In [165…
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
```

Data-Importing And Pre-processing

In [57]:
```
df=pd.read_csv("C:/Users/Dell/Downloads/archive/WA_Fn-UseC_-HR-Employee-Attrition.c
```

In [58]:
```
df.describe()
```

Out[58]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNum
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470.000
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024.865
std	9.135373	403.509100	8.106864	1.024165	0.0	602.024
min	18.000000	102.000000	1.000000	1.000000	1.0	1.000
25%	30.000000	465.000000	2.000000	2.000000	1.0	491.250
50%	36.000000	802.000000	7.000000	3.000000	1.0	1020.500
75%	43.000000	1157.000000	14.000000	4.000000	1.0	1555.750
max	60.000000	1499.000000	29.000000	5.000000	1.0	2068.000

8 rows × 26 columns

In [68]:
```
df.isnull().sum()
```

Out[68]:
```
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 [60]:
```
df.head(5)
```

Out[60]:

	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 [61]:
```
df.dtypes
```

Out[61]:
```
Age                        int64
Attrition                 object
BusinessTravel            object
DailyRate                  int64
Department                object
DistanceFromHome           int64
Education                  int64
EducationField            object
EmployeeCount              int64
EmployeeNumber             int64
EnvironmentSatisfaction    int64
Gender                    object
HourlyRate                 int64
JobInvolvement             int64
JobLevel                   int64
JobRole                   object
JobSatisfaction            int64
MaritalStatus             object
MonthlyIncome              int64
MonthlyRate                int64
NumCompaniesWorked         int64
Over18                    object
OverTime                  object
PercentSalaryHike          int64
PerformanceRating          int64
RelationshipSatisfaction   int64
StandardHours              int64
StockOptionLevel           int64
TotalWorkingYears          int64
TrainingTimesLastYear      int64
WorkLifeBalance            int64
YearsAtCompany             int64
YearsInCurrentRole         int64
YearsSinceLastPromotion    int64
YearsWithCurrManager       int64
dtype: object
```

In [69]:
```
# removingUnwanatedAttributes
df=df.drop(["BusinessTravel","Department","EducationField","Over18","OverTime","Jol
```

In [70]:
```
df=df.replace({"Gender":{"Male":1,"Female":0},"MaritalStatus":{"Married":0,"Single
```

In [75]:
```
x=df.drop("Attrition",axis=1)
y=df["Attrition"]
```

splliting data

In [166…
```
x_train,x_test,y_train,y_test=train_test_split(x,y,train_size=0.6,stratify=y)
```

In [167…
```
scaler = MinMaxScaler()
x_train= scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)
```

LogisticRegression Model and Training and Valadition

In [168…
```
model=LogisticRegression(C=12)
model.fit(x_train,y_train)
```

Out[168]:
```
LogisticRegression
LogisticRegression(C=12)
```

In [169…
```
y_pred=model.predict(x_test)
```

In [170…
```
accuracy_score(y_pred,y_test)
```

Out[170]:
```
0.8503401360544217
```

DecisionTree training And Validation

In [171…
```
model1=DecisionTreeClassifier()
model1.fit(x_train,y_train)
```

Out[171]:
```
DecisionTreeClassifier
DecisionTreeClassifier()
```

In [172…
```
y_pred1=model1.predict(x_test)
```

In [173…
```
accuracy_score(y_pred1,y_test)
```

Out[173]:
```
0.7568027210884354
```

In [164…
```
accuracy_scores.mean()
```

Out[164]:
```
0.8416666666666667
```

In [ ]:
```
# by comparing above tw0 logistic regressino is best option
```

prediction Using Logistic Regression

In [191…
```
model.predict(x_train[879].reshape(1,-1))
```

Out[191]:
```
array([0], dtype=int64)
```

In [ ]:

In [ ]: