

```
In [1]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
sns.set_theme(color_codes=True)
pd.set_option('display.max_columns', None)
```

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

Out[2]:

kOptionLevel	TotalWorkingYears	TrainingTimesLastYear	WorkLifeBalance	YearsAtCompany	YearsInCurrentRole	Yea
0	8	0	1	6		4
1	10	3	3	10		7
0	7	3	3	0		0
0	8	3	3	8		7
1	6	3	3	2		2

## Data Preprocessing Part 1

```
In [3]: #Check the number of unique value from all of the object datatype
df.select_dtypes(include='object').nunique()
```

Out[3]:

Attrition	2
BusinessTravel	3
Department	3
EducationField	6
Gender	2
JobRole	9
MaritalStatus	3
Over18	1
Overtime	2
dtype: int64	

```
In [4]: # Drop column with only 1 unique value
df.drop(columns = 'Over18', inplace=True)
```

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

Out[5]:

Age	43
Attrition	2
BusinessTravel	3
DailyRate	886
Department	3
DistanceFromHome	29
Education	5
EducationField	6
EmployeeCount	1
EmployeeNumber	1470
EnvironmentSatisfaction	4
Gender	2
HourlyRate	71
JobInvolvement	4
JobLevel	5
JobRole	9
JobSatisfaction	4
MaritalStatus	3
MonthlyIncome	1349
MonthlyRate	1427
NumCompaniesWorked	10
Overtime	2
PercentSalaryHike	15
PerformanceRating	2
RelationshipSatisfaction	4
StandardHours	1
StockOptionLevel	4
TotalWorkingYears	40
TrainingTimesLastYear	7
WorkLifeBalance	4
YearsAtCompany	37
YearsInCurrentRole	19
YearsSinceLastPromotion	16
YearsWithCurrManager	18

dtype: int64

In [6]: `# Delete other columns with only 1 unique value  
df.drop(columns = ['EmployeeCount', 'StandardHours'], inplace=True)`

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

Out[7]:

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

## Exploratory Data Analysis

```
In [8]: # Get the names of all columns with data type 'object' (categorical columns)
cat_vars = df.select_dtypes(include='object').columns.tolist()

# Create a figure with subplots
num_cols = len(cat_vars)
num_rows = (num_cols + 2) // 3
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

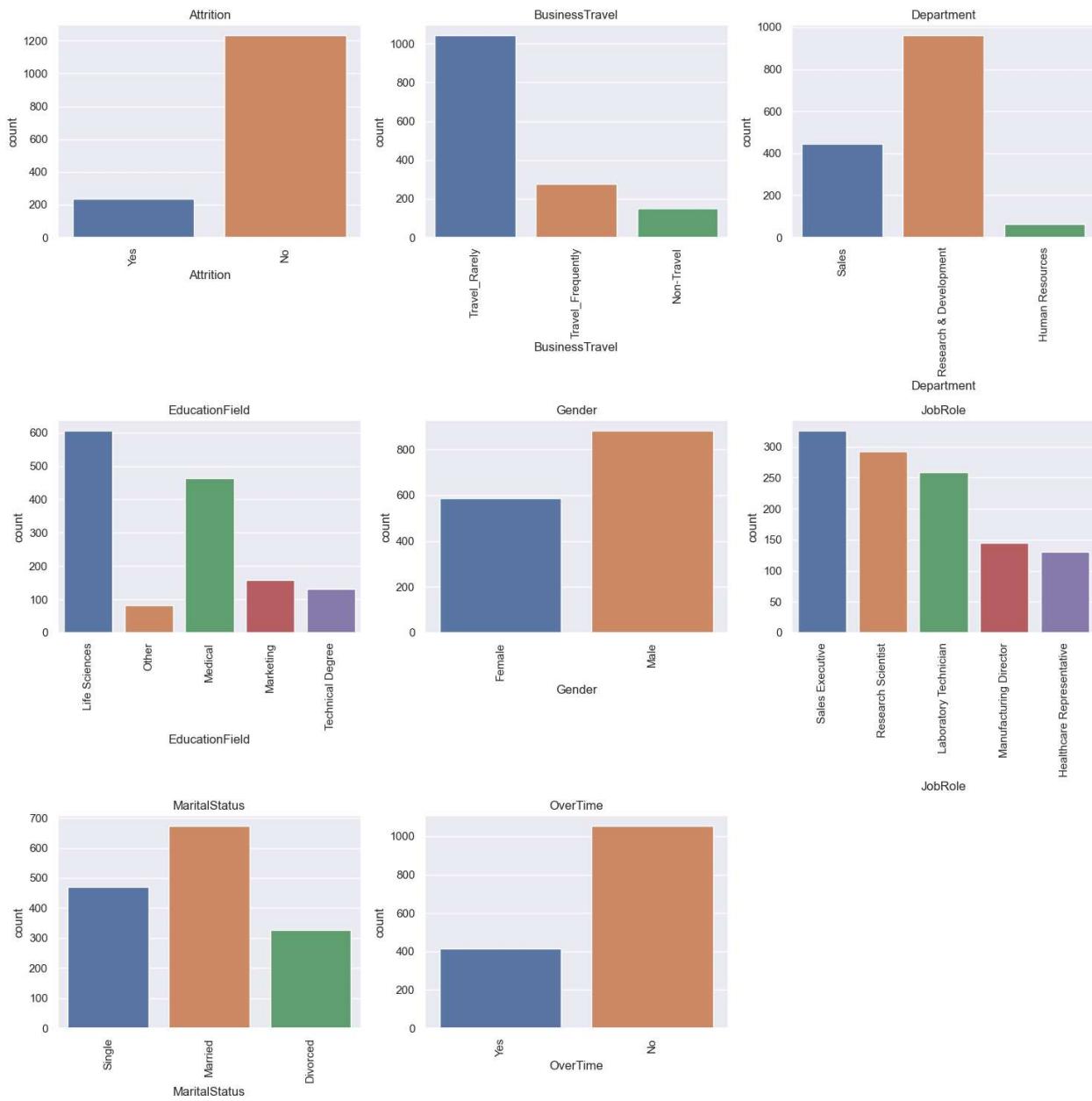
# Create a countplot for the top 5 values of each categorical variable using Seaborn
for i, var in enumerate(cat_vars):
    top_values = df[var].value_counts().nlargest(5).index
    filtered_df = df[df[var].isin(top_values)]
    sns.countplot(x=var, data=filtered_df, ax=axs[i])
    axs[i].set_title(var)
    axs[i].tick_params(axis='x', rotation=90)

# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust spacing between subplots
fig.tight_layout()

# Show plot
plt.show()
```

## IBM HR Analytics Employee Attrition - Jupyter Notebook



```
In [9]: # Get the names of all columns with data type 'int' or 'float'
num_vars = df.select_dtypes(include=['int', 'float']).columns.tolist()

# Create a figure with subplots
num_cols = len(num_vars)
num_rows = (num_cols + 2) // 3
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Create a box plot for each numerical variable using Seaborn
for i, var in enumerate(num_vars):
    sns.boxplot(x=df[var], ax=axs[i])
    axs[i].set_title(var)

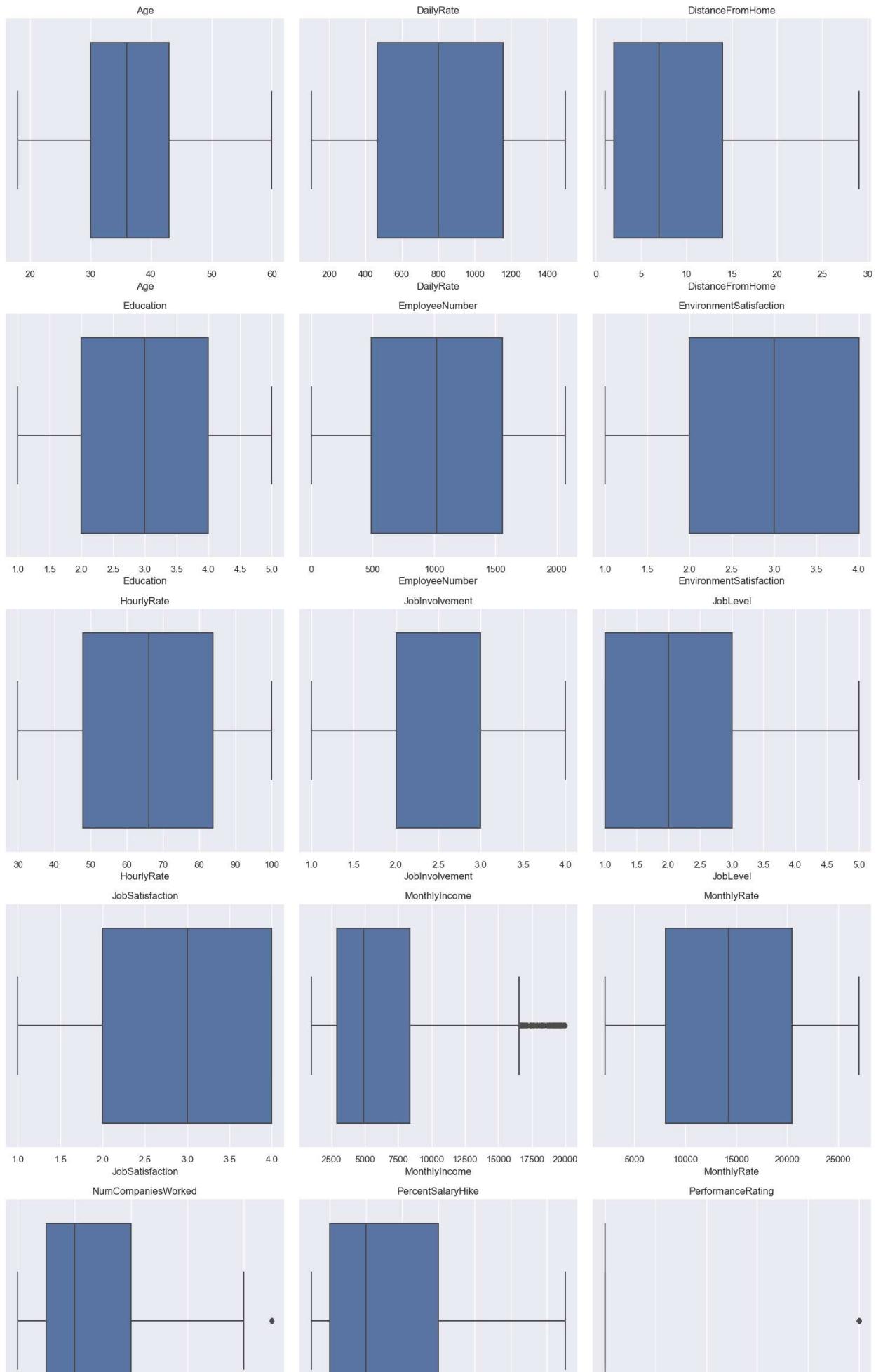
# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust spacing between subplots
fig.tight_layout()

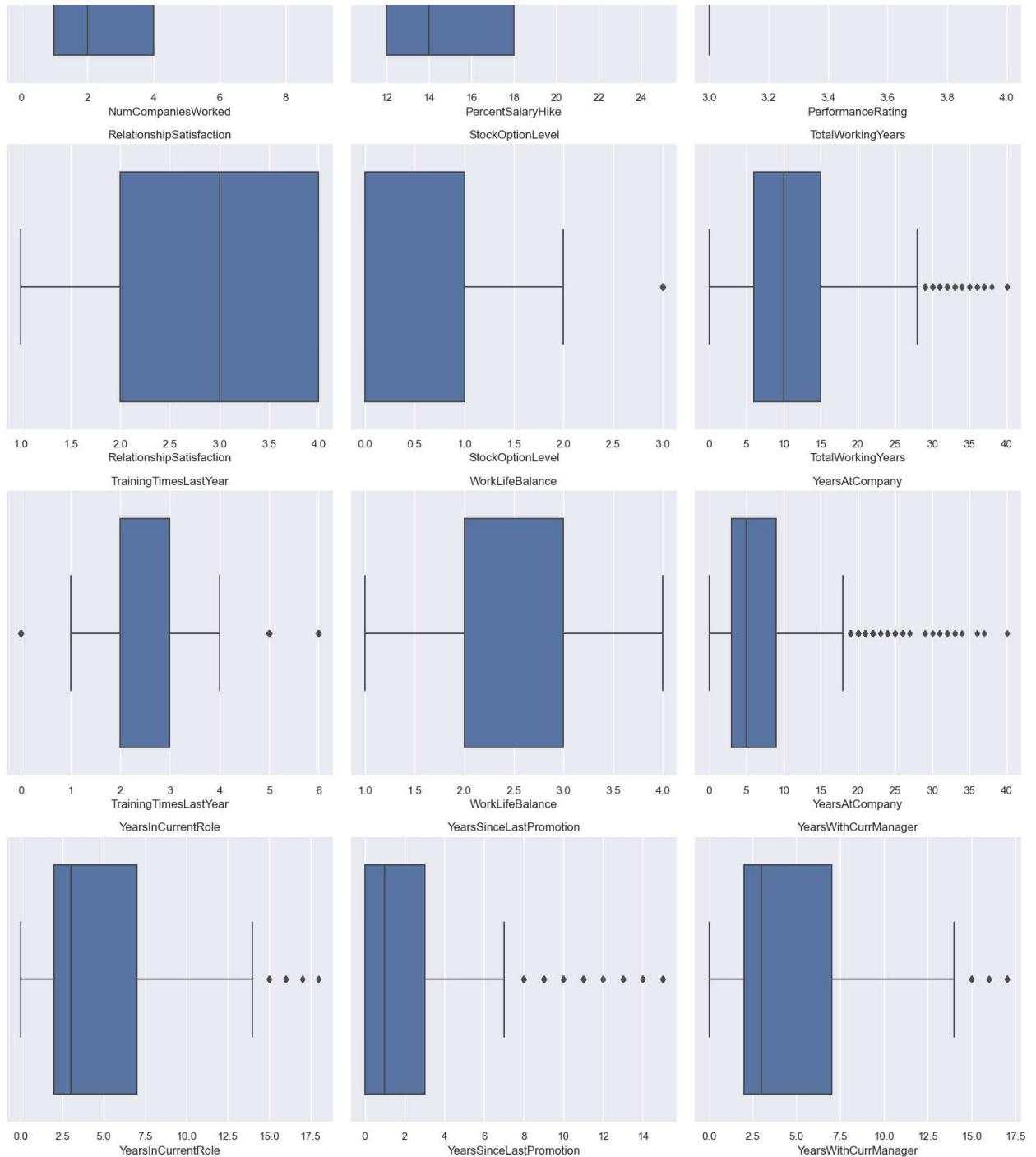
# Show plot
plt.show()
```



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## IBM HR Analytics Employee Attrition - Jupyter Notebook



```
In [11]: # Get the names of all columns with data type 'int'
int_vars = df.select_dtypes(include=['int', 'float']).columns.tolist()

# Create a figure with subplots
num_cols = len(int_vars)
num_rows = (num_cols + 2) // 3 # To make sure there are enough rows for the subplots
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Create a box plot for each integer variable using Seaborn with hue='Attrition'
for i, var in enumerate(int_vars):
    sns.boxplot(y=var, x='Attrition', data=df, ax=axs[i])
    axs[i].set_title(var)

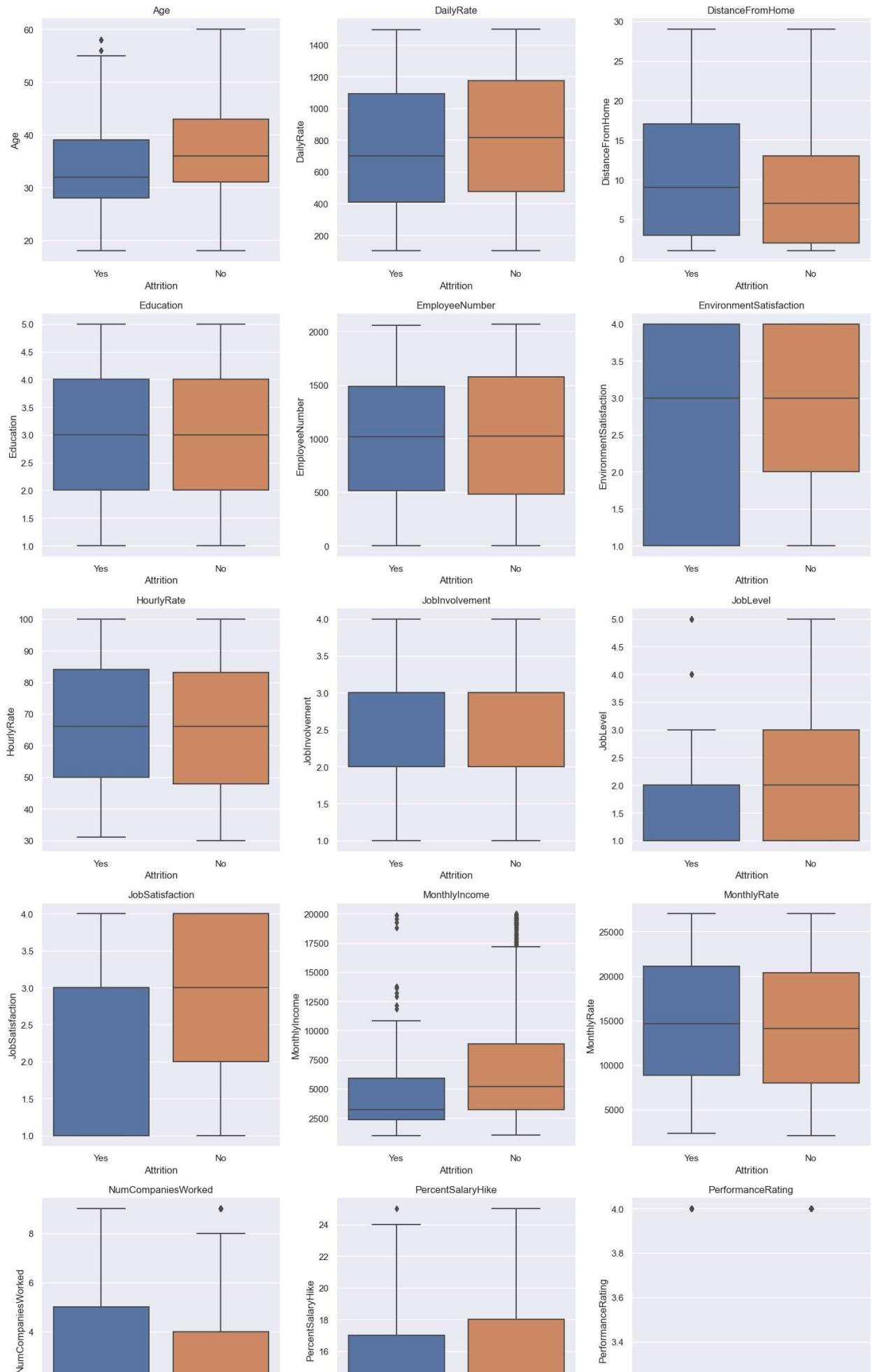
# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust spacing between subplots
fig.tight_layout()

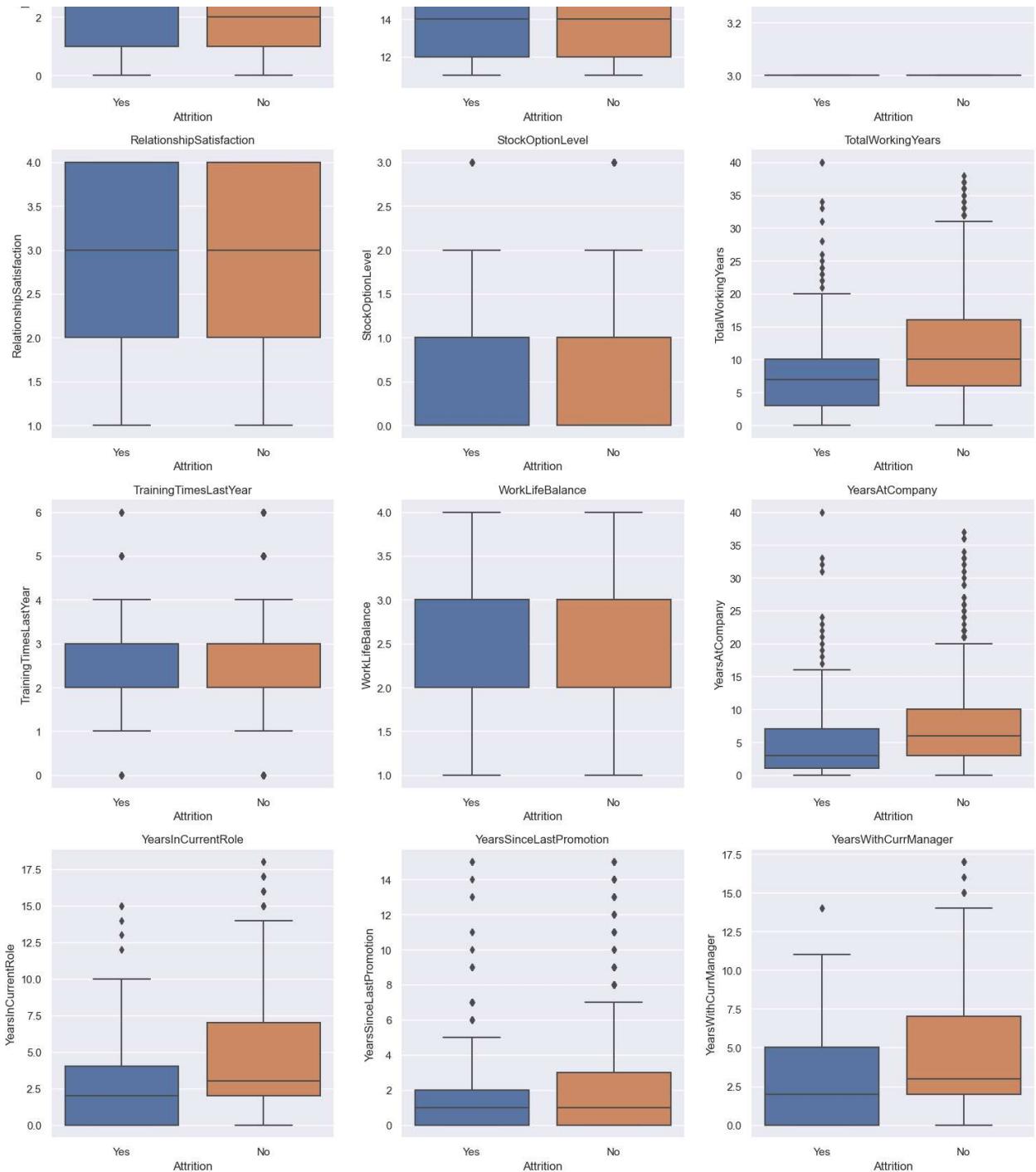
# Show plot
plt.show()
```



## IBM HR Analytics Employee Attrition - Jupyter Notebook



## IBM HR Analytics Employee Attrition - Jupyter Notebook



```
In [12]: # Get the names of all columns with data type 'int'
int_vars = df.select_dtypes(include=['int', 'float']).columns.tolist()

# Create a figure with subplots
num_cols = len(int_vars)
num_rows = (num_cols + 2) // 3 # To make sure there are enough rows for the subplots
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Create a histogram for each integer variable
for i, var in enumerate(int_vars):
    df[var].plot.hist(ax=axs[i])
    axs[i].set_title(var)

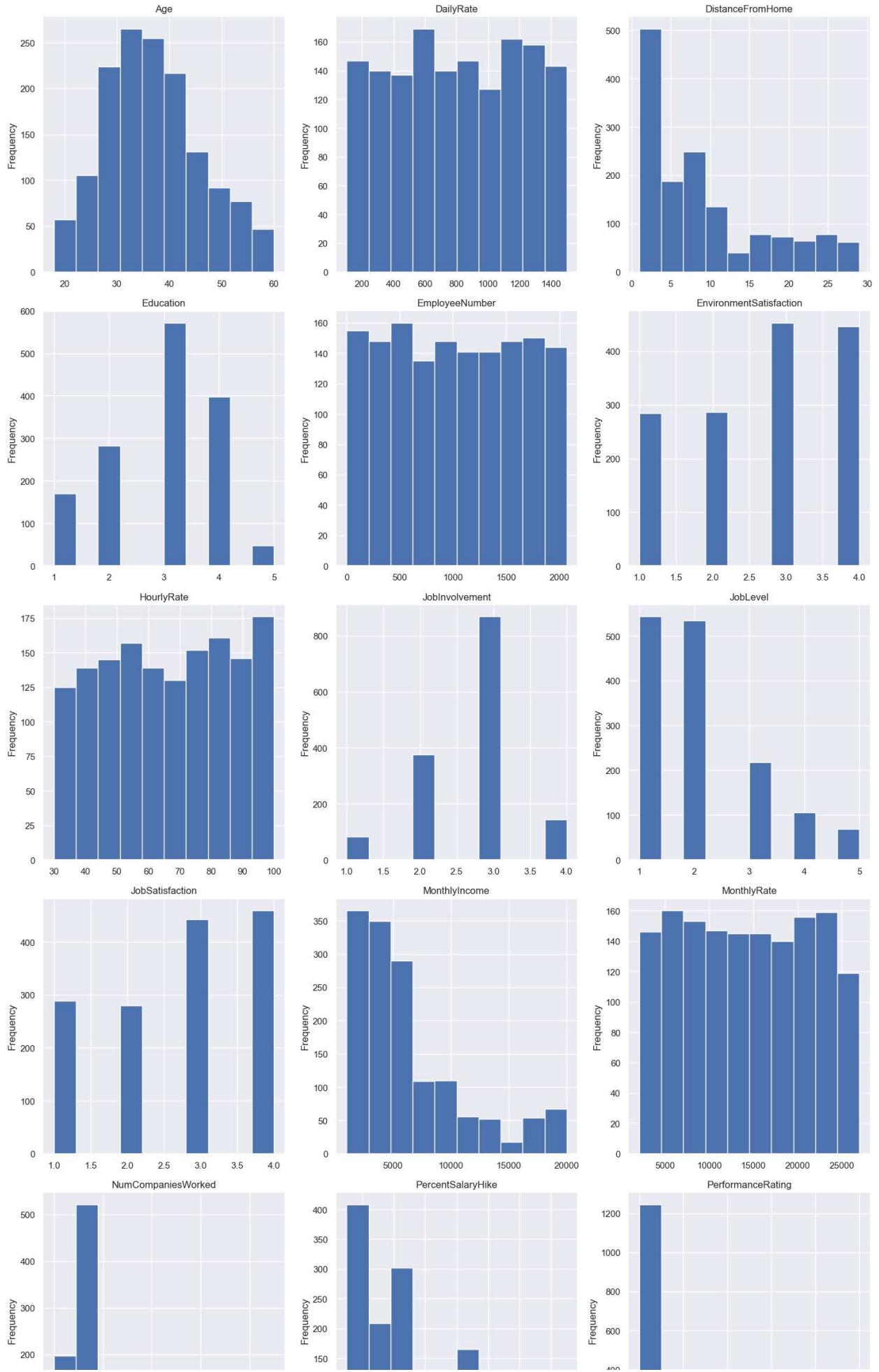
# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust spacing between subplots
fig.tight_layout()

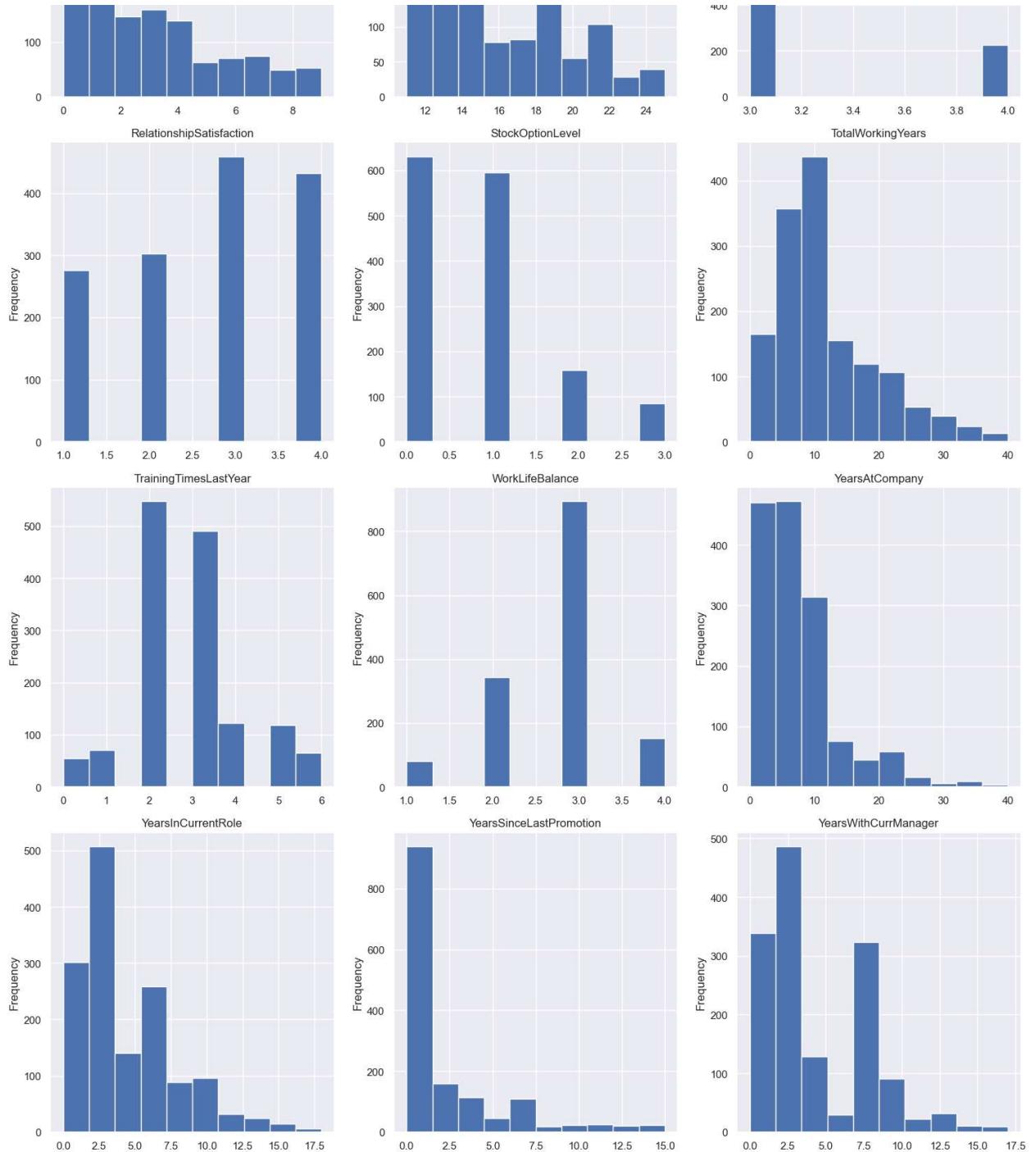
# Show plot
plt.show()
```



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## IBM HR Analytics Employee Attrition - Jupyter Notebook



```
In [13]: # Get the names of all columns with data type 'int'
int_vars = df.select_dtypes(include=['int', 'float']).columns.tolist()

# Create a figure with subplots
num_cols = len(int_vars)
num_rows = (num_cols + 2) // 3 # To make sure there are enough rows for the subplots
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Create a histogram for each integer variable with hue='Attrition'
for i, var in enumerate(int_vars):
    sns.histplot(data=df, x=var, hue='Attrition', kde=True, ax=axs[i])
    axs[i].set_title(var)

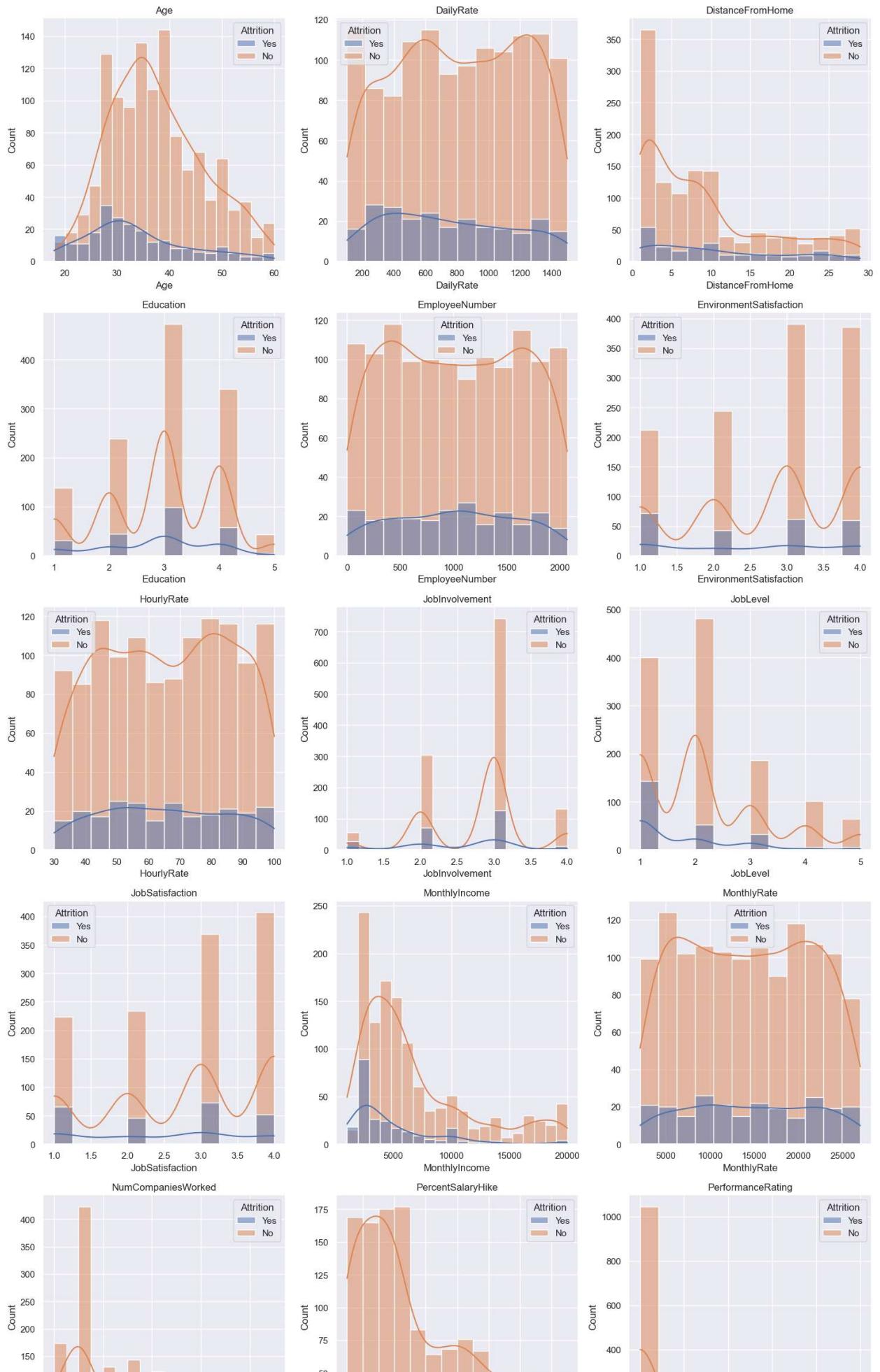
# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust spacing between subplots
fig.tight_layout()

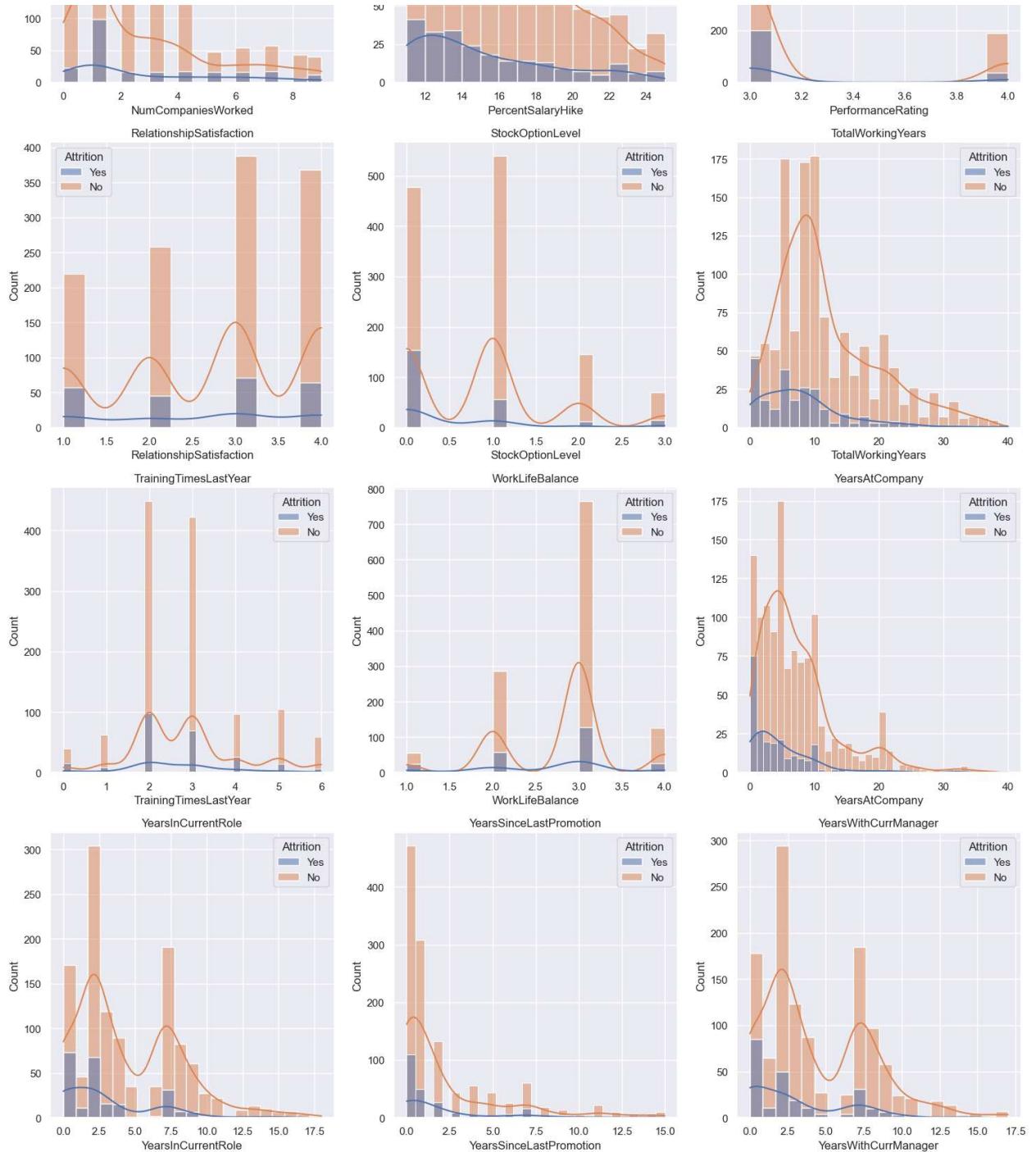
# Show plot
plt.show()
```



## IBM HR Analytics Employee Attrition - Jupyter Notebook



## IBM HR Analytics Employee Attrition - Jupyter Notebook



```
In [16]: # Get the names of all columns with data type 'object' (categorical variables)
cat_vars = df.select_dtypes(include=['object']).columns.tolist()

# Exclude 'Attrition' from the list if it exists in cat_vars
if 'Attrition' in cat_vars:
    cat_vars.remove('Attrition')

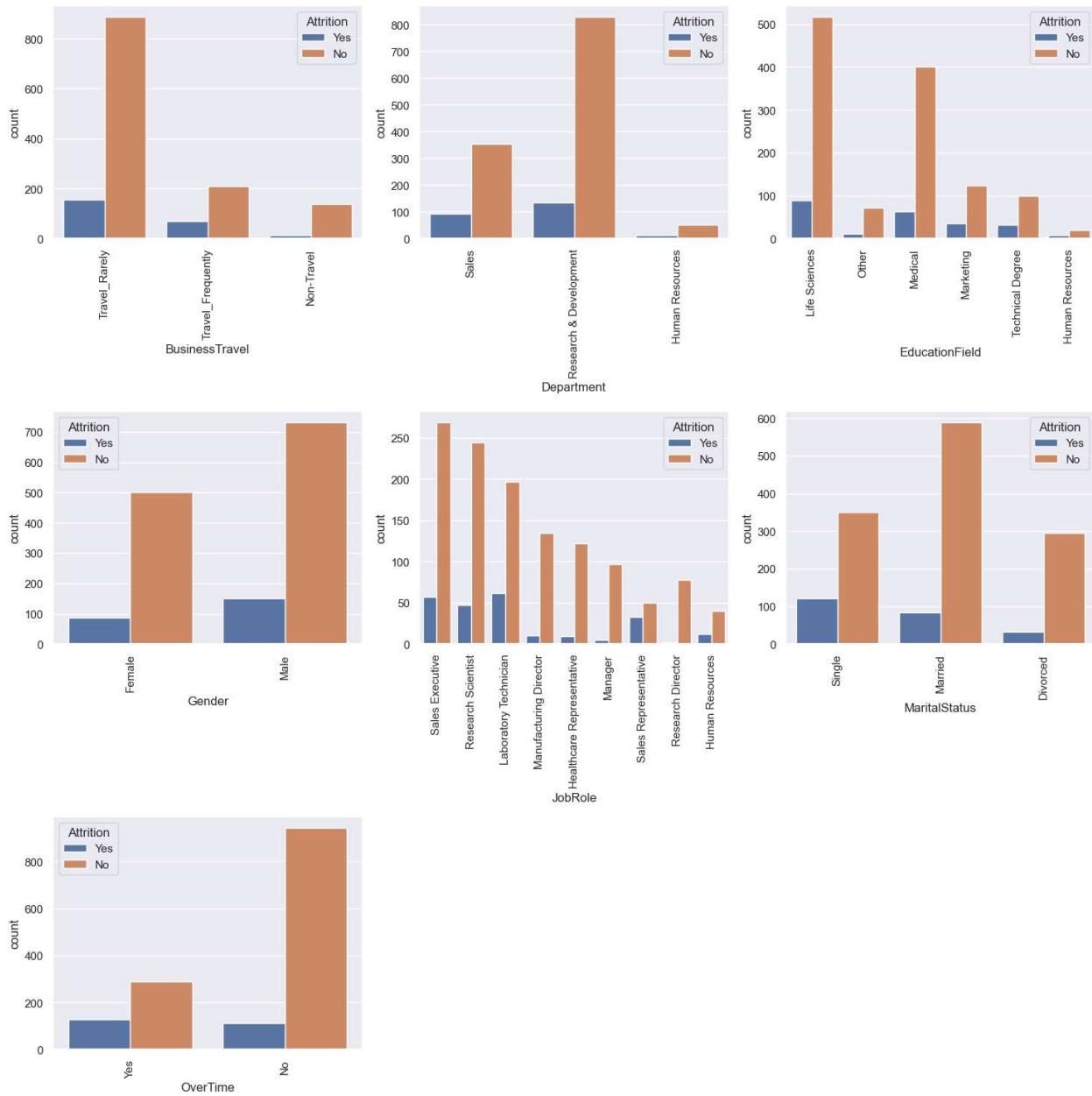
# Create a figure with subplots, but only include the required number of subplots
num_cols = len(cat_vars)
num_rows = (num_cols + 2) // 3 # To make sure there are enough rows for the subplots
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Create a count plot for each categorical variable
for i, var in enumerate(cat_vars):
    sns.countplot(x=var, hue='Attrition', data=df, ax=axs[i])
    axs[i].set_xticklabels(axs[i].get_xticklabels(), rotation=90)

# Remove any remaining blank subplots
for i in range(num_cols, len(axs)):
    fig.delaxes(axs[i])

# Adjust spacing between subplots
fig.tight_layout()

# Show the plot
plt.show()
```



```
In [17]: # Get the names of all columns with data type 'object' (categorical variables)
cat_vars = df.select_dtypes(include=['object']).columns.tolist()

# Exclude 'Attrition' from the list if it exists in cat_vars
if 'Attrition' in cat_vars:
    cat_vars.remove('Attrition')

# Create a figure with subplots, but only include the required number of subplots
num_cols = len(cat_vars)
num_rows = (num_cols + 2) // 3 # To make sure there are enough rows for the subplots
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Create a count plot for each categorical variable
for i, var in enumerate(cat_vars):
    sns.histplot(x=var, hue='Attrition', data=df, ax=axs[i], multiple="fill", kde=False, element="count")
    axs[i].set_xticklabels(df[var].unique(), rotation=90)
    axs[i].set_xlabel(var)

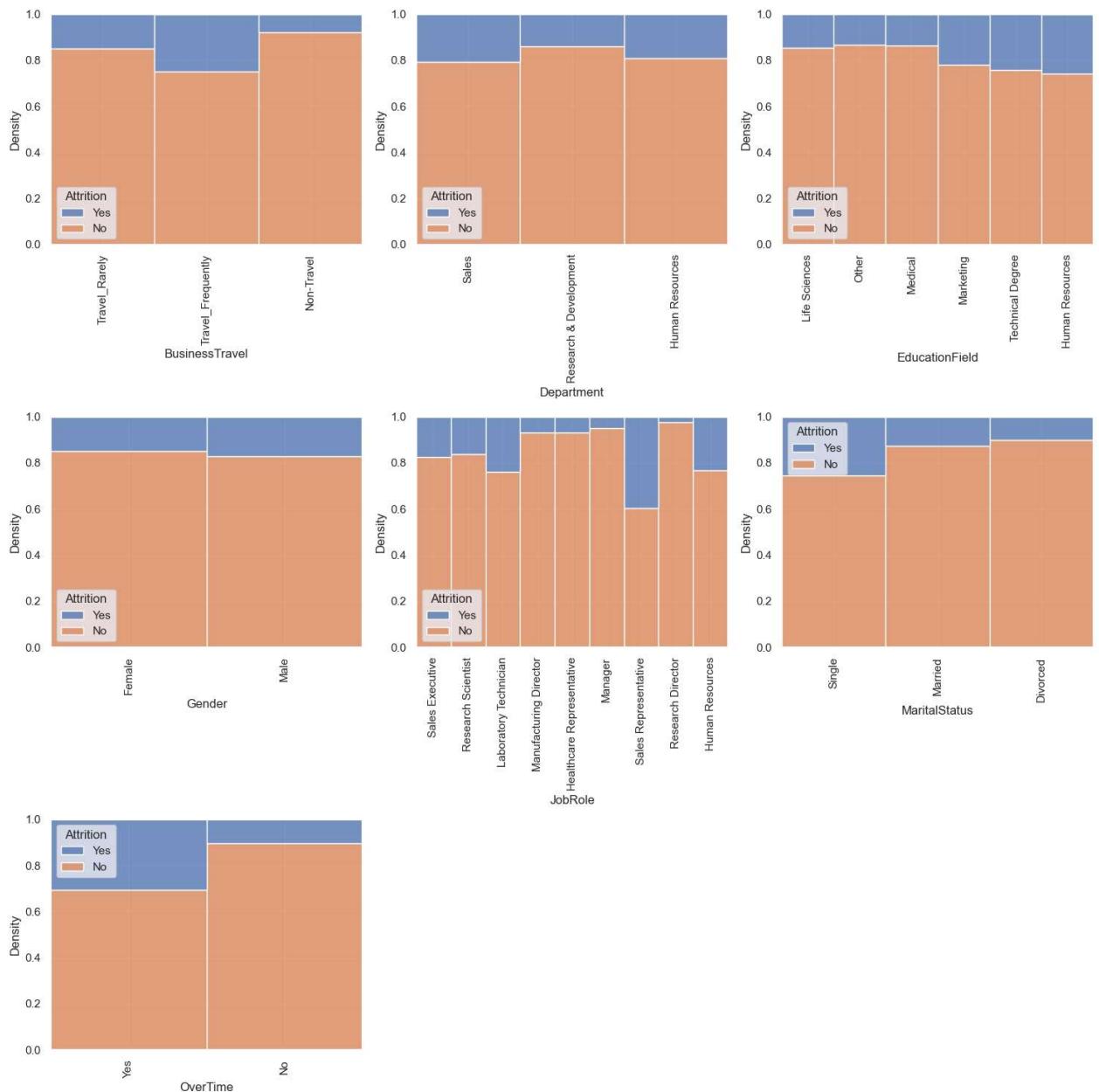
# Remove any remaining blank subplots
for i in range(num_cols, len(axs)):
    fig.delaxes(axs[i])

# Adjust spacing between subplots
fig.tight_layout()

# Show the plot
plt.show()
```

```
C:\Users\Michael\AppData\Local\Temp\ipykernel_24776\1288156870.py:17: UserWarning: FixedFor
matter should only be used together with FixedLocator
    axs[i].set_xticklabels(df[var].unique(), rotation=90)
C:\Users\Michael\AppData\Local\Temp\ipykernel_24776\1288156870.py:17: UserWarning: FixedFor
matter should only be used together with FixedLocator
    axs[i].set_xticklabels(df[var].unique(), rotation=90)
C:\Users\Michael\AppData\Local\Temp\ipykernel_24776\1288156870.py:17: UserWarning: FixedFor
matter should only be used together with FixedLocator
    axs[i].set_xticklabels(df[var].unique(), rotation=90)
C:\Users\Michael\AppData\Local\Temp\ipykernel_24776\1288156870.py:17: UserWarning: FixedFor
matter should only be used together with FixedLocator
    axs[i].set_xticklabels(df[var].unique(), rotation=90)
C:\Users\Michael\AppData\Local\Temp\ipykernel_24776\1288156870.py:17: UserWarning: FixedFor
matter should only be used together with FixedLocator
    axs[i].set_xticklabels(df[var].unique(), rotation=90)
C:\Users\Michael\AppData\Local\Temp\ipykernel_24776\1288156870.py:17: UserWarning: FixedFor
matter should only be used together with FixedLocator
    axs[i].set_xticklabels(df[var].unique(), rotation=90)
C:\Users\Michael\AppData\Local\Temp\ipykernel_24776\1288156870.py:17: UserWarning: FixedFor
matter should only be used together with FixedLocator
    axs[i].set_xticklabels(df[var].unique(), rotation=90)
```

## IBM HR Analytics Employee Attrition - Jupyter Notebook



```
In [21]: # Specify the maximum number of categories to show individually
max_categories = 5

# Filter categorical columns with 'object' data type
cat_cols = [col for col in df.columns if col != 'y' and df[col].dtype == 'object']

# Create a figure with subplots
num_cols = len(cat_cols)
num_rows = (num_cols + 2) // 3
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(20, 5*num_rows))

# Flatten the axs array for easier indexing
axs = axs.flatten()

# Create a pie chart for each categorical column
for i, col in enumerate(cat_cols):
    if i < len(axs): # Ensure we don't exceed the number of subplots
        # Count the number of occurrences for each category
        cat_counts = df[col].value_counts()

        # Group categories beyond the top max_categories as 'Other'
        if len(cat_counts) > max_categories:
            cat_counts_top = cat_counts[:max_categories]
            cat_counts_other = pd.Series(cat_counts[max_categories:].sum(), index=['Other'])
            cat_counts = cat_counts_top.append(cat_counts_other)

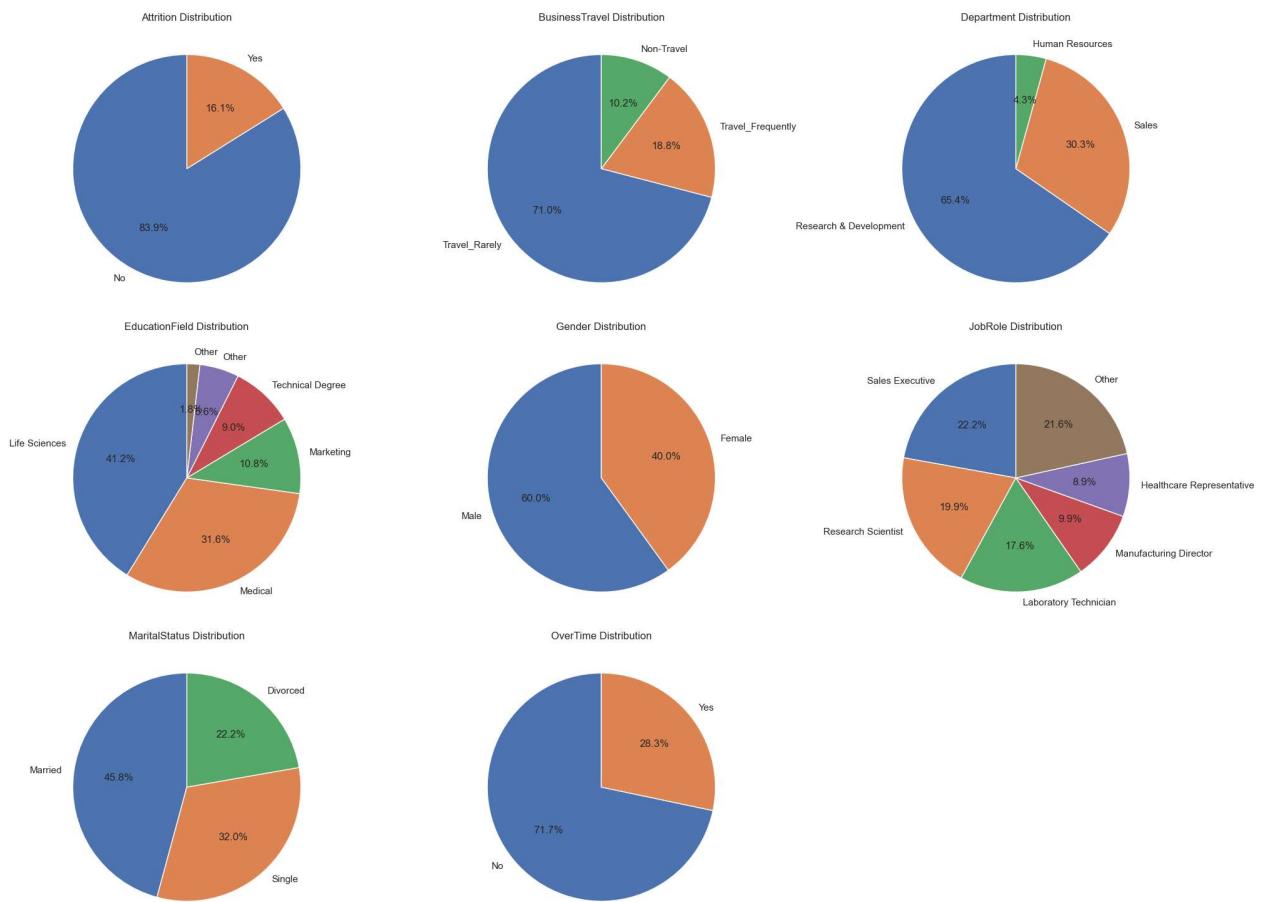
        # Create a pie chart
        axs[i].pie(cat_counts, labels=cat_counts.index, autopct='%1.1f%%', startangle=90)
        axs[i].set_title(f'{col} Distribution')

    # Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust spacing between subplots
fig.tight_layout()

# Show plot
plt.show()
```

C:\Users\Michael\AppData\Local\Temp\ipykernel\_24776\943223290.py:25: FutureWarning: The series.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.  
cat\_counts = cat\_counts\_top.append(cat\_counts\_other)  
C:\Users\Michael\AppData\Local\Temp\ipykernel\_24776\943223290.py:25: FutureWarning: The series.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.  
cat\_counts = cat\_counts\_top.append(cat\_counts\_other)



## Data Preprocessing Part 2

```
In [22]: # Check the amount of missing value
check_missing = df.isnull().sum() * 100 / df.shape[0]
check_missing[check_missing > 0].sort_values(ascending=False)
```

```
Out[22]: Series([], dtype: float64)
```

```
In [23]: df.shape
```

```
Out[23]: (1470, 32)
```

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

```
Out[24]:
```

Education	EducationField	EmployeeNumber	EnvironmentSatisfaction	Gender	HourlyRate	JobInvolvement	JobLevel
2	Life Sciences	1	2	Female	94	3	2
1	Life Sciences	2	3	Male	61	2	2
2	Other	4	4	Male	92	2	1
4	Life Sciences	5	4	Female	56	3	1
1	Medical	7	1	Male	40	3	1

# Label Encoding for Object Datatypes

```
In [25]: # Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Print the column name and the unique values
    print(f"{col}: {df[col].unique()}")
```

Attrition: ['Yes' 'No']  
BusinessTravel: ['Travel\_Rarely' 'Travel\_Frequently' 'Non-Travel']  
Department: ['Sales' 'Research & Development' 'Human Resources']  
EducationField: ['Life Sciences' 'Other' 'Medical' 'Marketing' 'Technical Degree'  
 'Human Resources']  
Gender: ['Female' 'Male']  
JobRole: ['Sales Executive' 'Research Scientist' 'Laboratory Technician'  
 'Manufacturing Director' 'Healthcare Representative' 'Manager'  
 'Sales Representative' 'Research Director' 'Human Resources']  
MaritalStatus: ['Single' 'Married' 'Divorced']  
OverTime: ['Yes' 'No']

```
In [26]: from sklearn import preprocessing

# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Initialize a LabelEncoder object
    label_encoder = preprocessing.LabelEncoder()

    # Fit the encoder to the unique values in the column
    label_encoder.fit(df[col].unique())

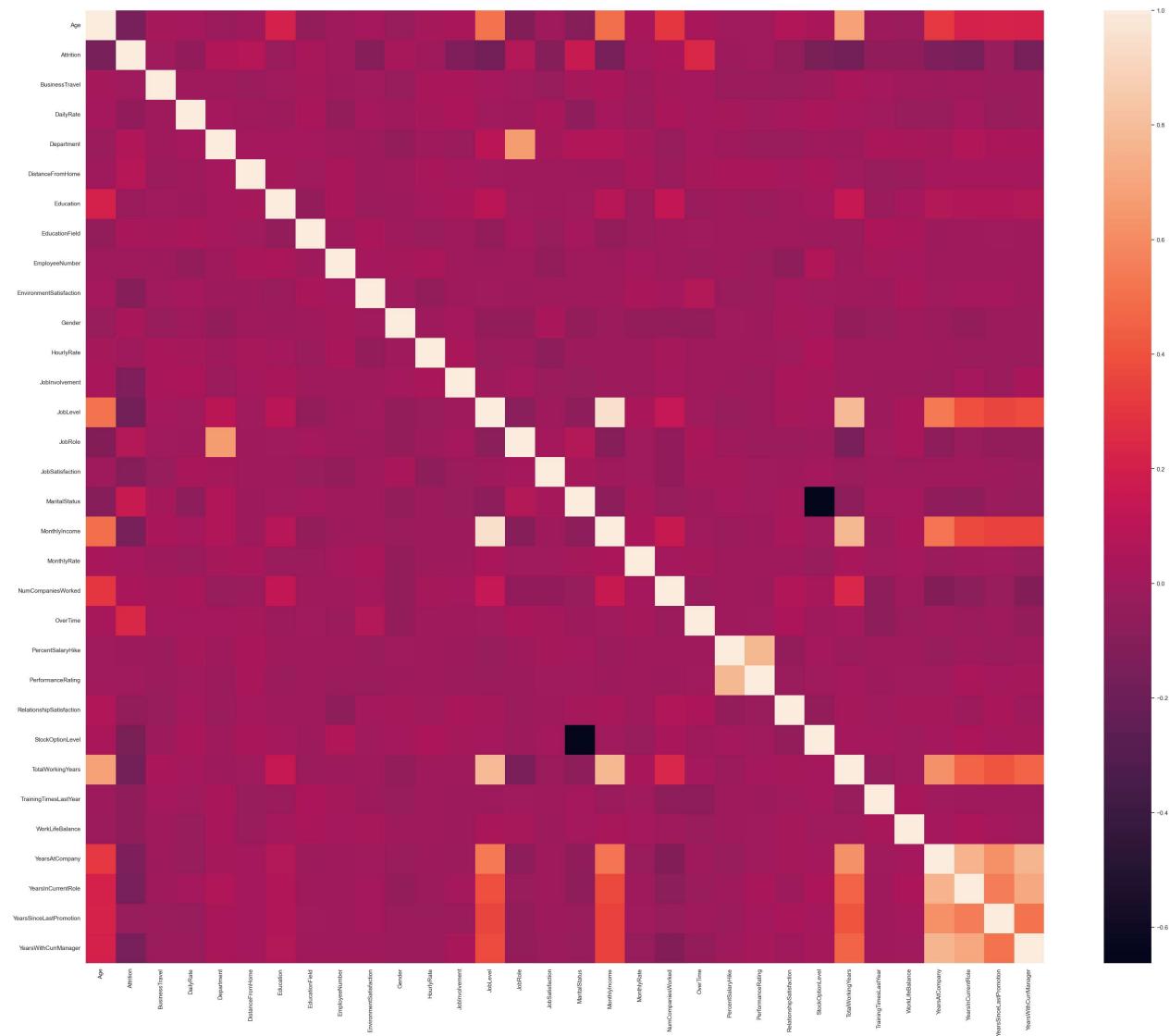
    # Transform the column using the encoder
    df[col] = label_encoder.transform(df[col])

    # Print the column name and the unique encoded values
    print(f"{col}: {df[col].unique()}")
```

Attrition: [1 0]  
BusinessTravel: [2 1 0]  
Department: [2 1 0]  
EducationField: [1 4 3 2 5 0]  
Gender: [0 1]  
JobRole: [7 6 2 4 0 3 8 5 1]  
MaritalStatus: [2 1 0]  
OverTime: [1 0]

```
In [27]: # Correlation Heatmap
plt.figure(figsize=(40, 32))
sns.heatmap(df.corr(), fmt='.2g', annot=False)
```

Out[27]: <AxesSubplot:>



```
In [28]: # Remove JobLevel column because it have 100% correlation with monthly income
df.drop(columns = 'JobLevel', inplace=True)
```

## Train Test Split

```
In [29]: X = df.drop('Attrition', axis=1)
y = df['Attrition']
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2,random_state=0)
```

## Remove Outlier from Train Data using Z-Score

```
In [30]: from scipy import stats

# Define the columns for which you want to remove outliers
selected_columns = ['MonthlyIncome', 'TotalWorkingYears', 'YearsAtCompany',
                    'YearsInCurrentRole', 'YearsSinceLastPromotion', 'YearsWithCurrManager']

# Calculate the Z-scores for the selected columns in the training data
z_scores = np.abs(stats.zscore(X_train[selected_columns]))

# Set a threshold value for outlier detection (e.g., 3)
threshold = 3

# Find the indices of outliers based on the threshold
outlier_indices = np.where(z_scores > threshold)[0]

# Remove the outliers from the training data
X_train = X_train.drop(X_train.index[outlier_indices])
y_train = y_train.drop(y_train.index[outlier_indices])
```

## Decision Tree Classifier

```
In [31]: from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
dtree = DecisionTreeClassifier(class_weight='balanced')
param_grid = {
    'max_depth': [3, 4, 5, 6, 7, 8],
    'min_samples_split': [2, 3, 4],
    'min_samples_leaf': [1, 2, 3, 4],
    'random_state': [0, 42]
}

# Perform a grid search with cross-validation to find the best hyperparameters
grid_search = GridSearchCV(dtree, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print(grid_search.best_params_)

{'max_depth': 3, 'min_samples_leaf': 1, 'min_samples_split': 2, 'random_state': 42}
```

```
In [32]: from sklearn.tree import DecisionTreeClassifier
dtree = DecisionTreeClassifier(random_state=42, max_depth=3, min_samples_leaf=1, min_samples_split=2)
dtree.fit(X_train, y_train)
```

```
Out[32]: DecisionTreeClassifier(class_weight='balanced', max_depth=3, random_state=42)
```

```
In [33]: from sklearn.metrics import accuracy_score
y_pred = dtree.predict(X_test)
print("Accuracy Score :", round(accuracy_score(y_test, y_pred)*100 ,2), "%")
```

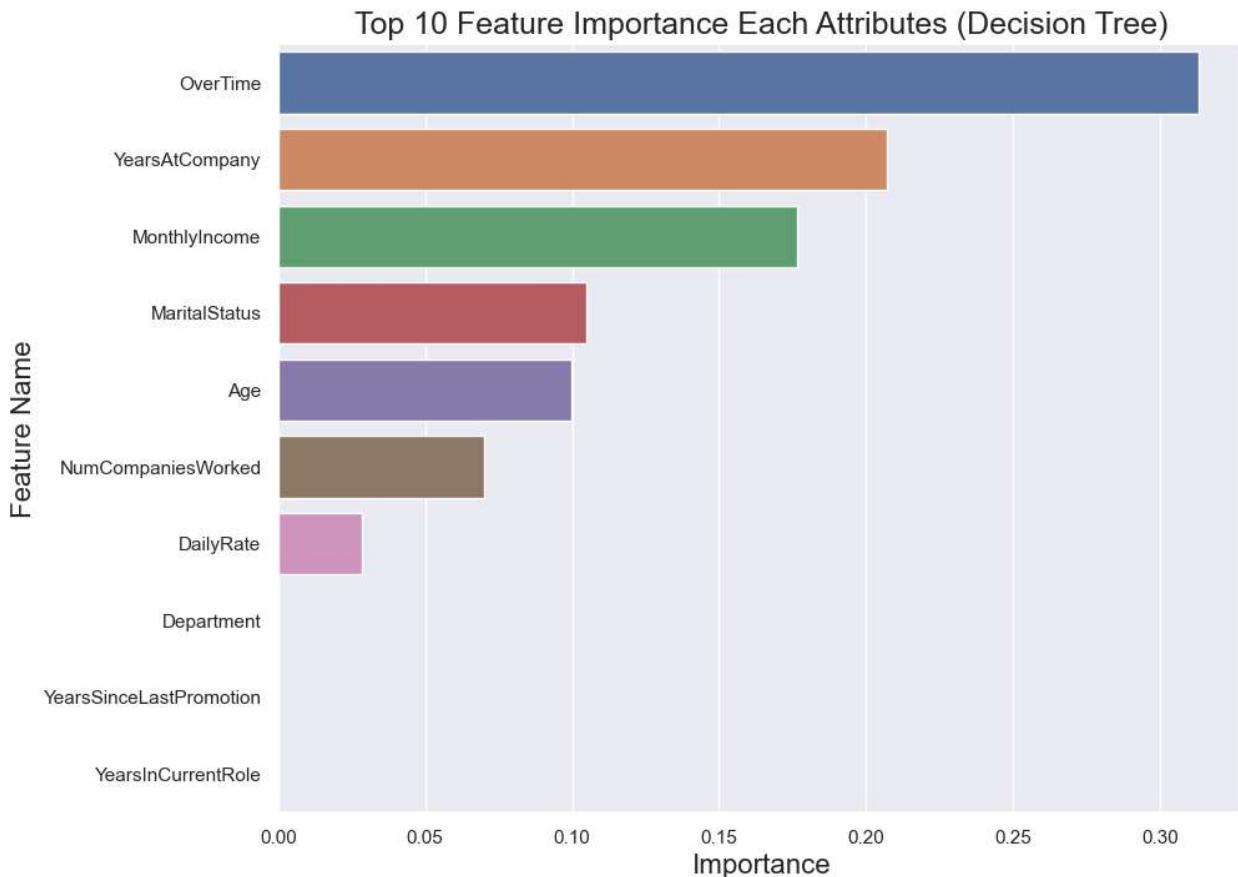
Accuracy Score : 78.57 %

```
In [34]: from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score, jaccard
print('F-1 Score : ',(f1_score(y_test, y_pred, average='micro')))
print('Precision Score : ',(precision_score(y_test, y_pred, average='micro')))
print('Recall Score : ',(recall_score(y_test, y_pred, average='micro')))
print('Jaccard Score : ',(jaccard_score(y_test, y_pred, average='micro')))
print('Log Loss : ',(log_loss(y_test, y_pred)))
```

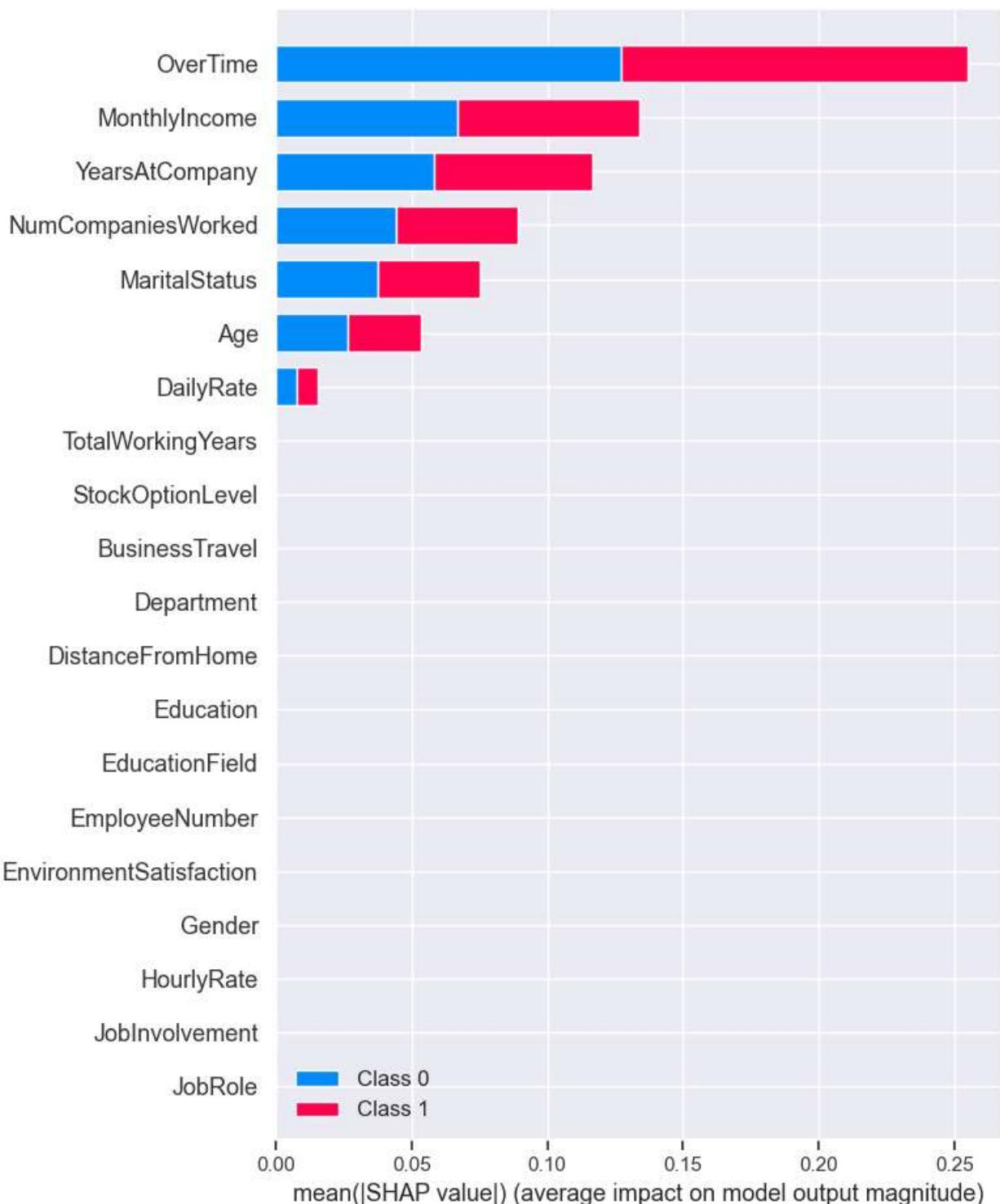
F-1 Score : 0.7857142857142857  
 Precision Score : 0.7857142857142857  
 Recall Score : 0.7857142857142857  
 Jaccard Score : 0.6470588235294118  
 Log Loss : 7.401264280227416

```
In [35]: imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": dtree.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

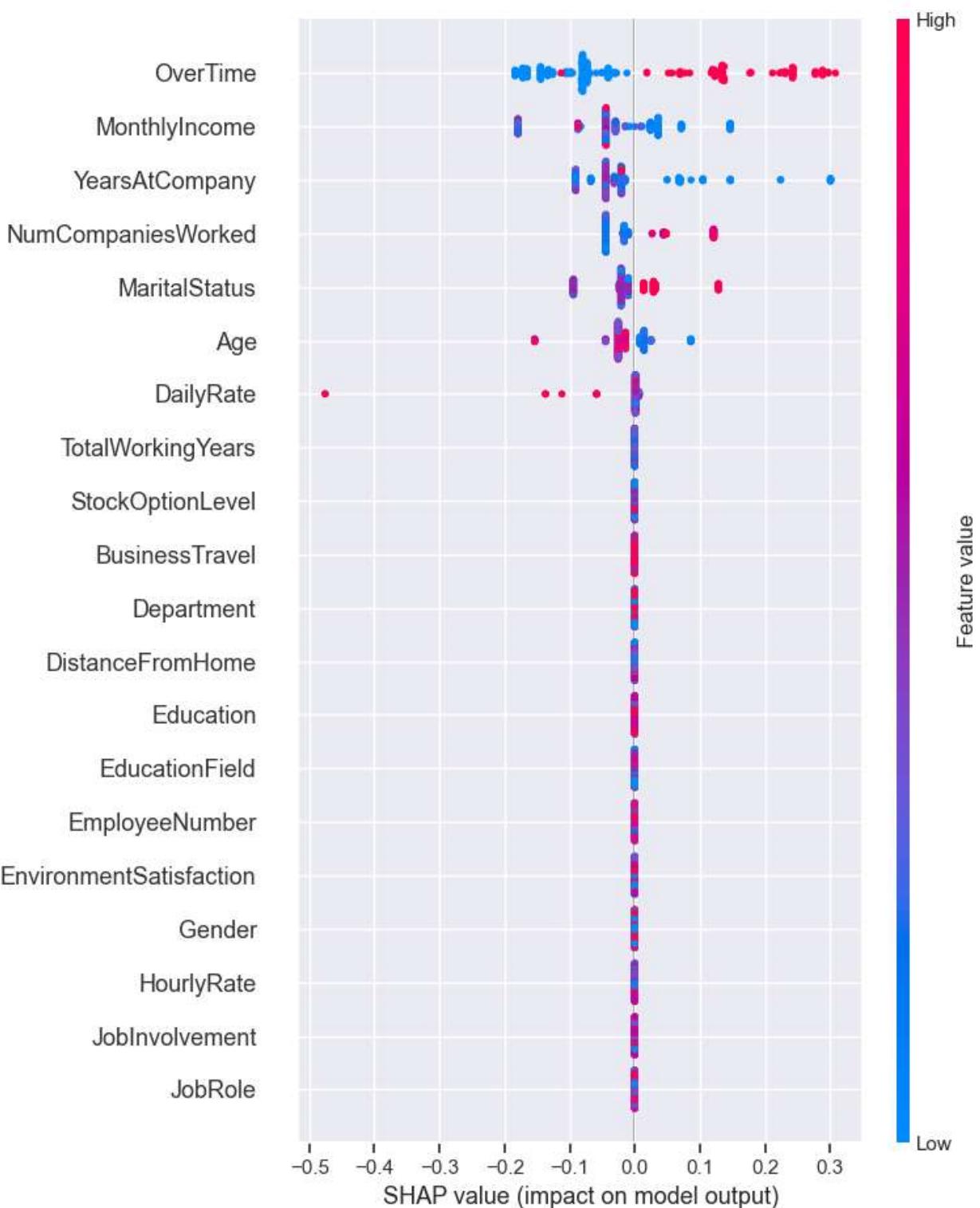
fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Top 10 Feature Importance Each Attributes (Decision Tree)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



```
In [36]: import shap  
explainer = shap.TreeExplainer(dtree)  
shap_values = explainer.shap_values(X_test)  
shap.summary_plot(shap_values, X_test)
```



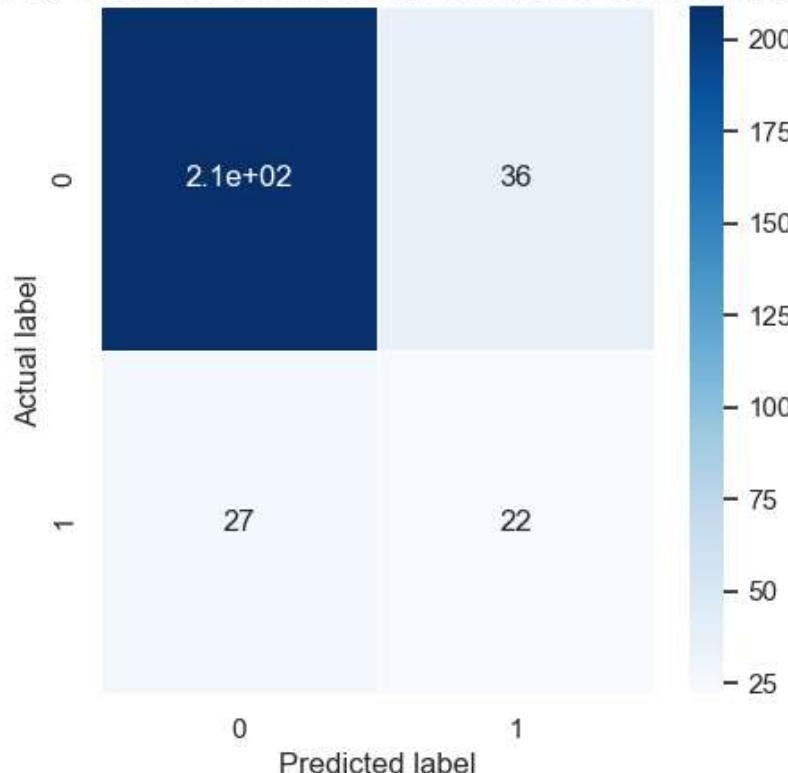
```
In [37]: # compute SHAP values
explainer = shap.TreeExplainer(dtree)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values[1], X_test.values, feature_names = X_test.columns)
```



```
In [38]: from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm, linewidths=.5, annot=True, cmap = 'Blues')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
all_sample_title = 'Accuracy Score for Decision Tree: {0}'.format(dtree.score(X_test, y_test))
plt.title(all_sample_title, size = 15)
```

Out[38]: Text(0.5, 1.0, 'Accuracy Score for Decision Tree: 0.7857142857142857')

Accuracy Score for Decision Tree: 0.7857142857142857



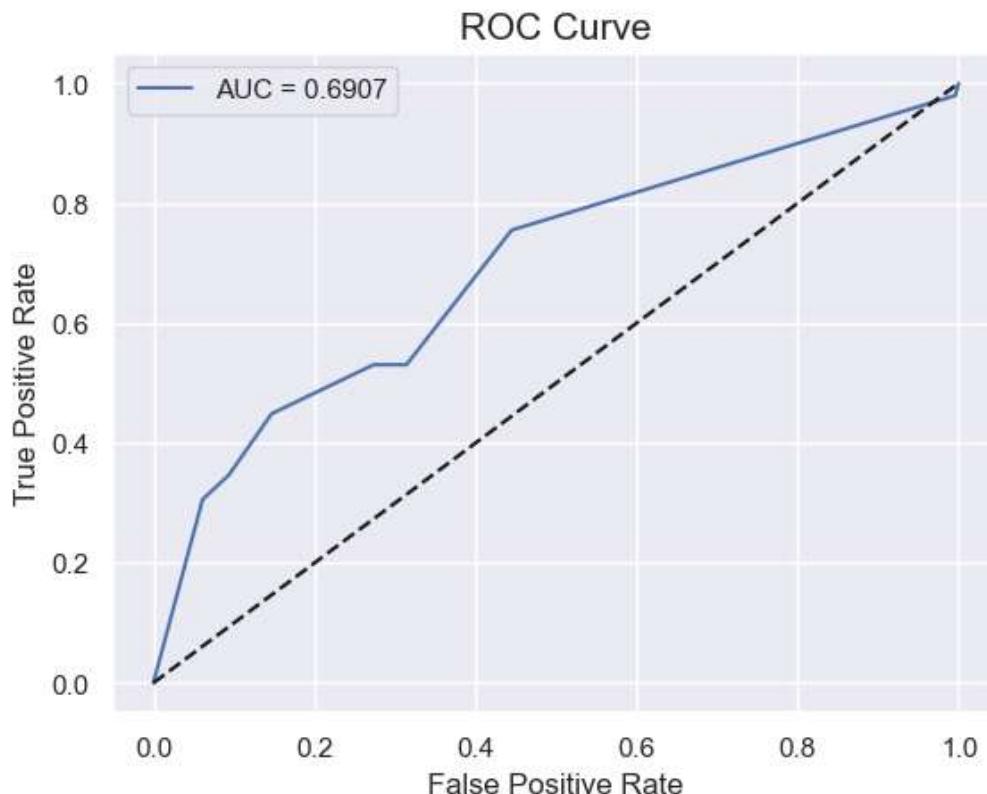
```
In [39]: from sklearn.metrics import roc_curve, roc_auc_score
y_pred_proba = dtree.predict_proba(X_test)[:, :, 1]

df_actual_predicted = pd.concat([pd.DataFrame(np.array(y_test), columns=['y_actual']), pd.DataFrame(df_actual_predicted.index = y_test.index)

fpr, tpr, tr = roc_curve(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])
auc = roc_auc_score(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])

plt.plot(fpr, tpr, label='AUC = %0.4f' %auc)
plt.plot(fpr, fpr, linestyle = '--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve', size = 15)
plt.legend()
```

```
Out[39]: <matplotlib.legend.Legend at 0x1f2afe522b0>
```



## Random Forest Classifier

```
In [40]: from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
rfc = RandomForestClassifier(class_weight='balanced')
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 5, 10],
    'max_features': ['sqrt', 'log2', None],
    'random_state': [0, 42]
}

# Perform a grid search with cross-validation to find the best hyperparameters
grid_search = GridSearchCV(rfc, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print(grid_search.best_params_)

{'max_depth': 5, 'max_features': 'sqrt', 'n_estimators': 200, 'random_state': 0}
```

```
In [41]: from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(random_state=0, max_depth=5, max_features='sqrt', n_estimators=200)
rfc.fit(X_train, y_train)
```

```
Out[41]: RandomForestClassifier(class_weight='balanced', max_depth=5,
                                 max_features='sqrt', n_estimators=200, random_state=0)
```

```
In [42]: y_pred = rfc.predict(X_test)
print("Accuracy Score : ", round(accuracy_score(y_test, y_pred)*100 ,2), "%")
```

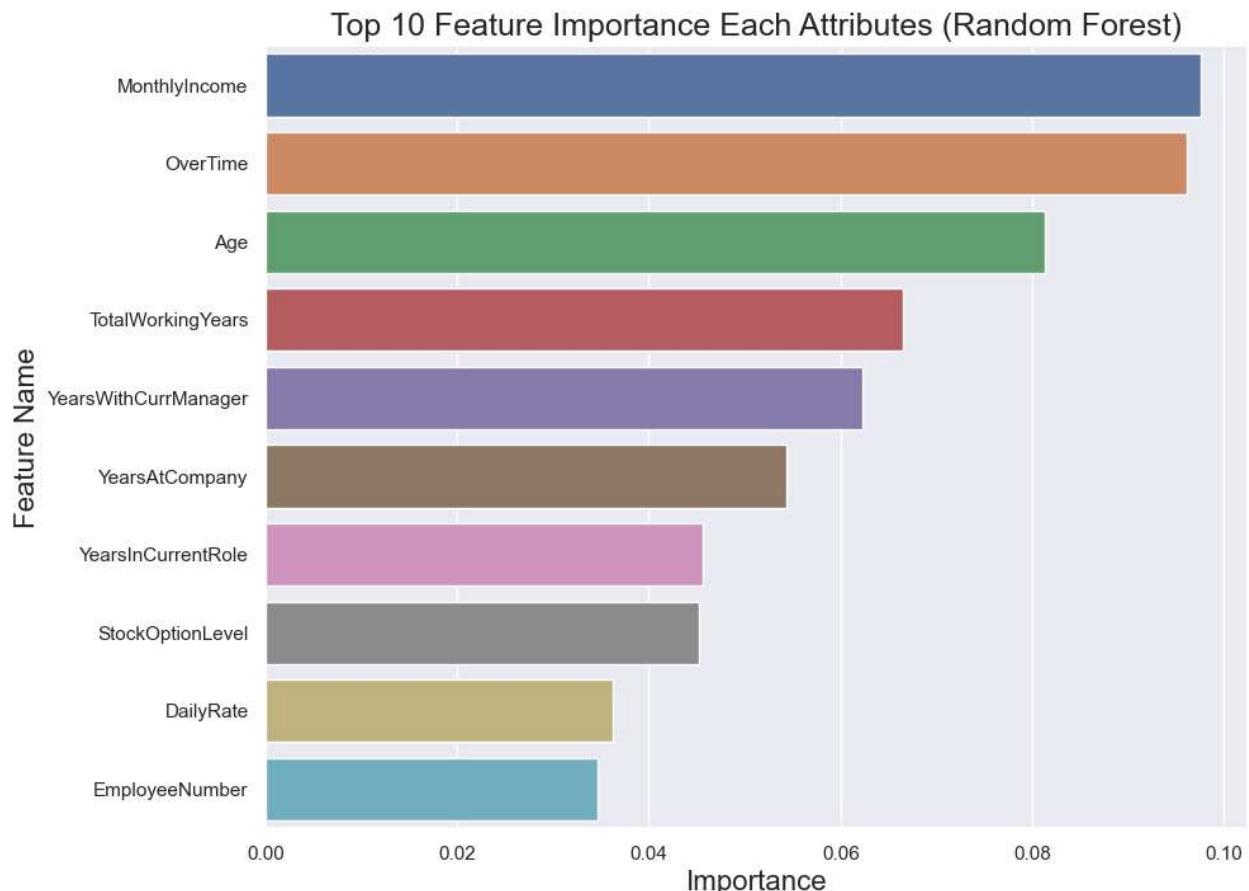
Accuracy Score : 82.65 %

```
In [43]: from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score, jaccard_score
print('F-1 Score : ',f1_score(y_test, y_pred, average='micro'))
print('Precision Score : ',precision_score(y_test, y_pred, average='micro'))
print('Recall Score : ',recall_score(y_test, y_pred, average='micro'))
print('Jaccard Score : ',jaccard_score(y_test, y_pred, average='micro'))
print('Log Loss : ',log_loss(y_test, y_pred))
```

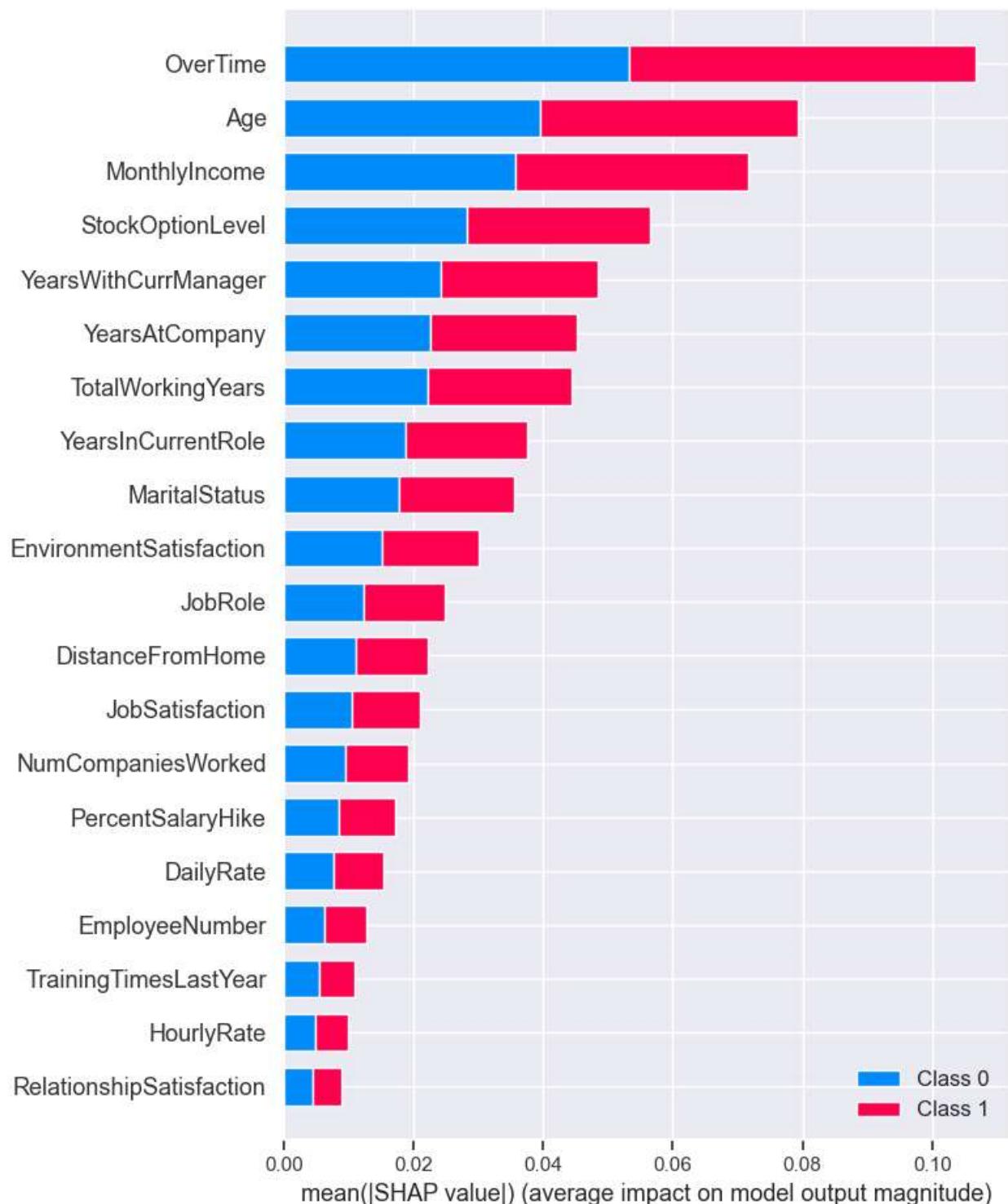
F-1 Score : 0.826530612244898  
 Precision Score : 0.826530612244898  
 Recall Score : 0.826530612244898  
 Jaccard Score : 0.7043478260869566  
 Log Loss : 5.991472069699383

```
In [44]: imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": rfc.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

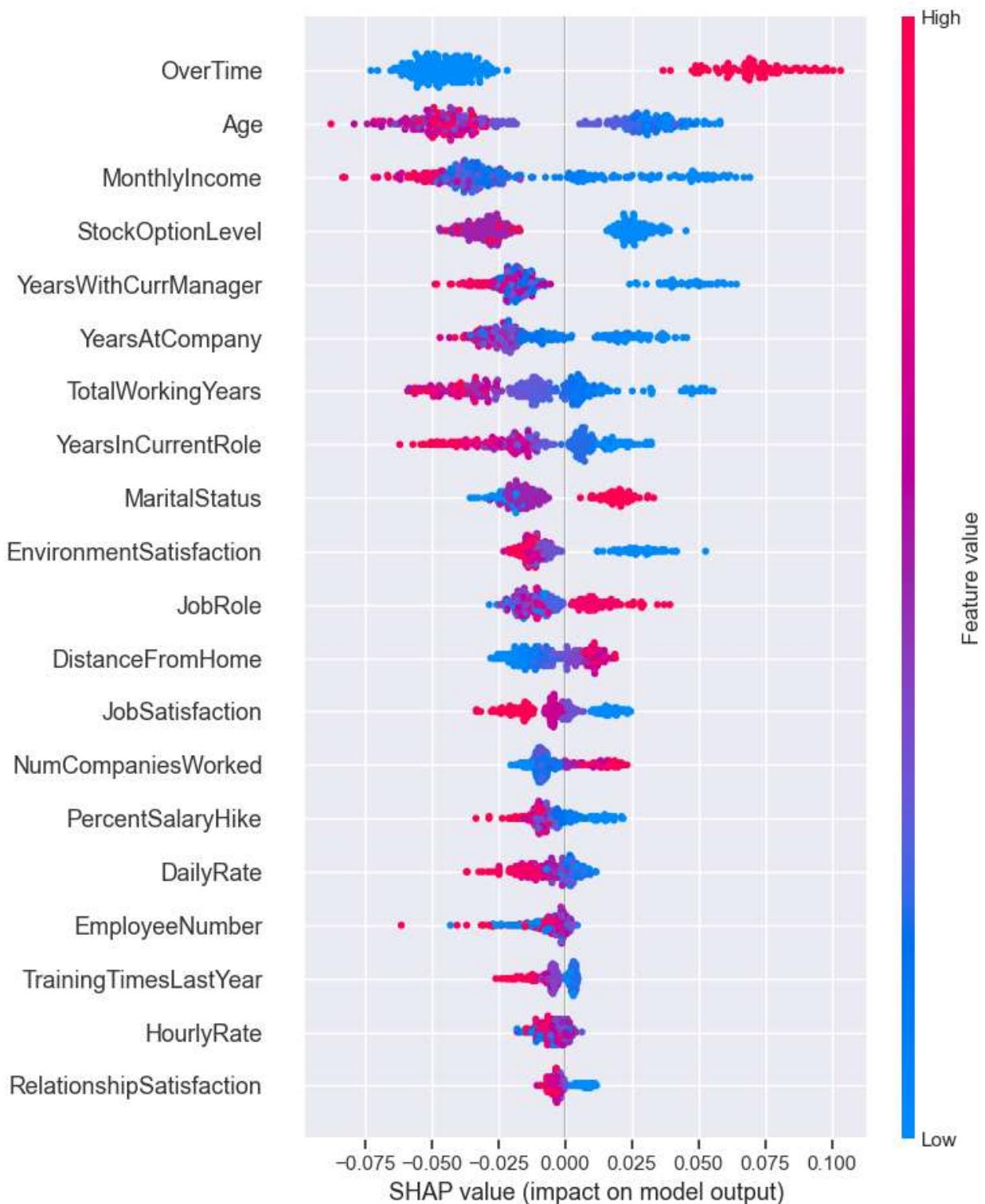
fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Top 10 Feature Importance Each Attributes (Random Forest)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



```
In [45]: import shap  
explainer = shap.TreeExplainer(rfc)  
shap_values = explainer.shap_values(X_test)  
shap.summary_plot(shap_values, X_test)
```

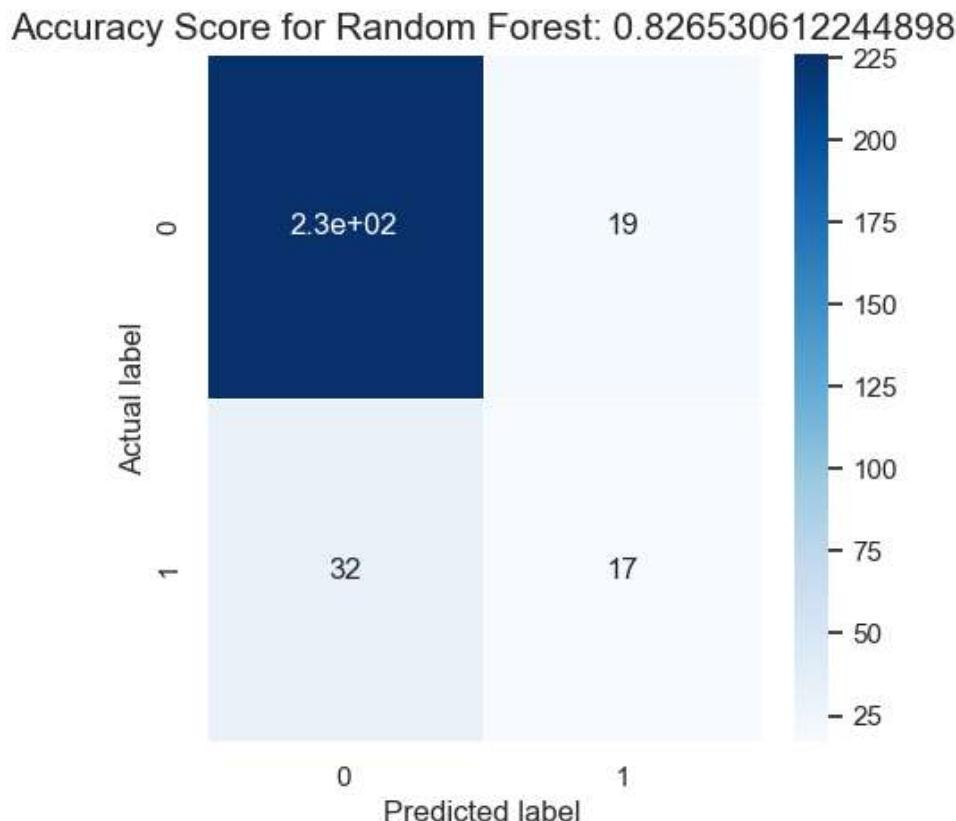


```
In [46]: # compute SHAP values
explainer = shap.TreeExplainer(rfc)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values[1], X_test.values, feature_names = X_test.columns)
```



```
In [47]: from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm, linewidths=.5, annot=True, cmap = 'Blues')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
all_sample_title = 'Accuracy Score for Random Forest: {0}'.format(rfc.score(X_test, y_test))
plt.title(all_sample_title, size = 15)
```

Out[47]: Text(0.5, 1.0, 'Accuracy Score for Random Forest: 0.826530612244898')



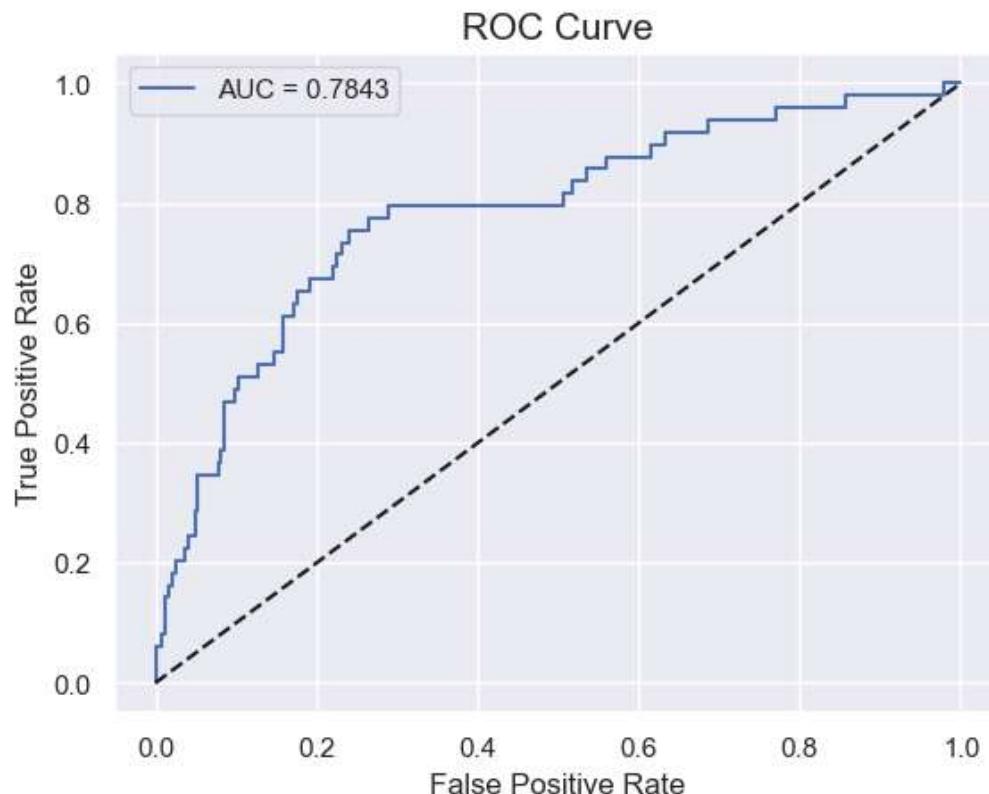
```
In [48]: from sklearn.metrics import roc_curve, roc_auc_score
y_pred_proba = rfc.predict_proba(X_test)[:,1]

df_actual_predicted = pd.concat([pd.DataFrame(np.array(y_test), columns=['y_actual']), pd.DataFrame(df_actual_predicted.index, columns=['y_pred_proba'])], axis=1)

fpr, tpr, tr = roc_curve(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])
auc = roc_auc_score(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])

plt.plot(fpr, tpr, label='AUC = %0.4f' %auc)
plt.plot(fpr, fpr, linestyle = '--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve', size = 15)
plt.legend()
```

Out[48]: <matplotlib.legend.Legend at 0x1f2b254b550>



## XGBoost Classifier

```
In [49]: from sklearn.model_selection import GridSearchCV
from xgboost import XGBClassifier

# Create an XGBoost classifier
xgb = XGBClassifier()

# Define the parameter grid for grid search
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [3, 5, 7],
    'learning_rate': [0.1, 0.01, 0.001],
    'gamma': [0, 0.1, 0.2]
}

# Perform a grid search with cross-validation to find the best hyperparameters
grid_search = GridSearchCV(xgb, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print(grid_search.best_params_)

{'gamma': 0.1, 'learning_rate': 0.1, 'max_depth': 7, 'n_estimators': 200}
```

```
In [50]: from xgboost import XGBClassifier
xgb = XGBClassifier(gamma=0.1, learning_rate=0.1, max_depth=7, n_estimators=200)
xgb.fit(X_train, y_train)
```

```
Out[50]: XGBClassifier(base_score=None, booster=None, callbacks=None,
                      colsample_bylevel=None, colsample_bynode=None,
                      colsample_bytree=None, early_stopping_rounds=None,
                      enable_categorical=False, eval_metric=None, feature_types=None,
                      gamma=0.1, gpu_id=None, grow_policy=None, importance_type=None,
                      interaction_constraints=None, learning_rate=0.1, max_bin=None,
                      max_cat_threshold=None, max_cat_to_onehot=None,
                      max_delta_step=None, max_depth=7, max_leaves=None,
                      min_child_weight=None, missing=nan, monotone_constraints=None,
                      n_estimators=200, n_jobs=None, num_parallel_tree=None,
                      predictor=None, random_state=None, ...)
```

```
In [51]: from sklearn.metrics import accuracy_score
y_pred = xgb.predict(X_test)
print("Accuracy Score : ", round(accuracy_score(y_test, y_pred)*100 ,2), "%")
```

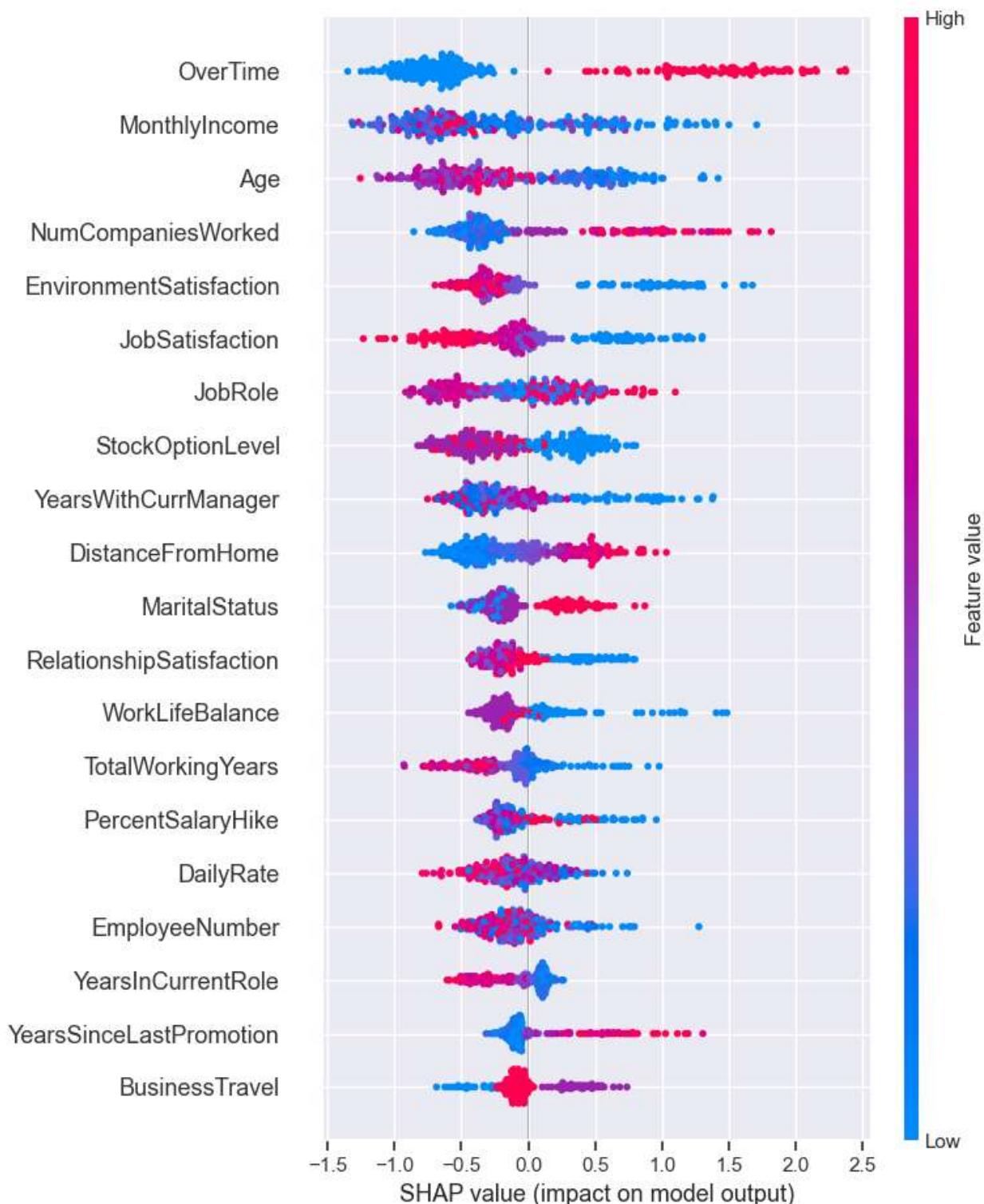
Accuracy Score : 86.05 %

```
In [52]: from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score, jaccard_
print('F-1 Score : ',(f1_score(y_test, y_pred, average='micro')))
print('Precision Score : ',(precision_score(y_test, y_pred, average='micro')))
print('Recall Score : ',(recall_score(y_test, y_pred, average='micro')))
print('Jaccard Score : ',(jaccard_score(y_test, y_pred, average='micro')))
print('Log Loss : ',(log_loss(y_test, y_pred)))
```

F-1 Score : 0.8605442176870749  
 Precision Score : 0.8605442176870748  
 Recall Score : 0.8605442176870748  
 Jaccard Score : 0.755223880597015  
 Log Loss : 4.816648400598365

```
In [53]: import shap  
explainer = shap.TreeExplainer(xgb)  
shap_values = explainer.shap_values(X_test)  
shap.summary_plot(shap_values, X_test)
```

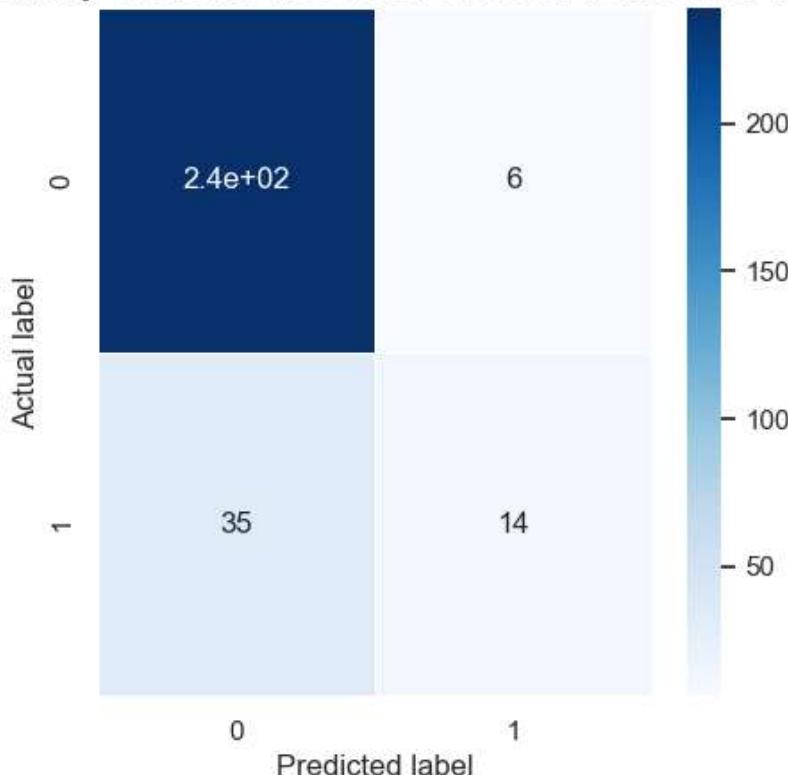
ntree\_limit is deprecated, use `iteration\_range` or model slicing instead.



```
In [54]: from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm, linewidths=.5, annot=True, cmap = 'Blues')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
all_sample_title = 'Accuracy Score for XGBoost: {0}'.format(xgb.score(X_test, y_test))
plt.title(all_sample_title, size = 15)
```

Out[54]: Text(0.5, 1.0, 'Accuracy Score for XGBoost: 0.8605442176870748')

Accuracy Score for XGBoost: 0.8605442176870748



```
In [55]: from sklearn.metrics import roc_curve, roc_auc_score
y_pred_proba = xgb.predict_proba(X_test)[:, :, 1]

df_actual_predicted = pd.concat([pd.DataFrame(np.array(y_test), columns=['y_actual']), pd.DataFrame(df_actual_predicted.index, columns=['y_pred_proba'])], axis=1)

fpr, tpr, tr = roc_curve(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])
auc = roc_auc_score(df_actual_predicted['y_actual'], df_actual_predicted['y_pred_proba'])

plt.plot(fpr, tpr, label='AUC = %0.4f' %auc)
plt.plot(fpr, fpr, linestyle = '--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve', size = 15)
plt.legend()
```

Out[55]: <matplotlib.legend.Legend at 0x1f2b2503be0>

