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IMPORT LIBRARIES

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

IMPORT DATASET

In [2]:
```
df=pd.read_csv("WA_Fn-UseC_-HR-Employee-Attrition.csv")
```

In [3]:
```
df
```

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
...	...	...	...	...	...	...	...	...	...	...
1465	36	No	Travel_Frequently	884	Research & Development	23	2	Medical	1	2061
1466	39	No	Travel_Rarely	613	Research & Development	6	1	Medical	1	2062
1467	27	No	Travel_Rarely	155	Research & Development	4	3	Life Sciences	1	2064
1468	49	No	Travel_Frequently	1023	Sales	2	3	Medical	1	2065
1469	34	No	Travel_Rarely	628	Research & Development	8	3	Medical	1	2068

1470 rows × 35 columns

In [4]:
```
df.head()
```

Out[4]:

	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 × 35 columns

In [5]:
```
df.tail()
```

Out[5]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber
1465	36	No	Travel_Frequently	884	Research & Development	23	2	Medical	1	2061
1466	39	No	Travel_Rarely	613	Research & Development	6	1	Medical	1	2062
1467	27	No	Travel_Rarely	155	Research & Development	4	3	Life Sciences	1	2064
1468	49	No	Travel_Frequently	1023	Sales	2	3	Medical	1	2065

1469	34	No	Travel_Rarely	628	Research & Development	8	3	Medical	1	206

5 rows × 35 columns

In [6]:

```
df.shape
```

Out[6]:

```
(1470, 35)
```

In [7]:

```
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 [8]:

```
df.describe()
```

Out[8]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	Jol
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 [9]:

