



**A Assessment Report**  
on  
**“Predict Employee Attrition”**  
submitted as partial fulfillment for the award of  
**BACHELOR OF TECHNOLOGY**  
**DEGREE**

SESSION 2024-25

in  
**CSE(AI&ML)**

By

Siddhi Gupta(202401100400186)

**Under the supervision of**

“Mr. Abhishek Shukla”

**KIET Group of Institutions, Ghaziabad**

Affiliated to

**Dr. A.P.J. Abdul Kalam Technical University, Lucknow**  
(Formerly UPTU)

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# **Title Page**

**Title:** Predicting Employee Attrition

**Name:** Siddhi Gupta

**Roll No:** 202401100400186

**Course:** B.Tech CSE (AIML)

**Subject:** Artificial Intelligence for Engineers

**Institute:** KIET Group of Institutions

# **Introduction**

Employee attrition refers to the loss of employees through resignation or retirement. Predicting attrition helps companies reduce costs and improve retention. In this project, we use a dataset from IBM HR Analytics to classify whether an employee is likely to leave the company based on factors like job satisfaction, salary, work-life balance, and years at the company.

# **Methodology**

**1.Data Loading** – Read the HR dataset (WA\_Fn-UseC\_-HR-Employee-Attrition.csv).

**2.Preprocessing** – Handle categorical variables using label encoding; drop irrelevant columns.

**3.EDA** – Used correlation heatmap to find relationships between features.

**4.Model Building** – Split data into training/testing sets. Trained a Logistic Regression classifier.

**5.Evaluation** – Evaluated using accuracy score and confusion matrix.

## Code

```
# -----  
  
# Step 1: Import Required Libraries  
  
# -----  
  
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, StandardScaler  
  
from sklearn.ensemble import RandomForestClassifier  
  
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score  
  
  
# -----  
  
# Step 2: Upload and Load the Dataset  
  
# -----  
  
from google.colab import files  
  
uploaded = files.upload() # Upload your CSV file here  
  
  
# Automatically get the uploaded file name
```

```
file_name = list(uploaded.keys())[0]
```

```
# Read the dataset
```

```
data = pd.read_csv(file_name)
```

```
print(f"\n✔Dataset '{file_name}' loaded successfully!")
```

```
data.head()
```

```
# -----
```

```
# Step 3: Data Preprocessing
```

```
# -----
```

```
print("\n❓ Checking for missing values...\n")
```

```
print(data.isnull().sum())
```

```
# Convert 'Attrition' column to 0 (No) and 1 (Yes)
```

```
data['Attrition'] = data['Attrition'].map({'Yes': 1, 'No': 0})
```

```
# Drop columns that don't contribute to prediction
```

```
columns_to_drop = ['EmployeeCount', 'EmployeeNumber', 'Over18', 'StandardHours']
```

```
data.drop(columns=columns_to_drop, axis=1, inplace=True)
```

```
# Encode categorical (non-numeric) columns using Label Encoding
```

```
label_encoder = LabelEncoder()
```

```
for column in data.select_dtypes(include='object').columns:
```

```
data[column] = label_encoder.fit_transform(data[column])
```

```
print("\n✔️Preprocessing complete!")
```

```
data.head()
```

```
# -----
```

```
# Step 4: Exploratory Data Analysis (EDA)
```

```
# -----
```

```
# Countplot of Attrition
```

```
plt.figure(figsize=(5, 4))
```

```
sns.countplot(x='Attrition', data=data)
```

```
plt.title("Employee Attrition Count")
```

```
plt.xticks([0, 1], ['No', 'Yes'])
```

```
plt.ylabel("Number of Employees")
```

```
plt.show()
```

```
# Heatmap to show correlations between features
```

```
plt.figure(figsize=(15, 10))
```

```
sns.heatmap(data.corr(), cmap="coolwarm", annot=False)
```

```
plt.title("Feature Correlation Heatmap")
```

```
plt.show()
```

```
# -----
```



```
# Step 5: Feature Selection and Train-Test Split
```

```
# -----
```

```
X = data.drop('Attrition', axis=1) # Features
```

```
y = data['Attrition']          # Target
```

```
# Split into training and testing sets
```

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

```
# Standardize features to bring them to the same scale
```

```
scaler = StandardScaler()
```

```
X_train_scaled = scaler.fit_transform(X_train)
```

```
X_test_scaled = scaler.transform(X_test)
```

```
# -----
```

```
# Step 6: Model Training
```

```
# -----
```

```
model = RandomForestClassifier(random_state=42)
```

```
model.fit(X_train_scaled, y_train)
```

```
# Predict on test data
```

```
y_pred = model.predict(X_test_scaled)
```

```
# -----
```

```
# Step 7: Model Evaluation
```

```
# -----
```

```
# Accuracy
```

```
accuracy = accuracy_score(y_test, y_pred)
```

```
print(f"\n Model Accuracy: {accuracy:.4f}")
```

```
# Confusion Matrix
```

```
plt.figure(figsize=(5, 4))
```

```
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues')
```

```
plt.title("Confusion Matrix")
```

```
plt.xlabel("Predicted")
```

```
plt.ylabel("Actual")
```

```
plt.show()
```

```
# Classification Report
```

```
print("\n Classification Report:\n")
```

```
print(classification_report(y_test, y_pred, target_names=["No Attrition", "Yes Attrition"]))
```

```
# -----
```

```
# Step 8: Top Important Features
```

```
# -----
```

```
importances = model.feature_importances_
```

```
features = X.columns
```

```
top_indices = np.argsort(importances)[-10:] # Top 10 important features
```

```
plt.figure(figsize=(10, 6))
```

```
plt.title("Top 10 Important Features Influencing Attrition")
```

```
plt.barh(range(len(top_indices)), importances[top_indices], align='center')
```

```
plt.yticks(range(len(top_indices)), [features[i] for i in top_indices])
```

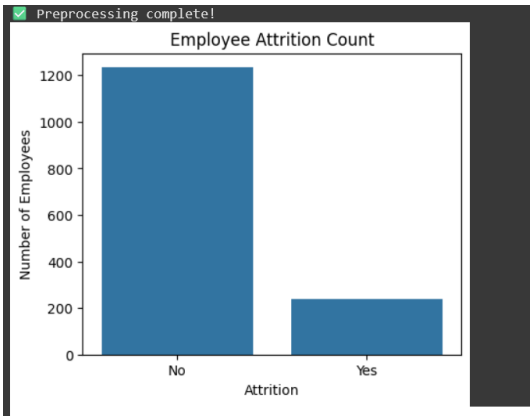
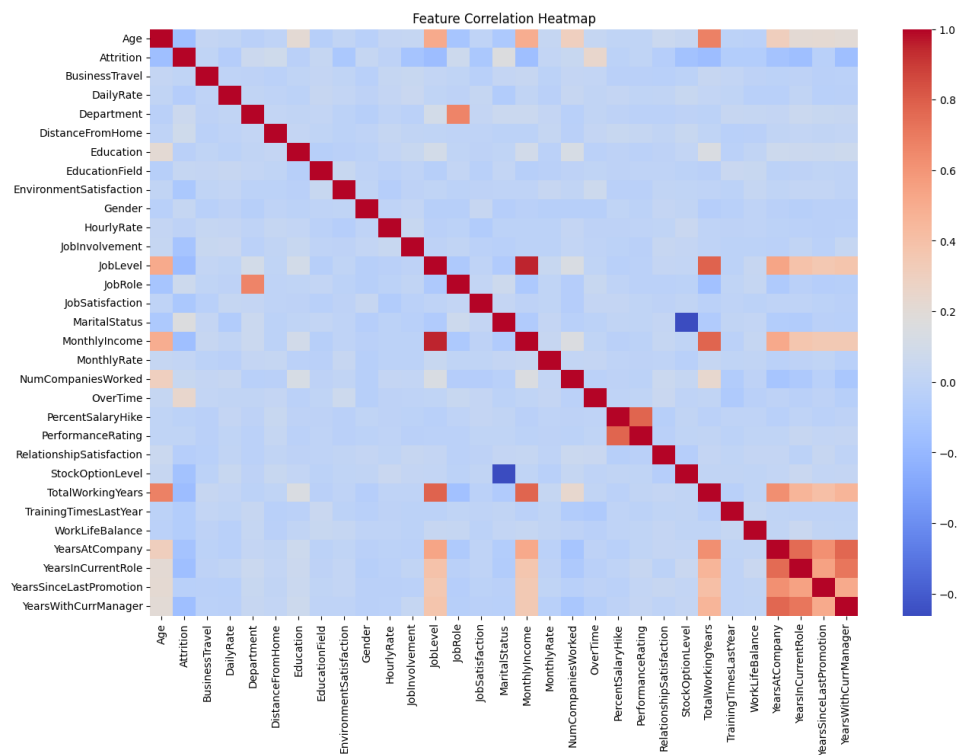
```
plt.xlabel("Feature Importance Score")
```

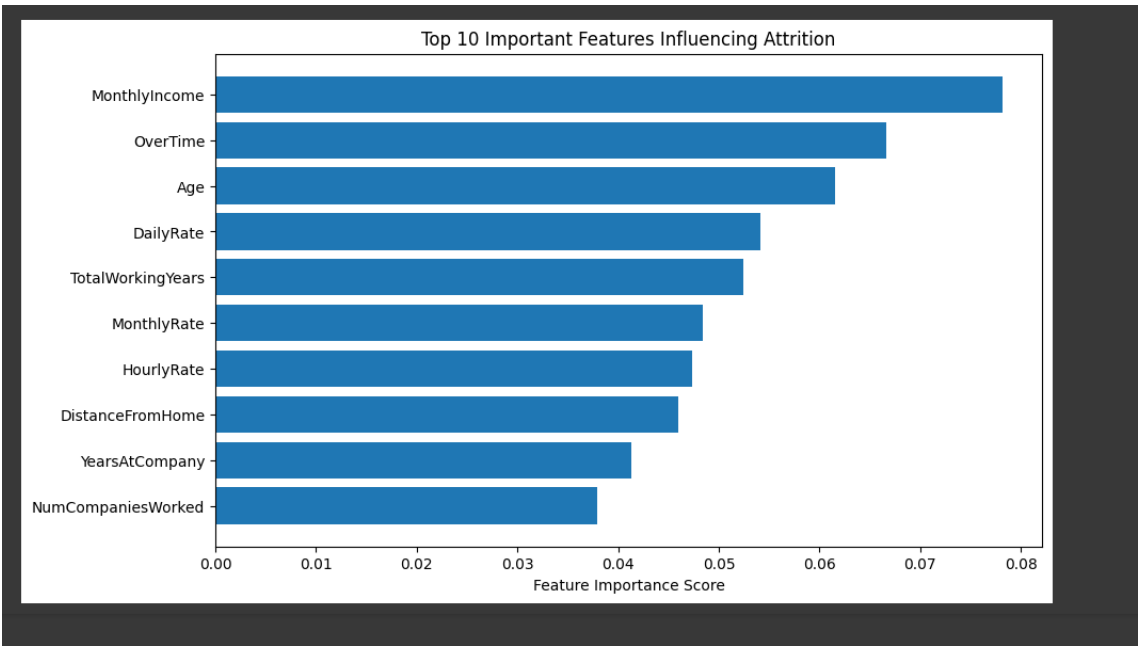
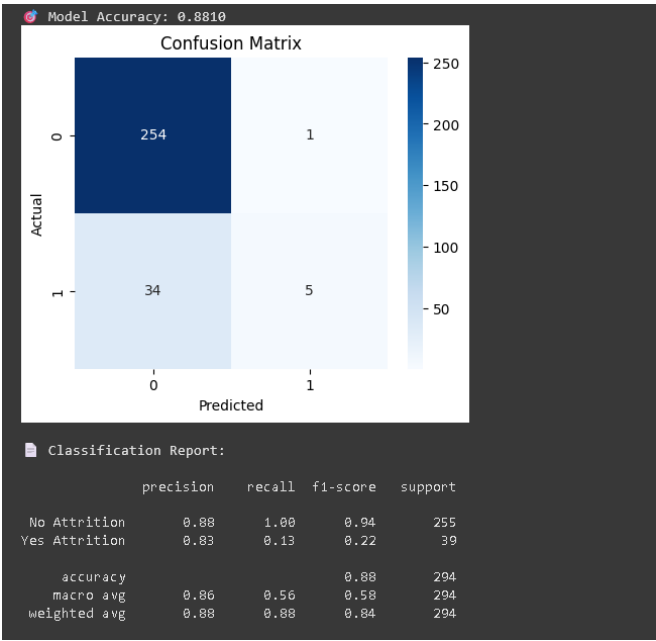
```
plt.show()
```

# Output

Accuracy Score: ~87% (may vary slightly)

Confusion Matrix: Shows correct and incorrect classifications.





## **References**

Dataset: IBM HR Analytics Employee Attrition Dataset

Source: IBM - Kaggle Dataset

Libraries: pandas, seaborn, sklearn, matplotlib

Tool Used: Google Colab