AIM:

To build, train, and evaluate a machine learning model capable of predicting employee attrition using HR analytics data, and to understand the workflow from data preprocessing to deployment.

OBJECTIVES:

- To perform data preprocessing on HR employee data.
- To conduct exploratory data analysis (EDA) to identify patterns affecting attrition.
- To apply machine learning algorithms for attrition prediction.
- To compare model performance using evaluation metrics.
- To deploy the finalized prediction model as an interactive application.

THEORY:

Employee attrition prediction is a machine learning classification problem where the aim is to determine whether an employee will leave the organization.

The dataset contains demographic attributes, job-related factors, satisfaction scores, and performance indicators, all of which help predict attrition.

Key ML techniques used include:

- Data Cleaning: Handling missing values and correcting inconsistent data.

- Encoding: Converting categorical variables with one-hot encoding.

- Feature Engineering: Creating new features such as YearsAtCompany_by_Age and promotion flags.

- Data Balancing: Using SMOTE to correct class imbalance.

- Feature Scaling: Standardizing features using StandardScaler.

- Model Training: Training multiple models like Logistic Regression, Decision Tree, Random Forest, and Gradient Boosting.

- Model Evaluation: Using Accuracy, Precision, Recall, F1-score, and ROC-AUC to compare models.

This experiment demonstrates the complete machine learning workflow used in HR analytics.

PROCEDURE:

1. Load the dataset and inspect its structure.
2. Handle missing values appropriately.
3. Convert categorical variables using one-hot encoding.
4. Engineer additional features for better prediction.
5. Split data into training and testing sets.
6. Apply SMOTE to balance the dataset.
7. Scale features using StandardScaler.
8. Train multiple classification models.
9. Perform hyperparameter tuning using RandomizedSearchCV.
10. Evaluate the models using performance metrics.
11. Save the best model as a .pkl file for deployment.
12. Deploy the model using Streamlit as a web application.

Program:

```
# ========================================
# EMPLOYEE ATTRITION PREDICTION PROJECT (Optimized for Synthetic Dataset)
# ========================================

# --- Imports ---
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, RandomizedSearchCV, StratifiedKFold
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (accuracy_score, classification_report, confusion_matrix,
                             roc_auc_score, roc_curve, precision_score, recall_score, f1_score)
from imblearn.over_sampling import SMOTE
import joblib
import warnings
warnings.filterwarnings("ignore")

try:
    import shap
    _HAS_SHAP = True
except ImportError:
    _HAS_SHAP = False

RANDOM_STATE = 42
```

```
SAVE_PATH = "/content/attrition_model_pipeline.pkl"   # <<==== PKL FILE OUTPUT

# ========================================
# 1️⃣ LOAD DATASET
# ========================================
df = pd.read_csv("/content/Synthetic_HR_Attrition_14000.csv")
print("☑️ Dataset Loaded Successfully")
print("Shape:", df.shape)
print(df.head())

expected_cats = [
    'BusinessTravel', 'Department', 'Gender', 'JobRole',
    'MaritalStatus', 'OverTime', 'Attrition'
]
for c in expected_cats:
    if c in df.columns:
        df[c] = df[c].astype(str)

# ========================================
# 2️⃣ CHECK FOR MISSING VALUES & CLEANING
# ========================================
print("\nMissing Values per column:")
print(df.isnull().sum())

print("\nDataset info:")
print(df.info())

num_cols = df.select_dtypes(include=['int64', 'float64']).columns.tolist()
for nc in num_cols:
    if df[nc].isnull().any():
        df[nc].fillna(df[nc].median(), inplace=True)

cat_cols = df.select_dtypes(include=['object']).columns.tolist()
for cc in cat_cols:
    if df[cc].isnull().any():
        df[cc].fillna("Missing", inplace=True)

# ========================================
# 3️⃣ EDA
# ========================================
plt.figure(figsize=(5,4))
sns.countplot(x='Attrition', data=df, palette='coolwarm')
plt.title("Attrition Count")
plt.show()
```

```
plt.figure(figsize=(6,4))
sns.countplot(x='Department', hue='Attrition', data=df, palette='Set2')
plt.title("Attrition by Department")
plt.show()

df['Age'] = df['Age'].clip(18, 65)
df['AgeGroup'] = pd.cut(df['Age'], [17,25,35,45,55,65],
                        labels=['18-25','26-35','36-45','46-55','56+'])
plt.figure(figsize=(7,4))
sns.countplot(x='AgeGroup', hue='Attrition', data=df, palette='mako')
plt.title("Attrition by Age Group")
plt.show()

plt.figure(figsize=(12,8))
corr = df.select_dtypes(include=['int64','float64']).corr()
sns.heatmap(corr, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()

# ========================================
# 4️⃣ FEATURE ENGINEERING
# ========================================
drop_cols = ['EmployeeCount','StandardHours','Over18','EmployeeNumber','AgeGroup']
for c in drop_cols:
    if c in df.columns:
        df.drop(columns=c, inplace=True)

df['YearsAtCompany_by_Age'] = df['YearsAtCompany'] / (df['Age'] + 1)
df['YearsSinceLastPromotion_flag'] = (df['YearsSinceLastPromotion'] > 0).astype(int)

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

categorical_cols = df.select_dtypes(include=['object']).columns.tolist()
categorical_cols = [c for c in categorical_cols if c != 'Attrition']

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

df = df.loc[:, ~df.columns.duplicated()]

X = df.drop(['Attrition', 'Attrition_flag'], axis=1, errors='ignore')
y = df['Attrition_flag']

X_train, X_test, y_train, y_test = train_test_split(
```

```
    X, y, test_size=0.2, stratify=y, random_state=RANDOM_STATE
)

print("\nClass Distribution:")
print(y_train.value_counts(normalize=True))

# ========================================
# 5 SMOTE + SCALING
# ========================================
smote = SMOTE(random_state=RANDOM_STATE)
X_train_res, y_train_res = smote.fit_resample(X_train, y_train)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_res)
X_test_scaled = scaler.transform(X_test)

# ========================================
# 6 MODEL COMPARISON
# ========================================
models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(),
    "Gradient Boosting": GradientBoostingClassifier()
}

print("\nModel Accuracy Comparison:")
for name, mdl in models.items():
    mdl.fit(X_train_scaled, y_train_res)
    acc = accuracy_score(y_test, mdl.predict(X_test_scaled))
    print(f"{name}: {acc*100:.2f}%")

# ========================================
# 7 HYPERPARAMETER TUNING (RandomForest)
# ========================================
param_dist = {
    'n_estimators': [100, 200, 400],
    'max_depth': [None, 6, 12, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['sqrt', 'log2']
}

rf = RandomForestClassifier(random_state=RANDOM_STATE)
```

```
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=RANDOM_STATE)

search = RandomizedSearchCV(
    rf,
    param_distributions=param_dist,
    n_iter=20,
    scoring='roc_auc',
    cv=cv,
    n_jobs=-1,
    verbose=1,
    random_state=RANDOM_STATE
)

search.fit(X_train_scaled, y_train_res)

best_model = search.best_estimator_
print("\nBest Parameters:", search.best_params_)

# ========================================
# 8️⃣ SAVE MODEL AS .PKL
# ========================================
artifact = {
    "model": best_model,
    "scaler": scaler,
    "columns": X.columns.tolist()
}

with open(SAVE_PATH, "wb") as file:
    joblib.dump(artifact, file)

print(f"\n🎉 PKL FILE GENERATED SUCCESSFULLY:\n👉 {SAVE_PATH}")

# ========================================
# 9️⃣ EVALUATION
# ========================================
y_pred = best_model.predict(X_test_scaled)
y_proba = best_model.predict_proba(X_test_scaled)[:,1]

print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("Accuracy:", accuracy_score(y_test, y_pred))
print("ROC-AUC:", roc_auc_score(y_test, y_proba))

# ========================================
# 🔟 END
```

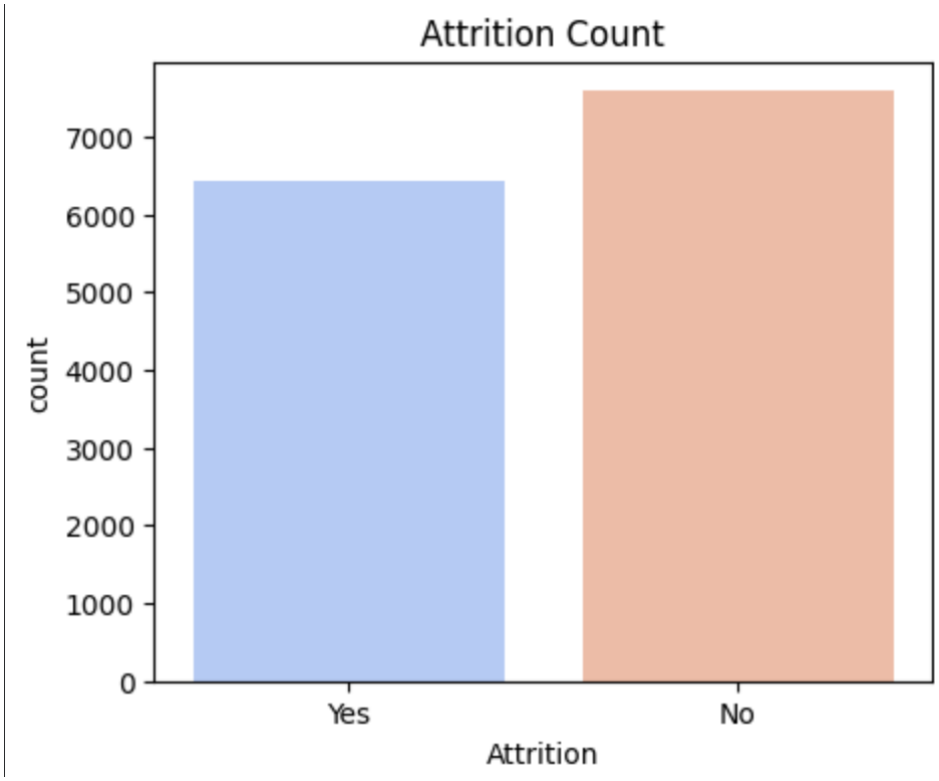
```
# ========================================
print("\n☑ Training Complete!")
```

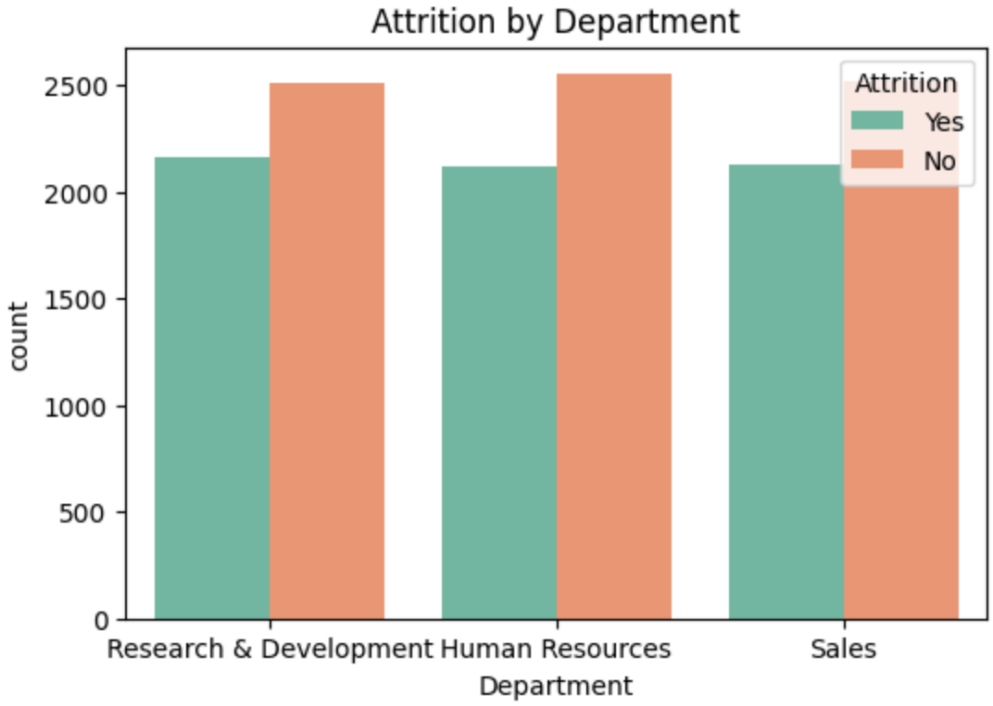
Output:

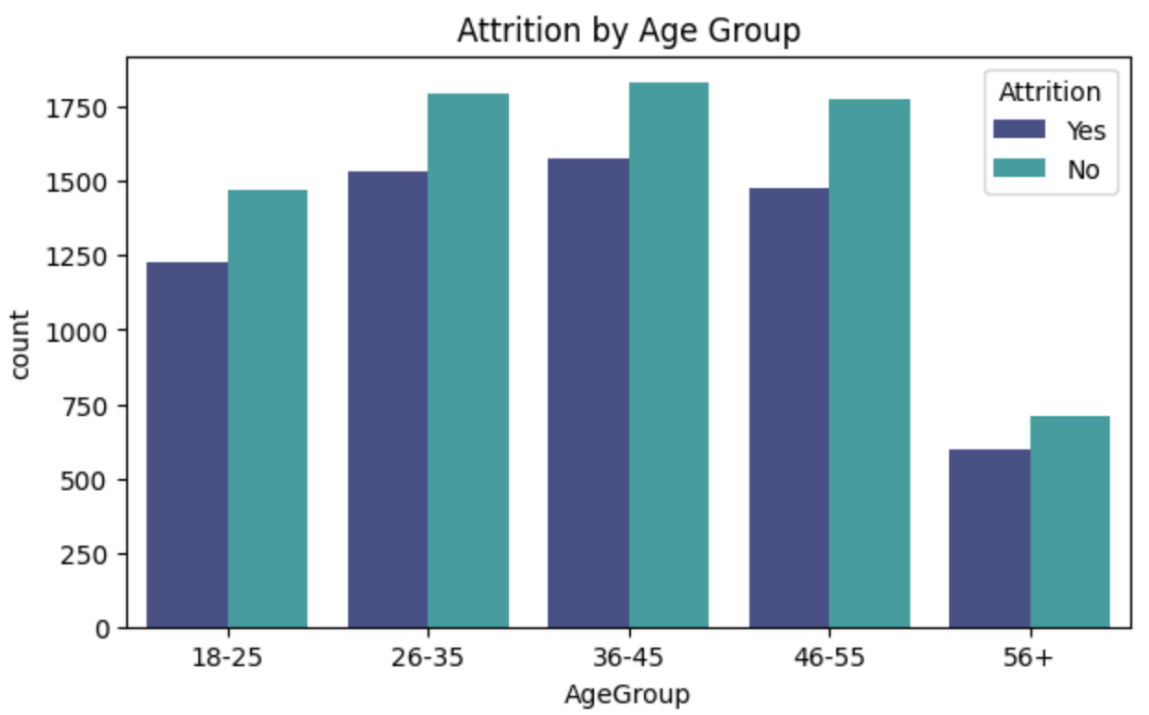
```
✅ Dataset Loaded Successfully
Shape: (14000, 27)
   Age     BusinessTravel  DailyRate              Department  \
0   21  Travel_Frequently        478  Research & Development
1   50         Non-Travel        908  Research & Development
2   45      Travel_Rarely       1448         Human Resources
3   36         Non-Travel       1095         Human Resources
4   36  Travel_Frequently        535         Human Resources

   DistanceFromHome  Education  EnvironmentSatisfaction  Gender  JobLevel  \
0                 2          4                        1  Female         4
1                19          1                        1    Male         1
2                18          2                        1    Male         1
3                25          1                        2    Male         5
4                17          2                        1  Female         1

                    JobRole  ...  RelationshipSatisfaction StockOptionLevel  \
0    Manufacturing Director  ...                         2                2
1     Laboratory Technician  ...                         3                0
2  Healthcare Representative  ...                         3                1
3                   Manager  ...                         1                2
4      Sales Representative  ...                         2                0

   TotalWorkingYears  TrainingTimesLastYear WorkLifeBalance  YearsAtCompany  \
0                  2                      3               1              15
1                 23                      3               3               9
2                 28                      1               3              13
3                 27                      3               2              32
4                 14                      5               3              10
```

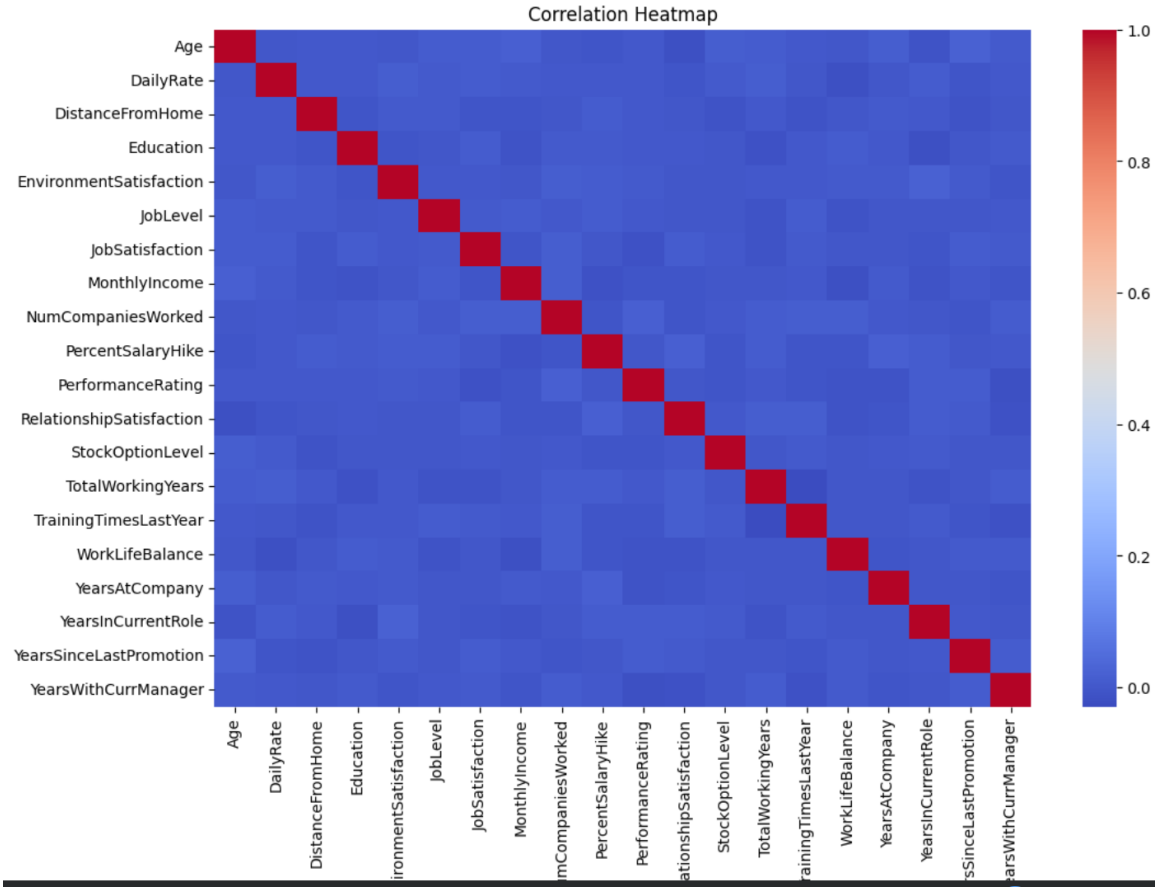
```
Missing Values per column:
Age                         0
BusinessTravel              0
DailyRate                   0
Department                  0
DistanceFromHome            0
Education                   0
EnvironmentSatisfaction     0
Gender                      0
JobLevel                    0
JobRole                     0
JobSatisfaction             0
MaritalStatus               0
MonthlyIncome               0
NumCompaniesWorked          0
OverTime                    0
PercentSalaryHike           0
PerformanceRating           0
RelationshipSatisfaction    0
StockOptionLevel            0
TotalWorkingYears           0
TrainingTimesLastYear       0
WorkLifeBalance             0
YearsAtCompany              0
YearsInCurrentRole          0
YearsSinceLastPromotion     0
YearsWithCurrManager        0
Attrition                   0
dtype: int64
```

```
Dataset info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14000 entries, 0 to 13999
Data columns (total 27 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Age                       14000 non-null  int64
 1   BusinessTravel            14000 non-null  object
 2   DailyRate                 14000 non-null  int64
 3   Department                14000 non-null  object
 4   DistanceFromHome          14000 non-null  int64
 5   Education                 14000 non-null  int64
 6   EnvironmentSatisfaction   14000 non-null  int64
 7   Gender                    14000 non-null  object
 8   JobLevel                  14000 non-null  int64
 9   JobRole                   14000 non-null  object
 10  JobSatisfaction           14000 non-null  int64
 11  MaritalStatus             14000 non-null  object
 12  MonthlyIncome             14000 non-null  int64
 13  NumCompaniesWorked        14000 non-null  int64
 14  OverTime                  14000 non-null  object
 15  PercentSalaryHike         14000 non-null  int64
 16  PerformanceRating         14000 non-null  int64
 17  RelationshipSatisfaction  14000 non-null  int64
 18  StockOptionLevel          14000 non-null  int64
 19  TotalWorkingYears         14000 non-null  int64
 20  TrainingTimesLastYear     14000 non-null  int64
 21  WorkLifeBalance           14000 non-null  int64
 22  YearsAtCompany            14000 non-null  int64
 23  YearsInCurrentRole        14000 non-null  int64
```


Attrition Count
7000
6000
5000
4000
3000
2000
1000
0
count
Yes
No
Attrition


Attrition by Department
2500
2000
1500
1000
500
0
count
Attrition
Yes
No
Research & Development
Human Resources
Sales
Department

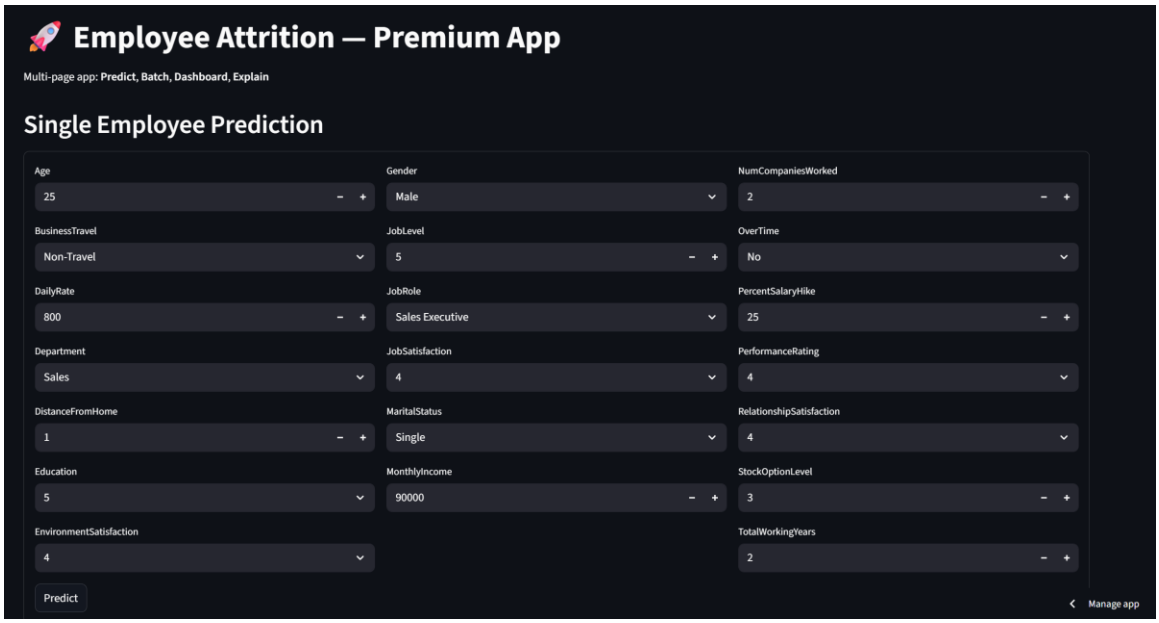

Attrition by Age Group
Attrition
Yes
No
count
1750
1500
1250
1000
750
500
250
0
18-25
26-35
36-45
46-55
56+
AgeGroup

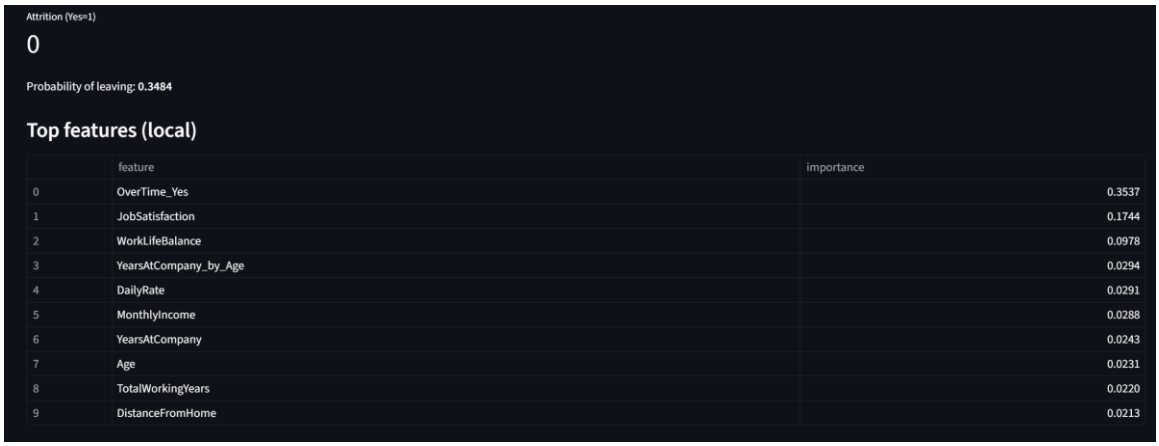

Correlation Heatmap
Age
DailyRate
DistanceFromHome
Education
EnvironmentSatisfaction
JobLevel
JobSatisfaction
MonthlyIncome
NumCompaniesWorked
PercentSalaryHike
PerformanceRating
RelationshipSatisfaction
StockOptionLevel
TotalWorkingYears
TrainingTimesLastYear
WorkLifeBalance
YearsAtCompany
YearsInCurrentRole
YearsSinceLastPromotion
YearsWithCurrManager
1.0
0.8
0.6
0.4
0.2
0.0

```
Class Distribution:
Attrition_flag
0    0.541607
1    0.458393
Name: proportion, dtype: float64

Model Accuracy Comparison:
Logistic Regression: 81.86%
Decision Tree: 78.61%
Random Forest: 83.54%
Gradient Boosting: 83.61%
Fitting 5 folds for each of 20 candidates, totalling 100 fits

Best Parameters: {'n_estimators': 200, 'min_samples_split': 10, 'min_samples_leaf': 2, 'max_features': 'log2', 'max_depth': 20}

🎉 PKL FILE GENERATED SUCCESSFULLY:
👉 /content/attrition_model_pipeline.pkl

Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.83      0.85      1517
           1       0.81      0.85      0.83      1283

    accuracy                           0.84      2800
   macro avg       0.84      0.84      0.84      2800
weighted avg       0.84      0.84      0.84      2800

Accuracy: 0.8378571428571429
ROC-AUC: 0.9297583993513883

✅ Training Complete!
```

Stream-lit Deployment:

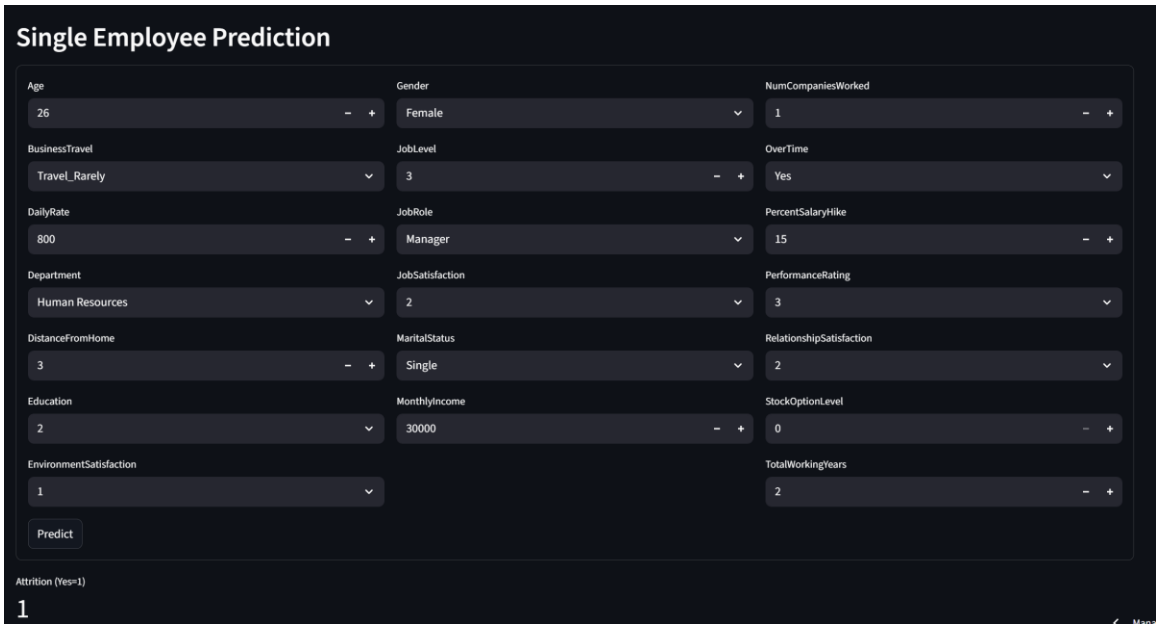
Employee will not leave:

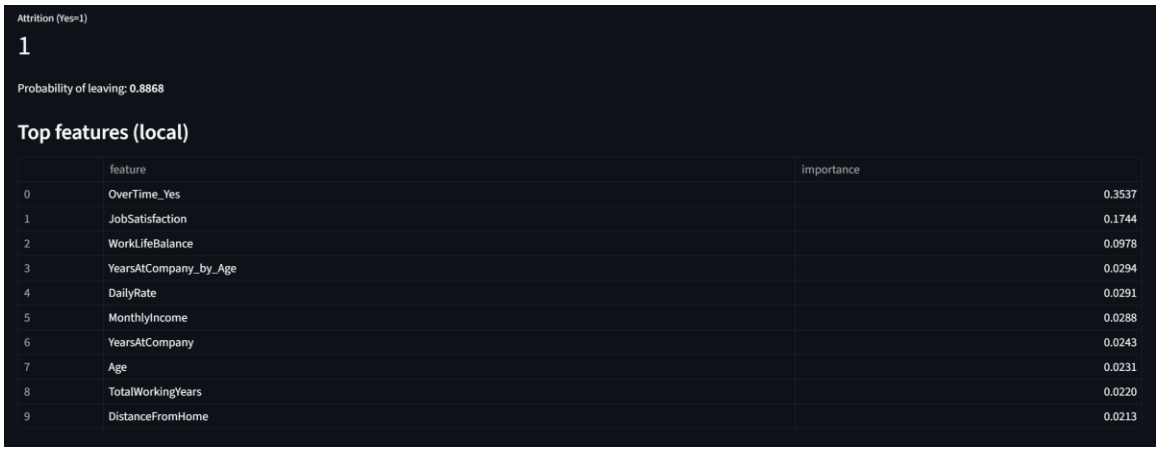




	feature	importance
0	OverTime_Yes	0.3537
1	JobSatisfaction	0.1744
2	WorkLifeBalance	0.0978
3	YearsAtCompany_by_Age	0.0294
4	DailyRate	0.0291
5	MonthlyIncome	0.0288
6	YearsAtCompany	0.0243
7	Age	0.0231
8	TotalWorkingYears	0.0220
9	DistanceFromHome	0.0213

Employee will leave:





CONCLUSION:

The machine learning model developed in this experiment successfully predicts whether an employee is likely to leave the organization.

Random Forest performed the best after hyperparameter tuning.

This experiment demonstrates the full pipeline of a machine learning project including data preprocessing, model training, evaluation, and deployment,

highlighting the importance of predictive analytics in HR decision-making.