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Internship Topic: Employee Attrition Prediction using HR Analytics

Overview of the Problem Statement

Employee attrition (resignation/exit from the company) is a major challenge for HR departments. The goal of this project is to analyze employee data, identify key factors leading to attrition, and build a prediction model that helps organizations reduce turnover and improve employee retention.

Target Variable

Attrition (Yes / No) This indicates whether an employee has left the company or not. This is the label we want to predict in Machine Learning.

Objective

Perform EDA (Exploratory Data Analysis) to find important trends and patterns.

Build a Machine Learning model to predict employee attrition.

Provide insights to HR that can help in decision-making.

Data Description

The dataset contains employee details like demographics, work experience, salary, performance, and job satisfaction.

Key Features (Columns):

Demographics: Age, Gender, MaritalStatus, Over18

Job & Role: Department, JobRole, JobLevel, BusinessTravel, DistanceFromHome

Performance & Work: JobInvolvement, PerformanceRating, TrainingTimesLastYear, WorkLifeBalance

Salary & Income: MonthlyIncome, DailyRate, HourlyRate, PercentSalaryHike, StockOptionLevel

Experience: TotalWorkingYears, YearsAtCompany, YearsInCurrentRole, YearsSinceLastPromotion, YearsWithCurrManager

Other: EmployeeNumber, EmployeeCount, StandardHours (constant)

Data Size

Rows (Employees): ~1470

Features (Columns): 35

Step 1: Load Data

```
# 1. Import libraries
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings("ignore")# to prevent warning msgs

# 2. Load dataset
df = pd.read_csv("Employee_HR_analytics.csv")

# 3. Basic info
print("□ Data Loaded Successfully!\n")
```

```
□ Data Loaded Successfully!
```

```
print("Shape of dataset (rows, columns):", df.shape)
```

```
Shape of dataset (rows, columns): (1000, 35)
```

```
print("\nFirst 5 rows:")
display(df.head())

print("\nColumn names:")
print(df.columns.tolist())

print("\nData types:")
print(df.dtypes)
```

```
First 5 rows:

   Age Attrition     BusinessTravel  DailyRate              Department  \
0   41       Yes      Travel_Rarely       1102                   Sales

1   49        No  Travel_Frequently        279  Research & Development
```

```
2   37       Yes      Travel_Rarely       1373  Research & Development

3   33        No  Travel_Frequently       1392  Research & Development

4   27        No      Travel_Rarely        591  Research & Development


   DistanceFromHome  Education EducationField  EmployeeCount
EmployeeNumber  \
0                 1          2  Life Sciences              1
1
1                 8          1  Life Sciences              1
2
2                 2          2          Other              1
4
3                 3          4  Life Sciences              1
5
4                 2          1        Medical              1
7

   ...  RelationshipSatisfaction StandardHours  StockOptionLevel  \
0  ...                         1            80                 0
1  ...                         4            80                 1
2  ...                         2            80                 0
3  ...                         3            80                 0
4  ...                         4            80                 1

   TotalWorkingYears  TrainingTimesLastYear WorkLifeBalance
YearsAtCompany  \
0                  8                      0               1
6
1                 10                      3               3
10
2                  7                      3               3
0
3                  8                      3               3
8
4                  6                      3               3
2

  YearsInCurrentRole  YearsSinceLastPromotion  YearsWithCurrManager
0                  4                        0                     5
1                  7                        1                     7
2                  0                        0                     0
3                  7                        3                     0
4                  2                        2                     2

[5 rows x 35 columns]
```

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

Data types:
Age                          int64
Attrition                   object
BusinessTravel              object
DailyRate                    int64
Department                  object
DistanceFromHome             int64
Education                    int64
EducationField              object
EmployeeCount                int64
EmployeeNumber               int64
EnvironmentSatisfaction      int64
Gender                      object
HourlyRate                   int64
JobInvolvement               int64
JobLevel                     int64
JobRole                     object
JobSatisfaction              int64
MaritalStatus               object
MonthlyIncome                int64
MonthlyRate                  int64
NumCompaniesWorked           int64
Over18                      object
OverTime                    object
PercentSalaryHike            int64
PerformanceRating            int64
RelationshipSatisfaction     int64
StandardHours                int64
StockOptionLevel             int64
TotalWorkingYears            int64
TrainingTimesLastYear        int64
WorkLifeBalance              int64
YearsAtCompany               int64
YearsInCurrentRole           int64
YearsSinceLastPromotion      int64
```

```
YearsWithCurrManager         int64
dtype: object
```

```
# 4. Missing values check
print("\nMissing values in each column:")
print(df.isnull().sum())
```

```
Missing values in each column:
Age                            0
Attrition                      0
BusinessTravel                 0
DailyRate                      0
Department                     0
DistanceFromHome               0
Education                      0
EducationField                 0
EmployeeCount                  0
EmployeeNumber                 0
EnvironmentSatisfaction        0
Gender                         0
HourlyRate                     0
JobInvolvement                 0
JobLevel                       0
JobRole                        0
JobSatisfaction                0
MaritalStatus                  0
MonthlyIncome                  0
MonthlyRate                    0
NumCompaniesWorked             0
Over18                         0
OverTime                       0
PercentSalaryHike              0
PerformanceRating              0
RelationshipSatisfaction       0
StandardHours                  0
StockOptionLevel               0
TotalWorkingYears              0
TrainingTimesLastYear          0
WorkLifeBalance                0
YearsAtCompany                 0
YearsInCurrentRole             0
YearsSinceLastPromotion        0
YearsWithCurrManager           0
dtype: int64
```

```
# 5. Quick statistics
print("\nSummary statistics:")
display(df.describe())
```

```
Summary statistics:
                Age    DailyRate  DistanceFromHome    Education
EmployeeCount  \
count  1000.000000  1000.000000         1000.0000  1000.000000
1000.0
mean     36.992000   808.437000            9.0670     2.868000
1.0
std       9.417783   405.508487            8.1089     1.030358
0.0
min      18.000000   102.000000            1.0000     1.000000
1.0
25%      30.000000   470.750000            2.0000     2.000000
1.0
50%      36.000000   817.000000            7.0000     3.000000
1.0
75%      43.000000  1157.250000           14.0000     4.000000
1.0
max      60.000000  1499.000000           29.0000     5.000000
1.0

       EmployeeNumber  EnvironmentSatisfaction   HourlyRate
JobInvolvement  \
count     1000.000000              1000.000000  1000.000000
1000.000000
mean       690.073000                 2.731000    65.163000
2.730000
std        406.416188                 1.083426    20.209227
0.703986
min          1.000000                 1.000000    30.000000
1.000000
25%        341.750000                 2.000000    48.000000
2.000000
50%        678.000000                 3.000000    65.000000
3.000000
75%       1038.250000                 4.000000    83.000000
3.000000
max       1408.000000                 4.000000   100.000000
4.000000

          JobLevel  ...  RelationshipSatisfaction  StandardHours  \
count  1000.000000  ...               1000.000000         1000.0
mean      2.095000  ...                  2.741000           80.0
std       1.139857  ...                  1.087705            0.0
min       1.000000  ...                  1.000000           80.0
25%       1.000000  ...                  2.000000           80.0
50%       2.000000  ...                  3.000000           80.0
75%       3.000000  ...                  4.000000           80.0
max       5.000000  ...                  4.000000           80.0
```

```
       StockOptionLevel  TotalWorkingYears  TrainingTimesLastYear  \
count       1000.000000        1000.000000            1000.000000   
mean           0.762000          11.410000               2.773000   
std            0.836694           8.006748               1.311942   
min            0.000000           0.000000               0.000000   
25%            0.000000           6.000000               2.000000   
50%            1.000000          10.000000               3.000000   
75%            1.000000          16.000000               3.000000   
max            3.000000          40.000000               6.000000   

       WorkLifeBalance  YearsAtCompany  YearsInCurrentRole  \
count      1000.000000     1000.000000          1000.00000   
mean          2.763000        7.134000             4.26600   
std           0.698082        6.355032             3.63572   
min           1.000000        0.000000             0.00000   
25%           2.000000        3.000000             2.00000   
50%           3.000000        5.000000             3.00000   
75%           3.000000        9.000000             7.00000   
max           4.000000       40.000000            18.00000   

       YearsSinceLastPromotion  YearsWithCurrManager  
count               1000.00000           1000.000000  
mean                   2.23500              4.168000  
std                    3.30283              3.630283  
min                    0.00000              0.000000  
25%                    0.00000              2.000000  
50%                    1.00000              3.000000  
75%                    3.00000              7.000000  
max                   15.00000             17.000000  

[8 rows x 26 columns]
```

```python
# 6. Unique values in categorical columns
categorical_cols = df.select_dtypes(include=['object']).columns
for col in categorical_cols:
    print(f"\nUnique values in {col}: {df[col].unique()}")
```

```

Unique values in Attrition: ['Yes' 'No']

Unique values in BusinessTravel: ['Travel_Rarely' 'Travel_Frequently'
'Non-Travel']

Unique values in Department: ['Sales' 'Research & Development' 'Human
Resources']

Unique values in EducationField: ['Life Sciences' 'Other' 'Medical'
'Marketing' 'Technical Degree'
 'Human Resources']
```

```
Unique values in Gender: ['Female' 'Male']

Unique values in JobRole: ['Sales Executive' 'Research Scientist'
'Laboratory Technician'
 'Manufacturing Director' 'Healthcare Representative' 'Manager'
 'Sales Representative' 'Research Director' 'Human Resources']

Unique values in MaritalStatus: ['Single' 'Married' 'Divorced']

Unique values in Over18: ['Y']

Unique values in OverTime: ['Yes' 'No']
```

Step 2: Basic EDA Plots

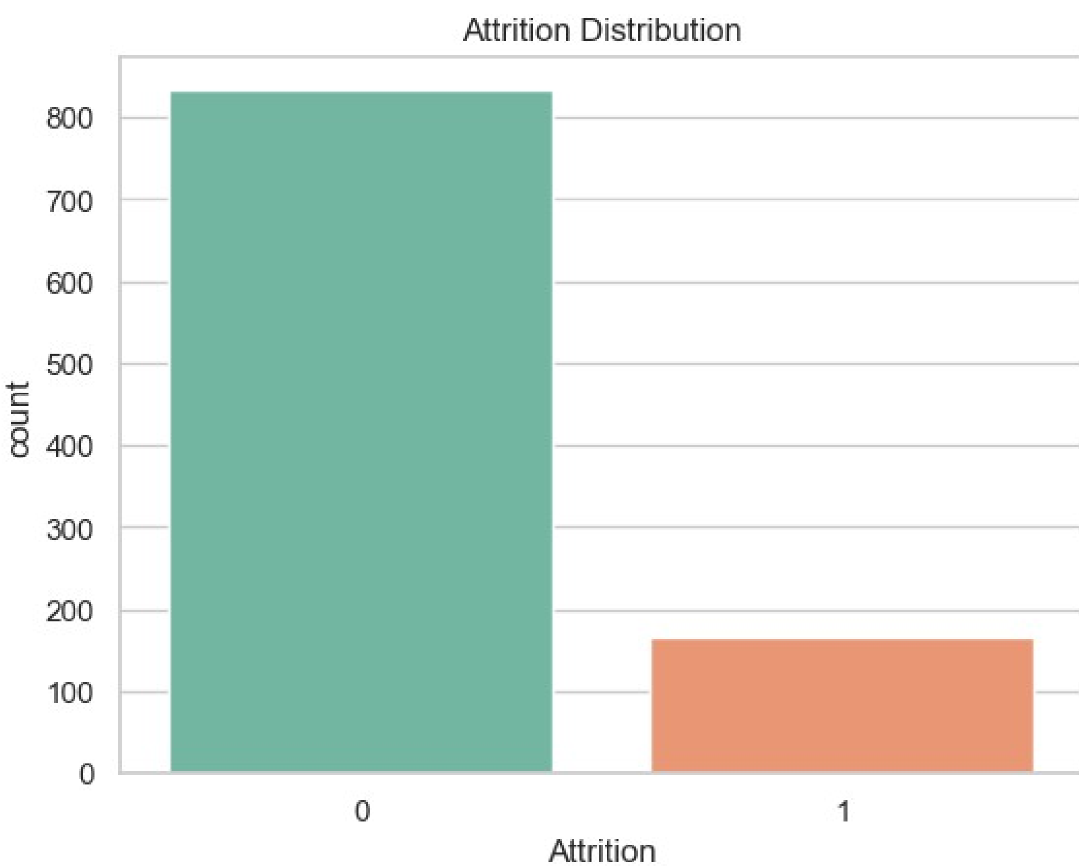
```python
import matplotlib.pyplot as plt
import seaborn as sns

# 2.1 Check missing values
print("Missing values:\n", df.isnull().sum())
```

```
Missing values:
 Age                                 0
Attrition                           0
DailyRate                           0
DistanceFromHome                    0
Education                           0
EducationField                      0
EnvironmentSatisfaction             0
HourlyRate                          0
JobInvolvement                      0
JobLevel                            0
JobSatisfaction                     0
MonthlyIncome                       0
MonthlyRate                         0
NumCompaniesWorked                  0
OverTime                            0
PercentSalaryHike                   0
PerformanceRating                   0
RelationshipSatisfaction            0
StandardHours                       0
StockOptionLevel                    0
TotalWorkingYears                   0
TrainingTimesLastYear               0
WorkLifeBalance                     0
YearsAtCompany                      0
YearsInCurrentRole                  0
```

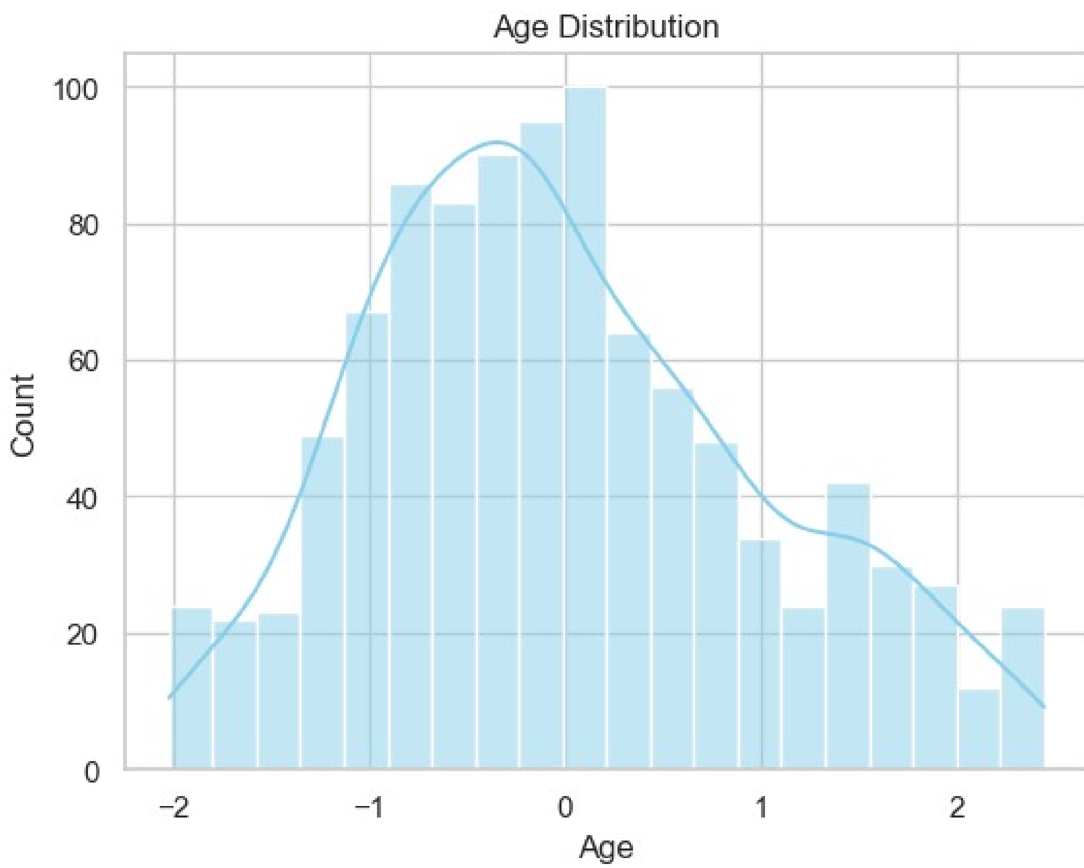
```
YearsSinceLastPromotion              0
YearsWithCurrManager                 0
Department_Research & Development    0
Department_Sales                     0
Gender_Male                          0
BusinessTravel_Travel_Frequently     0
BusinessTravel_Travel_Rarely         0
JobRole_Human Resources              0
JobRole_Laboratory Technician        0
JobRole_Manager                      0
JobRole_Manufacturing Director       0
JobRole_Research Director            0
JobRole_Research Scientist           0
JobRole_Sales Executive              0
JobRole_Sales Representative         0
MaritalStatus_Married                0
MaritalStatus_Single                 0
dtype: int64

# 2.2 Summary statistics
print("\nSummary statistics:\n", df.describe())


Summary statistics:
                  Age    Attrition    DailyRate  DistanceFromHome
Education  \
count  1.000000e+03  1000.000000  1000.000000      1.000000e+03
1000.000000
mean   2.842171e-16     0.167000   808.437000     -2.486900e-17
2.868000
std    1.000500e+00     0.373162   405.508487      1.000500e+00
1.030358
min   -2.017620e+00     0.000000   102.000000     -9.953306e-01
1.000000
25%   -7.427968e-01     0.000000   470.750000     -8.719476e-01
2.000000
50%   -1.053854e-01     0.000000   817.000000     -2.550326e-01
3.000000
75%    6.382613e-01     0.000000  1157.250000      6.086483e-01
4.000000
max    2.444260e+00     1.000000  1499.000000      2.459393e+00
5.000000

       EnvironmentSatisfaction   HourlyRate  JobInvolvement
JobLevel  \
count              1000.000000  1000.000000     1000.000000
1000.000000
mean                  2.731000    65.163000        2.730000
2.095000
std                   1.083426    20.209227        0.703986
```

```
1.139857
min                      1.000000    30.000000        1.000000
1.000000
25%                      2.000000    48.000000        2.000000
1.000000
50%                      3.000000    65.000000        3.000000
2.000000
75%                      4.000000    83.000000        3.000000
3.000000
max                      4.000000   100.000000        4.000000
5.000000

       JobSatisfaction  ...  RelationshipSatisfaction
StandardHours  \
count      1000.000000  ...               1000.000000         1000.0

mean          2.769000  ...                  2.741000           80.0

std           1.098565  ...                  1.087705            0.0

min           1.000000  ...                  1.000000           80.0

25%           2.000000  ...                  2.000000           80.0

50%           3.000000  ...                  3.000000           80.0

75%           4.000000  ...                  4.000000           80.0

max           4.000000  ...                  4.000000           80.0


       StockOptionLevel  TotalWorkingYears  TrainingTimesLastYear  \
count       1000.000000       1.000000e+03            1000.000000
mean           0.762000      -1.243450e-17               2.773000
std            0.836694       1.000500e+00               1.311942
min            0.000000      -1.425761e+00               0.000000
25%            0.000000      -6.760182e-01               2.000000
50%            1.000000      -1.761896e-01               3.000000
75%            1.000000       5.735533e-01               3.000000
max            3.000000       3.572525e+00               6.000000

       WorkLifeBalance  YearsAtCompany  YearsInCurrentRole  \
count      1000.000000    1.000000e+03          1000.00000
mean          2.763000   -5.329071e-17             4.26600
std           0.698082    1.000500e+00             3.63572
min           1.000000   -1.123137e+00             0.00000
25%           2.000000   -6.508336e-01             2.00000
50%           3.000000   -3.359649e-01             3.00000
75%           3.000000    2.937725e-01             7.00000
max           4.000000    5.174238e+00            18.00000
```

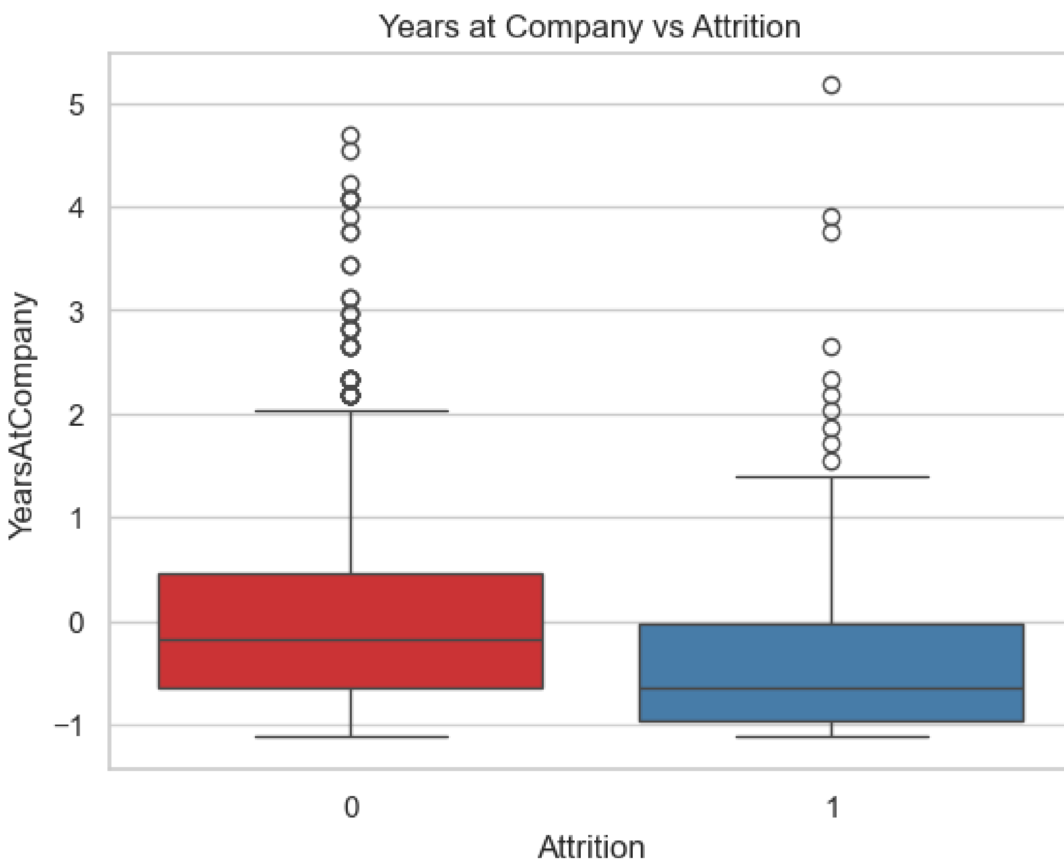
```
       YearsSinceLastPromotion  YearsWithCurrManager
count               1000.00000           1000.000000
mean                   2.23500              4.168000
std                    3.30283              3.630283
min                    0.00000              0.000000
25%                    0.00000              2.000000
50%                    1.00000              3.000000
75%                    3.00000              7.000000
max                   15.00000             17.000000

[8 rows x 25 columns]

# 2.3 Target distribution
sns.countplot(x='Attrition', data=df, palette="Set2")
plt.title("Attrition Distribution")
plt.show()
```




```
# 2.4 Numeric feature example visualization
sns.histplot(df['Age'], kde=True, bins=20, color="skyblue")
plt.title("Age Distribution")
plt.show()
```




```
# 2.5 Boxplot example
sns.boxplot(x="Attrition", y="YearsAtCompany", data=df,
hue="Attrition", palette="Set1", legend=False)
plt.title("Years at Company vs Attrition")
plt.show()
```



Step 3: Data Preprocessing (Simplified & Clean)

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

# 3.1 Drop EmployeeNumber (ID-like, not useful)
df = df.drop(columns=["EmployeeNumber"], errors="ignore")

# 3.2 Handle missing values
print("\n Missing values before cleaning:")
print(df.isnull().sum())

df = df.dropna()

print("\n Missing values handled")
print("Remaining rows:", df.shape[0])
```

```
 Missing values before cleaning:
Age                            0
Attrition                      0
BusinessTravel                 0
```

```
DailyRate                   0
Department                  0
DistanceFromHome            0
Education                   0
EducationField              0
EmployeeCount               0
EnvironmentSatisfaction     0
Gender                      0
HourlyRate                  0
JobInvolvement              0
JobLevel                    0
JobRole                     0
JobSatisfaction             0
MaritalStatus               0
MonthlyIncome               0
MonthlyRate                 0
NumCompaniesWorked          0
Over18                      0
OverTime                    0
PercentSalaryHike           0
PerformanceRating           0
RelationshipSatisfaction    0
StandardHours               0
StockOptionLevel            0
TotalWorkingYears           0
TrainingTimesLastYear       0
WorkLifeBalance             0
YearsAtCompany              0
YearsInCurrentRole          0
YearsSinceLastPromotion     0
YearsWithCurrManager        0
dtype: int64

 Missing values handled
Remaining rows: 1000

# 3.3 Encode categorical variables
categorical_cols = df.select_dtypes(include=["object"]).columns
print("\nCategorical columns to encode:", categorical_cols.tolist())

df_encoded = pd.get_dummies(df, columns=categorical_cols,
drop_first=True)

print("\n Encoding done")
print("New shape:", df_encoded.shape)


Categorical columns to encode: ['Attrition', 'BusinessTravel',
'Department', 'EducationField', 'Gender', 'JobRole', 'MaritalStatus',
'Over18', 'OverTime']
```

```
 Encoding done
New shape: (1000, 47)
```

```
# 3.4 Define features (X) and target (y)
X = df_encoded.drop(columns=["Attrition_Yes"], errors="ignore")
y = df_encoded["Attrition_Yes"]

print("\nTarget variable distribution (y):")
print(y.value_counts())
```

```
Target variable distribution (y):
Attrition_Yes
False    833
True     167
Name: count, dtype: int64
```

```
# 3.5 Train-Test Split (stratify to keep balance)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

print("\n Train-Test Split Completed")
print("Training set:", X_train.shape, "Testing set:", X_test.shape)
print("y_train distribution:\n", y_train.value_counts())
print("y_test distribution:\n", y_test.value_counts())
```

```
 Train-Test Split Completed
Training set: (800, 46) Testing set: (200, 46)
y_train distribution:
 Attrition_Yes
False    666
True     134
Name: count, dtype: int64
y_test distribution:
 Attrition_Yes
False    167
True      33
Name: count, dtype: int64
```

Step 4: Machine Learning Model Training & Evaluation

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

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

# 4.1 Logistic Regression
log_reg = LogisticRegression(max_iter=1000, random_state=42)
log_reg.fit(X_train, y_train)   # Train the model
```

```
LogisticRegression(max_iter=1000, random_state=42)
```

```python
# Predictions
y_pred_log = log_reg.predict(X_test)

print(" Logistic Regression Model Trained Successfully!\n")
```

```
 Logistic Regression Model Trained Successfully!
```

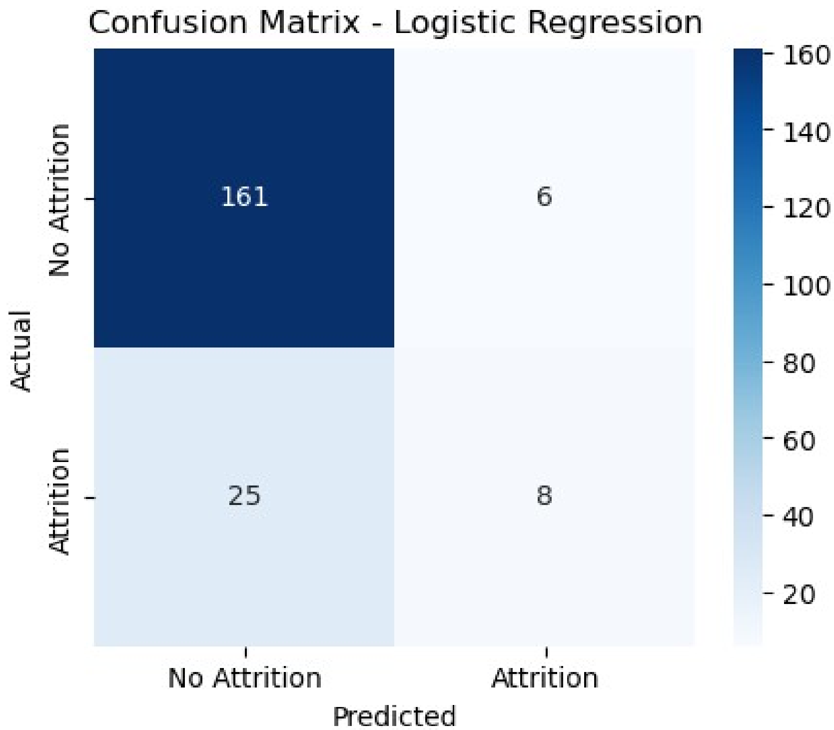
```python
# Accuracy
print("Accuracy on Test Data:", accuracy_score(y_test, y_pred_log))
```

```
Accuracy on Test Data: 0.845
```

```python
# Classification Report
print("\nClassification Report:\n", classification_report(y_test, y_pred_log))
```

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

       False       0.87      0.96      0.91       167
        True       0.57      0.24      0.34        33

    accuracy                           0.84       200
   macro avg       0.72      0.60      0.63       200
weighted avg       0.82      0.84      0.82       200
```

```python
# Confusion Matrix
cm = confusion_matrix(y_test, y_pred_log)

plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["No Attrition","Attrition"], yticklabels=["No Attrition","Attrition"])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix - Logistic Regression")
plt.show()
```



Step 5 – Save Model & Export Predictions

```
import joblib
import pandas as pd

# 5.1 Save the trained Logistic Regression model
joblib.dump(log_reg, "logistic_model_hr.pkl")
print(" Model saved as 'logistic_model_hr.pkl'")
```

```
 Model saved as 'logistic_model_hr.pkl'
```

```
# 5.2 Make predictions on test data
y_pred = log_reg.predict(X_test)

# 5.3 Save predictions to CSV (optional for reporting/presentation)
predictions = pd.DataFrame({
    "EmployeeIndex": X_test.index,   # or EmployeeNumber if kept in X
    "ActualAttrition": y_test,
    "PredictedAttrition": y_pred
})

predictions.to_csv("attrition_predictions.csv", index=False)
print(" Predictions saved as 'attrition_predictions.csv'")
```

```
 Predictions saved as 'attrition_predictions.csv'
```

Step 6: Display Model Accuracy

```
import pandas as pd

# Load prediction results
df_pred = pd.read_csv("attrition_predictions.csv")

# Calculate accuracy
accuracy = (df_pred['ActualAttrition'] ==
df_pred['PredictedAttrition']).mean()
print(f" Model Accuracy: {accuracy*100:.2f}%")
```

```
 Model Accuracy: 84.50%
```

Step 7: Conclusion

1.The Logistic Regression model was trained to predict employee attrition.

2.The model achieved an accuracy of 84.50% on the test dataset.

3.Predictions were generated for all employees and saved in attrition_predictions.csv.

4.The trained model was saved as logistic_model_hr.pkl for future use.