DevikaJainProject2

April 10, 2025

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.feature_selection import SelectKBest, f_classif

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import classification_report, accuracy_score
from imblearn.over_sampling import SMOTE
```

[2]:
```
from google.colab import files
uploaded = files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving HR-Employee-Attrition.csv to HR-Employee-Attrition.csv
```

[3]:
```
df = pd.read_csv("HR-Employee-Attrition.csv")
df.head()
```

[3]:
```
   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]
```

[4]:
```python
df.shape
df.info()
df.describe()
```

```
<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
```

[4]:

```
               Age    DailyRate  DistanceFromHome    Education  EmployeeCount  \
count  1470.000000  1470.000000       1470.000000  1470.000000         1470.0
mean     36.923810   802.485714          9.192517     2.912925            1.0
std       9.135373   403.509100          8.106864     1.024165            0.0
min      18.000000   102.000000          1.000000     1.000000            1.0
25%      30.000000   465.000000          2.000000     2.000000            1.0
50%      36.000000   802.000000          7.000000     3.000000            1.0
75%      43.000000  1157.000000         14.000000     4.000000            1.0
max      60.000000  1499.000000         29.000000     5.000000            1.0

       EmployeeNumber  EnvironmentSatisfaction   HourlyRate  JobInvolvement  \
count     1470.000000              1470.000000  1470.000000     1470.000000
mean      1024.865306                 2.721769    65.891156        2.729932
std        602.024335                 1.093082    20.329428        0.711561
min          1.000000                 1.000000    30.000000        1.000000
25%        491.250000                 2.000000    48.000000        2.000000
50%       1020.500000                 3.000000    66.000000        3.000000
75%       1555.750000                 4.000000    83.750000        3.000000
max       2068.000000                 4.000000   100.000000        4.000000

          JobLevel  …  RelationshipSatisfaction  StandardHours  \
count  1470.000000  …               1470.000000         1470.0
```

```
mean      2.063946  …                   2.712245           80.0
std       1.106940  …                   1.081209            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       1470.000000        1470.000000            1470.000000
mean           0.793878          11.279592               2.799320
std            0.852077           7.780782               1.289271
min            0.000000           0.000000               0.000000
25%            0.000000           6.000000               2.000000
50%            1.000000          10.000000               3.000000
75%            1.000000          15.000000               3.000000
max            3.000000          40.000000               6.000000

       WorkLifeBalance  YearsAtCompany  YearsInCurrentRole  \
count      1470.000000     1470.000000         1470.000000
mean          2.761224        7.008163            4.229252
std           0.706476        6.126525            3.623137
min           1.000000        0.000000            0.000000
25%           2.000000        3.000000            2.000000
50%           3.000000        5.000000            3.000000
75%           3.000000        9.000000            7.000000
max           4.000000       40.000000           18.000000

       YearsSinceLastPromotion  YearsWithCurrManager
count              1470.000000           1470.000000
mean                  2.187755              4.123129
std                   3.222430              3.568136
min                   0.000000              0.000000
25%                   0.000000              2.000000
50%                   1.000000              3.000000
75%                   3.000000              7.000000
max                  15.000000             17.000000

[8 rows x 26 columns]
```

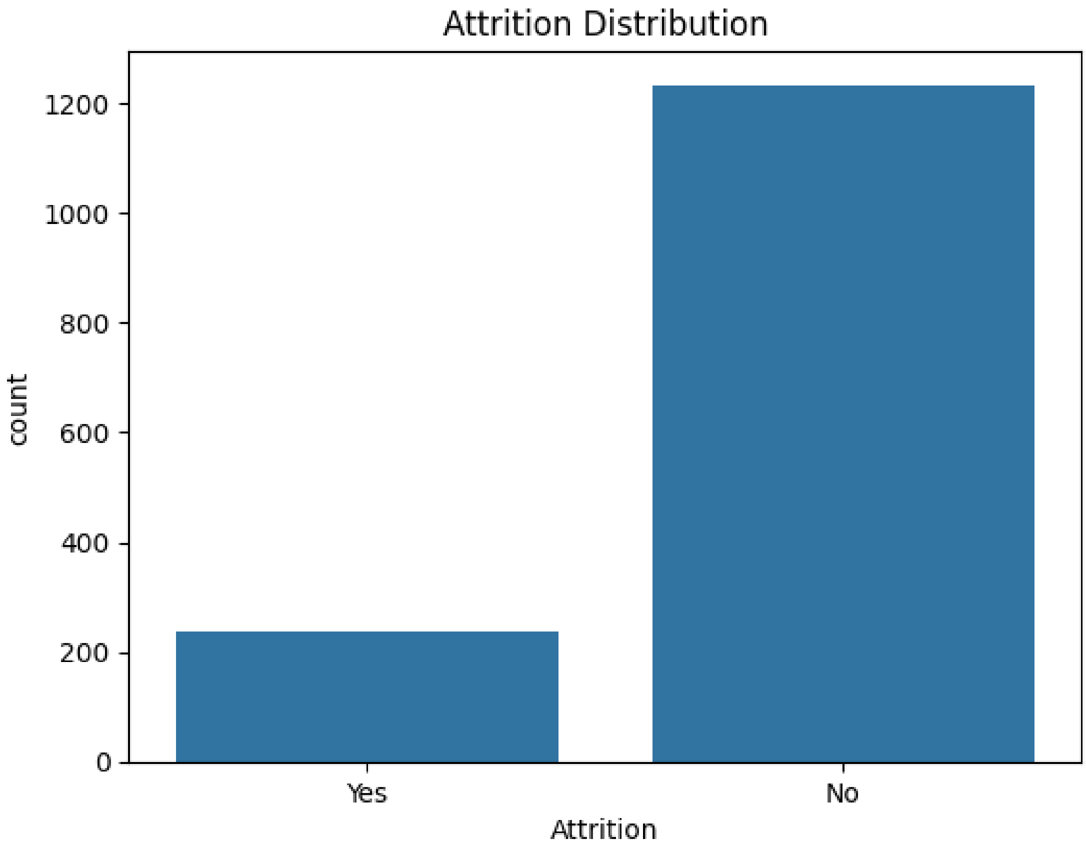
[5]:

```python
# Check for nulls and basic info
print(df.info())
print(df['Attrition'].value_counts())

# Visualize class imbalance
sns.countplot(data=df, x='Attrition')
plt.title("Attrition Distribution")
```

```
plt.show()
```

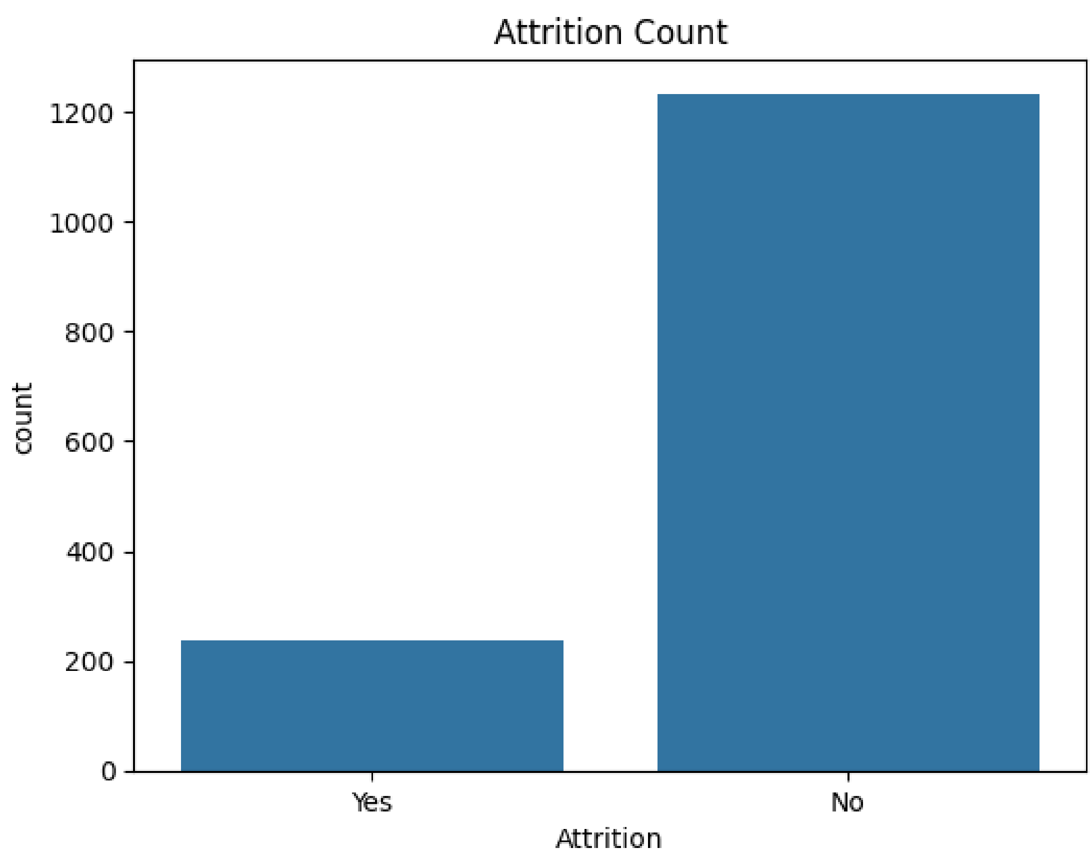
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 35 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   Age                       1470 non-null   int64 
 1   Attrition                 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
None
Attrition
No     1233
```

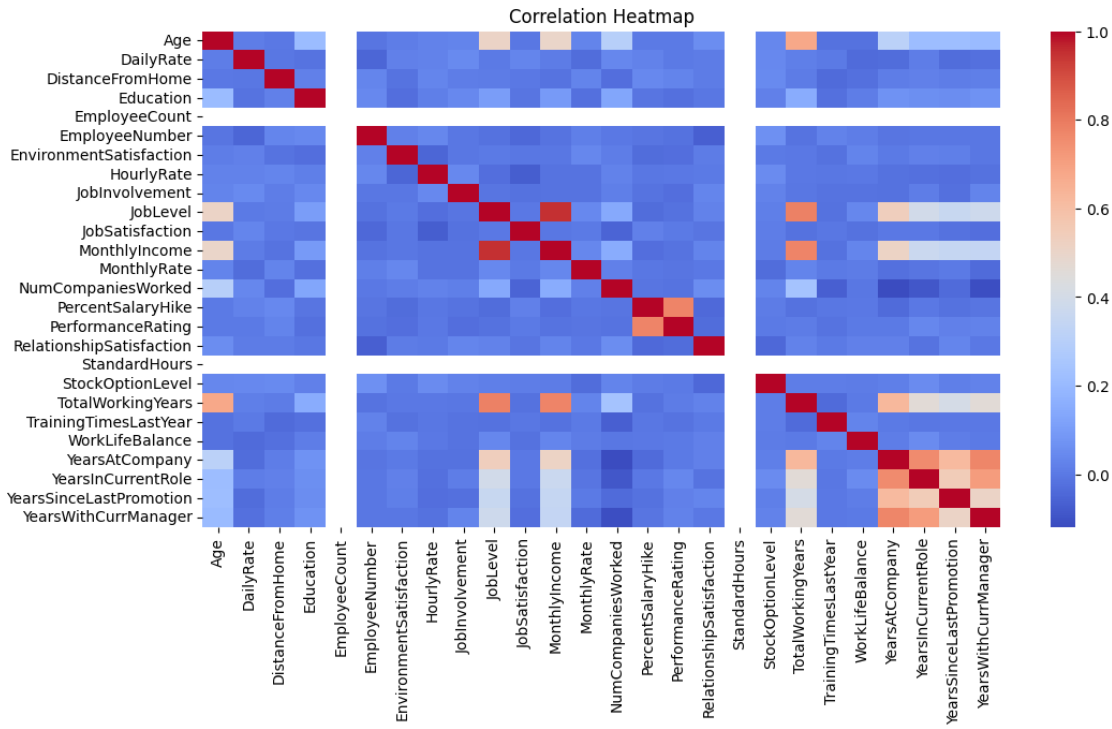
```
Yes     237
Name: count, dtype: int64
```

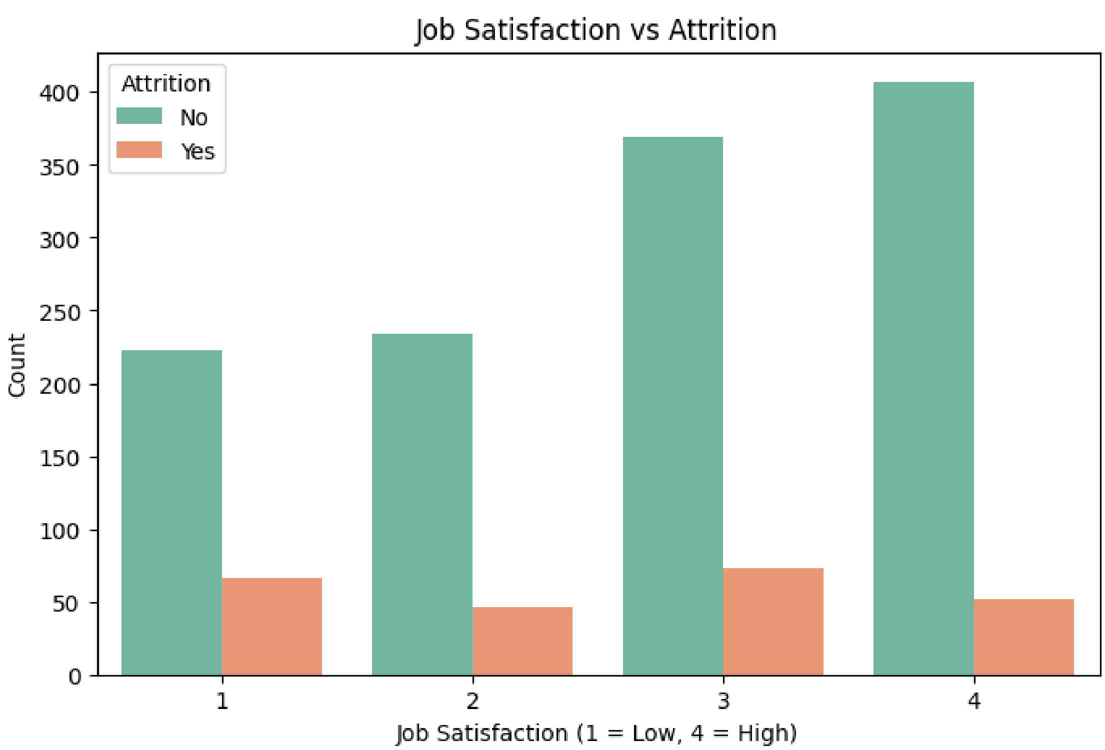



```
[6]: # Check target distribution
sns.countplot(data=df, x='Attrition')
plt.title("Attrition Count")
plt.show()
# This graph displays the distribution of the target variable - whether an␣
↪employee has left the company (Attrition = Yes)
# or not (Attrition = No).
# It helps us understand the class imbalance in the dataset.
# If one class (e.g., "No") is significantly higher than the other, it␣
↪indicates the need for balancing techniques like SMOTE.

# Correlation Heatmap
plt.figure(figsize=(12, 6))
sns.heatmap(df.corr(numeric_only=True), cmap='coolwarm', annot=False)
plt.title("Correlation Heatmap")
plt.show()
```

```
# This heatmap displays the correlation coefficients between all numerical␣
↪features in the dataset.
# Values range from -1 to +1.
#     +1 indicates a strong positive correlation.
#     -1 indicates a strong negative correlation.
#     0 means no linear correlation.
# This helps us identify features that might be strongly related, which can␣
↪guide feature selection or removal to avoid multicollinearity.
# Job Satisfaction Countplot split by Attrition
plt.figure(figsize=(8, 5))
sns.countplot(data=df, x='JobSatisfaction', hue='Attrition', palette='Set2')
plt.title("Job Satisfaction vs Attrition")
plt.xlabel("Job Satisfaction (1 = Low, 4 = High)")
plt.ylabel("Count")
plt.legend(title="Attrition")
plt.show()
# If attrition is higher at satisfaction level 1, it suggests low satisfaction␣
↪is linked to higher attrition.
# If level 4 shows mostly "No", it implies higher satisfaction may retain␣
↪employees better.
```




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


Job Satisfaction vs Attrition
Attrition
No
Yes
Count
0
50
100
150
200
250
300
350
400
1
2
3
4
Job Satisfaction (1 = Low, 4 = High)

[7]:
```
#  Drop unnecessary columns
df = df.drop(['EmployeeCount', 'EmployeeNumber', 'Over18', 'StandardHours'],␣
 ↪axis=1)
# we dropped :
# EmployeeCount: This column has the same value for all employees(usually 1),so␣
 ↪it doesn't provide any useful information for the model.
# EmployeeNumber: It's a unique identifier for each employee, like an ID. It␣
 ↪creates noise.
# Over18:  Like EmployeeCount, it's constant across the dataset, so it adds no␣
 ↪value
# StandardHours: All employees have the same standard hours (usually 40).No␣
 ↪variation = no influence on model prediction.
```

[8]:
```
# Encode categorical variables
le = LabelEncoder()
for col in df.select_dtypes(include=['object']).columns:
    df[col] = le.fit_transform(df[col])
```

[9]:
```
# Impute missing values (if any)
imputer = SimpleImputer(strategy='mean')
df = pd.DataFrame(imputer.fit_transform(df), columns=df.columns)
```

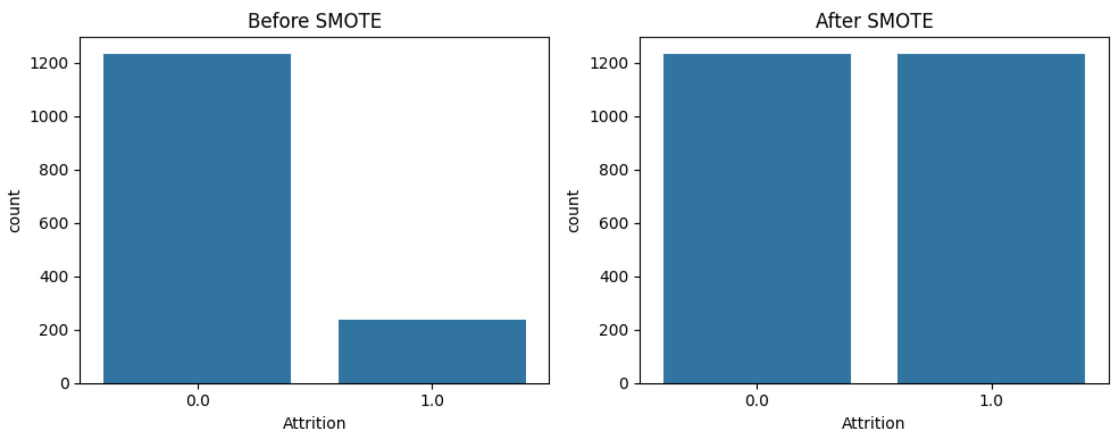
[10]:
```
# Feature Scaling
scaler = StandardScaler()
# StandardScaler normalizes the features so they all have:
    # Mean = 0
    # Standard Deviation = 1
X_scaled = pd.DataFrame(scaler.fit_transform(df.drop('Attrition', axis=1)),␣
 ↪columns=df.drop('Attrition', axis=1).columns)
y = df['Attrition']
# since in ml:
    # X = Features (input variables we use to make predictions)
    # y = Target (what we want to predict)
# X_scaled = All employee-related attributes (like Age, JobSatisfaction,␣
 ↪Department, etc.)
# y = Whether the employee left the company or not → the Attrition column␣
 ↪(usually "Yes"/"No", or 0/1 after encoding)
```

[11]:
```
# Show class distribution before SMOTE
print("Before SMOTE - Class distribution:")
print(y.value_counts())

# Handle Class Imbalance with SMOTE
sm = SMOTE(random_state=42)
X_resampled, y_resampled = sm.fit_resample(X_scaled, y)
```

```
# Show class distribution after SMOTE
print("\nAfter SMOTE - Class distribution:")
print(pd.Series(y_resampled).value_counts())
```

```
Before SMOTE - Class distribution:
Attrition
0.0    1233
1.0     237
Name: count, dtype: int64

After SMOTE - Class distribution:
Attrition
1.0    1233
0.0    1233
Name: count, dtype: int64
```

[12]:
```
plt.figure(figsize=(10, 4))

# Before SMOTE
plt.subplot(1, 2, 1)
sns.countplot(x=y)
plt.title("Before SMOTE")
plt.xlabel("Attrition")

# SMOTE (Synthetic Minority Over-sampling Technique) creates synthetic samples␣
↪of
# the minority class (e.g., employees who left) so that the dataset becomes␣
↪balanced.
# Purpose: Fix imbalance so the model won't be biased toward the majority class.
# After SMOTE
plt.subplot(1, 2, 2)
sns.countplot(x=y_resampled)
plt.title("After SMOTE")
plt.xlabel("Attrition")
plt.tight_layout()
plt.show()
```



[13]:
```
# Feature Selection
selector = SelectKBest(score_func=f_classif, k=10)
# SelectKBest is a feature selection technique.
# It selects the top k features that have the strongest relationship with the␣
↪target variable (y_resampled, which is Attrition here).
# You set k=10, so it will keep only the 10 most important features.
X_selected = selector.fit_transform(X_resampled, y_resampled)
selected_features = X_scaled.columns[selector.get_support()]
print("Top features:", selected_features)
```

```
Top features: Index(['Age', 'JobLevel', 'MaritalStatus', 'MonthlyIncome',
'OverTime',
       'StockOptionLevel', 'TotalWorkingYears', 'YearsAtCompany',
       'YearsInCurrentRole', 'YearsWithCurrManager'],
      dtype='object')
```

[14]:
```
X_train, X_test, y_train, y_test = train_test_split(X_selected, y_resampled,␣
↪test_size=0.2, random_state=42)

models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Random Forest": RandomForestClassifier(),
    "Support Vector Machine": SVC(probability = True)
}
model_accuracies = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    model_accuracies[name] = acc
    print(f"--- {name} ---")
    print(f"{name} Accuracy: {acc:.4f}")
```

```
    print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
--- Logistic Regression ---
Logistic Regression Accuracy: 0.6943
Classification Report:
               precision    recall  f1-score   support

         0.0       0.71      0.68      0.69       250
         1.0       0.68      0.71      0.70       244

    accuracy                           0.69       494
   macro avg       0.69      0.69      0.69       494
weighted avg       0.69      0.69      0.69       494

--- Random Forest ---
Random Forest Accuracy: 0.8664
Classification Report:
               precision    recall  f1-score   support

         0.0       0.85      0.89      0.87       250
         1.0       0.88      0.84      0.86       244

    accuracy                           0.87       494
   macro avg       0.87      0.87      0.87       494
weighted avg       0.87      0.87      0.87       494

--- Support Vector Machine ---
Support Vector Machine Accuracy: 0.7429
Classification Report:
               precision    recall  f1-score   support

         0.0       0.75      0.75      0.75       250
         1.0       0.74      0.74      0.74       244

    accuracy                           0.74       494
   macro avg       0.74      0.74      0.74       494
weighted avg       0.74      0.74      0.74       494
```

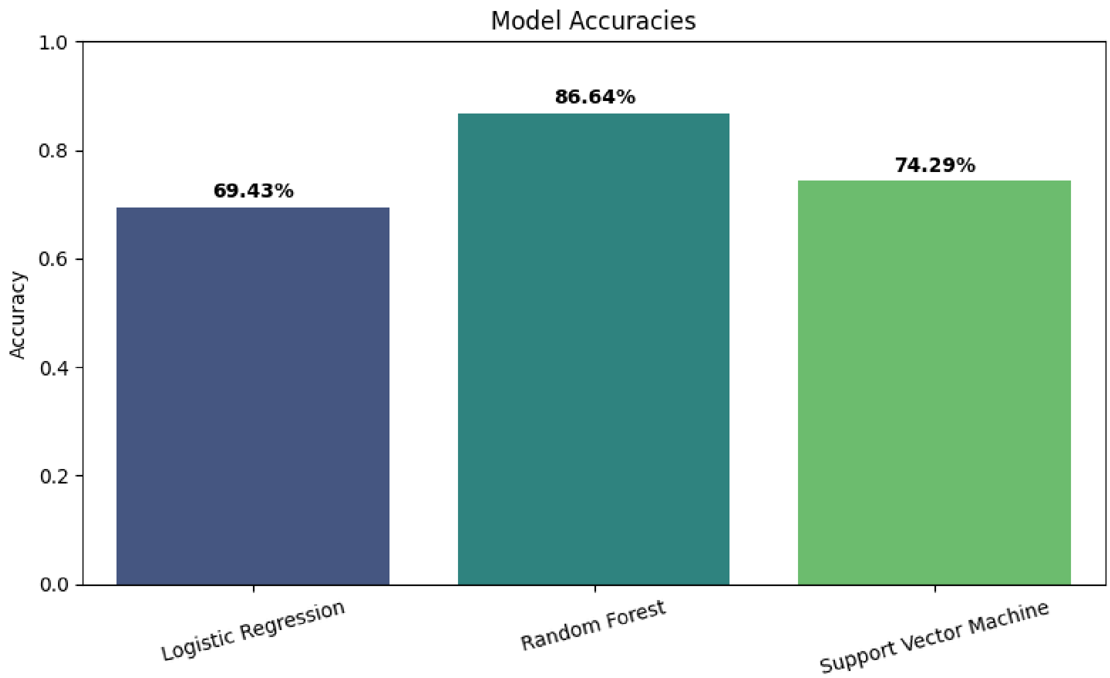
[15]:
```
for name, model in models.items():
    scores = cross_val_score(model, X_selected, y_resampled, cv=5)
    print(f"{name} Average CV Score: {np.mean(scores):.4f}")
```

```
Logistic Regression Average CV Score: 0.7271
Random Forest Average CV Score: 0.8906
Support Vector Machine Average CV Score: 0.7851
```

[16]:

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

# Plot accuracies
plt.figure(figsize=(8, 5))
bars = sns.barplot(
    x=list(model_accuracies.keys()),
    y=list(model_accuracies.values()),
    palette='viridis',
    legend=False
)

plt.ylabel("Accuracy")
plt.title("Model Accuracies")
plt.ylim(0, 1)
plt.xticks(rotation=15)


for bar in bars.patches:
    height = bar.get_height()
    plt.text(
        bar.get_x() + bar.get_width() / 2,
        height + 0.01,
        f"{height * 100:.2f}%",
        ha='center',
        va='bottom',
        fontsize=10,
        fontweight='bold'
    )

plt.tight_layout()
plt.show()
```

```
<ipython-input-16-3143671cc981>:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  bars = sns.barplot(
```



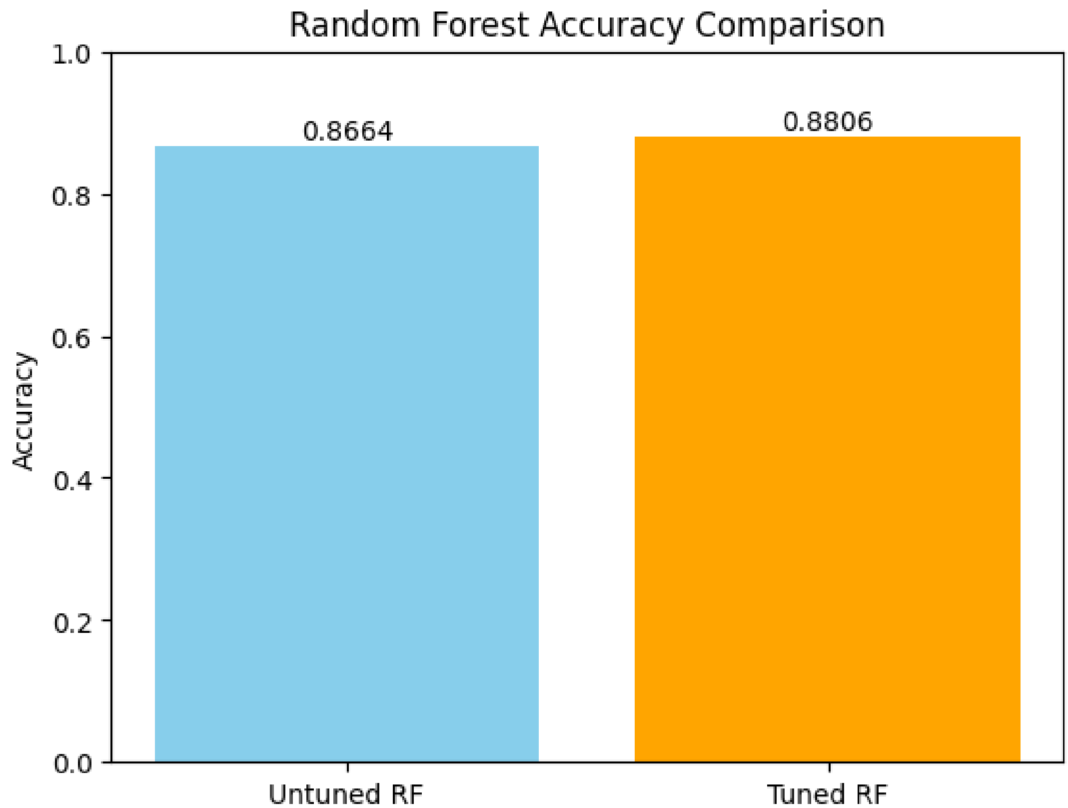
[17]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectKBest, f_classif

# --- Feature Selection (already done) ---
selector = SelectKBest(score_func=f_classif, k=10)
X_selected = selector.fit_transform(X_resampled, y_resampled)
selected_features = X_scaled.columns[selector.get_support()]
print("Selected Top Features:", selected_features)

# --- Train-Test Split ---
X_train, X_test, y_train, y_test = train_test_split(X_selected, y_resampled,␣
↪test_size=0.2, random_state=42)

# --- Hyperparameter Tuning for Random Forest ---
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2],
    'bootstrap': [True, False]
}

rf = RandomForestClassifier(random_state=42)
```

```python
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid,
                           cv=5, n_jobs=-1, verbose=1, scoring='accuracy')

grid_search.fit(X_train, y_train)

print("Best Parameters Found:", grid_search.best_params_)
print("Best Accuracy Score:", grid_search.best_score_)

# --- Evaluate on Test Data ---
best_rf = grid_search.best_estimator_
y_pred = best_rf.predict(X_test)
print("Test Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Selected Top Features: Index(['Age', 'JobLevel', 'MaritalStatus',
'MonthlyIncome', 'OverTime',
       'StockOptionLevel', 'TotalWorkingYears', 'YearsAtCompany',
       'YearsInCurrentRole', 'YearsWithCurrManager'],
      dtype='object')
Fitting 5 folds for each of 48 candidates, totalling 240 fits
Best Parameters Found: {'bootstrap': False, 'max_depth': None,
'min_samples_leaf': 2, 'min_samples_split': 2, 'n_estimators': 200}
Best Accuracy Score: 0.8965507935488016
Test Accuracy: 0.8805668016194332
Classification Report:
               precision    recall  f1-score   support

         0.0       0.86      0.92      0.89       250
         1.0       0.91      0.84      0.87       244

    accuracy                           0.88       494
   macro avg       0.88      0.88      0.88       494
weighted avg       0.88      0.88      0.88       494
```

[18]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt

# Split the data (assuming X_selected and y_resampled are already defined)
X_train, X_test, y_train, y_test = train_test_split(X_selected, y_resampled,␣
 ↪test_size=0.2, random_state=42)

# Untuned Random Forest
rf_default = RandomForestClassifier(random_state=42)
rf_default.fit(X_train, y_train)
```

```python
y_pred_default = rf_default.predict(X_test)
acc_default = accuracy_score(y_test, y_pred_default)

# GridSearchCV for Tuned Random Forest
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2],
    'bootstrap': [True, False]
}
grid_search = GridSearchCV(RandomForestClassifier(random_state=42), param_grid,␣
 ↪cv=5, n_jobs=-1)
grid_search.fit(X_train, y_train)
best_rf = grid_search.best_estimator_
y_pred_tuned = best_rf.predict(X_test)
acc_tuned = accuracy_score(y_test, y_pred_tuned)

# Plotting comparison
plt.bar(['Untuned RF', 'Tuned RF'], [acc_default, acc_tuned], color=['skyblue',␣
 ↪'orange'])
plt.title('Random Forest Accuracy Comparison')
plt.ylabel('Accuracy')
plt.ylim(0, 1)
plt.text(0, acc_default + 0.01, f'{acc_default:.4f}', ha='center')
plt.text(1, acc_tuned + 0.01, f'{acc_tuned:.4f}', ha='center')
plt.show()
```


Random Forest Accuracy Comparison
0.8664
0.8806
Accuracy
1.0
0.8
0.6
0.4
0.2
0.0
Untuned RF
Tuned RF