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 [3]:
```
df=pd.read_csv("WA_Fn-UseC_-HR-Employee-Attrition.csv")
```

In [4]:
```
df
```

Out[4]:

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

1470 rows × 35 columns

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

Out[5]:

	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 [6]:
```
df.tail()
```

Out[6]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Ed
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 [7]:
```
df.shape
```

Out[7]:
```
(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	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 [10]:

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

```
C:\Users\DELL\AppData\Local\Temp\ipykernel_3716\3182140910.py:1: FutureWarning: Th
e default value of numeric_only in DataFrame.corr is deprecated. In a future versi
on, it will default to False. Select only valid columns or specify the value of nu
meric_only to silence this warning.
  corr=df.corr()
```

Out[10]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	En
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	

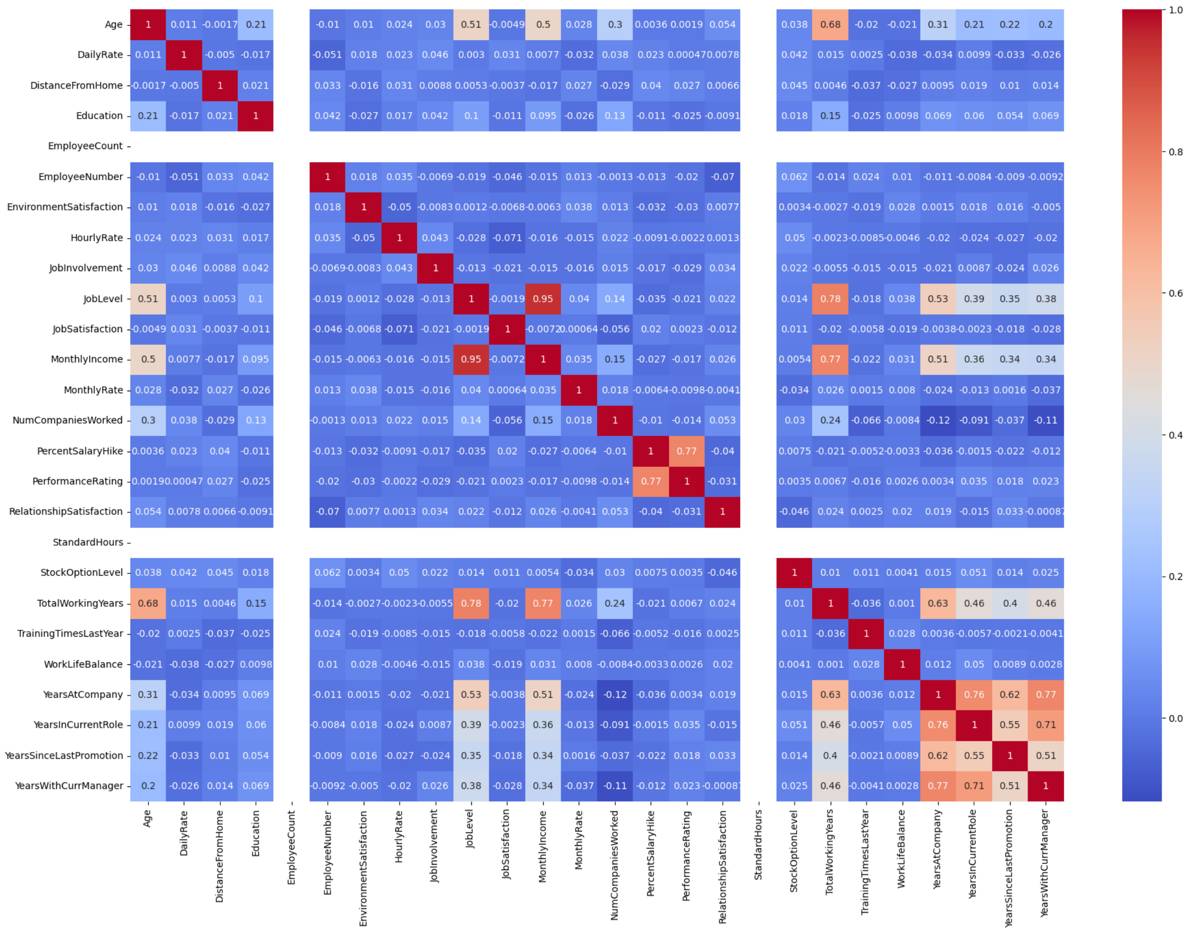
26 rows × 26 columns

In [11]:

```
plt.subplots(figsize=(22,15))
sns.heatmap(corr,annot=True,cmap="coolwarm")
```

Out[11]:

```
<Axes: >
```



```
In [12]: df.Attrition.value_counts()
```

```
Out[12]: No      1233
         Yes      237
         Name: Attrition, dtype: int64
```

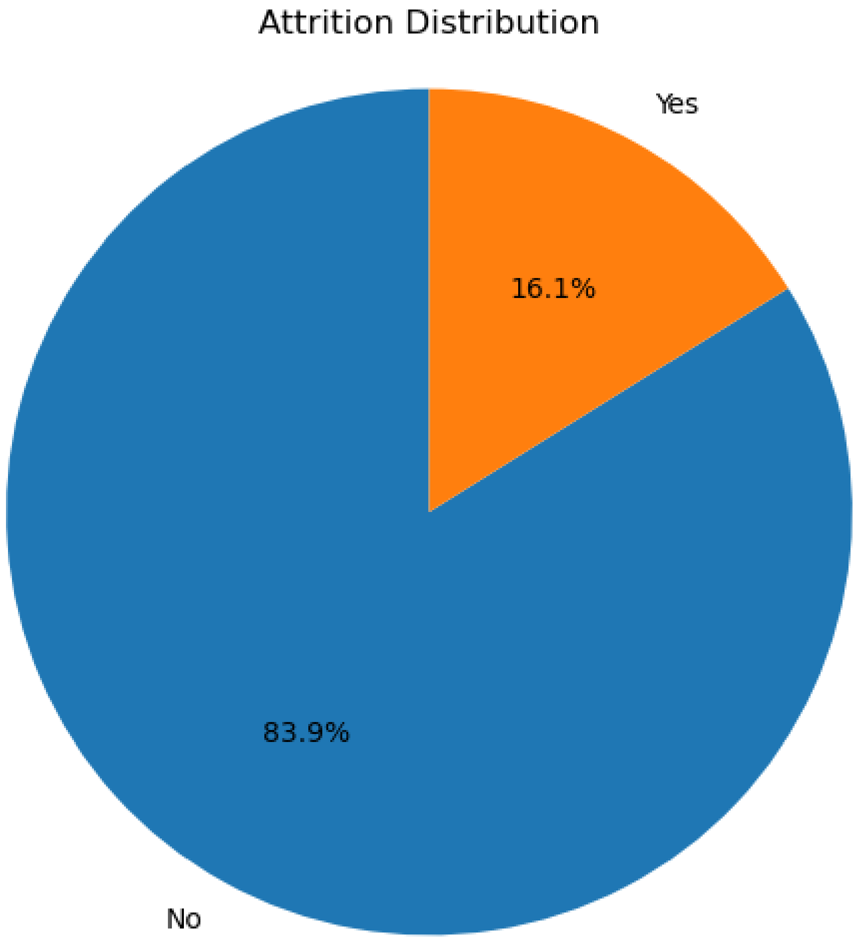
Checking for NULL Values

```
In [13]: df.isnull().any()
```

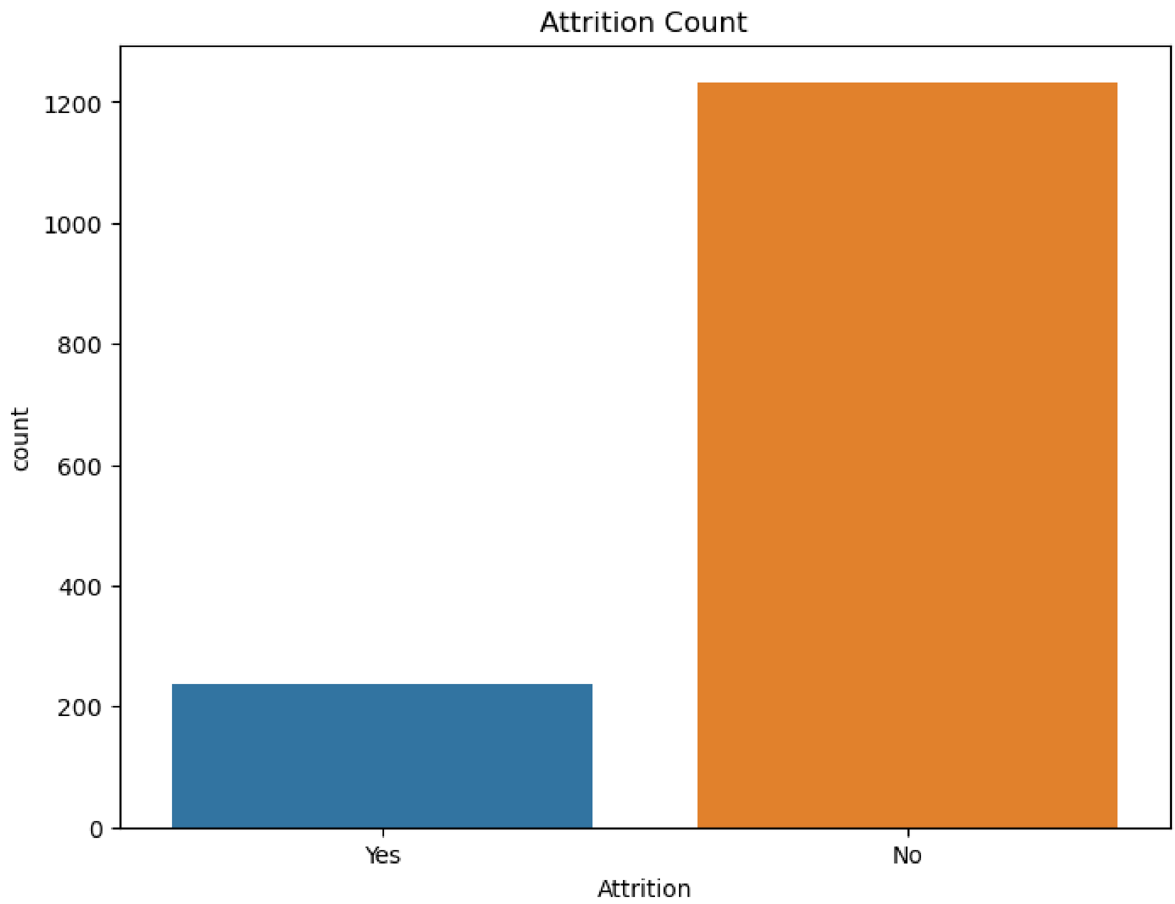
Out[13]:
```
Age                         False
Attrition                   False
BusinessTravel              False
DailyRate                   False
Department                  False
DistanceFromHome            False
Education                   False
EducationField              False
EmployeeCount               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

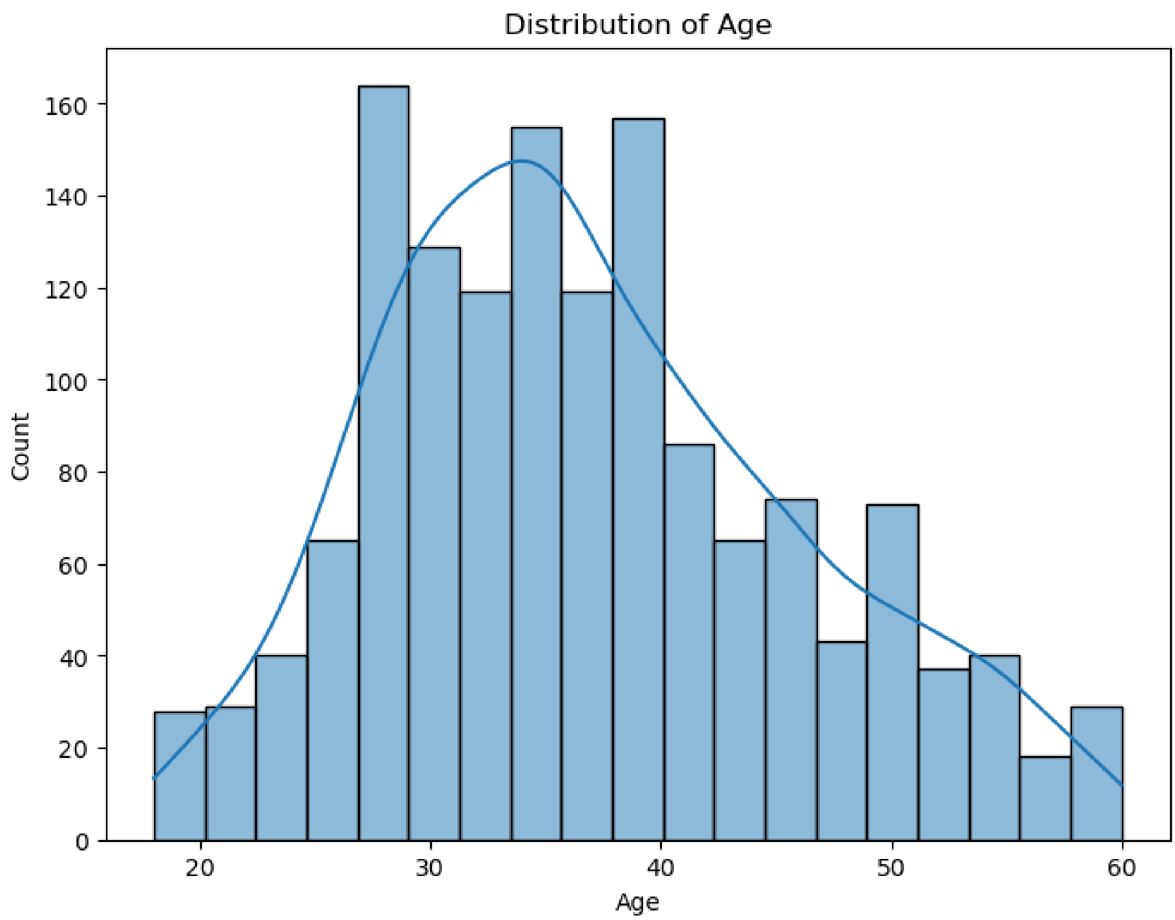
In [15]:
```
attrition_counts = df['Attrition'].value_counts()
plt.figure(figsize=(6, 6))
plt.pie(attrition_counts, labels=attrition_counts.index, autopct='%1.1f%%', startar
plt.title('Attrition Distribution')
plt.axis('equal')

plt.show()
```



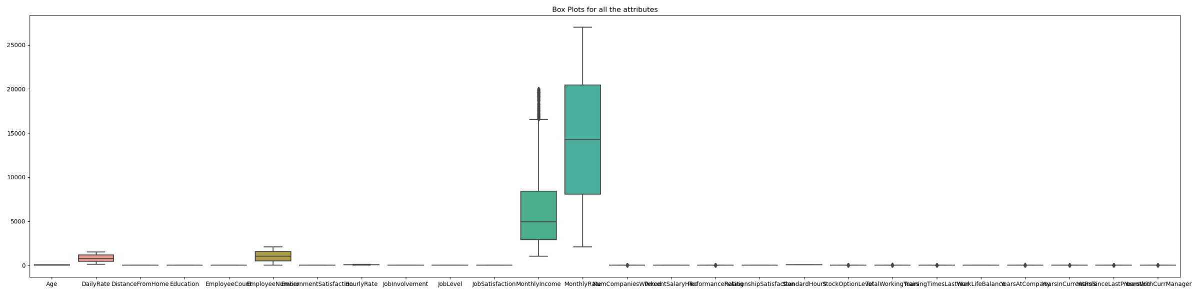
In [16]:
```
plt.figure(figsize=(8, 6))
sns.countplot(x="Attrition", data=df)
plt.title("Attrition Count")
plt.show()
```



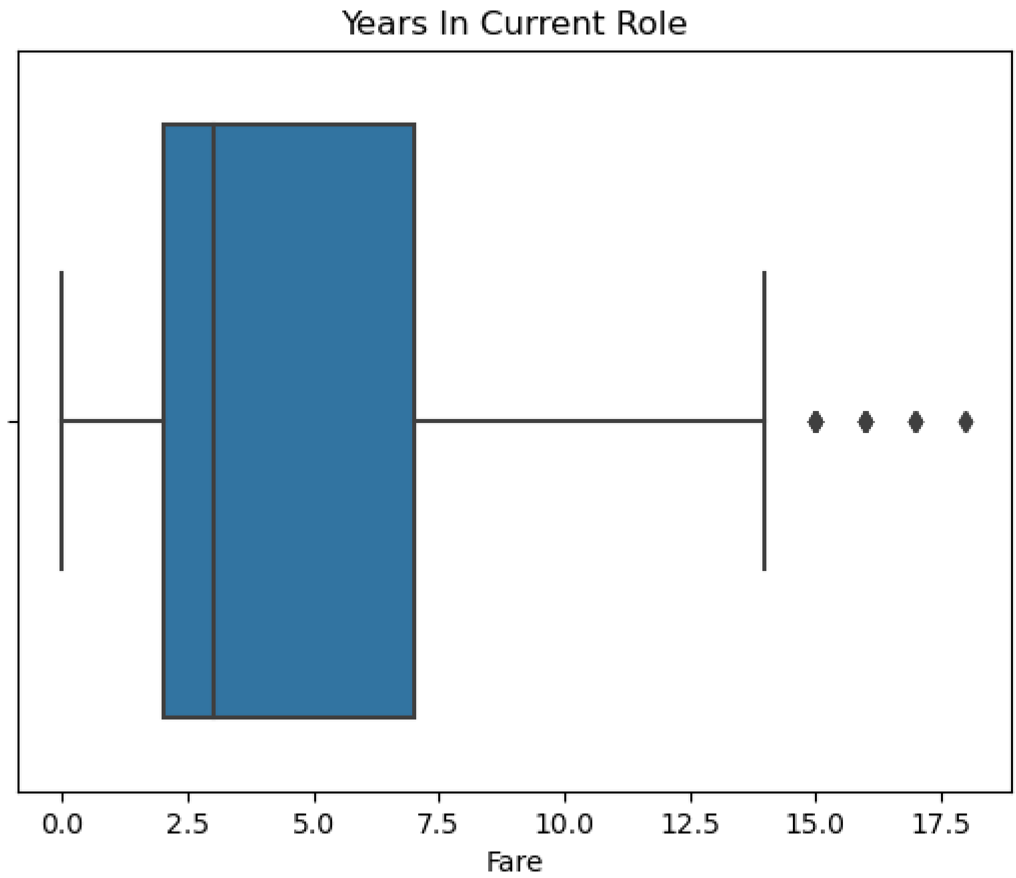
In [17]:
```
plt.figure(figsize=(8, 6))
sns.histplot(data=df, x="Age", kde=True)
plt.title("Distribution of Age")
plt.show()
```



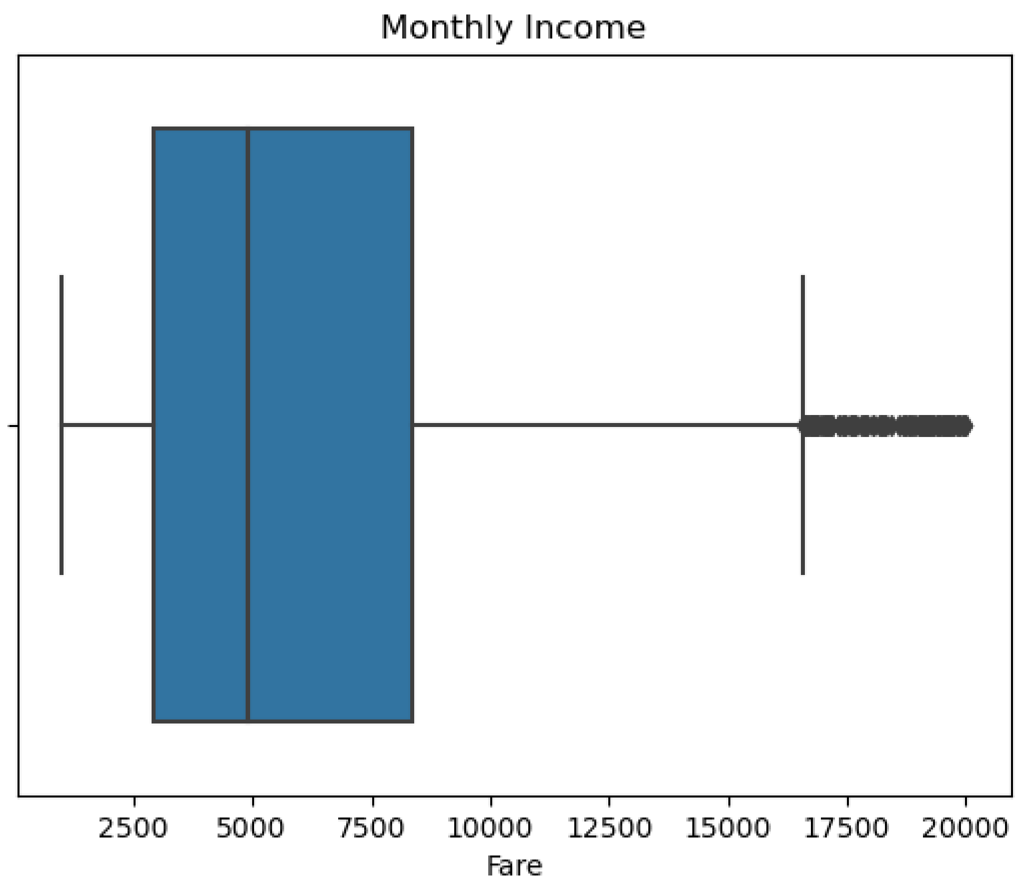
In [18]:
```python
plt.figure(figsize=(35, 8))
sns.boxplot(data=df)
plt.title('Box Plots for all the attributes')
plt.show()
```



In [19]:
```python
sns.boxplot(data=df, x='YearsInCurrentRole')
plt.title('Years In Current Role')
plt.xlabel('Fare')
plt.show()
```

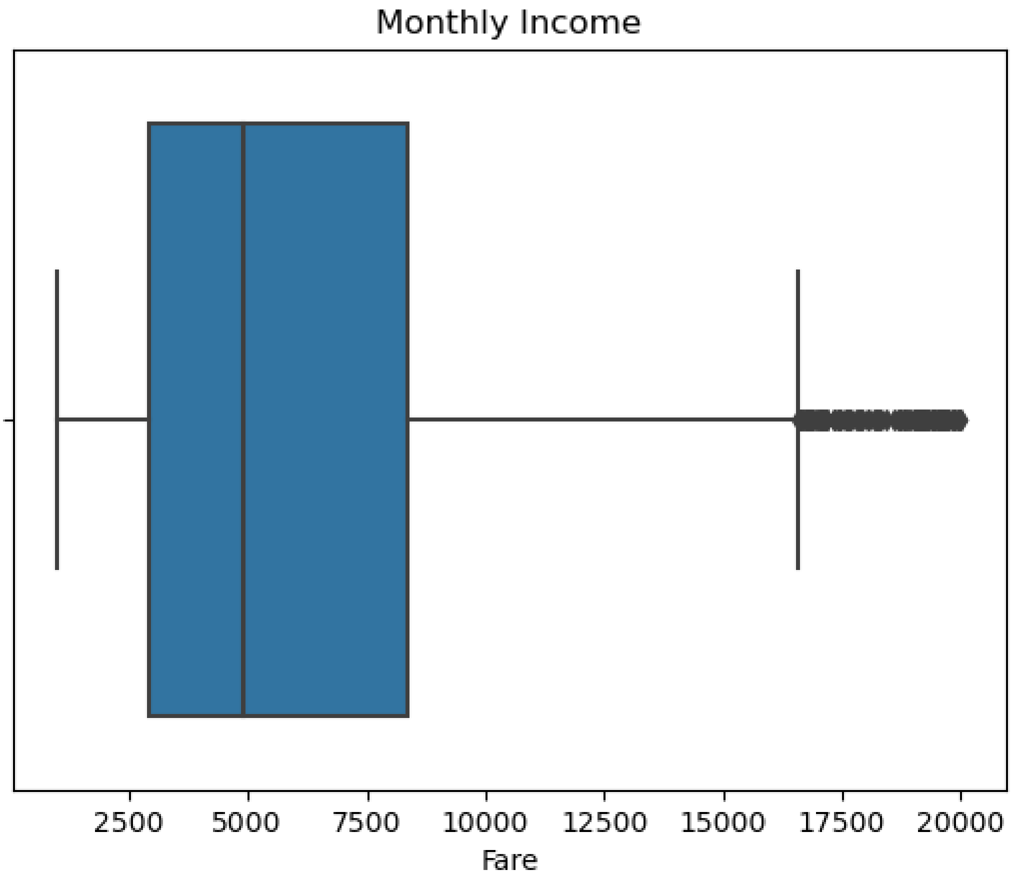


In [20]:
```python
sns.boxplot(data=df, x='MonthlyIncome')
plt.title('Monthly Income')
plt.xlabel('Fare')
plt.show()
```



In [21]:
```
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 [22]:
```
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 [23]:
```
x= df.drop(columns=["Attrition"])
y = df["Attrition"]
```

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

Out[24]:

	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 [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)
```

In [27]:
```
x_encoded.head()
```

Out[27]:

	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

FEATURE SCALING

In [28]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
x_scaled = pd.DataFrame(scaler.fit_transform(x_encoded), columns=x_encoded.columns)
```

In [29]:
```
x_scaled.head()
```

Out[29]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	Enviro
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

In [30]:
```
x=x_scaled
```

Train and test split

In [32]:
```
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_sta
```

MODEL BUILDING

In [33]:
```
# Import the necessary libraries
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matri
from joblib import dump
```

In [34]:
```
logreg_model = LogisticRegression(random_state=42)
dt_model = DecisionTreeClassifier(random_state=42)
```

In [35]:
```
logreg_model.fit(x_train, y_train)
dt_model.fit(x_train, y_train)
```

Out[35]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

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