```
df.Attrition.value_counts()
```

Out[9]:
```
No     1233
Yes     237
Name: Attrition, dtype: int64
```

Checking for NULL Values

In [10]:
```
df.isnull().any()
```

Out[10]:
```
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
```

Data Visualization

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

Out[11]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	Hou
Age	1.000000	0.010661	-0.001686	0.208034	NaN	-0.010145	0.010146	0.0
DailyRate	0.010661	1.000000	-0.004985	-0.016806	NaN	-0.050990	0.018355	0.0
DistanceFromHome	-0.001686	-0.004985	1.000000	0.021042	NaN	0.032916	-0.016075	0.0
Education	0.208034	-0.016806	0.021042	1.000000	NaN	0.042070	-0.027128	0.0
EmployeeCount	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
EmployeeNumber	-0.010145	-0.050990	0.032916	0.042070	NaN	1.000000	0.017621	0.0
EnvironmentSatisfaction	0.010146	0.018355	-0.016075	-0.027128	NaN	0.017621	1.000000	-0.0
HourlyRate	0.024287	0.023381	0.031131	0.016775	NaN	0.035179	-0.049857	1.0
JobInvolvement	0.029820	0.046135	0.008783	0.042438	NaN	-0.006888	-0.008278	0.0
JobLevel	0.509604	0.002966	0.005303	0.101589	NaN	-0.018519	0.001212	-0.0
JobSatisfaction	-0.004892	0.030571	-0.003669	-0.011296	NaN	-0.046247	-0.006784	-0.0
MonthlyIncome	0.497855	0.007707	-0.017014	0.094961	NaN	-0.014829	-0.006259	-0.0
MonthlyRate	0.028051	-0.032182	0.027473	-0.026084	NaN	0.012648	0.037600	-0.0
NumCompaniesWorked	0.299635	0.038153	-0.029251	0.126317	NaN	-0.001251	0.012594	0.0
PercentSalaryHike	0.003634	0.022704	0.040235	-0.011111	NaN	-0.012944	-0.031701	-0.0
PerformanceRating	0.001904	0.000473	0.027110	-0.024539	NaN	-0.020359	-0.029548	-0.0
RelationshipSatisfaction	0.053535	0.007846	0.006557	-0.009118	NaN	-0.069861	0.007665	0.0

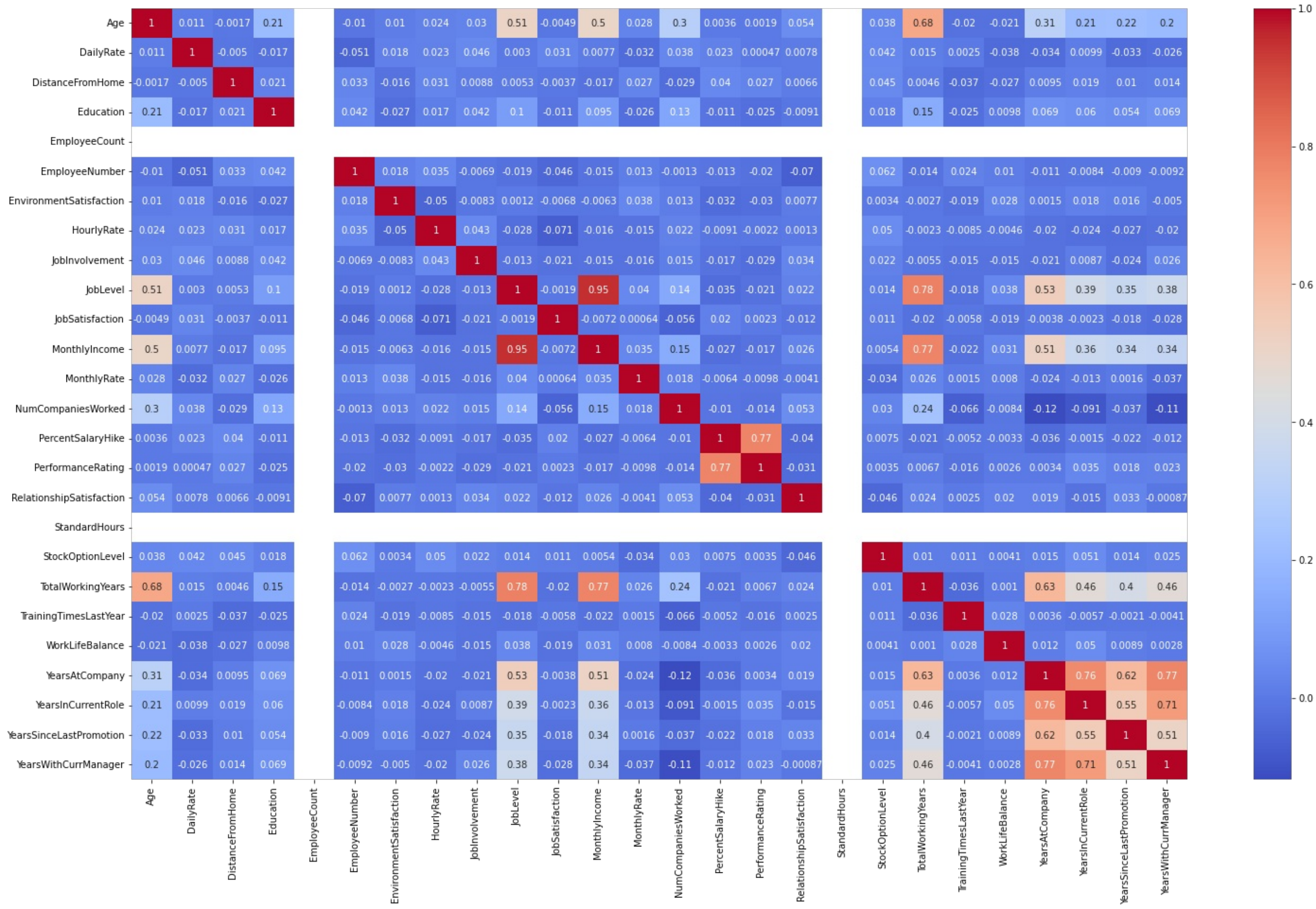
StandardHours	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
StockOptionLevel	0.037510	0.042143	0.044872	0.018422	NaN	0.062227	0.003432	0.(
TotalWorkingYears	0.680381	0.014515	0.004628	0.148280	NaN	-0.014365	-0.002693	-0.(
TrainingTimesLastYear	-0.019621	0.002453	-0.036942	-0.025100	NaN	0.023603	-0.019359	-0.(
WorkLifeBalance	-0.021490	-0.037848	-0.026556	0.009819	NaN	0.010309	0.027627	-0.(
YearsAtCompany	0.311309	-0.034055	0.009508	0.069114	NaN	-0.011240	0.001458	-0.(
YearsInCurrentRole	0.212901	0.009932	0.018845	0.060236	NaN	-0.008416	0.018007	-0.(
YearsSinceLastPromotion	0.216513	-0.033229	0.010029	0.054254	NaN	-0.009019	0.016194	-0.(
YearsWithCurrManager	0.202089	-0.026363	0.014406	0.069065	NaN	-0.009197	-0.004999	-0.(

26 rows × 26 columns

In [12]:

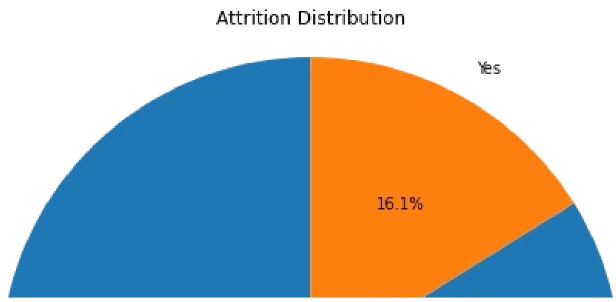
```
plt.subplots(figsize=(25,15))
sns.heatmap(corr,annot=True,cmap="coolwarm")
```

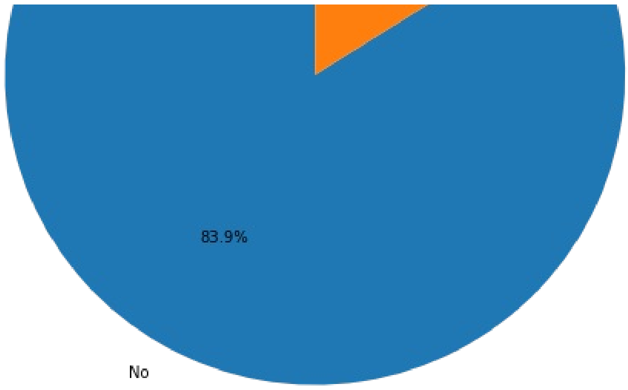
Out[12]: <AxesSubplot:>



In [13]:

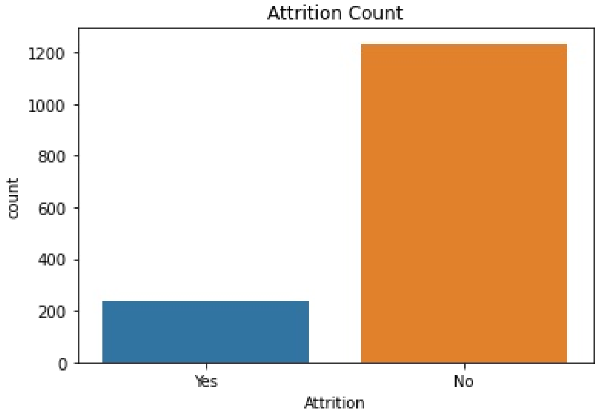
```
attrition_counts = df['Attrition'].value_counts()
plt.figure(figsize=(8, 8))
plt.pie(attrition_counts, labels=attrition_counts.index, autopct='%1.1f%%', startangle=90)
plt.title('Attrition Distribution')
plt.axis('equal')

plt.show()
```





In [14]:

```
sns.countplot(x="Attrition", data=df)
plt.title("Attrition Count")
plt.show()
```

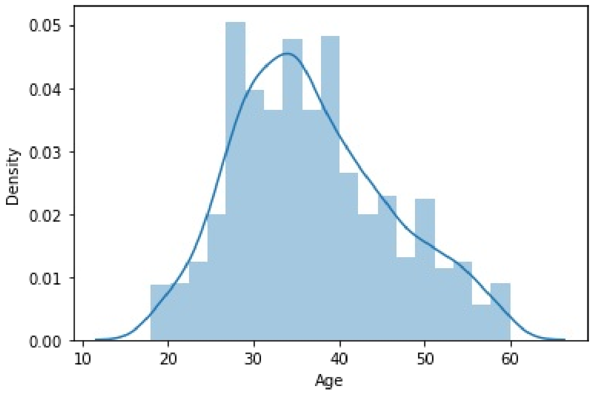


In [15]:

```
sns.distplot(df["Age"])
```

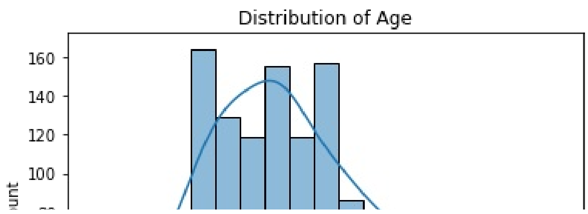
```
C:\Users\SRUJANA\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprec
ated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-l
evel function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

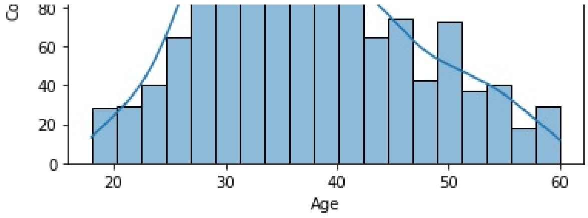
Out[15]: <AxesSubplot:xlabel='Age', ylabel='Density'>



In [16]:

```
sns.histplot(data=df, x="Age", kde=True)
plt.title("Distribution of Age")
plt.show()
```

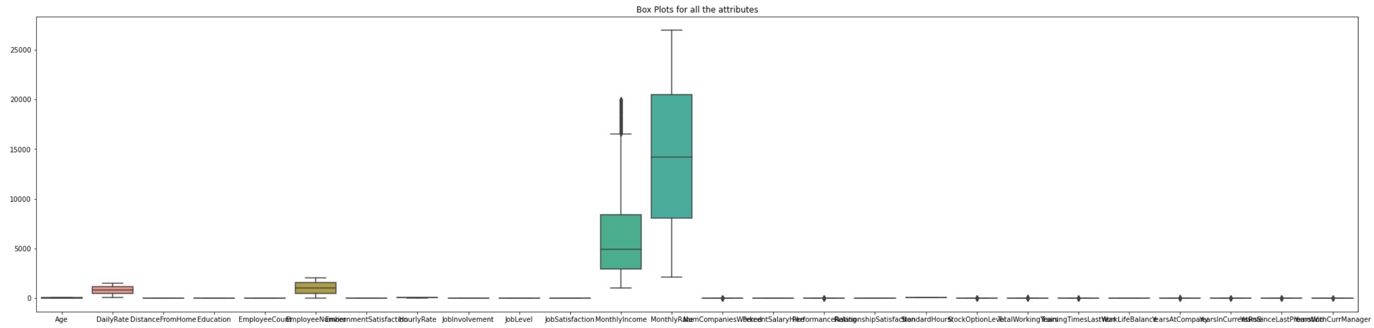




Outlier Detection

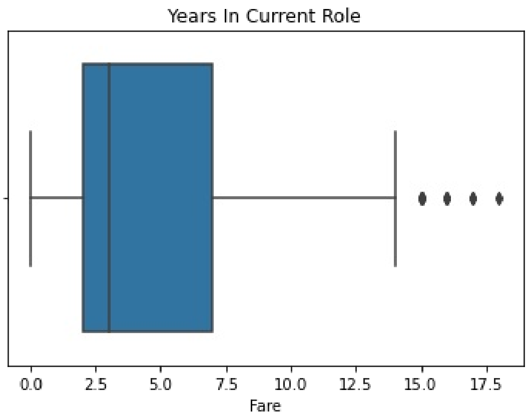
In [17]:

```
plt.figure(figsize=(35, 8))
sns.boxplot(data=df)
plt.title('Box Plots for all the attributes')
plt.show()
```



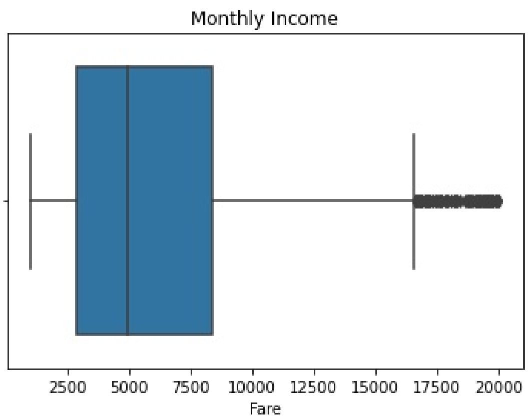
In [18]:

```
sns.boxplot(data=df, x='YearsInCurrentRole')
plt.title('Years In Current Role')
plt.xlabel('Fare')
plt.show()
```



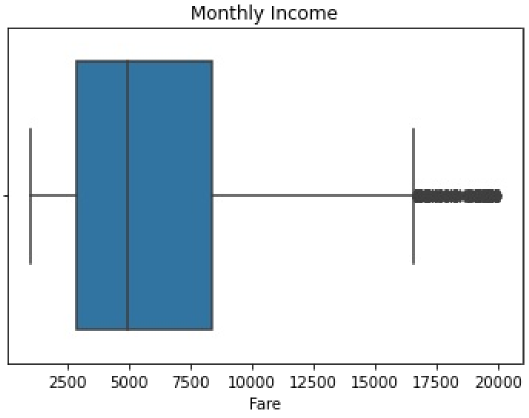
In [19]:

```
sns.boxplot(data=df, x='MonthlyIncome')
plt.title('Monthly Income')
plt.xlabel('Fare')
plt.show()
```



In [20]:
```
from scipy import stats

z_scores = stats.zscore(df['MonthlyIncome'])
z_score_threshold = 3
df_cleaned = df[(np.abs(z_scores) <= z_score_threshold)]
```

In [21]:
```
sns.boxplot(data=df_cleaned, x='MonthlyIncome')
plt.title('Monthly Income')
plt.xlabel('Fare')
plt.show()
```



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

SPLITTING INDEPENDENT AND DEPENDENT VARIABLES

In [22]:
```
x= df.drop(columns=["Attrition"])
y = df["Attrition"]
#since there are so many null values
```

In [23]:
```
x.head()
```

Out[23]:

	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

In [24]:
```
y.head()
```

Out[24]:
```
0     Yes
1      No
2     Yes
3      No
4      No
Name: Attrition, dtype: object
```

ENCODING

In [25]:
```
categorical_features = x.select_dtypes(include=['object']).columns.tolist()
x_encoded = pd.get_dummies(x, columns=categorical_features, drop_first=True)
```

In [26]:

```
x_encoded.head()
```

Out[26]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement	Job
0	41	1102	1	2	1	1	2	94	3	
1	49	279	8	1	1	2	3	61	2	
2	37	1373	2	2	1	4	4	92	2	
3	33	1392	3	4	1	5	4	56	3	
4	27	591	2	1	1	7	1	40	3	

5 rows × 47 columns

FEATURE SCALING

In [27]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
x_scaled = pd.DataFrame(scaler.fit_transform(x_encoded), columns=x_encoded.columns)
x_scaled
```

Out[27]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvem
0	0.446350	0.742527	-1.010909	-0.891688	0.0	-1.701283	-0.660531	1.383138	0.379
1	1.322365	-1.297775	-0.147150	-1.868426	0.0	-1.699621	0.254625	-0.240677	-1.026
2	0.008343	1.414363	-0.887515	-0.891688	0.0	-1.696298	1.169781	1.284725	-1.026
3	-0.429664	1.461466	-0.764121	1.061787	0.0	-1.694636	1.169781	-0.486709	0.379
4	-1.086676	-0.524295	-0.887515	-1.868426	0.0	-1.691313	-1.575686	-1.274014	0.379
...	...	...	...	...	...	...	...	...	
1465	-0.101159	0.202082	1.703764	-0.891688	0.0	1.721670	0.254625	-1.224807	1.785
1466	0.227347	-0.469754	-0.393938	-1.868426	0.0	1.723332	1.169781	-1.175601	-1.026
1467	-1.086676	-1.605183	-0.640727	0.085049	0.0	1.726655	-0.660531	1.038693	1.785
1468	1.322365	0.546677	-0.887515	0.085049	0.0	1.728317	1.169781	-0.142264	-1.026
1469	-0.320163	-0.432568	-0.147150	0.085049	0.0	1.733302	-0.660531	0.792660	1.785

1470 rows × 47 columns

In [28]:

```
x_scaled.head()
```

Out[28]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement
0	0.446350	0.742527	-1.010909	-0.891688	0.0	-1.701283	-0.660531	1.383138	0.379672
1	1.322365	-1.297775	-0.147150	-1.868426	0.0	-1.699621	0.254625	-0.240677	-1.026167
2	0.008343	1.414363	-0.887515	-0.891688	0.0	-1.696298	1.169781	1.284725	-1.026167
3	-0.429664	1.461466	-0.764121	1.061787	0.0	-1.694636	1.169781	-0.486709	0.379672
4	-1.086676	-0.524295	-0.887515	-1.868426	0.0	-1.691313	-1.575686	-1.274014	0.379672

5 rows × 47 columns

Train test and split

In [29]:

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

In [30]:

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

Out[30]:

```
((1176, 47), (294, 47), (1176,), (294,))
```

MODEL BUILDING

In [31]:

```python
# Import the necessary libraries
from sklearn.linear_model import LogisticRegression
logreg_model = LogisticRegression(random_state=42)

from sklearn.tree import DecisionTreeClassifier
dt_model = DecisionTreeClassifier(random_state=42)
```

In [32]:

```python
logreg_model.fit(x_train, y_train)
dt_model.fit(x_train, y_train)
```

Out[32]:

```
DecisionTreeClassifier(random_state=42)
```

In [33]:

```python
logreg_predictions = logreg_model.predict(x_test)
logreg_predictions
```

Out[33]:

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

In [34]:

```python
dt_predictions = dt_model.predict(x_test)
dt_predictions
```

Out[34]:

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

In [35]:
```
y_test
```

Out[35]:
```
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
```

In [36]:
```
df
```

Out[36]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumbe
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
...	...	...	...	...	...	...	...	...	...	...
1465	36	No	Travel_Frequently	884	Research & Development	23	2	Medical	1	2061
1466	39	No	Travel_Rarely	613	Research & Development	6	1	Medical	1	2062
1467	27	No	Travel_Rarely	155	Research & Development	4	3	Life Sciences	1	2064
1468	49	No	Travel_Frequently	1023	Sales	2	3	Medical	1	2065
1469	34	No	Travel_Rarely	628	Research & Development	8	3	Medical	1	2068

1470 rows × 35 columns

Evaluation of the model

In [37]:
```python
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from joblib import dump
```

In [38]:
```python
logreg_accuracy = accuracy_score(y_test, logreg_predictions)
print("Logistic Regression Accuracy:", logreg_accuracy)
```

```
Logistic Regression Accuracy: 0.8809523809523809
```

In [39]:
```python
dt_accuracy = accuracy_score(y_test, dt_predictions)
print("Decision Tree Accuracy:", dt_accuracy)
```

```
Decision Tree Accuracy: 0.7721088435374149
```

In [40]:
```python
logreg_report = classification_report(y_test, logreg_predictions)
print("Classification Report for Logistic Regression:\n", logreg_report)
```

```
Classification Report for Logistic Regression:
               precision    recall  f1-score   support
```

```
          No       0.92      0.95      0.93       255
         Yes       0.56      0.46      0.51        39

    accuracy                           0.88       294
   macro avg       0.74      0.70      0.72       294
weighted avg       0.87      0.88      0.88       294
```

In [41]:

```
dt_report = classification_report(y_test, dt_predictions)
print("Classification Report for Decision Tree Classifier:\n", dt_report)
```

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

          No       0.87      0.86      0.87       255
         Yes       0.17      0.18      0.17        39

    accuracy                           0.77       294
   macro avg       0.52      0.52      0.52       294
weighted avg       0.78      0.77      0.78       294
```

In [42]:

```
logreg_conf_matrix = confusion_matrix(y_test, logreg_predictions)
print("Confusion Matrix for Logistic Regression:\n", logreg_conf_matrix)
```

```
Confusion Matrix for Logistic Regression:
 [[241  14]
 [ 21  18]]
```

In [43]:

```
dt_conf_matrix = confusion_matrix(y_test, dt_predictions)
print("Confusion Matrix for Decision Tree Classifier:\n", dt_conf_matrix)
```

```
Confusion Matrix for Decision Tree Classifier:
 [[220  35]
 [ 32   7]]
```

Random Forest

In [45]:

```
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier()
```

In [46]:

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

In [51]:

```
from sklearn.model_selection import GridSearchCV
rfc_cv= GridSearchCV(rfc,param_grid=forest_params,cv=10,scoring="accuracy")
rfc_cv
```

Out[51]:

```
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')
```