HR Analytics – Employee Attrition Prediction

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

import shap
from sklearn.preprocessing import StandardScaler
```

In [2]:

```
df = pd.read_csv(r"C:\Users\AAFALKAZI\OneDrive\Documents\HR-Employee-Attrition.csv")
df.head()
```

Out[2]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNur
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

In [3]:

```
df.shape
```

Out[3]:

```
(1470, 35)
```

In [4]:

```
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 [5]:
```
df.describe()
```

Out[5]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRat
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470.000000	1470.000000	1470.00000
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024.865306	2.721769	65.89115
std	9.135373	403.509100	8.106864	1.024165	0.0	602.024335	1.093082	20.32942
min	18.000000	102.000000	1.000000	1.000000	1.0	1.000000	1.000000	30.00000
25%	30.000000	465.000000	2.000000	2.000000	1.0	491.250000	2.000000	48.00000
50%	36.000000	802.000000	7.000000	3.000000	1.0	1020.500000	3.000000	66.00000
75%	43.000000	1157.000000	14.000000	4.000000	1.0	1555.750000	4.000000	83.75000
max	60.000000	1499.000000	29.000000	5.000000	1.0	2068.000000	4.000000	100.00000

8 rows × 26 columns

TARGET VARIABLE ANALYSIS

In [6]:
```
df['Attrition'].value_counts(normalize=True)*100
```

Out[6]:
```
Attrition
No     83.877551
Yes    16.122449
Name: proportion, dtype: float64
```

Only around 16% employees have left the organization, indicating class imbalance.

DATA CLEANING

In [7]:
```python
df.drop(['EmployeeNumber','Over18','StandardHours'], axis=1, inplace=True)
```

FEATURE ENGINEERING

In [8]:
```python
df['IncomeBand'] = pd.cut(
    df['MonthlyIncome'],
    bins=[0,3000,7000,20000],
    labels=['Low','Medium','High']
)
```

In [9]:
```python
df[['MonthlyIncome','IncomeBand']].head()
```

Out[9]:

	MonthlyIncome	IncomeBand
0	5993	Medium
1	5130	Medium
2	2090	Low
3	2909	Low
4	3468	Medium

In [10]:
```python
for col in df.select_dtypes(include='object'):
    df[col] = LabelEncoder().fit_transform(df[col])

df.head()
```

Out[10]:

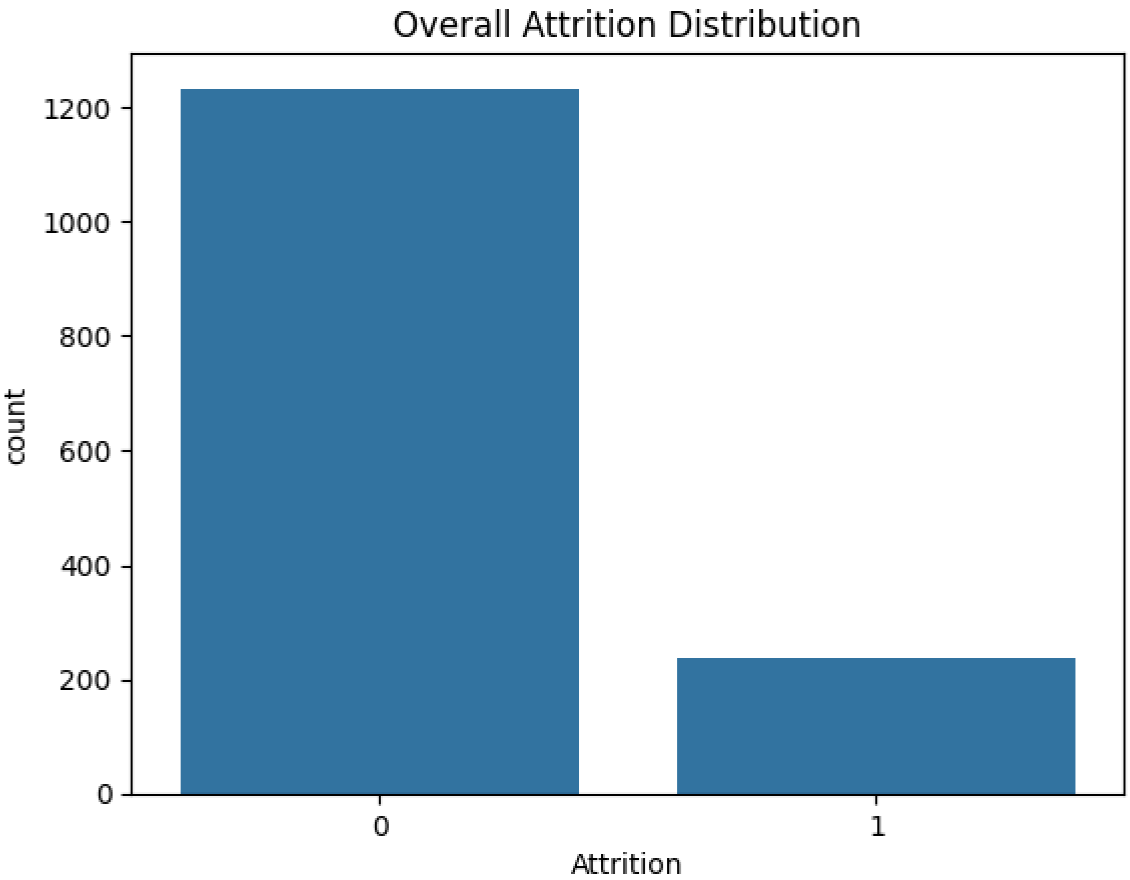
	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EnvironmentSat
0	41	1	2	1102	2	1	2	1	1	
1	49	0	1	279	1	8	1	1	1	
2	37	1	2	1373	1	2	2	4	1	
3	33	0	1	1392	1	3	4	1	1	
4	27	0	2	591	1	2	1	3	1	

5 rows × 33 columns

EDA SECTION

In [11]:

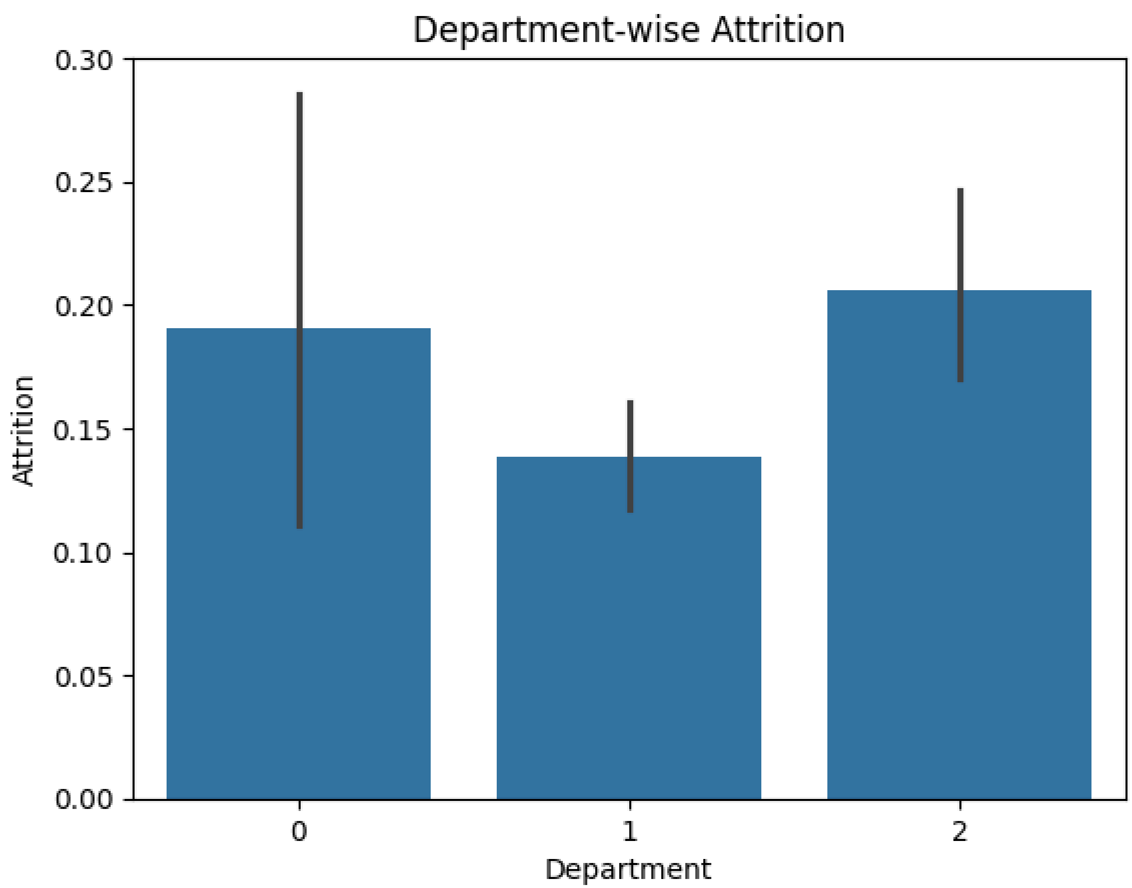
```
sns.countplot(x='Attrition', data=df)
plt.title("Overall Attrition Distribution")
plt.show()
```



