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```
21BCE7334
VITAP
```

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 [3]:

```
df=pd.read_csv("WA_Fn-UseC_-HR-Employee-Attrition.csv")
df
```

Out[3]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	...	RelationshipSatisfaction	StandardHours	StockOptionLevel	TotalWorkingYears
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1	...	1	80	0	8
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	2	...	4	80	1	10
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	4	...	2	80	0	7
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	5	...	3	80	0	8
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	7	...	4	80	1	6
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1465	36	No	Travel_Frequently	884	Research & Development	23	2	Medical	1	2061	...	3	80	1	17
1466	39	No	Travel_Rarely	613	Research & Development	6	1	Medical	1	2062	...	1	80	1	9
1467	27	No	Travel_Rarely	155	Research & Development	4	3	Life Sciences	1	2064	...	2	80	1	6
1468	49	No	Travel_Frequently	1023	Sales	2	3	Medical	1	2065	...	4	80	0	17
1469	34	No	Travel_Rarely	628	Research & Development	8	3	Medical	1	2068	...	1	80	0	6

1470 rows × 35 columns

In [4]:

```
df.head()
```

Out[4]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	...	RelationshipSatisfaction	StandardHours	StockOptionLevel	TotalWorkingYears
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1	...	1	80	0	8
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	2	...	4	80	1	10
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	4	...	2	80	0	7
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	5	...	3	80	0	8
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	7	...	4	80	1	6

5 rows × 35 columns

In [5]:

```
df.tail()
```

Out[5]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	...	RelationshipSatisfaction	StandardHours	StockOptionLevel	TotalWorkingYears
1465	36	No	Travel_Frequently	884	Research & Development	23	2	Medical	1	2061	...	3	80	1	17
1466	39	No	Travel_Rarely	613	Research & Development	6	1	Medical	1	2062	...	1	80	1	9
1467	27	No	Travel_Rarely	155	Research & Development	4	3	Life Sciences	1	2064	...	2	80	1	6
1468	49	No	Travel_Frequently	1023	Sales	2	3	Medical	1	2065	...	4	80	0	17
1469	34	No	Travel_Rarely	628	Research & Development	8	3	Medical	1	2068	...	1	80	0	6

5 rows × 35 columns

In [6]:

```
df.shape
```

Out[6]:

```
(1470, 35)
```

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	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement	JobLevel	...	RelationshipSatisfaction	StandardHours	StockOptionLe
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470.000000	1470.000000	1470.000000	1470.000000	1470.000000	...	1470.000000	1470.0	1470.000
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024.865306	2.721769	65.891156	2.729932	2.063946	...	2.712245	80.0	0.793
std	9.135373	403.509100	8.106864	1.024165	0.0	602.024335	1.093082	20.329428	0.711561	1.106940	...	1.081209	0.0	0.852
min	18.000000	102.000000	1.000000	1.000000	1.0	1.000000	1.000000	30.000000	1.000000	1.000000	...	1.000000	80.0	0.000
25%	30.000000	465.000000	2.000000	2.000000	1.0	491.250000	2.000000	48.000000	2.000000	1.000000	...	2.000000	80.0	0.000
50%	36.000000	802.000000	7.000000	3.000000	1.0	1020.500000	3.000000	66.000000	3.000000	2.000000	...	3.000000	80.0	1.000
75%	43.000000	1157.000000	14.000000	4.000000	1.0	1555.750000	4.000000	83.750000	3.000000	3.000000	...	4.000000	80.0	1.000
max	60.000000	1499.000000	29.000000	5.000000	1.0	2068.000000	4.000000	100.000000	4.000000	5.000000	...	4.000000	80.0	3.000

8 rows × 26 columns

In [10]:

```
corr=df.corr()
corr
```

Out[10]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement	JobLevel	...	RelationshipSatisfaction	StandardHours	Stock
Age	1.000000	0.010661	-0.001686	0.208034	NaN	-0.010145	0.010146	0.024287	0.029820	0.509604	...	0.053535	NaN	
DailyRate	0.010661	1.000000	-0.004985	-0.016806	NaN	-0.050990	0.018355	0.023381	0.046135	0.002966	...	0.007846	NaN	
DistanceFromHome	-0.001686	-0.004985	1.000000	0.021042	NaN	0.032916	-0.016075	0.031131	0.008783	0.005303	...	0.006557	NaN	
Education	0.208034	-0.016806	0.021042	1.000000	NaN	0.042070	-0.027128	0.016775	0.042438	0.101589	...	-0.009118	NaN	
EmployeeCount	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	
EmployeeNumber	-0.010145	-0.050990	0.032916	0.042070	NaN	1.000000	0.017621	0.035179	-0.006888	-0.018519	...	-0.069861	NaN	
EnvironmentSatisfaction	0.010146	0.018355	-0.016075	-0.027128	NaN	0.017621	1.000000	-0.049857	-0.008278	0.001212	...	0.007665	NaN	
HourlyRate	0.024287	0.023381	0.031131	0.016775	NaN	0.035179	-0.049857	1.000000	0.042861	-0.027853	...	0.001330	NaN	
JobInvolvement	0.029820	0.046135	0.008783	0.042438	NaN	-0.006888	-0.008278	0.042861	1.000000	-0.012630	...	0.034297	NaN	
JobLevel	0.509604	0.002966	0.005303	0.101589	NaN	-0.018519	0.001212	-0.027853	-0.012630	1.000000	...	0.021642	NaN	
JobSatisfaction	-0.004892	0.030571	-0.003669	-0.011296	NaN	-0.046247	-0.006784	-0.071335	-0.021476	-0.001944	...	-0.012454	NaN	
MonthlyIncome	0.497855	0.007707	-0.017014	0.094961	NaN	-0.014829	-0.006259	-0.015794	-0.015271	0.950300	...	0.025873	NaN	
MonthlyRate	0.028051	-0.032182	0.027473	-0.026084	NaN	0.012648	0.037600	-0.015297	-0.016322	0.039563	...	-0.004085	NaN	
NumCompaniesWorked	0.299635	0.038153	-0.029251	0.126317	NaN	-0.001251	0.012594	0.022157	0.015012	0.142501	...	0.052733	NaN	
PercentSalaryHike	0.003634	0.022704	0.040235	-0.011111	NaN	-0.012944	-0.031701	-0.009062	-0.017205	-0.034730	...	-0.040490	NaN	
PerformanceRating	0.001904	0.000473	0.027110	-0.024539	NaN	-0.020359	-0.029548	-0.002172	-0.029071	-0.021222	...	-0.031351	NaN	
RelationshipSatisfaction	0.053535	0.007846	0.006557	-0.009118	NaN	-0.069861	0.007665	0.001330	0.034297	0.021642	...	1.000000	NaN	
StandardHours	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	
StockOptionLevel	0.037510	0.042143	0.044872	0.018422	NaN	0.062227	0.003432	0.050263	0.021523	0.013984	...	-0.045952	NaN	
TotalWorkingYears	0.680381	0.014515	0.004628	0.148280	NaN	-0.014365	-0.002693	-0.002334	-0.005533	0.782208	...	0.024054	NaN	
TrainingTimesLastYear	-0.019621	0.002453	-0.036942	-0.025100	NaN	0.023603	-0.019359	-0.008548	-0.015338	-0.018191	...	0.002497	NaN	
WorkLifeBalance	-0.021490	-0.037848	-0.026556	0.009819	NaN	0.010309	0.027627	-0.004607	-0.014617	0.037818	...	0.019604	NaN	
YearsAtCompany	0.311309	-0.034055	0.009508	0.069114	NaN	-0.011240	0.001458	-0.019582	-0.021355	0.534739	...	0.019367	NaN	
YearsInCurrentRole	0.212901	0.009932	0.018845	0.060236	NaN	-0.008416	0.018007	-0.024106	0.008717	0.389447	...	-0.015123	NaN	
YearsSinceLastPromotion	0.216513	-0.033229	0.010029	0.054254	NaN	-0.009019	0.016194	-0.026716	-0.024184	0.353885	...	0.033493	NaN	
YearsWithCurrManager	0.202089	-0.026363	0.014406	0.069065	NaN	-0.009197	-0.004999	-0.020123	0.025976	0.375281	...	-0.000867	NaN	

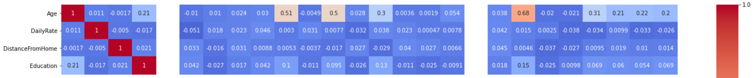
26 rows × 26 columns

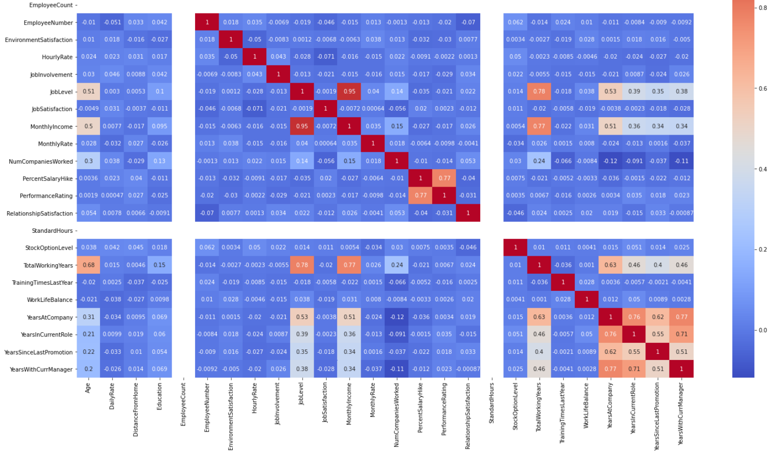
In [12]:

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

Out[12]:

```
<AxesSubplot:>
```





In [13]:

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

Out[13]:

```
No     1233
Yes     237
Name: Attrition, dtype: int64
```

In [14]:

```
df.isnull().any()
```

Out[14]:

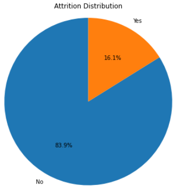
```
Age                         False
Attrition                   False
BusinessTravel              False
DailyRate                   False
Department                  False
DistanceFromHome            False
Education                   False
EducationField              False
EmployeeCount               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 [15]:

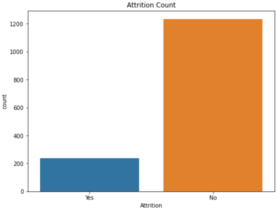
```
attrition_counts = df['Attrition'].value_counts()
plt.figure(figsize=(6, 6))
plt.pie(attrition_counts, labels=attrition_counts.index, autopct='%1.1f%%', startangle=90)
plt.title('Attrition Distribution')
plt.axis('equal')

plt.show()
```



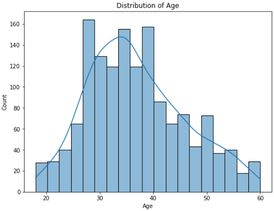
In [16]:

```
plt.figure(figsize=(8, 6))
sns.countplot(x="Attrition", data=df)
plt.title("Attrition Count")
plt.show()
```



In [17]:

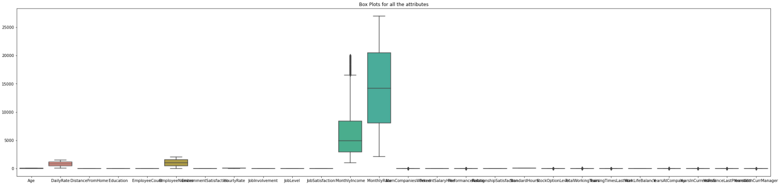
```
plt.figure(figsize=(8, 6))
sns.histplot(data=df, x="Age", kde=True)
plt.title("Distribution of Age")
plt.show()
```



outlier detection

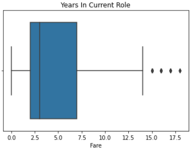
In [18]:

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



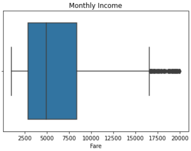
In [19]:

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



In [20]:

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

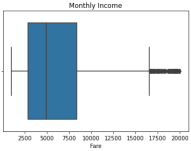


In [21]:

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

In [22]:

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



There is no need to remove the outliers as they are in large quantity and inside the threshold.

splitting independent and dependent variable

In [23]:

```
x= df.drop(columns=["Attrition"])
y = df["Attrition"]
```

In [24]:

```
x.head()
```

Out[24]:

	Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	...	RelationshipSatisfaction	StandardHours	StockOptionLevel	TotalWo
0	41	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1	2	...	1	80	0	
1	49	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	2	3	...	4	80	1	
2	37	Travel_Rarely	1373	Research & Development	2	2	Other	1	4	4	...	2	80	0	
3	33	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	5	4	...	3	80	0	
4	27	Travel_Rarely	591	Research & Development	2	1	Medical	1	7	1	...	4	80	1	

5 rows × 34 columns

In [25]:

```
y.head()
```

Out[25]:

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

Encoding

In [26]:

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

Out[26]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement	JobLevel	...	JobRole_Laboratory Technician	JobRole_Manager	JobRole_Manufacturing Director	JobRole_R
0	41	1102	1	2	1	1	2	94	3	2	...	0	0	0	
1	49	279	8	1	1	2	3	61	2	2	...	0	0	0	
2	37	1373	2	2	1	4	4	92	2	1	...	1	0	0	
3	33	1392	3	4	1	5	4	56	3	1	...	0	0	0	
4	27	591	2	1	1	7	1	40	3	1	...	1	0	0	

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.head()
```

Out[27]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement	JobLevel	...	JobRole_Laboratory Technician	JobRole_Manager	JobRole_Manufacturing Director	JobR
0	0.446350	0.742527	-1.010909	-0.891688	0.0	-1.701283	-0.660531	1.383138	0.379672	-0.057788	...	-0.462464	-0.273059	-0.330808	
1	1.322365	-1.297775	-0.147150	-1.868426	0.0	-1.699621	0.254625	-0.240677	-1.026167	-0.057788	...	-0.462464	-0.273059	-0.330808	
2	0.008343	1.414363	-0.887515	-0.891688	0.0	-1.696298	1.169781	1.284725	-1.026167	-0.961486	...	2.162331	-0.273059	-0.330808	
3	-0.429664	1.461466	-0.764121	1.061787	0.0	-1.694636	1.169781	-0.486709	0.379672	-0.961486	...	-0.462464	-0.273059	-0.330808	
4	-1.086676	-0.524295	-0.887515	-1.868426	0.0	-1.691313	-1.575686	-1.274014	0.379672	-0.961486	...	2.162331	-0.273059	-0.330808	

5 rows × 47 columns

In [29]:

```
x=x_scaled
x
```

Out[29]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement	JobLevel	...	JobRole_Laboratory Technician	JobRole_Manager	JobRole_Manufacturing Director	Jo
0	0.446350	0.742527	-1.010909	-0.891688	0.0	-1.701283	-0.660531	1.383138	0.379672	-0.057788	...	-0.462464	-0.273059	-0.330808	
1	1.322365	-1.297775	-0.147150	-1.868426	0.0	-1.699621	0.254625	-0.240677	-1.026167	-0.057788	...	-0.462464	-0.273059	-0.330808	
2	0.008343	1.414363	-0.887515	-0.891688	0.0	-1.696298	1.169781	1.284725	-1.026167	-0.961486	...	2.162331	-0.273059	-0.330808	
3	-0.429664	1.461466	-0.764121	1.061787	0.0	-1.694636	1.169781	-0.486709	0.379672	-0.961486	...	-0.462464	-0.273059	-0.330808	
4	-1.086676	-0.524295	-0.887515	-1.868426	0.0	-1.691313	-1.575686	-1.274014	0.379672	-0.961486	...	2.162331	-0.273059	-0.330808	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1465	-0.101159	0.202082	1.703764	-0.891688	0.0	1.721670	0.254625	-1.224807	1.785511	-0.057788	...	2.162331	-0.273059	-0.330808	
1466	0.227347	-0.469754	-0.393938	-1.868426	0.0	1.723332	1.169781	-1.175601	-1.026167	0.845911	...	-0.462464	-0.273059	-0.330808	
1467	-1.086676	-1.605183	-0.640727	0.085049	0.0	1.726655	-0.660531	1.038693	1.785511	-0.057788	...	-0.462464	-0.273059	3.022901	
1468	1.322365	0.546677	-0.887515	0.085049	0.0	1.728317	1.169781	-0.142264	-1.026167	-0.057788	...	-0.462464	-0.273059	-0.330808	
1469	-0.320163	-0.432568	-0.147150	0.085049	0.0	1.733302	-0.660531	0.792660	1.785511	-0.057788	...	2.162331	-0.273059	-0.330808	

1470 rows × 47 columns

splitting training and testing data

In [30]:

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

Building model

In [31]:

```
#importing necessary libraries
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from joblib import dump
```

In [32]:

```
logreg_model = LogisticRegression(random_state=42)
dt_model = DecisionTreeClassifier(random_state=42)
```

In [33]:

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

Out[33]:

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

In [34]:

```
logreg_predictions = logreg_model.predict(x_test)

dt_predictions = dt_model.predict(x_test)

logreg_accuracy = accuracy_score(y_test, logreg_predictions)
print("Logistic Regression Accuracy:", logreg_accuracy)

dt_accuracy = accuracy_score(y_test, dt_predictions)
print("Decision Tree Accuracy:", dt_accuracy)

logreg_report = classification_report(y_test, logreg_predictions)
print("Classification Report for Logistic Regression:\n", logreg_report)

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

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

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

```
Logistic Regression Accuracy: 0.8809523809523809
Decision Tree Accuracy: 0.7721088435374149
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

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

Confusion Matrix for Logistic Regression:
 [[241  14]
 [ 21  18]]
Confusion Matrix for Decision Tree Classifier:
 [[220  35]
 [ 32   7]]
```

In [ ]: