Expolratory Data Analysis

Employee Attrition Analysis

```
import pandas as pd
import numpy as np
```

Initial exploration

```
df=pd.read_csv('/content/WA_Fn-UseC_-HR-Employee-Attrition.csv')
df.head()
```

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

5 rows × 35 columns

```
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
```

```
df.shape
```

```
(1470, 35)
```

The dataset contains 1,470 records with 35 features. The target variable is Attrition, which indicates whether an employee has left the company (Yes) or not (No).

```
print(df.nunique())
```

```
Age                         43
Attrition                    2
BusinessTravel               3
DailyRate                  886
Department                   3
DistanceFromHome            29
Education                    5
EducationField               6
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
StockOptionLevel             4
TotalWorkingYears           40
TrainingTimesLastYear        7
WorkLifeBalance              4
YearsAtCompany              37
YearsInCurrentRole          19
YearsSinceLastPromotion     16
YearsWithCurrManager        18
dtype: int64
```

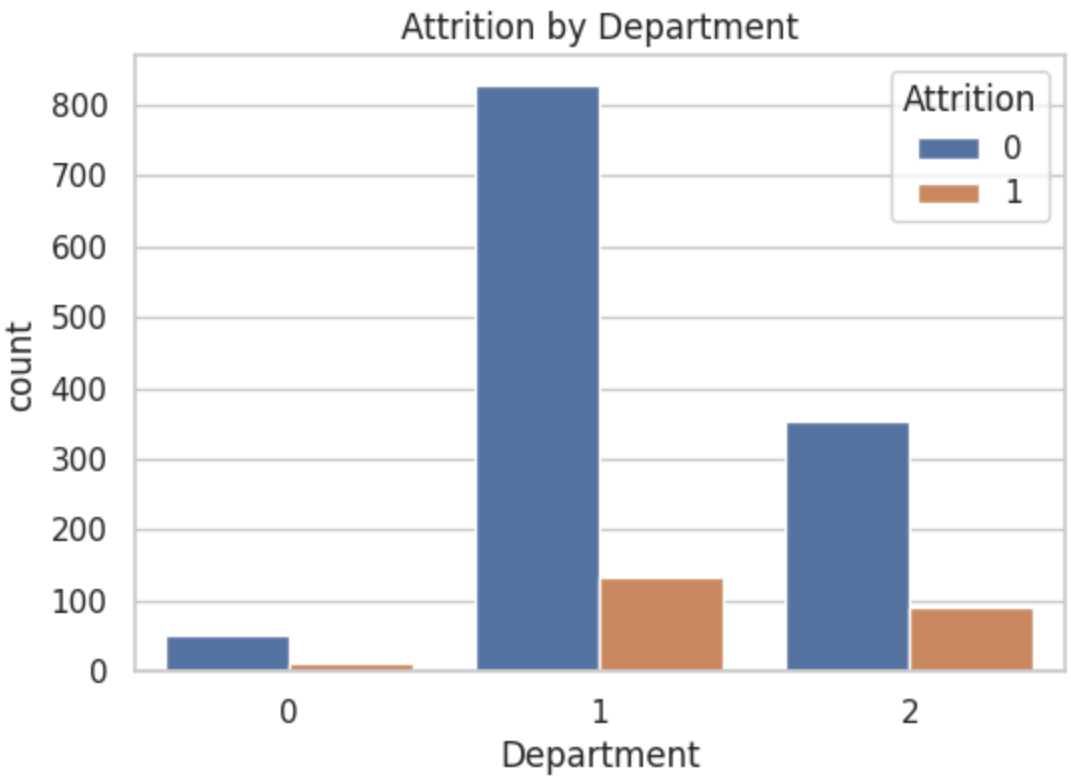
Data Cleaning

```
# Dropping columns with no predictive power
df = df.drop(['EmployeeCount', 'Over18', 'StandardHours', 'EmployeeNumber'], axis=1)

# Converting categorical variables to numerical
cat_cols = df.select_dtypes(include=['object']).columns
le = LabelEncoder()
for col in cat_cols:
    df[col] = le.fit_transform(df[col])

# Check class imbalance
print("\nAttrition distribution:\n", df['Attrition'].value_counts())
```

```
Attrition distribution:
 Attrition
0    1233
1     237
Name: count, dtype: int64
```

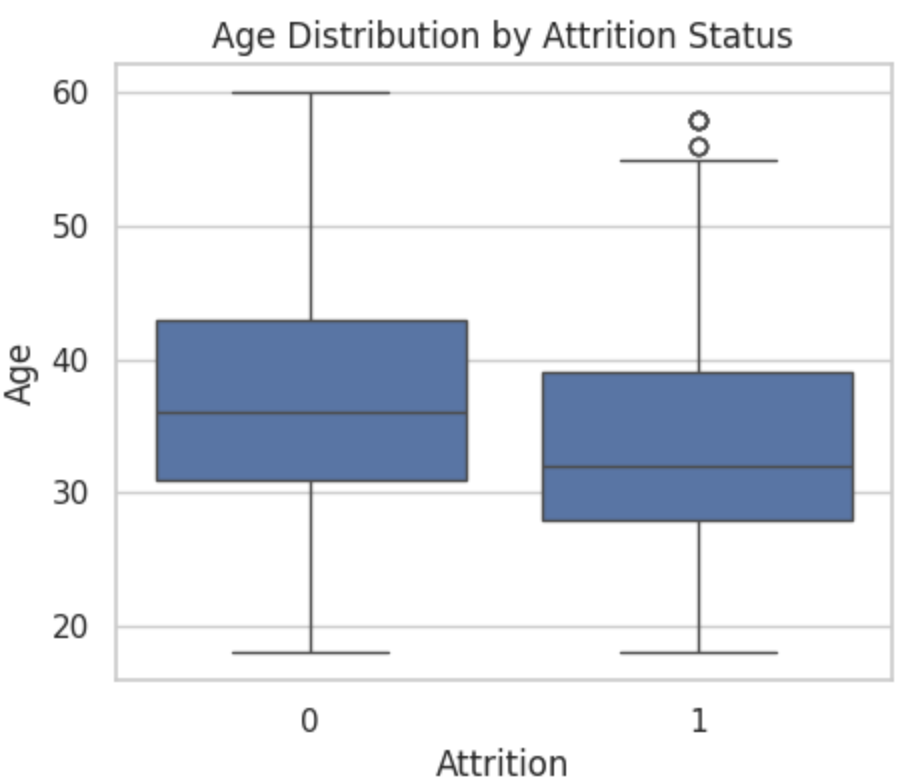
visualizing the relationships between features and attrition:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Set style
sns.set(style="whitegrid")

# Plot attrition by department
plt.figure(figsize=(6,4))
sns.countplot(x='Department', hue='Attrition', data=df)
plt.title('Attrition by Department')
plt.show()
```



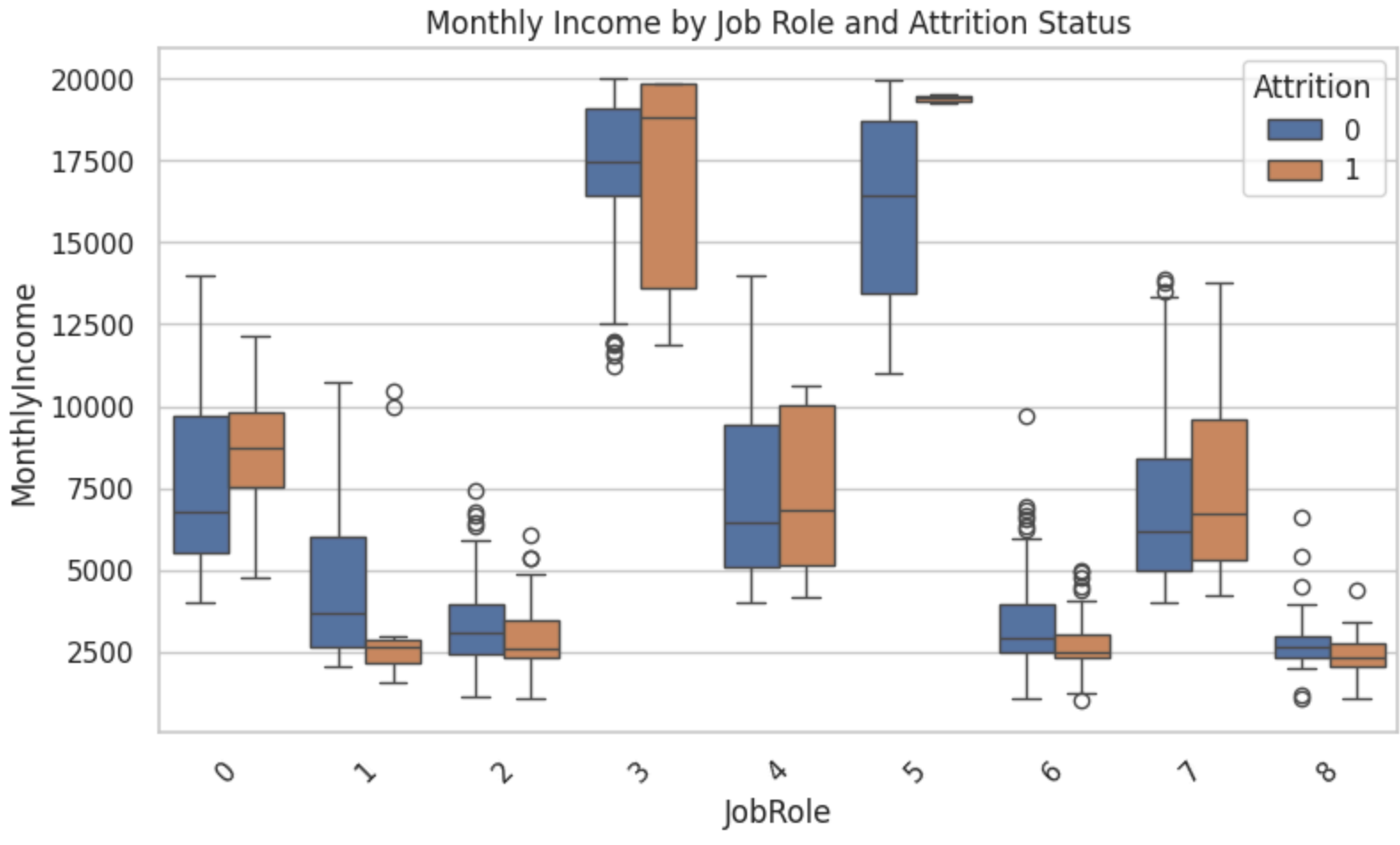
Shows how many employees stayed or left in each department.

```
# Age distribution by attrition
plt.figure(figsize=(5,4))
sns.boxplot(x='Attrition', y='Age', data=df)
plt.title('Age Distribution by Attrition Status')
plt.show()
```



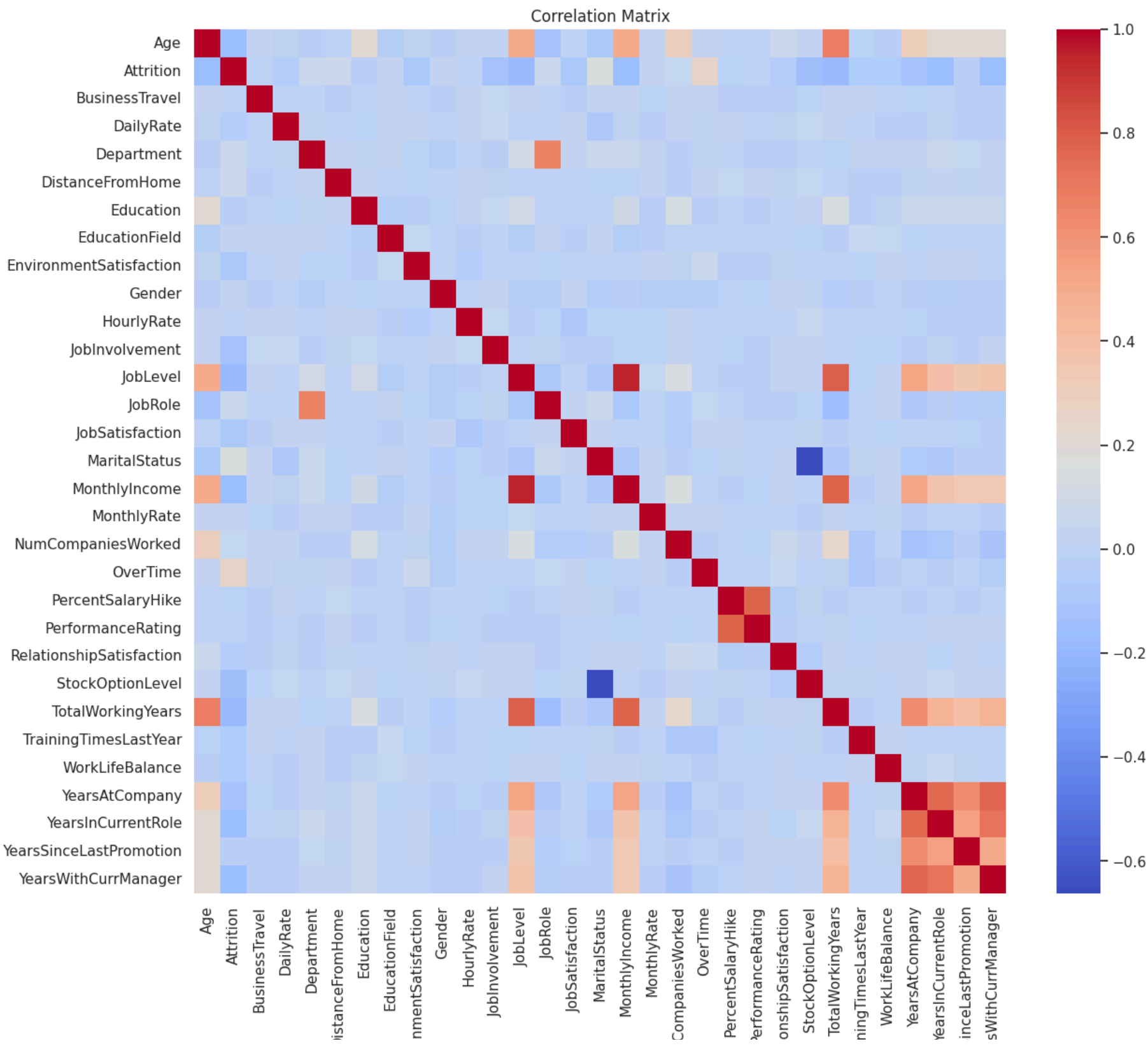
Illustrates age spread among employees who stayed vs those who left. Generally, younger employees tend to leave more often.

```
# Monthly income by job role and attrition
plt.figure(figsize=(9,5))
sns.boxplot(x='JobRole', y='MonthlyIncome', hue='Attrition', data=df)
plt.xticks(rotation=45)
plt.title('Monthly Income by Job Role and Attrition Status')
plt.show()
```



Highlights income disparities across job roles and how income relates to attrition. Employees in lower-paying roles show higher attrition.

```
# Correlation matrix
plt.figure(figsize=(14,12))
corr = df.corr()
sns.heatmap(corr, annot=False, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



Displays relationships among numerical features. Strong correlations are seen between variables like Monthly Income and Job Level.

Feature Engineering and Selection

```
df.columns
```

```
Index(['Age', 'Attrition', 'BusinessTravel', 'DailyRate', 'Department',
       'DistanceFromHome', 'Education', 'EducationField',
       'EnvironmentSatisfaction', 'Gender', 'HourlyRate', 'JobInvolvement',
       'JobLevel', 'JobRole', 'JobSatisfaction', 'MaritalStatus',
       'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorked', 'OverTime',
       'PercentSalaryHike', 'PerformanceRating', 'RelationshipSatisfaction',
       'StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear',
       'WorkLifeBalance', 'YearsAtCompany', 'YearsInCurrentRole',
       'YearsSinceLastPromotion', 'YearsWithCurrManager'],
      dtype='object')
```

```
# Calculate correlation with target
corr_with_target = df.corr()['Attrition'].sort_values(ascending=False)
print("\nCorrelation with Attrition:\n", corr_with_target)

# Select important features based on correlation and domain knowledge
selected_features = ['Age', 'DailyRate', 'DistanceFromHome', 'EnvironmentSatisfaction',
                     'JobInvolvement', 'JobLevel', 'JobSatisfaction', 'MonthlyIncome',
                     'NumCompaniesWorked', 'OverTime', 'PercentSalaryHike',
                     'RelationshipSatisfaction', 'StockOptionLevel', 'TotalWorkingYears',
                     'TrainingTimesLastYear', 'WorkLifeBalance', 'YearsAtCompany',
                     'YearsInCurrentRole', 'YearsSinceLastPromotion', 'YearsWithCurrManager',
                     'Department', 'EducationField', 'Gender', 'JobRole', 'MaritalStatus']

# Prepare data for modeling
X = df[selected_features]
y = df['Attrition']
```

```
Correlation with Attrition:
 Attrition                  1.000000
OverTime                   0.246118
MaritalStatus              0.162070
DistanceFromHome           0.077924
JobRole                    0.067151
Department                 0.063991
NumCompaniesWorked         0.043494
Gender                     0.029453
EducationField             0.026846
MonthlyRate                0.015170
PerformanceRating          0.002889
BusinessTravel             0.000074
HourlyRate                -0.006846
PercentSalaryHike         -0.013478
Education                 -0.031373
YearsSinceLastPromotion   -0.033019
RelationshipSatisfaction  -0.045872
DailyRate                 -0.056652
TrainingTimesLastYear     -0.059478
WorkLifeBalance           -0.063939
EnvironmentSatisfaction   -0.103369
JobSatisfaction           -0.103481
JobInvolvement            -0.130016
YearsAtCompany            -0.134392
StockOptionLevel          -0.137145
YearsWithCurrManager      -0.156199
Age                       -0.159205
MonthlyIncome             -0.159840
YearsInCurrentRole        -0.160545
JobLevel                  -0.169105
TotalWorkingYears         -0.171063
Name: Attrition, dtype: float64
```

```
from imblearn.over_sampling import SMOTE

# Handle class imbalance with SMOTE
smote = SMOTE(random_state=42)
X_res, y_res = smote.fit_resample(X, y)
```

```
from sklearn.model_selection import train_test_split

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_size=0.3, random_state=42)
```

```
from sklearn.preprocessing import StandardScaler
# Scale numerical features
scaler = StandardScaler()
num_cols = ['Age', 'DailyRate', 'DistanceFromHome', 'MonthlyIncome', 'NumCompaniesWorked',
            'PercentSalaryHike', 'TotalWorkingYears', 'TrainingTimesLastYear',
            'YearsAtCompany', 'YearsInCurrentRole', 'YearsSinceLastPromotion',
            'YearsWithCurrManager']

X_train[num_cols] = scaler.fit_transform(X_train[num_cols])
X_test[num_cols] = scaler.transform(X_test[num_cols])
```

Model Building and Evaluation

Random Forest Classifier

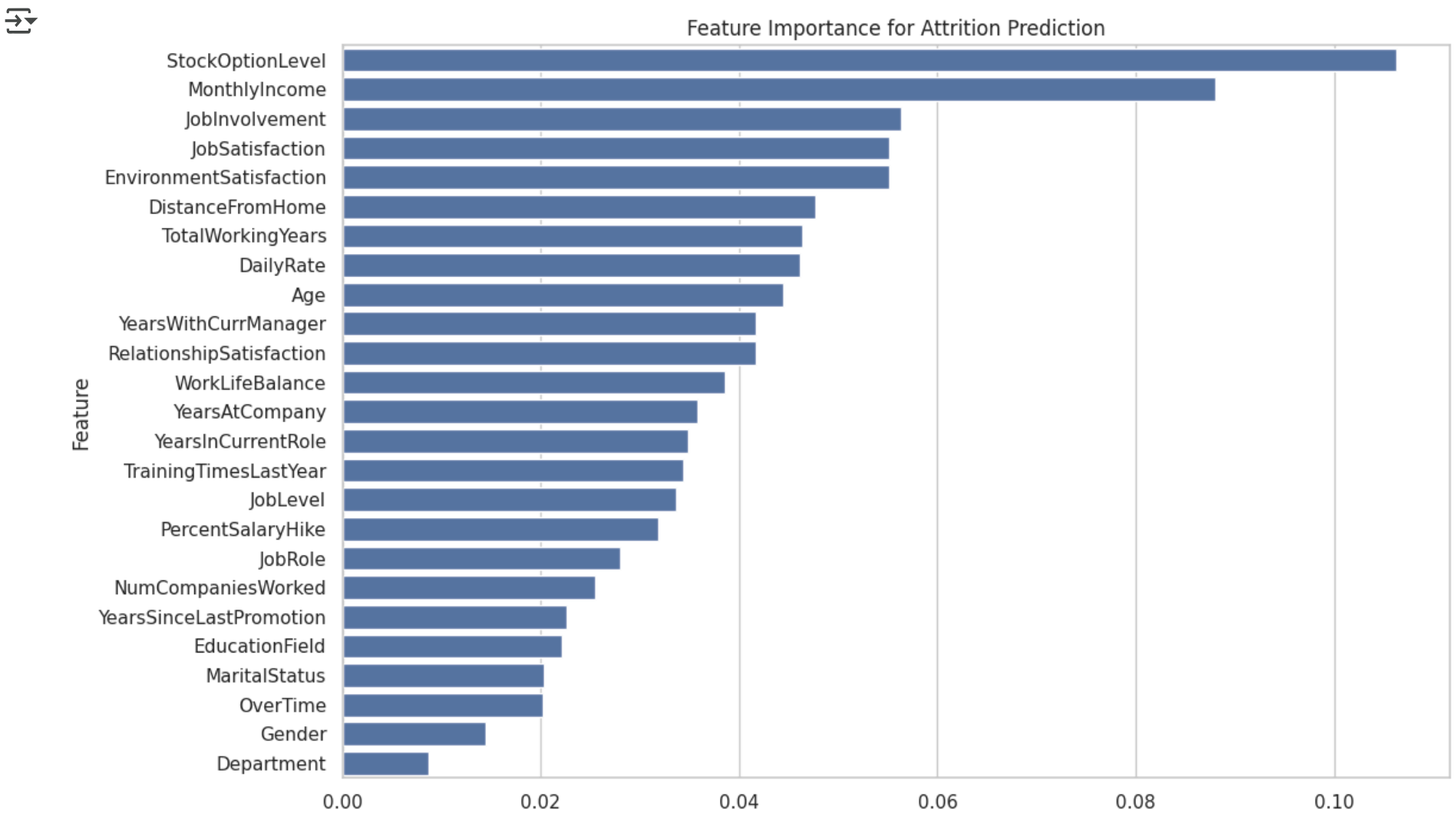
```
from sklearn.ensemble import RandomForestClassifier

# Initialize and train the model
rf = RandomForestClassifier(random_state=42)
rf.fit(X_train, y_train)

# Make predictions
y_pred = rf.predict(X_test)
```

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

# Evaluate the model
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nAccuracy:", accuracy_score(y_test, y_pred))

# Feature importance
feature_importance = pd.DataFrame({'Feature': selected_features,
                                   'Importance': rf.feature_importances_}).sort_values('Importance', ascending=False)
print("\nFeature Importance:\n", feature_importance)
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.88      0.91      0.90       369
           1       0.91      0.87      0.89       371

    accuracy                           0.89       740
   macro avg       0.89      0.89      0.89       740
weighted avg       0.89      0.89      0.89       740


Confusion Matrix:
 [[337  32]
 [ 47 324]]

Accuracy: 0.8932432432432432

Feature Importance:
                     Feature  Importance
12          StockOptionLevel    0.106314
7              MonthlyIncome    0.088038
4              JobInvolvement    0.056382
6            JobSatisfaction    0.055194
3    EnvironmentSatisfaction    0.055189
2           DistanceFromHome    0.047643
13         TotalWorkingYears    0.046428
1                  DailyRate    0.046144
0                        Age    0.044474
19      YearsWithCurrManager    0.041727
11  RelationshipSatisfaction    0.041709
15           WorkLifeBalance    0.038517
16            YearsAtCompany    0.035777
17        YearsInCurrentRole    0.034877
14     TrainingTimesLastYear    0.034372
5                   JobLevel    0.033610
10         PercentSalaryHike    0.031820
23                    JobRole    0.027960
8         NumCompaniesWorked    0.025441
18   YearsSinceLastPromotion    0.022619
21            EducationField    0.022097
24             MaritalStatus    0.020351
9                   OverTime    0.020225
22                    Gender    0.014432
```

```
20              Department    0.008663
```

```
# Plot feature importance
plt.figure(figsize=(12,8))
sns.barplot(x='Importance', y='Feature', data=feature_importance)
plt.title('Feature Importance for Attrition Prediction')
plt.show()
```



Key Findings and Insights Based on the analysis:

Top Factors Influencing Attrition:

OverTime: Employees working overtime are much more likely to leave

MonthlyIncome: Lower income correlates with higher attrition

Age: Younger employees are more likely to leave

StockOptionLevel: Employees with fewer stock options leave more often

JobSatisfaction: Lower satisfaction leads to higher attrition

YearsAtCompany: Employees with fewer years at company are more likely to leave

Department Impact: Sales department shows higher attrition rates compared to R&D

Job Role Impact: Sales Representatives and Laboratory Technicians show higher attrition

Managers and Research Directors have lower attrition

Work-Life Balance: Employees reporting poor work-life balance have higher attrition