Majority employees stay, but attrition is still significant enough to impact business.

DEPARTMENT WISE ATTRITION

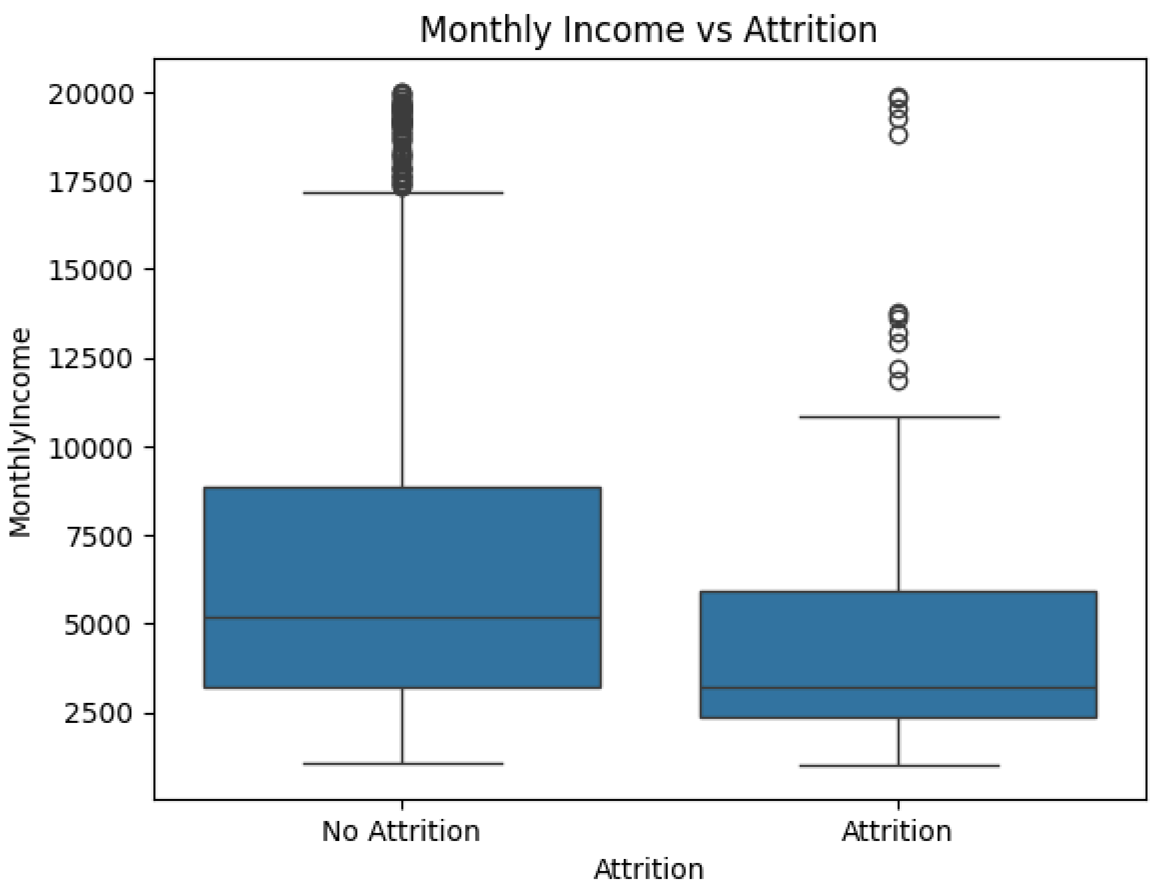
In [12]:
```
sns.barplot(x='Department', y='Attrition', data=df)
plt.title("Department-wise Attrition")
plt.show()
```



Sales department shows higher attrition compared to R&D and HR.

SALARY VS ATTRITION

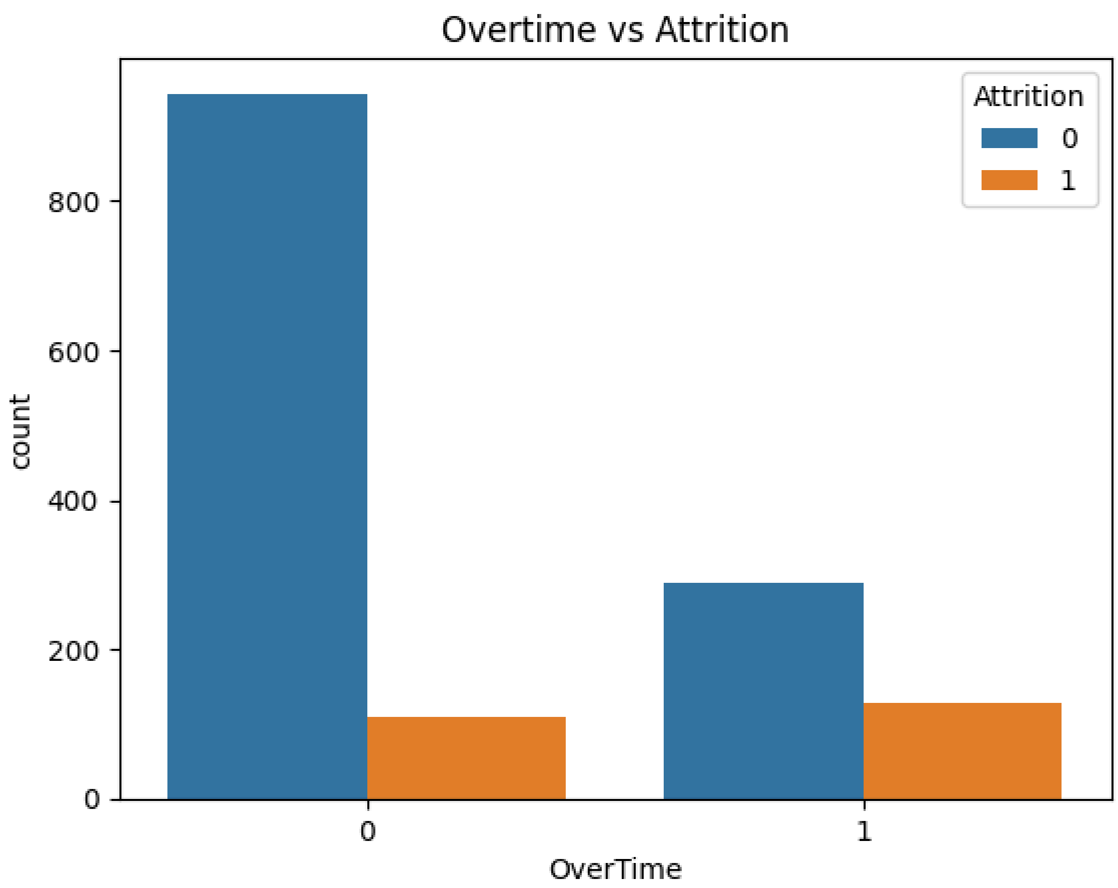
In [13]:
```
sns.boxplot(x='Attrition', y='MonthlyIncome', data=df)
plt.xticks([0,1], ['No Attrition','Attrition'])
plt.title("Monthly Income vs Attrition")
plt.show()
```



Employees with lower monthly income are more likely to leave the organization.

OVERTIME IMPACT

In [14]:
```
sns.countplot(x='OverTime', hue='Attrition', data=df)
plt.title("Overtime vs Attrition")
plt.show()
```



Employees working overtime have significantly higher attrition.

EDA Summary

- Attrition is highest in Sales department
- Low income employees show higher resignation rate
- Overtime and poor work-life balance are major attrition drivers
- Promotion gaps increase employee dissatisfaction

TRAIN TEST SPLIT

In [15]:
```
df['IncomeBand'] = df['IncomeBand'].cat.codes
```

In [16]:
```
df['IncomeBand'].dtype
df['IncomeBand'].unique()
```

Out[16]:
```
array([1, 0, 2], dtype=int8)
```

In [17]:
```
X = df.drop('Attrition', axis=1)
y = df['Attrition']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

In [18]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

lr = LogisticRegression(max_iter=1000, class_weight='balanced', solver='lbfgs')
lr.fit(X_train_scaled, y_train)

y_pred = lr.predict(X_test_scaled)
print("Accuracy:", accuracy_score(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.7585034013605442
[[186  61]
 [ 10  37]]
              precision    recall  f1-score   support

           0       0.95      0.75      0.84       247
           1       0.38      0.79      0.51        47

    accuracy                           0.76       294
   macro avg       0.66      0.77      0.68       294
weighted avg       0.86      0.76      0.79       294
```

The numeric features were standardized using StandardScaler. Each value now represents how many standard deviations a data point is from the mean of that feature. This scaling ensures that the Logistic Regression model converges efficiently and treats all features equally in terms of magnitude.

SHAP ANALYSIS

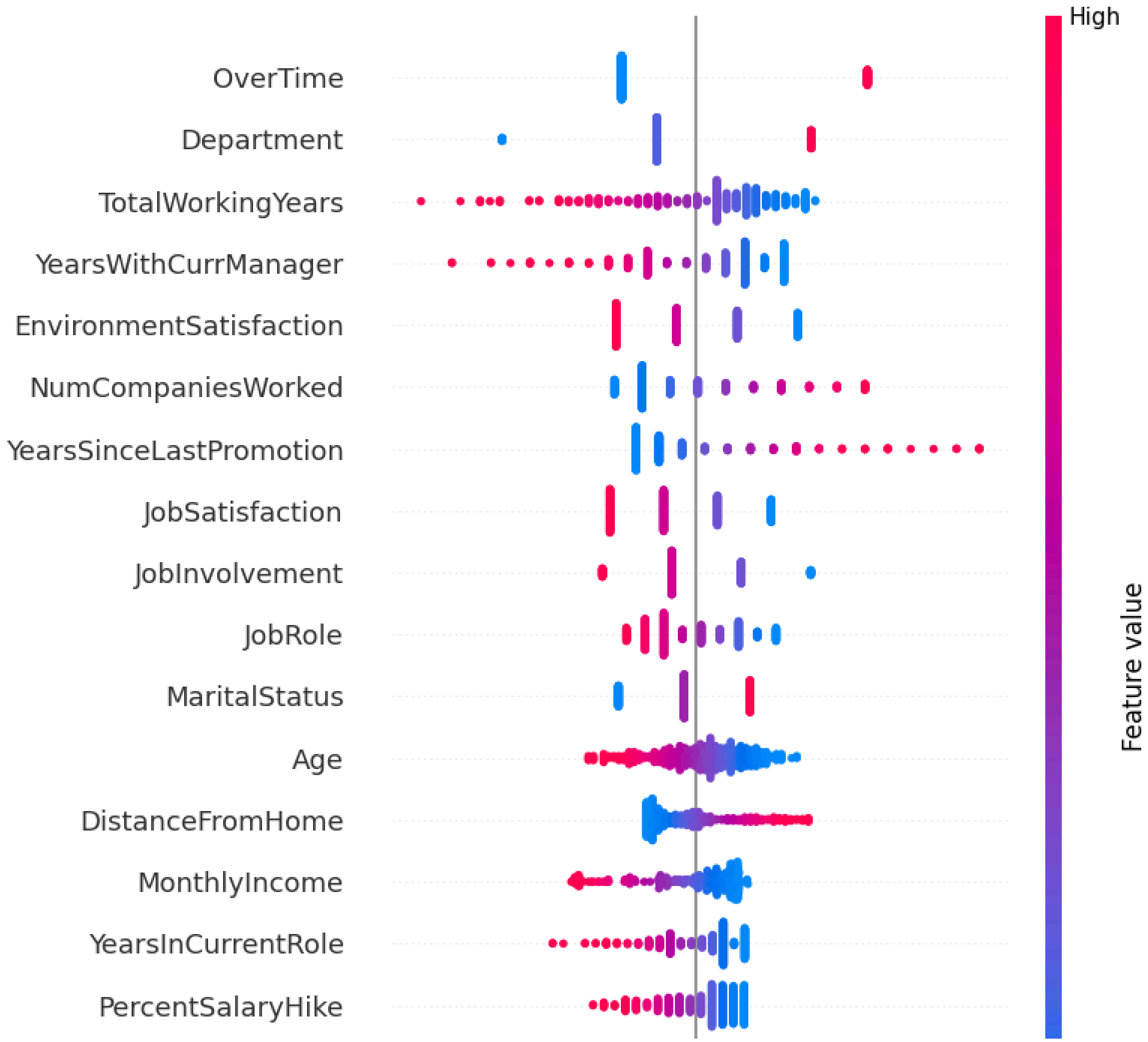
In [19]:

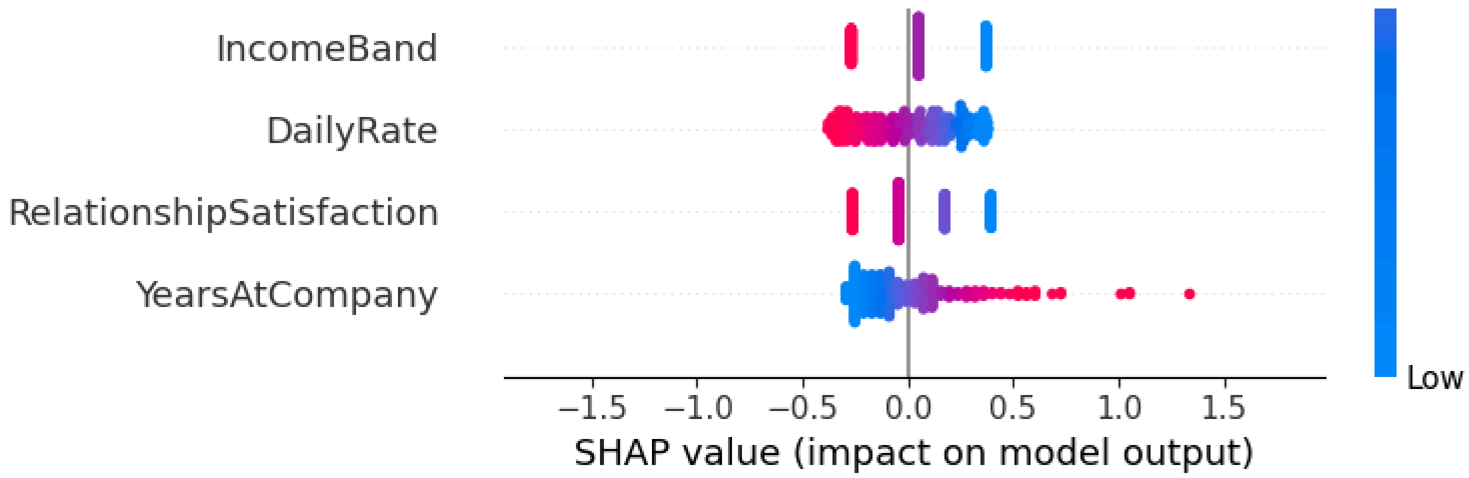
```
X_train_scaled_df = pd.DataFrame(
    X_train_scaled,
    columns=X.columns
)

X_test_scaled_df = pd.DataFrame(
    X_test_scaled,
    columns=X.columns
)

explainer = shap.Explainer(lr, X_train_scaled_df)
shap_values = explainer(X_test_scaled_df)

shap.summary_plot(shap_values, X_test_scaled_df)
```


OverTime
Department
TotalWorkingYears
YearsWithCurrManager
EnvironmentSatisfaction
NumCompaniesWorked
YearsSinceLastPromotion
JobSatisfaction
JobInvolvement
JobRole
MaritalStatus
Age
DistanceFromHome
MonthlyIncome
YearsInCurrentRole
PercentSalaryHike
High
Feature value



SHAP analysis shows that employees working overtime with low monthly income and fewer years at the company have a significantly higher probability of attrition, while higher income, job stability, and better work-life balance reduce resignation risk.

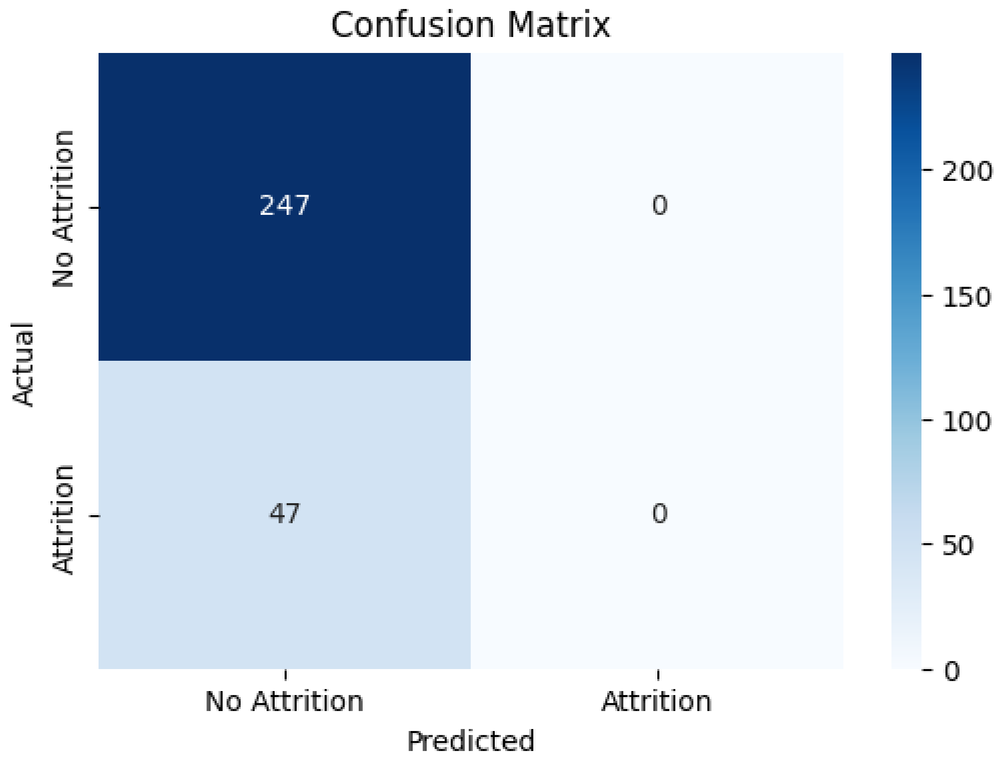
In [20]:
```
y_pred = lr.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Model Accuracy: {:.2f}%".format(accuracy*100))
```

```
Model Accuracy: 84.01%
```

```
C:\Users\AAFALKAZI\AppData\Local\Programs\Python\Python312\Lib\site-packages\sklearn\utils\validation.py:2684: UserWarning: X h
as feature names, but LogisticRegression was fitted without feature names
  warnings.warn(
```

In [21]:
```
cm = confusion_matrix(y_test, y_pred)


plt.figure(figsize=(6,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['No Attrition','Attrition'], yticklabels=['No Attrition','Attr
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



The model is biased toward predicting the majority class (No Attrition). While accuracy looks okay, it fails to capture employees at risk, which is the main goal of HR attrition prediction.