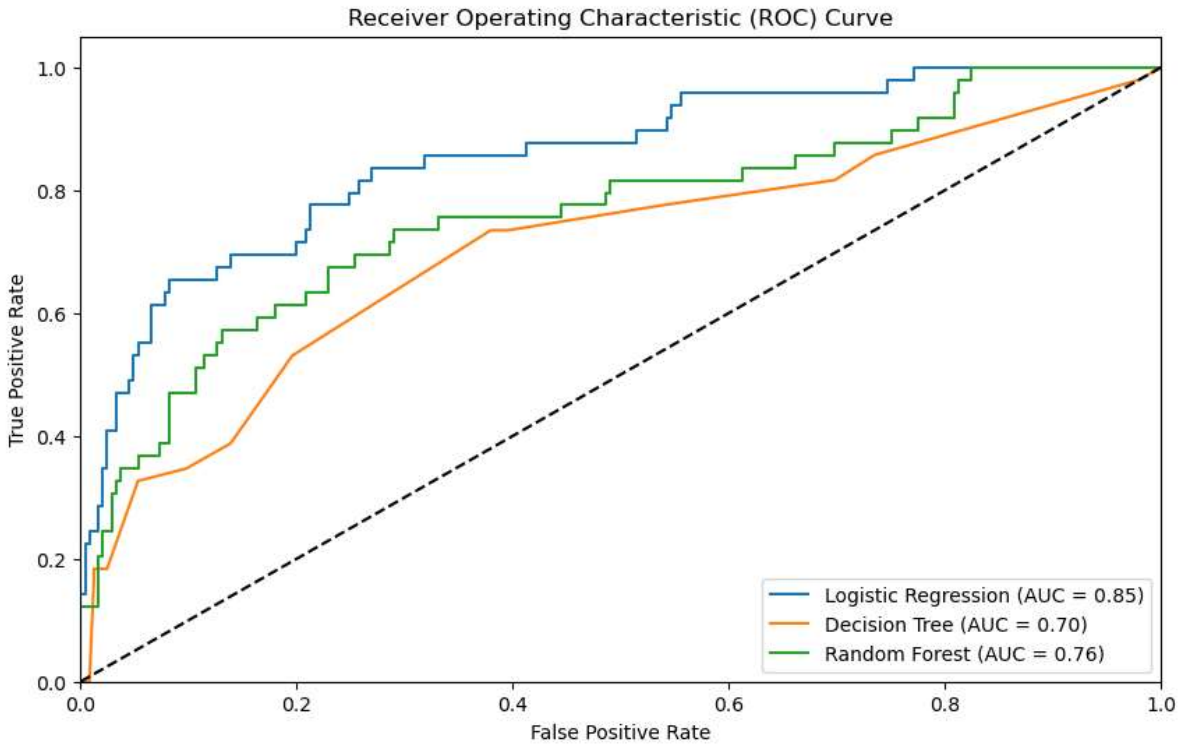
Out[93]:
```
{'max_depth': 12, 'max_features': 9}
```

In [94]:
```
probability=rfc.predict_proba(x_test)[:,1]
```

In [95]:
```
probability
```

Out[95]:
```
array([0.13, 0.05, 0.18, 0.15, 0.71, 0.36, 0.3 , 0.11, 0.11, 0.13, 0.06,
       0.11, 0.07, 0.47, 0.1 , 0.02, 0.16, 0.08, 0.11, 0.16, 0.56, 0.07,
       0.05, 0.11, 0.39, 0.21, 0.06, 0.12, 0.57, 0.07, 0.06, 0.13, 0.13,
       0.16, 0.07, 0.09, 0.16, 0.14, 0.03, 0.25, 0.19, 0.08, 0.11, 0.2 ,
       0.05, 0.36, 0.31, 0.08, 0.65, 0.33, 0.26, 0.48, 0.14, 0.21, 0.41,
       0.14, 0.14, 0.1 , 0.05, 0.26, 0.03, 0.16, 0.11, 0.15, 0.37, 0.12,
       0.21, 0.14, 0.09, 0.16, 0.1 , 0.3 , 0.12, 0.09, 0.1 , 0.11, 0.1 ,
       0.04, 0.39, 0.05, 0.05, 0.11, 0.23, 0.1 , 0.18, 0.08, 0.09, 0.25,
       0.02, 0.04, 0.65, 0.1 , 0.13, 0.26, 0.06, 0.07, 0.1 , 0.32, 0.14,
       0.13, 0.27, 0.24, 0.36, 0.05, 0.07, 0.03, 0.09, 0.47, 0.23, 0.27,
       0.2 , 0.12, 0.04, 0.07, 0.15, 0.16, 0.1 , 0.19, 0.04, 0.01, 0.11,
       0.03, 0.04, 0.58, 0.12, 0.16, 0.02, 0.06, 0.11, 0.12, 0.01, 0.29,
       0.5 , 0.21, 0.18, 0.14, 0.35, 0.2 , 0.14, 0.16, 0.1 , 0.24, 0.09,
       0.15, 0.24, 0.17, 0.06, 0.05, 0.15, 0.15, 0.1 , 0.23, 0.13, 0.23,
       0.15, 0.12, 0.11, 0.21, 0.12, 0.09, 0.23, 0.07, 0.28, 0.51, 0.1 ,
       0.14, 0.23, 0.06, 0.11, 0.04, 0.12, 0.05, 0.1 , 0.25, 0.07, 0.43,
       0.12, 0.25, 0.21, 0.09, 0.04, 0.02, 0.01, 0.37, 0.07, 0.03, 0.37,
       0.07, 0.2 , 0.13, 0.24, 0.5 , 0.2 , 0.04, 0.1 , 0.08, 0.06, 0.04,
       0.46, 0.12, 0.29, 0.19, 0.16, 0.04, 0.11, 0.17, 0.35, 0.07, 0.08,
       0.01, 0.1 , 0.16, 0.09, 0.23, 0.1 , 0.08, 0.06, 0.25, 0.11, 0.37,
       0.17, 0.36, 0.38, 0.17, 0.11, 0.08, 0.13, 0.27, 0.52, 0.12, 0.03,
       0.31, 0.05, 0.08, 0.05, 0.26, 0.28, 0.03, 0.08, 0.1 , 0.21, 0.13,
       0.1 , 0.13, 0.15, 0.09, 0.05, 0.32, 0.06, 0.15, 0.2 , 0.14, 0.24,
       0.07, 0.18, 0.14, 0.08, 0.61, 0.23, 0.31, 0.16, 0.08, 0.13, 0.11,
       0.1 , 0.22, 0.06, 0.28, 0.24, 0.03, 0.06, 0.02, 0.09, 0.1 , 0.07,
       0.05, 0.13, 0.32, 0.09, 0.19, 0.32, 0.1 , 0.11, 0.24, 0.17, 0.22,
       0.01, 0.1 , 0.1 , 0.12, 0.13, 0.28, 0.09, 0.11])
```

In [105]:
```
# Import the necessary libraries
from sklearn.metrics import roc_curve, roc_auc_score
import matplotlib.pyplot as plt

logreg_roc_auc = roc_auc_score(y_test, lr.predict_proba(x_test)[:, 1])

# Calculate the ROC AUC score for Decision Tree Classifier
dt_roc_auc = roc_auc_score(y_test, grid_search.predict_proba(x_test)[:, 1])

# Compute ROC curve for Logistic Regression
logreg_fpr, logreg_tpr, _ = roc_curve(y_test, lr.predict_proba(x_test)[:, 1])

# Compute ROC curve for Decision Tree Classifier
dt_fpr, dt_tpr, _ = roc_curve(y_test, grid_search.predict_proba(x_test)[:, 1])

# Calculate the ROC AUC score for Random Forest
rf_roc_auc = roc_auc_score(y_test, rfc_cv.predict_proba(x_test)[:, 1])

# Compute ROC curve for Random Forest
rf_fpr, rf_tpr, _ = roc_curve(y_test, rfc_cv.predict_proba(x_test)[:, 1])

# Plot ROC AUC curves
plt.figure(figsize=(10, 6))
plt.plot(logreg_fpr, logreg_tpr, label='Logistic Regression (AUC = %0.2f)' % l
plt.plot(dt_fpr, dt_tpr, label='Decision Tree (AUC = %0.2f)' % dt_roc_auc)
plt.plot(rf_fpr, rf_tpr, label='Random Forest (AUC = %0.2f)' % rf_roc_auc)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```


Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Logistic Regression (AUC = 0.85)
Decision Tree (AUC = 0.70)
Random Forest (AUC = 0.76)

In [ ]: