HR Analytics – Employee Attrition project

```
Problem: High employee attrition increases business costs.
Goal: Build a predictive model to identify at-risk employees.
```

Reading the Data

In [56]:
```
#import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [58]:
```
# read dataset
df = pd.read_csv('WA_Fn-UseC_-HR-Employee-Attrition.csv')
df.head()
```

Out[58]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education
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

5 rows × 35 columns

In [60]:
```
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 [62]:

```
# Separate categorical columns
categorical_cols = df.select_dtypes(include=['object']).columns.tolist()

# Separate numerical columns
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns.tolist()

print("Categorical Columns:", categorical_cols)
print("
print("Numerical Columns:", numerical_cols)
```

```
Categorical Columns: ['Attrition', 'BusinessTravel', 'Department', 'EducationField', 'Gender', 'JobRole', 'MaritalStatus', 'Over18', 'OverTime']
_____________________________________________________________________________
Numerical Columns: ['Age', 'DailyRate', 'DistanceFromHome', 'Education', 'EmployeeCount', 'EmployeeNumber', 'EnvironmentSatisfaction', 'HourlyRate', 'JobInvolvement', 'JobLevel', 'JobSatisfaction', 'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorked', 'PercentSalaryHike', 'PerformanceRating', 'RelationshipSatisfaction', 'StandardHours', 'StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear', 'WorkLifeBalance', 'YearsAtCompany', 'YearsInCurrentRole', 'YearsSinceLastPromotion', 'YearsWithCurrManager']
```

In [64]:
```
df.describe()
```

Out[64]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	Employ
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1
mean	36.923810	802.485714	9.192517	2.912925	1.0	1
std	9.135373	403.509100	8.106864	1.024165	0.0	
min	18.000000	102.000000	1.000000	1.000000	1.0	
25%	30.000000	465.000000	2.000000	2.000000	1.0	
50%	36.000000	802.000000	7.000000	3.000000	1.0	1
75%	43.000000	1157.000000	14.000000	4.000000	1.0	1
max	60.000000	1499.000000	29.000000	5.000000	1.0	2

8 rows × 26 columns

In [66]:
```
for col in categorical_cols:
    print(f"\n Column: {col}")
    print("Unique Values:", df[col].unique())
    print("Value Counts:\n", df[col].value_counts())
```

```
 Column: Attrition
Unique Values: ['Yes' 'No']
Value Counts:
 Attrition
No     1233
Yes     237
Name: count, dtype: int64

 Column: BusinessTravel
Unique Values: ['Travel_Rarely' 'Travel_Frequently' 'Non-Travel']
Value Counts:
 BusinessTravel
Travel_Rarely        1043
Travel_Frequently     277
Non-Travel            150
Name: count, dtype: int64

 Column: Department
Unique Values: ['Sales' 'Research & Development' 'Human Resources']
Value Counts:
 Department
Research & Development    961
Sales                     446
Human Resources            63
Name: count, dtype: int64

 Column: EducationField
Unique Values: ['Life Sciences' 'Other' 'Medical' 'Marketing' 'Technical Degree'
 'Human Resources']
Value Counts:
 EducationField
Life Sciences       606
Medical             464
Marketing           159
Technical Degree    132
Other                82
Human Resources      27
Name: count, dtype: int64

 Column: Gender
Unique Values: ['Female' 'Male']
Value Counts:
 Gender
Male      882
Female    588
Name: count, dtype: int64

 Column: JobRole
Unique Values: ['Sales Executive' 'Research Scientist' 'Laboratory Technician'
 'Manufacturing Director' 'Healthcare Representative' 'Manager'
 'Sales Representative' 'Research Director' 'Human Resources']
Value Counts:
 JobRole
Sales Executive              326
Research Scientist           292
Laboratory Technician        259
```

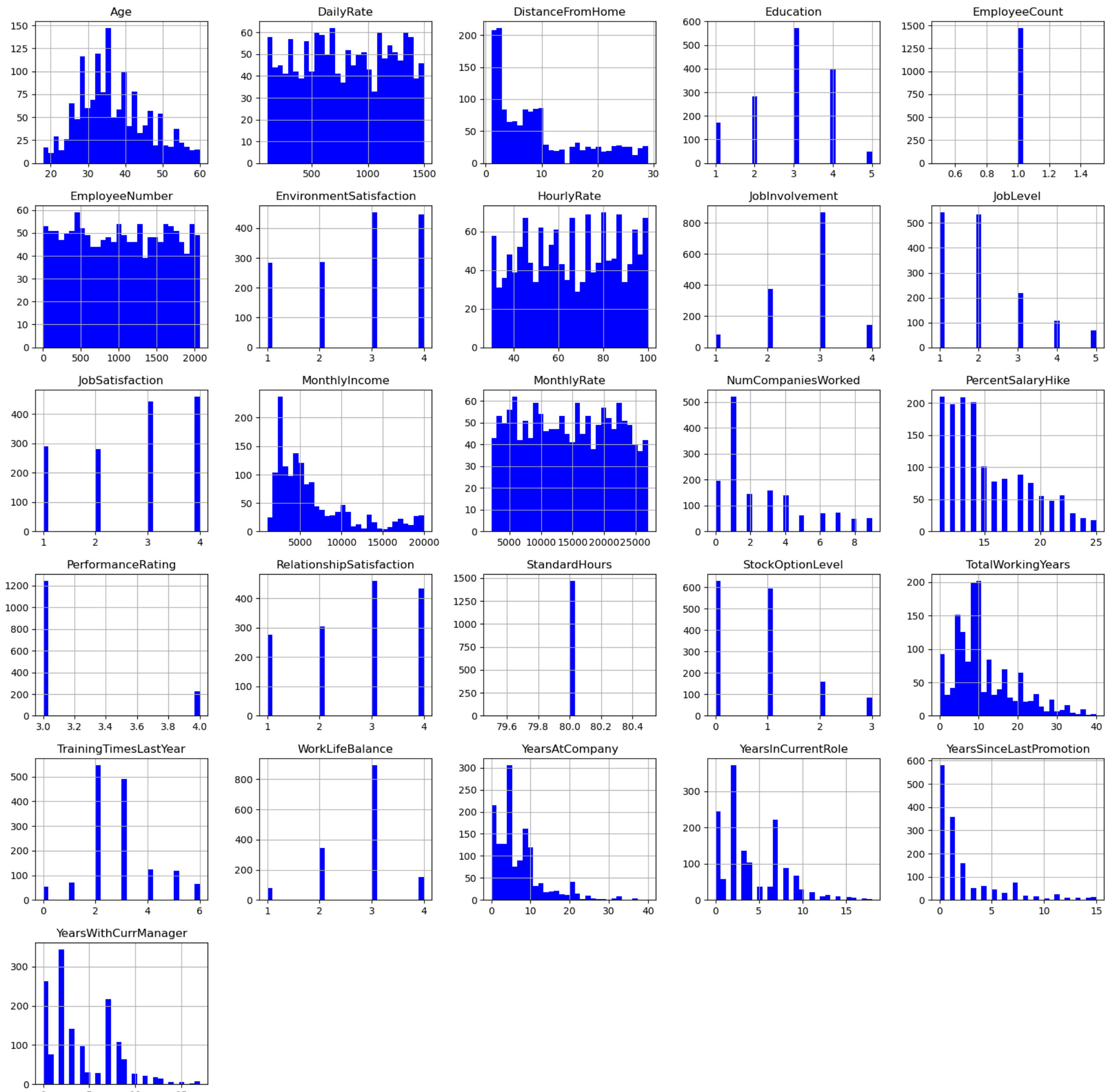
```
Manufacturing Director       145
Healthcare Representative    131
Manager                      102
Sales Representative          83
Research Director             80
Human Resources               52
Name: count, dtype: int64

 Column: MaritalStatus
Unique Values: ['Single' 'Married' 'Divorced']
Value Counts:
 MaritalStatus
Married     673
Single      470
Divorced    327
Name: count, dtype: int64

 Column: Over18
Unique Values: ['Y']
Value Counts:
 Over18
Y    1470
Name: count, dtype: int64

 Column: OverTime
Unique Values: ['Yes' 'No']
Value Counts:
 OverTime
No     1054
Yes     416
Name: count, dtype: int64
```

VISUALIZE DATASET

In [69]:

```
# visulizaing data distribution using histogram plot.
df.hist(bins = 30, figsize = (20,20), color = 'b')
```

Out[69]:
```
array([[<Axes: title={'center': 'Age'}>,
        <Axes: title={'center': 'DailyRate'}>,
        <Axes: title={'center': 'DistanceFromHome'}>,
        <Axes: title={'center': 'Education'}>,
        <Axes: title={'center': 'EmployeeCount'}>],
       [<Axes: title={'center': 'EmployeeNumber'}>,
        <Axes: title={'center': 'EnvironmentSatisfaction'}>,
        <Axes: title={'center': 'HourlyRate'}>,
        <Axes: title={'center': 'JobInvolvement'}>,
        <Axes: title={'center': 'JobLevel'}>],
       [<Axes: title={'center': 'JobSatisfaction'}>,
        <Axes: title={'center': 'MonthlyIncome'}>,
        <Axes: title={'center': 'MonthlyRate'}>,
        <Axes: title={'center': 'NumCompaniesWorked'}>,
        <Axes: title={'center': 'PercentSalaryHike'}>],
       [<Axes: title={'center': 'PerformanceRating'}>,
        <Axes: title={'center': 'RelationshipSatisfaction'}>,
        <Axes: title={'center': 'StandardHours'}>,
        <Axes: title={'center': 'StockOptionLevel'}>,
        <Axes: title={'center': 'TotalWorkingYears'}>],
       [<Axes: title={'center': 'TrainingTimesLastYear'}>,
        <Axes: title={'center': 'WorkLifeBalance'}>,
        <Axes: title={'center': 'YearsAtCompany'}>,
        <Axes: title={'center': 'YearsInCurrentRole'}>,
        <Axes: title={'center': 'YearsSinceLastPromotion'}>],
       [<Axes: title={'center': 'YearsWithCurrManager'}>, <Axes: >,
        <Axes: >, <Axes: >, <Axes: >]], dtype=object)
```



In [70]:

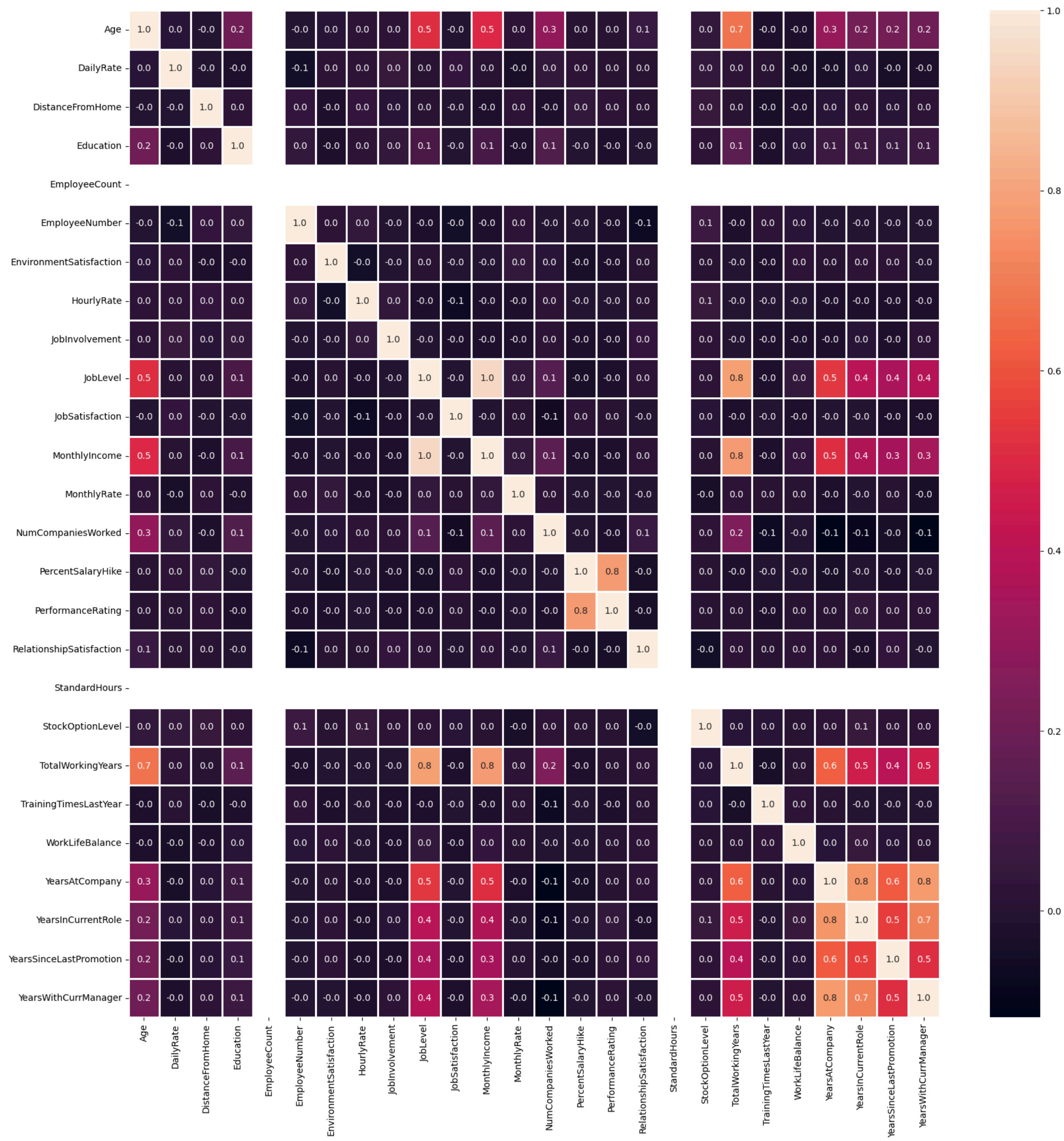
```
 # Several features such as 'MonthlyIncome' and 'TotalWorkingYears' are tail heavy
# Wecan drop 'EmployeeCount' and 'Standardhours' astey are constant for all employe
```

In [71]:

```
# let's see the correlation between numeric features
numeric_features = df.select_dtypes(include = [np.number])

correlations = numeric_features .corr()
f, ax = plt.subplots(figsize = (20, 20))
sns.heatmap(correlations, annot = True, linewidths = 2, fmt = '.1f', ax=ax)
```

Out[71]:

```
<Axes: >
```



In [ ]:

- **Job Level shows a strong positive correlation with Total Working Years**, indicating that as employees accumulate more experience, they tend to move up the organizational hierarchy.
- **Monthly Income is highly correlated with both Job Level and Total Working Years**, reflecting the typical structure where compensation increases with seniority and experience.
- **Age exhibits a significant correlation with Monthly Income**, suggesting that older employees generally earn more—likely due to accumulated experience and higher positions within the company.

Data Cleaning & Preprocessing

In [78]:
```
# Column: Over18 has Unique Values: ['Y'] which is same for all the rows, ence drop

df.drop('Over18', axis=1, inplace= True)
df.head()
```

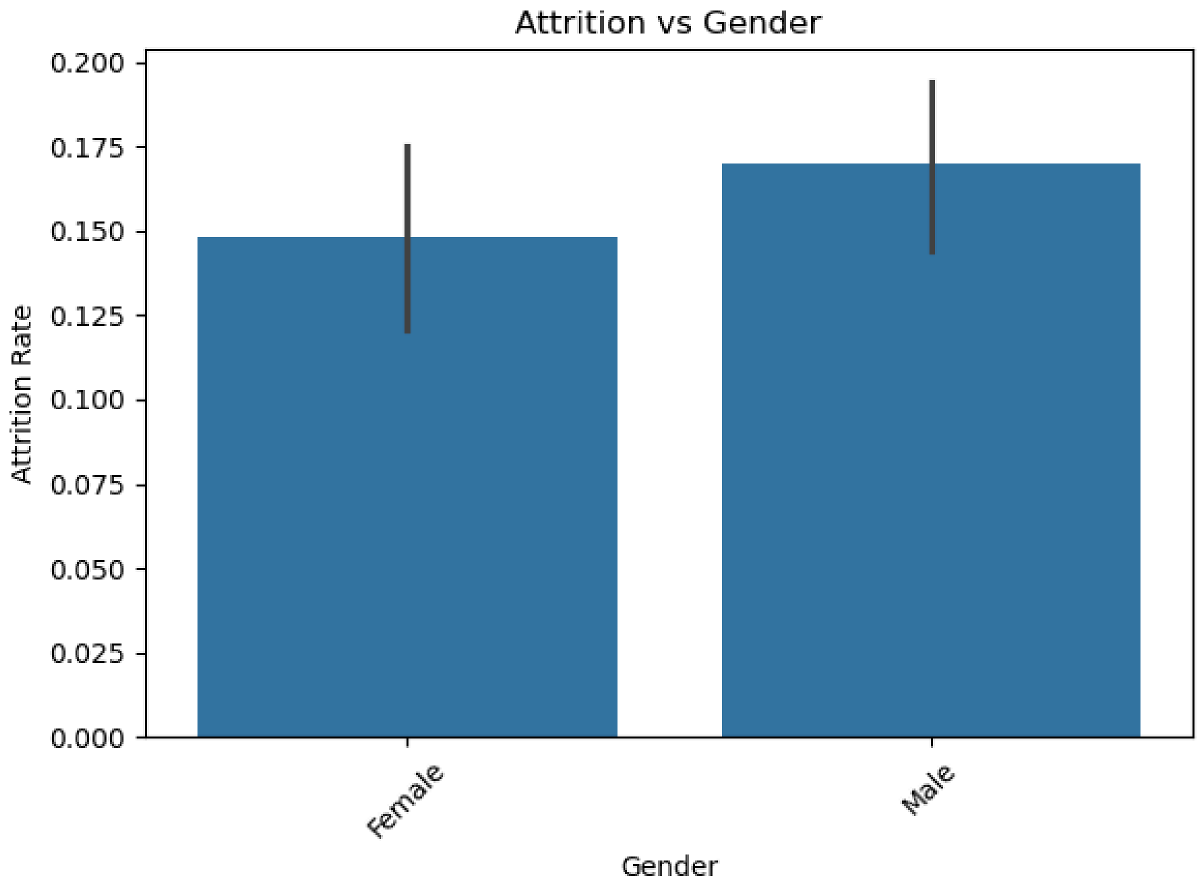
Out[78]:

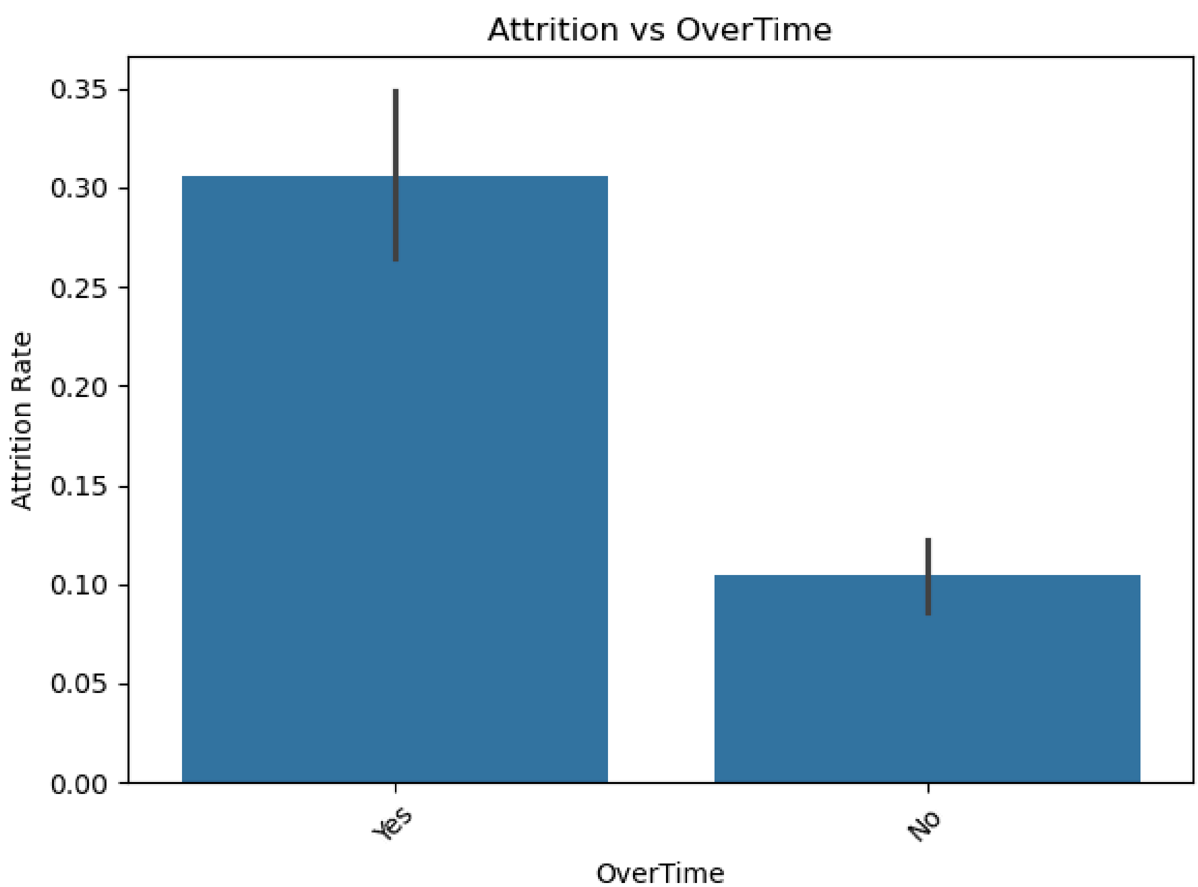
	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education
0	41	Yes	Travel_Rarely	1102	Sales	1	2
1	49	No	Travel_Frequently	279	Research & Development	8	1
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2
3	33	No	Travel_Frequently	1392	Research & Development	3	4
4	27	No	Travel_Rarely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

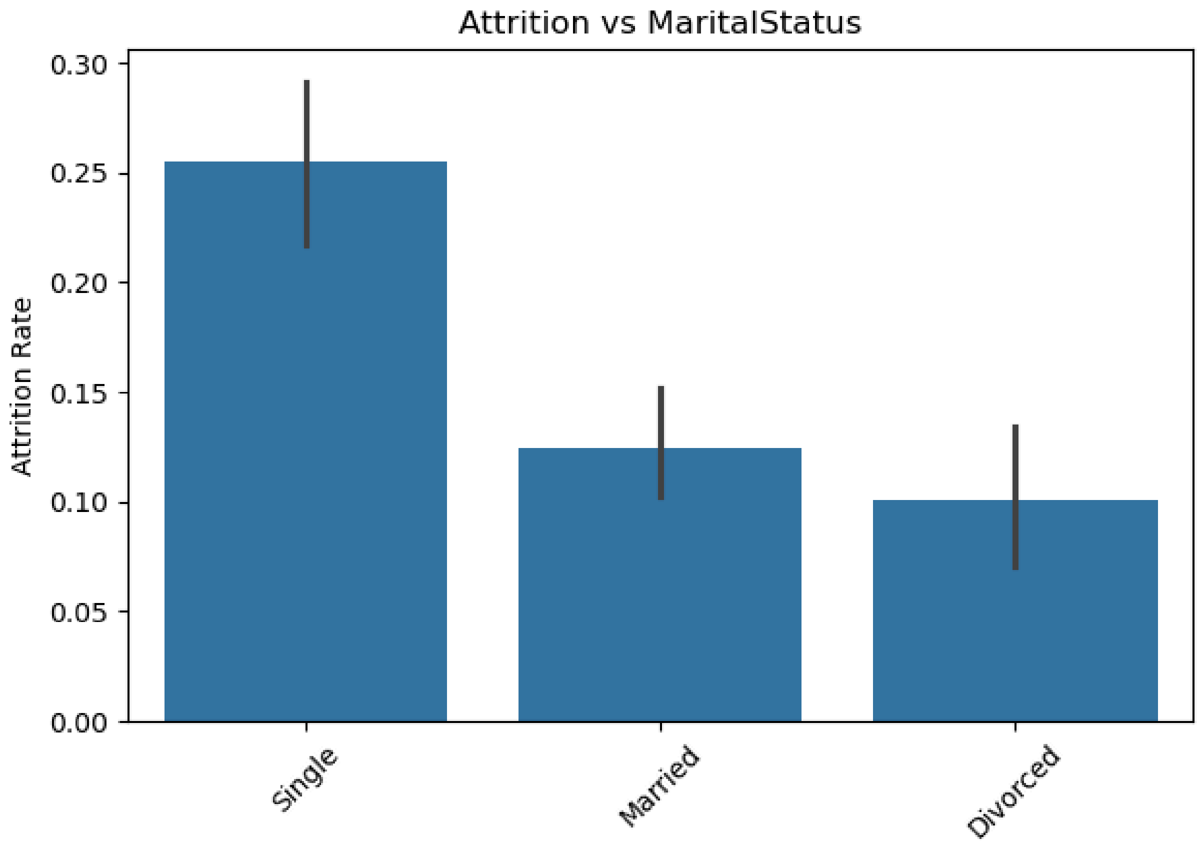
5 rows × 34 columns

In [80]:
```
#'EmployeeCount' , 'Standardhours' since they do not change from one employee to th
# Let's drop 'EmployeeNumber' as well, not needed
df.drop(['EmployeeCount', 'StandardHours',  'EmployeeNumber'], axis=1, inplace=True
```

In [82]:
```
categorical_cols = ['Gender', 'OverTime', 'MaritalStatus']

for col in categorical_cols:
    # Add temporary attrition column using assign
    temp_df = df.assign(attrition_eda=df['Attrition'].map({'Yes': 1, 'No': 0}))

    sns.barplot(x=col, y='attrition_eda', data=temp_df)
    plt.title(f'Attrition vs {col}')
    plt.ylabel('Attrition Rate')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
```

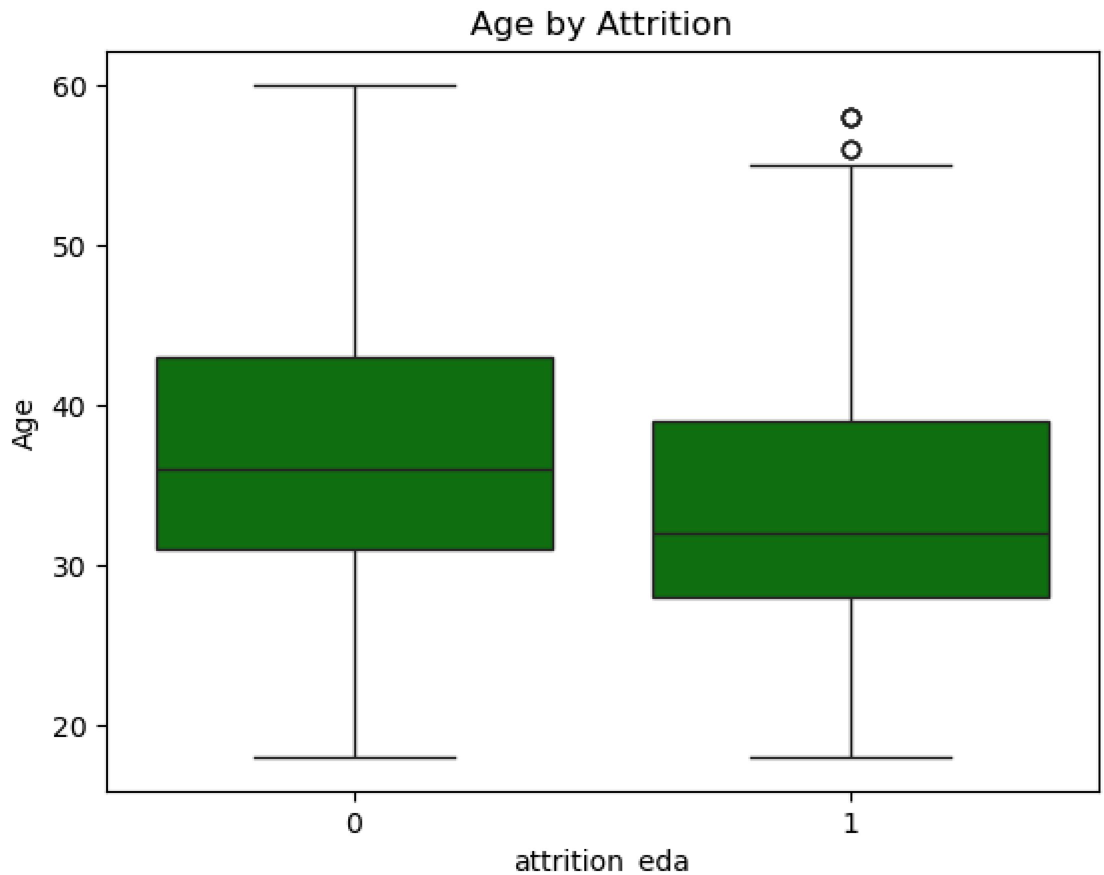

Attrition vs Gender
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
Attrition Rate
Female
Male
Gender

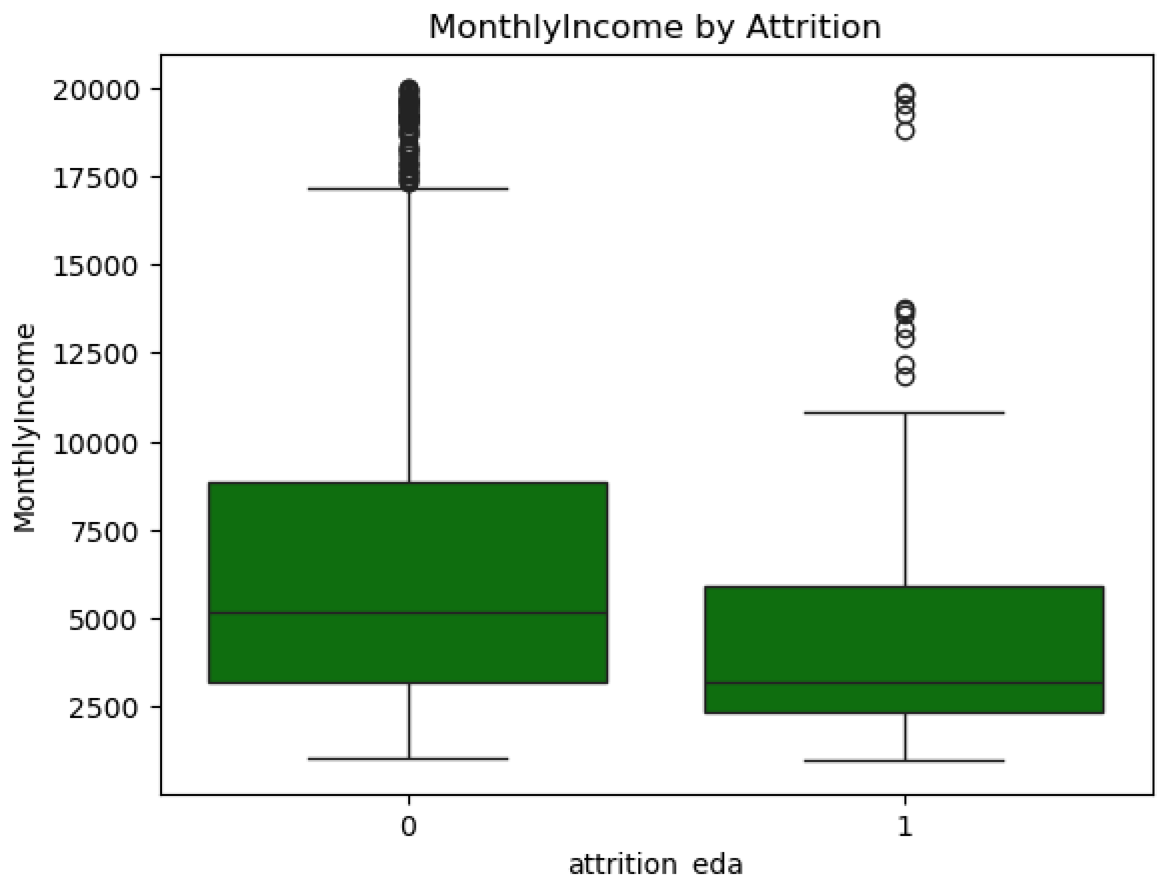

Attrition vs OverTime
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Attrition Rate
Yes
No
OverTime

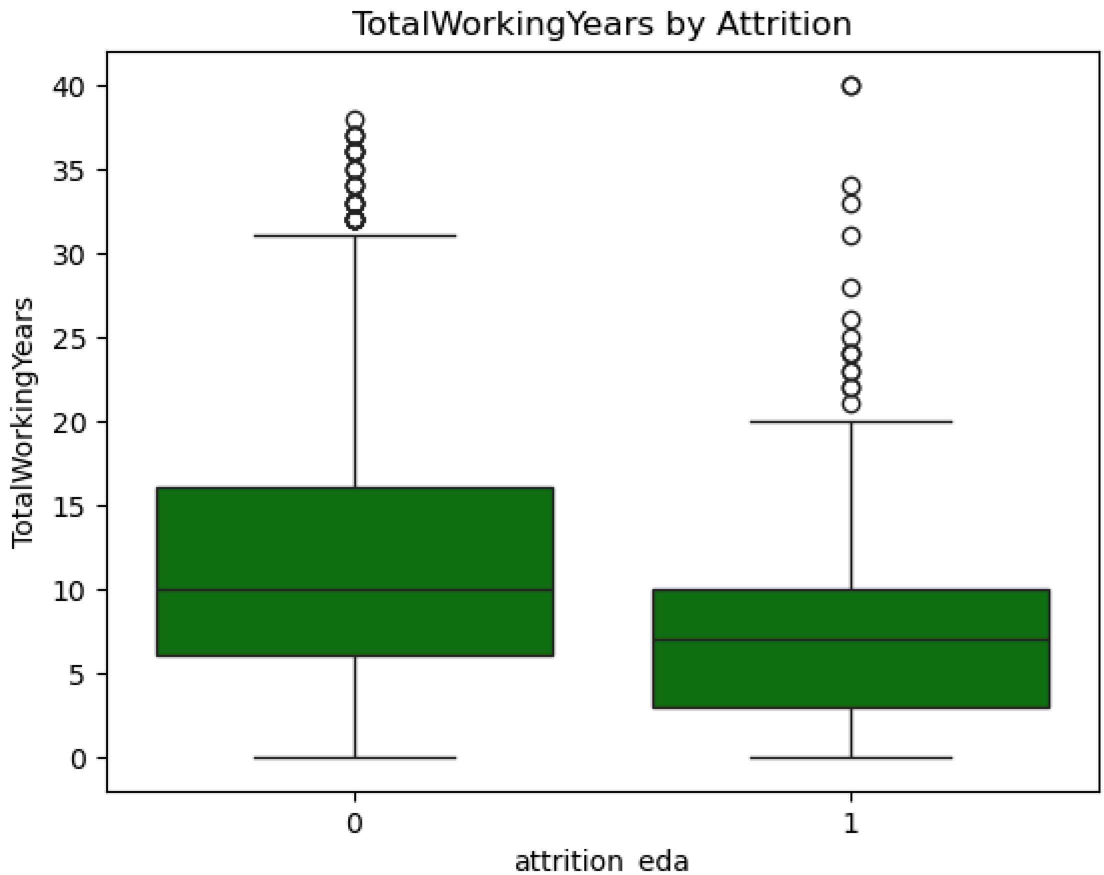


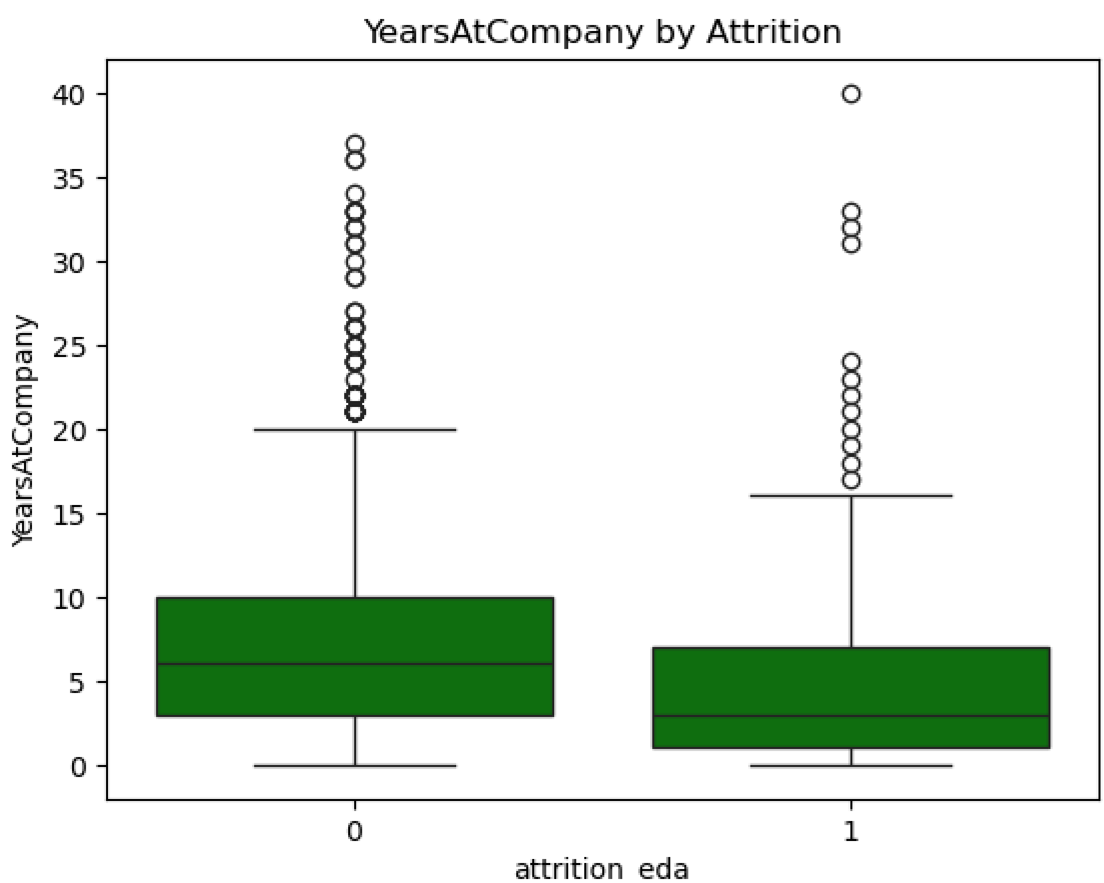
In [83]:

```
# Attrition vs continuous features (boxplots)
continuous = ['Age', 'MonthlyIncome', 'TotalWorkingYears', 'YearsAtCompany']
for col in continuous:
    temp_df = df.assign(attrition_eda=df['Attrition'].map({'Yes': 1, 'No': 0}))

    sns.boxplot(x='attrition_eda', y=col, color= 'green', data=temp_df)
    plt.title(f'{col} by Attrition')
    plt.show()
```


Age by Attrition
Age
60
50
40
30
20
0
1
attrition_eda


MonthlyIncome by Attrition
MonthlyIncome
20000
17500
15000
12500
10000
7500
5000
2500
0
1
attrition_eda


TotalWorkingYears by Attrition
TotalWorkingYears
40
35
30
25
20
15
10
5
0
0
1
attrition_eda


YearsAtCompany by Attrition
YearsAtCompany
40
35
30
25
20
15
10
5
0
0
1
attrition_eda

Label encoding

In [87]:
```
le_cols = ['Attrition', 'Gender', 'OverTime']
ohe_cols = ['BusinessTravel', 'Department', 'MaritalStatus']
be_cols = ['JobRole', 'EducationField']
```

In [89]:
```
from sklearn.preprocessing import LabelEncoder
import category_encoders as ce
```

In [90]:
```
# Label Encoding
le = LabelEncoder()
for col in le_cols:
    df[col] = le.fit_transform(df[col])

# One-Hot Encoding
df = pd.get_dummies(df, columns=ohe_cols, dtype = int, drop_first=True)

# Binary Encoding
be = ce.BinaryEncoder(cols=be_cols)
df = be.fit_transform(df)
```

In [91]:
```
df.head()
```

Out[91]:

	Age	Attrition	DailyRate	DistanceFromHome	Education	EducationField_0	EducationFi
0	41	1	1102	1	2	0	
1	49	0	279	8	1	0	
2	37	1	1373	2	2	0	
3	33	0	1392	3	4	0	
4	27	0	591	2	1	0	

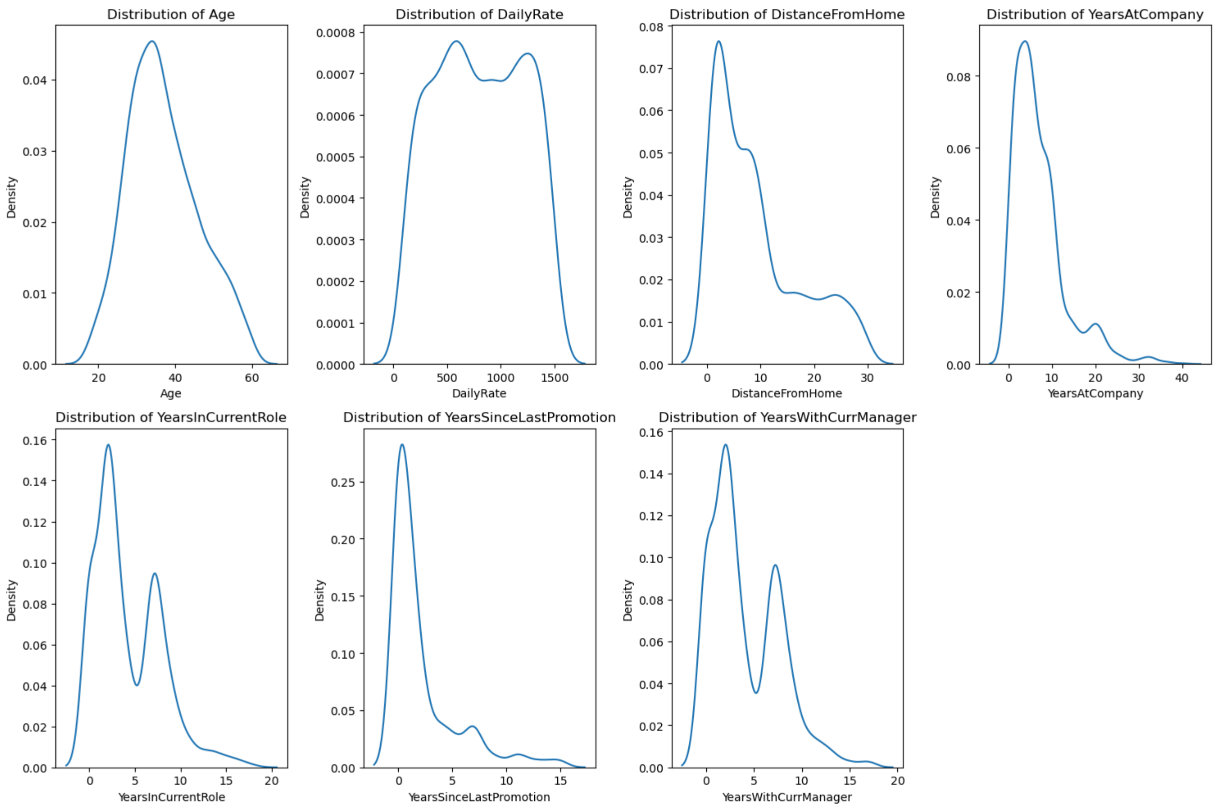
5 rows × 39 columns

feature scaling

In [94]:
```
scaling_cols = ['Age', 'DailyRate', 'DistanceFromHome', 'YearsAtCompany', 'YearsInC
```

In [95]:
```
# Function to plot distribution before imputation

def plot_distribution(data, cols):
    plt.figure(figsize=(15,10))
    for i,col in enumerate(cols):
        plt.subplot(2, 4, i + 1)
        sns.kdeplot(df[col])
        plt.title(f'Distribution of {col}')
        plt.xlabel(col)
```

```
    plt.tight_layout()
    plt.show()

plot_distribution(df, scaling_cols)
```




```
As most of the features are not normal, Age is nearly normal.
Hence, we will go with Normalization for scaling the features.
```

Feature Scaling (normalization)

In [101…

```
from sklearn.preprocessing import MinMaxScaler
```

In [102…

```
# normalization

# initialize
scaler = MinMaxScaler()
df[scaling_cols] = scaler.fit_transform(df[scaling_cols])
df.head()
```

Out[102…

	Age	Attrition	DailyRate	DistanceFromHome	Education	EducationField_0	Educati
0	0.547619	1	0.715820	0.000000	2	0	
1	0.738095	0	0.126700	0.250000	1	0	
2	0.452381	1	0.909807	0.035714	2	0	
3	0.357143	0	0.923407	0.071429	4	0	
4	0.214286	0	0.350036	0.035714	1	0	

5 rows × 39 columns

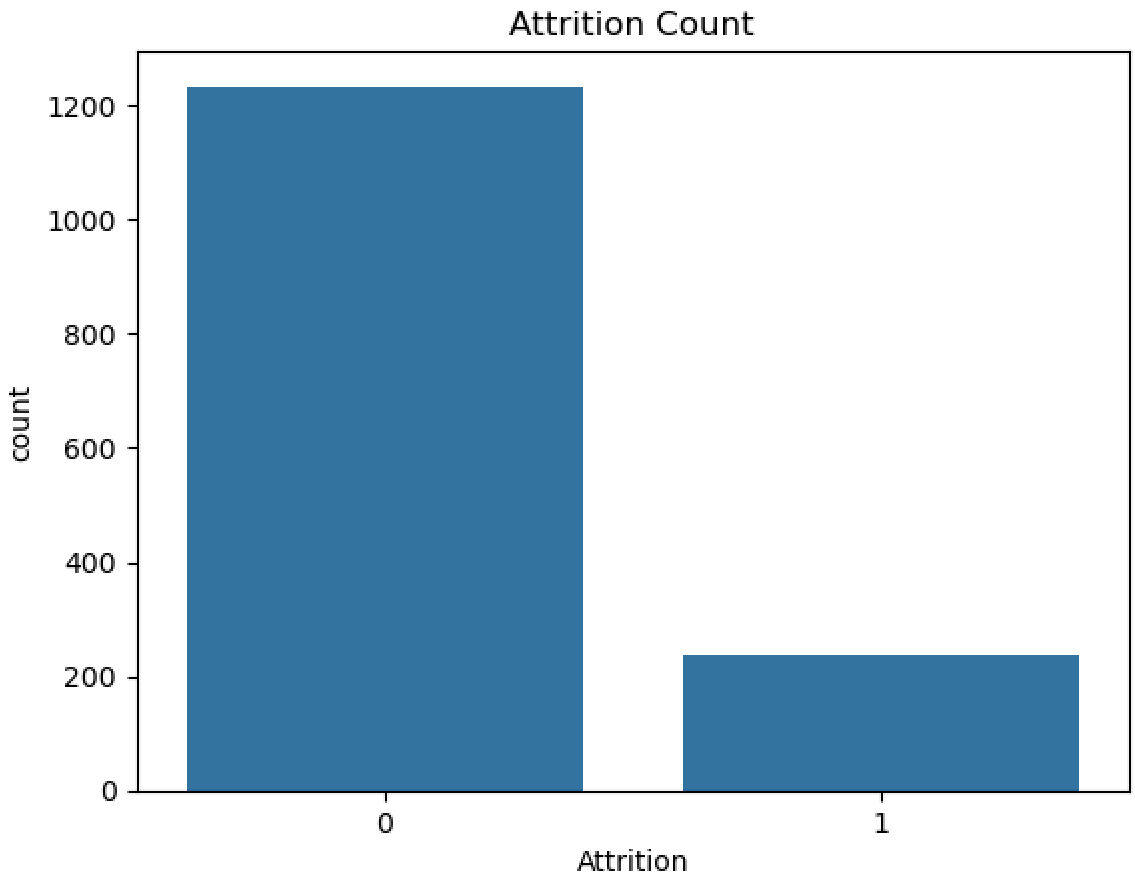
In [103…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 39 columns):
 #   Column                             Non-Null Count  Dtype  
---  ------                             --------------  -----  
 0   Age                                1470 non-null   float64
 1   Attrition                          1470 non-null   int32  
 2   DailyRate                          1470 non-null   float64
 3   DistanceFromHome                   1470 non-null   float64
 4   Education                          1470 non-null   int64  
 5   EducationField_0                   1470 non-null   int64  
 6   EducationField_1                   1470 non-null   int64  
 7   EducationField_2                   1470 non-null   int64  
 8   EnvironmentSatisfaction            1470 non-null   int64  
 9   Gender                             1470 non-null   int32  
 10  HourlyRate                         1470 non-null   int64  
 11  JobInvolvement                     1470 non-null   int64  
 12  JobLevel                           1470 non-null   int64  
 13  JobRole_0                          1470 non-null   int64  
 14  JobRole_1                          1470 non-null   int64  
 15  JobRole_2                          1470 non-null   int64  
 16  JobRole_3                          1470 non-null   int64  
 17  JobSatisfaction                    1470 non-null   int64  
 18  MonthlyIncome                      1470 non-null   int64  
 19  MonthlyRate                        1470 non-null   int64  
 20  NumCompaniesWorked                 1470 non-null   int64  
 21  OverTime                           1470 non-null   int32  
 22  PercentSalaryHike                  1470 non-null   int64  
 23  PerformanceRating                  1470 non-null   int64  
 24  RelationshipSatisfaction           1470 non-null   int64  
 25  StockOptionLevel                   1470 non-null   int64  
 26  TotalWorkingYears                  1470 non-null   int64  
 27  TrainingTimesLastYear              1470 non-null   int64  
 28  WorkLifeBalance                    1470 non-null   int64  
 29  YearsAtCompany                     1470 non-null   float64
 30  YearsInCurrentRole                 1470 non-null   float64
 31  YearsSinceLastPromotion            1470 non-null   float64
 32  YearsWithCurrManager               1470 non-null   float64
 33  BusinessTravel_Travel_Frequently   1470 non-null   int32  
 34  BusinessTravel_Travel_Rarely       1470 non-null   int32  
 35  Department_Research & Development  1470 non-null   int32  
 36  Department_Sales                   1470 non-null   int32  
 37  MaritalStatus_Married              1470 non-null   int32  
 38  MaritalStatus_Single               1470 non-null   int32  
dtypes: float64(7), int32(9), int64(23)
memory usage: 396.3 KB
```

In [104…

```python
# Distribution of target variable
sns.countplot(x='Attrition', data=df)
plt.title('Attrition Count')
plt.show()
```



In [105…
```
df.Attrition.value_counts()
```

Out[105…
```
Attrition
0    1233
1     237
Name: count, dtype: int64
```

Imbalanced data

```
Total = 1470
Number of employees who left the company = 237

Number of employees who did not leave the company (stayed) = 1233
```

In [113…
```
#splitting the data

x = df.drop('Attrition', axis=1)  # independent features
y = df.Attrition                   # dependent feature
```

Train test split

In [116…
```
from sklearn.model_selection import train_test_split
```

In [118…
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_sta
```

Balance Training Data

In [121…
```
df.Attrition.value_counts()
```

Out[121…
```
Attrition
0    1233
1     237
Name: count, dtype: int64
```

In [123…
```
from imblearn.over_sampling import SMOTE
```

In [138…
```
# Instantiate SMOTE
smt = SMOTE(sampling_strategy='minority')

# Resample training data

x_train_smt,y_train_smt = smt.fit_resample(x_train,y_train)
```

Model Building

Logistic Regression

In [142…
```
from sklearn.linear_model import LogisticRegression
```

In [399…
```
LR = LogisticRegression()

LR.fit(x_train_smt, y_train_smt)
```

Out[399…
```
▾ LogisticRegression
LogisticRegression()
```

In [400…
```
# Predict on the balanced TEST set
y_pred_test_lr = LR.predict(x_test)
y_pred_train_lr = LR.predict(x_train)
```

In [403…
```
y_pred_test_lr
```

Out[403…
```
array([1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0,
       0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0,
       0, 1, 0, 0, 0, 0, 1, 0])
```

In [405…
```python
# Evaluation of the logistic regression

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

In [407…
```python
print('Testing Accuracy score is: ', accuracy_score(y_test, y_pred_test_lr))
print('Training Accuracy score is: ', accuracy_score(y_train, y_pred_train_lr))
```

```
Testing Accuracy score is:  0.7448979591836735
Training Accuracy score is:  0.7159863945578231
```

In [409…
```python
print('Confusion Matrix:\n', confusion_matrix(y_test, y_pred_test_lr))
print('Classification Report:\n', classification_report(y_test, y_pred_test_lr))
```

```
Confusion Matrix:
 [[204  51]
 [ 24  15]]
Classification Report:
               precision    recall  f1-score   support

           0       0.89      0.80      0.84       255
           1       0.23      0.38      0.29        39

    accuracy                           0.74       294
   macro avg       0.56      0.59      0.57       294
weighted avg       0.81      0.74      0.77       294
```

KNN Classifier

In [463…
```python
from sklearn.neighbors import KNeighborsClassifier
```

In [477…
```python
knn = KNeighborsClassifier(n_neighbors=3, weights='distance')
knn.fit(x_train_smt, y_train_smt)
```

Out[477…

```
KNeighborsClassifier

KNeighborsClassifier(n_neighbors=3, weights='distance')
```

In [503…

```
y_pred_knn = knn.predict(x_test)
y_pred_train_knn = knn.predict(x_train)
```

In [505…

```
print("KNN Accuracy:",accuracy_score(y_test, y_pred_knn))
```

```
KNN Accuracy: 0.6632653061224489
```

In [461…

```
from sklearn.model_selection import RandomizedSearchCV


param_grid = {
    'n_neighbors': range(1, 15),  # Testing values from 1 to 15
    'weights': ['uniform', 'distance'],
    'metric': ['euclidean', 'manhattan', 'minkowski']
}


random_search = RandomizedSearchCV(knn, param_grid, cv=5, scoring='accuracy', n_ite
random_search.fit(x_train_smt, y_train_smt)
```

Out[461…

```
RandomizedSearchCV
best_estimator_:
KNeighborsClassifier
KNeighborsClassifier
```

In [485…

```
print("Best Parameters:", random_search.best_params_)
print("Best Accuracy:", random_search.best_score_)
```

```
Best Parameters: {'weights': 'distance', 'n_neighbors': 7, 'metric': 'manhattan'}
Best Accuracy: 0.7740474450649825
```

In [495…

```
# Retrain KNN
KNN = KNeighborsClassifier(n_neighbors=7, weights='distance', metric='manhattan')

# Fit the model on training data
KNN.fit(x_train_smt, y_train_smt)
```

Out[495…

```
KNeighborsClassifier
KNeighborsClassifier(metric='manhattan', n_neighbors=7, weights='distanc
e')
```

In [497…

```
# Make predictions on the test set
y_pred_KNN = KNN.predict(x_test)
```

In [499…

```
from sklearn.metrics import accuracy_score
# Evaluate accuracy
tuned_accuracy = accuracy_score(y_test, y_pred_KNN)
print("Tuned KNN Accuracy:", tuned_accuracy)
```

```
Tuned KNN Accuracy: 0.6156462585034014
```

Decision Tree Classifier

In [227…

```python
from sklearn.tree import DecisionTreeClassifier
```

In [229…

```python
dt = DecisionTreeClassifier()
dt.fit(x_train_smt, y_train_smt)
```

Out[229…

```
▾ DecisionTreeClassifier

DecisionTreeClassifier()
```

In [231…

```python
y_pred_test_dt = dt.predict(x_test)
```

In [233…

```python
print('Accuracy Score:', accuracy_score(y_test, y_pred_test_dt))
print('Confusion Matrix:\n', confusion_matrix(y_test, y_pred_test_dt))
print('Classification Report:\n', classification_report(y_test, y_pred_test_dt))
```

```
Accuracy Score: 0.7789115646258503
Confusion Matrix:
 [[213  42]
 [ 23  16]]
Classification Report:
               precision    recall  f1-score   support

           0       0.90      0.84      0.87       255
           1       0.28      0.41      0.33        39

    accuracy                           0.78       294
   macro avg       0.59      0.62      0.60       294
weighted avg       0.82      0.78      0.80       294
```

Hyperparameter tunning

In [289…

```python
params = {
    'criterion' : ['gini', 'entropy', 'log_loss'],
    'splitter' : ['best', 'random'],
    'max_depth' : [1,2,3,4,5,6,7,11,12,15],
    'max_features' : ["auto", "sqrt", "log2"]
}
```

In [291…

```python
# GridSearchCV
from sklearn.model_selection import GridSearchCV

treemodel = DecisionTreeClassifier()

gscv = GridSearchCV(treemodel, param_grid= params, cv = 5, scoring= 'accuracy')

gscv.fit(x_train_smt, y_train_smt)
```

Out[291…

GridSearchCV

best_estimator_:
DecisionTreeClassifier

DecisionTreeClassifier

In [293…

```
gscv.best_params_
```

Out[293…

```
{'criterion': 'gini',
 'max_depth': 15,
 'max_features': 'log2',
 'splitter': 'best'}
```

In [295…

```
DT = DecisionTreeClassifier(criterion= 'gini', max_depth= 15, max_features= 'log2',
```

In [297…

```
DT.fit(x_train_smt, y_train_smt)
```

Out[297…

DecisionTreeClassifier

```
DecisionTreeClassifier(max_depth=15, max_features='log2')
```

In [299…

```
# Prediction

y_pred_train_DT = DT.predict(x_train_smt)

y_pred_test_DT = DT.predict(x_test)
```

In [301…

```
print(f'Training Accuracy {accuracy_score(y_train_smt, y_pred_train_DT)}')
print(f'Testing Accuracy {accuracy_score(y_test, y_pred_test_DT )}')
```

```
Training Accuracy 0.9979550102249489
Testing Accuracy 0.7210884353741497
```

In [303…

```
print('Confusion Matrix:\n', confusion_matrix(y_test, y_pred_test_DT))
print('Classification Report:\n', classification_report(y_test, y_pred_test_DT))
```

```
Confusion Matrix:
 [[198  57]
 [ 25  14]]
Classification Report:
               precision    recall  f1-score   support

           0       0.89      0.78      0.83       255
           1       0.20      0.36      0.25        39

    accuracy                           0.72       294
   macro avg       0.54      0.57      0.54       294
weighted avg       0.80      0.72      0.75       294
```

Random Forest Classifier

In [372…
```
from sklearn.ensemble import RandomForestClassifier
```

In [374…
```
rf = RandomForestClassifier()
```

In [376…
```
rf.fit(x_train_smt, y_train_smt)
```

Out[376…
```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [377…
```
y_pred_rf = rf.predict(x_test)
y_pred_train_rf = rf.predict(x_train)
```

In [378…
```
print('Accuracy Score Testing:', accuracy_score(y_test, y_pred_rf))
print('Accuracy Score Training:', accuracy_score(y_train, y_pred_train_rf))
```

```
Accuracy Score Testing: 0.8707482993197279
Accuracy Score Training: 1.0
```

Hyperparameter tunning

In [383…
```
params = {
    'n_estimators' : [100,200,300],
    'criterion' : ['gini','entropy'],
    'max_depth' : [5,10,15,None],
    'min_samples_split':np.arange(2,10),
    'min_samples_leaf' : np.arange(1,10)
}
```

In [397…
```
#rf_gscv = GridSearchCV(rf, param_grid= params)
```

In [ ]:
```
#rf_gscv.fit(x_train_smt, y_train_smt)
```

In [ ]:
```
#rf_gscv.best_params_
```

In [ ]:
```
#RF = RandomForestClassifier(n_estimators = 100, criterion='gini', max_depth = 15,
```

In [ ]:
```
#RF.fit(x_train_smt, y_train_smt)
```

In [ ]:
```
#y_pred_test_RF = RF.predict(x_test_smt)
```

print('Accuracy Score (final)):', accuracy_score(y_test_smt, y_pred_test_RF)) print('Confusion Matrix:\n', confusion_matrix((y_test_smt, y_pred_test_RF)) print('Classification Report:\n', classification_report((y_test_smt, y_pred_test_RF))

AdaBoost Classifier

In [320…

```
from sklearn.ensemble import AdaBoostClassifier
```

In [322…

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

In [324…

```
# define base estimator (decision stump)
abc = AdaBoostClassifier(estimator= base_est, random_state=42)

abc.fit(x_train_smt, y_train_smt)
```

Out[324…

```
AdaBoostClassifier
estimator: DecisionTreeClassifier
DecisionTreeClassifier
```

In [326…

```
y_pred_test_abc = abc.predict(x_test)
y_pred_train_abc = abc.predict(x_train)
```

In [328…

```
## Evaluation parameters
print('Testing Accuracy Score:', accuracy_score(y_test, y_pred_test_abc))
print('Training Accuracy Score:', accuracy_score(y_train, y_pred_train_abc))
```

```
Testing Accuracy Score: 0.8061224489795918
Training Accuracy Score: 1.0
```

Hyperparameter tunning

In [331…

```
# Define parameter grid
params = {
    'n_estimators': [50, 100, 150],
    'learning_rate': [0.01, 0.1, 1],
}
```

In [333…

```
treemodel = AdaBoostClassifier()

# GridSearchCV

gscv = GridSearchCV(estimator=treemodel, param_grid=params, cv=5, scoring='accuracy
```

In [335…

```
gscv.fit(x_train_smt, y_train_smt)
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits
```

Out[335…

```
▸ GridSearchCV

▸ best_estimator_:
  AdaBoostClassifier

  ▸ AdaBoostClassifier
```

In [337…

```
gscv.best_params_
```

Out[337…

```
{'learning_rate': 1, 'n_estimators': 100}
```

In [339…

```
# Retrain final model
ABC = AdaBoostClassifier(learning_rate= 1, n_estimators= 100, random_state=42)

ABC.fit(x_train_smt, y_train_smt)
```

Out[339…

```
▾ AdaBoostClassifier
AdaBoostClassifier(learning_rate=1, n_estimators=100, random_state=42)
```

In [347…

```
# Predict on test data
y_pred_ABC = ABC.predict(x_test)
y_pred_train_ABC = ABC.predict(x_train)
```

In [351…

```
# Evaluate

print('Testing Accuracy:', accuracy_score(y_test, y_pred_ABC))
print('Training Accuracy:', accuracy_score(y_train, y_pred_train_ABC))
print('Confusion Matrix:\n', confusion_matrix(y_test, y_pred_ABC))
print('Classification Report:\n', classification_report(y_test, y_pred_ABC))
```

```
Testing Accuracy: 0.8401360544217688
Training Accuracy: 0.8579931972789115
Confusion Matrix:
 [[225  30]
 [ 17  22]]
Classification Report:
               precision    recall  f1-score   support

           0       0.93      0.88      0.91       255
           1       0.42      0.56      0.48        39

    accuracy                           0.84       294
   macro avg       0.68      0.72      0.69       294
weighted avg       0.86      0.84      0.85       294
```

GradientBoosting Classifier

In [354…

```
from sklearn.ensemble import GradientBoostingClassifier
```

In [356…

```
# Instantiate model
gb = GradientBoostingClassifier()

# Fit the model
gb.fit(x_train_smt, y_train_smt)
```

Out[356…

```
▾ GradientBoostingClassifier
GradientBoostingClassifier()
```

In [275…

```
y_pred_gb = gb.predict(x_test)
y_pred_train_gb = gb.predict(x_train)
```

In [358…

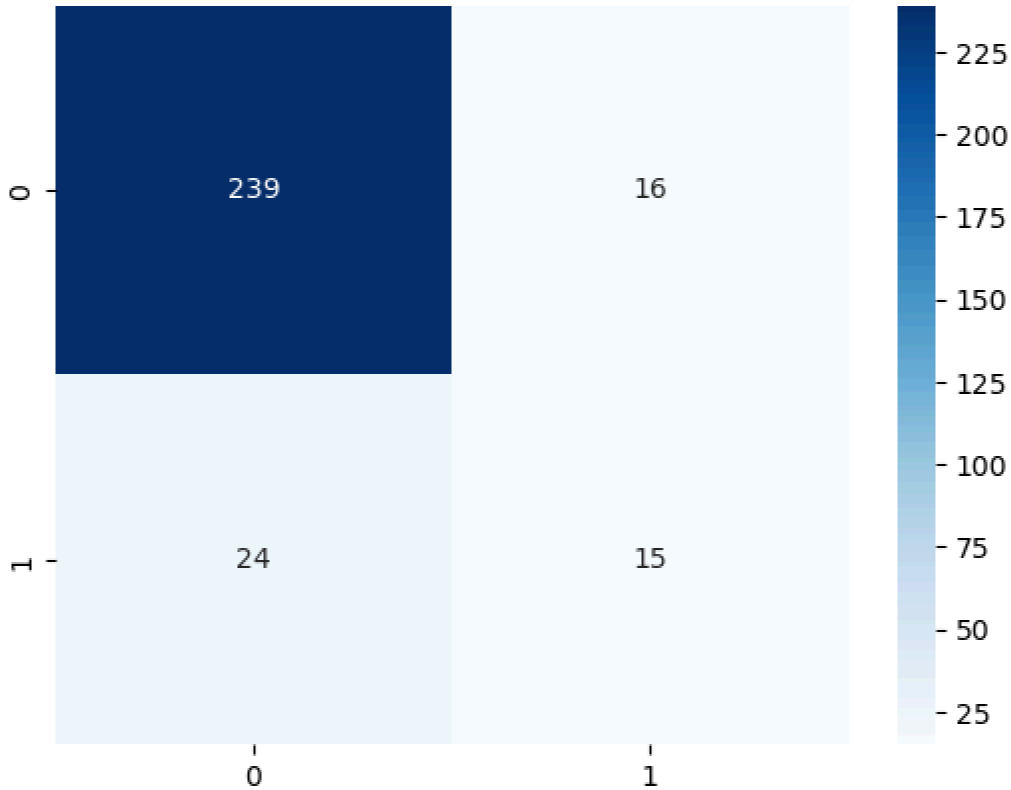
```
# Evaluation parameters
print("Accuracy:", accuracy_score(y_test, y_pred_gb))
print("Accuracy:", accuracy_score(y_train, y_pred_train_gb))
print("\nClassification Report:\n", classification_report(y_test, y_pred_gb))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred_gb))
```

```
Accuracy: 0.8639455782312925
Accuracy: 0.9345238095238095

Classification Report:
               precision    recall  f1-score   support

           0       0.91      0.94      0.92       255
           1       0.48      0.38      0.43        39

    accuracy                           0.86       294
   macro avg       0.70      0.66      0.68       294
weighted avg       0.85      0.86      0.86       294


Confusion Matrix:
 [[239  16]
 [ 24  15]]
```

In [360…

```
print("\nConfusion Matrix:\n")
sns.heatmap(confusion_matrix(y_test, y_pred_gb), annot=True, fmt='d', cmap='Blues')
plt.show()
```

```
Confusion Matrix:
```



XGBoost

In [362…

```
import xgboost as xgb
```

In [364…

```
from xgboost import XGBClassifier

xgb = XGBClassifier()

xgb.fit(x_train_smt, y_train_smt)
```

Out[364…

```
XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=No
ne,
              enable_categorical=False, eval_metric=None, feature_types=No
ne,
              feature_weights=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=None, max_bin=None, max_cat_threshold=None,
```

In [366…

```
# Predictions
y_pred_xgb = xgb.predict(x_test)
y_pred_train_xgb = xgb.predict(x_train)
```

In [368…

```
# Evaluation parameters
print("Testing Accuracy:", accuracy_score(y_test, y_pred_xgb))
print("Training Accuracy:", accuracy_score(y_train, y_pred_train_xgb))
print("\nClassification Report:\n", classification_report(y_test, y_pred_xgb))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred_xgb))
```

```
Testing Accuracy: 0.8741496598639455
Training Accuracy: 1.0

Classification Report:
               precision    recall  f1-score   support

           0       0.90      0.96      0.93       255
           1       0.55      0.31      0.39        39

    accuracy                           0.87       294
   macro avg       0.72      0.63      0.66       294
weighted avg       0.85      0.87      0.86       294


Confusion Matrix:
 [[245  10]
 [ 27  12]]
```

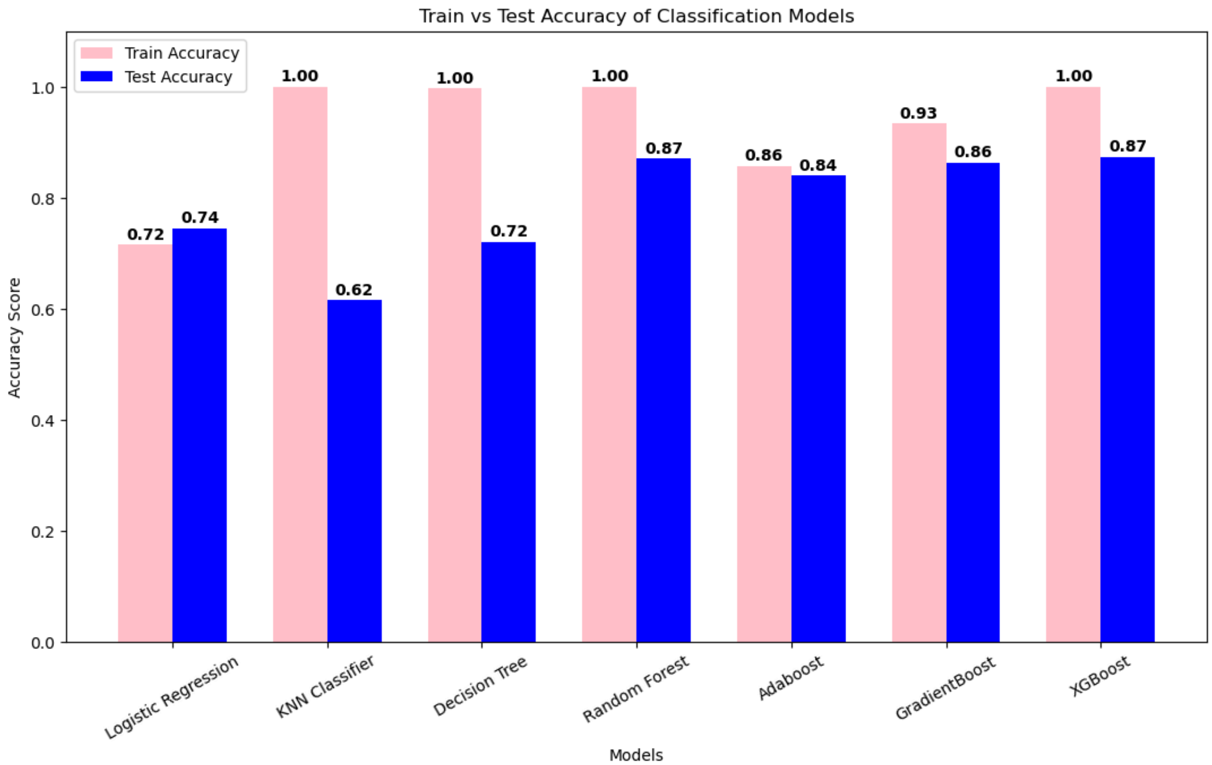
In [ ]:

Model Comparison and Interpretation

In [507…

```
# Model names and classifiers
models = {
    "Logistic Regression": LR,
    "KNN Classifier": KNN,
    "Decision Tree": DT,
    "Random Forest": rf,
    "Adaboost": ABC,
    "GradientBoost": gb,
    "XGBoost": xgb
}

# Compute train & test accuracy
train_accuracy = [accuracy_score(y_train, model.predict(x_train)) for model in mode
test_accuracy = [accuracy_score(y_test, model.predict(x_test)) for model in models.

# Plot
x = np.arange(len(models))
width = 0.35

plt.figure(figsize=(13, 7))
plt.bar(x - width/2, train_accuracy, width, label='Train Accuracy', color='pink')
plt.bar(x + width/2, test_accuracy, width, label='Test Accuracy', color='blue')

# Annotate values
for i, (train_acc, test_acc) in enumerate(zip(train_accuracy, test_accuracy)):
    plt.text(x[i] - width/2, train_acc + 0.01, f"{train_acc:.2f}", ha='center', fon
```

```
    plt.text(x[i] + width/2, test_acc + 0.01, f"{test_acc:.2f}", ha='center', fontw

plt.xticks(x, models.keys(), rotation=30)
plt.xlabel('Models')
plt.ylabel('Accuracy Score')
plt.title('Train vs Test Accuracy of Classification Models')
plt.ylim(0, 1.1)
plt.legend()
plt.show()
```



Best Models for Production Use

```
Random Forest, GradientBoost, and XGBoost are top performers.

All show high test accuracy, indicating they generalize well on
unseen data.

GradientBoost seems best balanced (less overfitting, strong test
accuracy).
```

Models to Avoid

```
KNN: Severe overfitting, poor real-world use.

Decision Tree: High training accuracy but drops on test — classic
overfitting
```

In [ ]: