Task_4_Churn_Prediction_Model

November 24, 2025

1 1. Load and Clean the Dataset

1.1 Import Libraries
1.2 Data From GitHub
1.3 Check the missing values
1.4 Convert TotalCharges to Numeric
1.5 Fill the missing value with median
1.6 Also Check the " " value
1.7 Convert types

[73]:
```
# 1.1 Import Libraries
import pandas as pd
import numpy as np

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, classification_report, confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

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

[74]:
```
# 1.2 Data From GitHub

# GitHub raw URL
url = 'https://raw.githubusercontent.com/abuthahir17/Dataset/main/
↪Telco_Customer_Churn_Dataset.csv'

# Read CSV file
data = pd.read_csv(url)

print("Dataset Loaded Successfully!")
```

```
Dataset Loaded Successfully!
```

[75]:
```python
# 1.3 Check the missing values
data.replace(" ", None, inplace=True)
print("Missing Value: \n", data.isnull().sum())
```

```
Missing Value:
 customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges       11
Churn               0
dtype: int64
```

[76]:
```python
# 1.4 Convert TotalCharges to Numeric
data["TotalCharges"] = pd.to_numeric(data["TotalCharges"], errors="coerce")
```

[77]:
```python
# 1.5 Fill the missing value with median
data["TotalCharges"] = data["TotalCharges"].fillna(data["TotalCharges"].
 ↪median())
```

[78]:
```python
# 1.6 Also Check the " " value
data.replace(" ", None, inplace=True)
print("Missing Value after Cleaning: \n", data.isnull().sum())
```

```
Missing Value after Cleaning:
 customerID         0
gender             0
SeniorCitizen      0
Partner            0
Dependents         0
tenure             0
PhoneService       0
MultipleLines      0
```

```
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

[79]:
```
# 1.7 Convert types
data["Churn"] = data["Churn"].map({"Yes":1, "No":0})
```

2 2. Encoding Categorical Variables

2.1 Identify Numerical and Categorical Columns
2.2 Before Encoding
2.3 During Encoding
2.4 After Encoding

[80]:
```
# 2.1 Identify numerical columns
numerical_cols = data.select_dtypes(include=['int64', 'float64']).columns
print("Total number of Numerical Columns:", len(numerical_cols))
print("All Numerical Columns:" ,list(numerical_cols), "\n")

# 2.1 Identify categorical columns
categorical_cols = data.select_dtypes(include=['object']).columns
print("Total number of Categorical Columns:", len(categorical_cols))
print("All Categorical Columns:" , list(categorical_cols))
```

```
Total number of Numerical Columns: 5
All Numerical Columns: ['SeniorCitizen', 'tenure', 'MonthlyCharges',
'TotalCharges', 'Churn']

Total number of Categorical Columns: 16
All Categorical Columns: ['customerID', 'gender', 'Partner', 'Dependents',
'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod']
```

[81]:
```
# 2.2 Before Encoding

print("Before encoding:\n", data.head())
```

```
print("Shape before encoding:", data.shape)
```

```
Before encoding:
   customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1           No
1  5575-GNVDE    Male              0      No         No      34          Yes
2  3668-QPYBK    Male              0      No         No       2          Yes
3  7795-CFOCW    Male              0      No         No      45           No
4  9237-HQITU  Female              0      No         No       2          Yes

      MultipleLines InternetService OnlineSecurity  … DeviceProtection  \
0  No phone service             DSL             No  …               No
1                No             DSL            Yes  …              Yes
2                No             DSL            Yes  …               No
3  No phone service             DSL            Yes  …              Yes
4                No     Fiber optic             No  …               No

  TechSupport StreamingTV StreamingMovies        Contract PaperlessBilling  \
0          No          No              No  Month-to-month              Yes
1          No          No              No        One year               No
2          No          No              No  Month-to-month              Yes
3         Yes          No              No        One year               No
4          No          No              No  Month-to-month              Yes

               PaymentMethod MonthlyCharges  TotalCharges  Churn
0           Electronic check          29.85         29.85      0
1               Mailed check          56.95       1889.50      0
2               Mailed check          53.85        108.15      1
3  Bank transfer (automatic)          42.30       1840.75      0
4           Electronic check          70.70        151.65      1

[5 rows x 21 columns]
Shape before encoding: (7043, 21)
```

[82]:
```
# 2.3 During Encoding

from sklearn.preprocessing import LabelEncoder

# Binary columns (2 unique values)
binary_cols = [col for col in categorical_cols if data[col].nunique() == 2]
print("Binary Columns (LabelEncode):", binary_cols, "\n")

# Multi-category columns (>2 unique values)
multi_cat_cols = [col for col in categorical_cols if data[col].nunique() > 2␣
 ↪and col not in binary_cols]
print("Multi-category Columns (One-hot Encode):", multi_cat_cols, "\n")
```

```python
label_encoder = LabelEncoder()

# Binary
for col in binary_cols:
    data[col] = label_encoder.fit_transform(data[col])

# Multi-Category (One-Hot Encoding)
data = pd.get_dummies(data, columns=multi_cat_cols, drop_first=True)

print("Categorical Encoding Completed.")
```

```
Binary Columns (LabelEncode): ['gender', 'Partner', 'Dependents',
'PhoneService', 'PaperlessBilling']

Multi-category Columns (One-hot Encode): ['customerID', 'MultipleLines',
'InternetService', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
'TechSupport', 'StreamingTV', 'StreamingMovies', 'Contract', 'PaymentMethod']

Categorical Encoding Completed.
```

[83]:

```python
# 2.4 After Encoding

print("After encoding:\n", data.head())
print("New Shape After Encoding:", data.shape)
```

```
After encoding:
    gender  SeniorCitizen  Partner  Dependents  tenure  PhoneService  \
0       0              0        1           0       1             0
1       1              0        0           0      34             1
2       1              0        0           0       2             1
3       1              0        0           0      45             0
4       0              0        0           0       2             1

   PaperlessBilling  MonthlyCharges  TotalCharges  Churn  …  \
0                 1           29.85         29.85      0  …
1                 0           56.95       1889.50      0  …
2                 1           53.85        108.15      1  …
3                 0           42.30       1840.75      0  …
4                 1           70.70        151.65      1  …

   TechSupport_Yes  StreamingTV_No internet service  StreamingTV_Yes  \
0            False                            False            False
1            False                            False            False
2            False                            False            False
3             True                            False            False
4            False                            False            False

   StreamingMovies_No internet service  StreamingMovies_Yes  \
```

```
0                              False                False
1                              False                False
2                              False                False
3                              False                False
4                              False                False

   Contract_One year  Contract_Two year  \
0              False              False
1               True              False
2              False              False
3               True              False
4              False              False

   PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
0                                  False                            True
1                                  False                           False
2                                  False                           False
3                                  False                           False
4                                  False                            True

   PaymentMethod_Mailed check
0                       False
1                        True
2                        True
3                       False
4                       False

[5 rows x 7073 columns]
New Shape After Encoding: (7043, 7073)
```

3 3. Dataset Splitting (Train/Test)

```
3.1 Fix the target variable
3.2 Split the Dataset
```

[84]:

```
#3.1 Fix the target variable
from sklearn.model_selection import train_test_split

# Target variable
X = data.drop("Churn", axis=1)
y = data["Churn"]
```

[85]:

```
# 3.2 Split the dataset into 2 set (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

```
print("Training set shape:", X_train.shape)
print("Testing set shape:", X_test.shape)
```

```
Training set shape: (5634, 7072)
Testing set shape: (1409, 7072)
```

4 4. Standardize Numerical Features

[86]:
```
scaler = StandardScaler()
num_cols = ['tenure', 'MonthlyCharges', 'TotalCharges']

# scale only if columns exist in X (safety)
num_cols = [c for c in num_cols if c in X_train.columns]

X_train[num_cols] = scaler.fit_transform(X_train[num_cols])
X_test[num_cols] = scaler.transform(X_test[num_cols])
```

5 5. Fix class imbalance on training set using SMOTE

[87]:
```
from imblearn.over_sampling import SMOTE

# Synthetic Minority Oversampling Technique (SMOTE) -> To fix class imbalance␣
↪in your churn dataset.

smote = SMOTE(random_state=42)
X_train_sm, y_train_sm = smote.fit_resample(X_train, y_train)
print("After SMOTE ->", X_train_sm.shape, y_train_sm.sum(), "positive samples")
```

```
After SMOTE -> (8278, 7072) 4139 positive samples
```

6 6. Model Training

6.1 Logistic Regression
6.2 Decision Tree
6.3 Random Forest

[88]:
```
# 6.1 Logistic Regression

log = LogisticRegression(max_iter=1000, random_state=42)
log.fit(X_train_sm, y_train_sm)
y_pred_log = log.predict(X_test)

print("Logistic Regression Results:")
print(classification_report(y_test, y_pred_log))
```

```
Logistic Regression Results:
              precision    recall  f1-score   support
```

```
           0       0.86      0.83      0.84      1035
           1       0.57      0.62      0.59       374

    accuracy                           0.78      1409
   macro avg       0.71      0.73      0.72      1409
weighted avg       0.78      0.78      0.78      1409
```

[89]:
```
# 6.2 Decision Tree

dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train_sm, y_train_sm)
y_pred_tree = dt.predict(X_test)

print("Decision Tree Results:")
print(classification_report(y_test, y_pred_tree))
```

```
Decision Tree Results:
              precision    recall  f1-score   support

           0       0.85      0.84      0.84      1035
           1       0.57      0.60      0.59       374

    accuracy                           0.77      1409
   macro avg       0.71      0.72      0.71      1409
weighted avg       0.78      0.77      0.78      1409
```

[90]:
```
# 6.3 Random Forest

rf = RandomForestClassifier(n_estimators=200, random_state=42)
rf.fit(X_train_sm, y_train_sm)
y_pred_rf = rf.predict(X_test)

print("Random Forest Results:")
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Results:
              precision    recall  f1-score   support

           0       0.86      0.86      0.86      1035
           1       0.61      0.61      0.61       374

    accuracy                           0.79      1409
   macro avg       0.73      0.74      0.74      1409
weighted avg       0.79      0.79      0.79      1409
```

7 7. Hyperparameter tuning for RandomForest (GridSearchCV)

[91]:
```
# Hyperparameter Tuning (Decision Tree Example)
from sklearn.model_selection import GridSearchCV

param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [5, 10, None],
    'min_samples_split': [2, 5]
}

grid = GridSearchCV(
    RandomForestClassifier(random_state=42),
    param_grid,
    scoring='f1',
    cv=3,
    n_jobs=-1,
    verbose=1
)

grid.fit(X_train_sm, y_train_sm)
best_rf = grid.best_estimator_
print("\nGridSearch best params:", grid.best_params_)
```

```
Fitting 3 folds for each of 12 candidates, totalling 36 fits

GridSearch best params: {'max_depth': None, 'min_samples_split': 2,
'n_estimators': 200}
```

8 8. Tuned Random Forest Evaluation

```
8.1 Classification Report of Tuned Random Forest
8.2 Confusion Matrix of Tuned Random Forest
8.3 ROC Curve and AUC Score
```

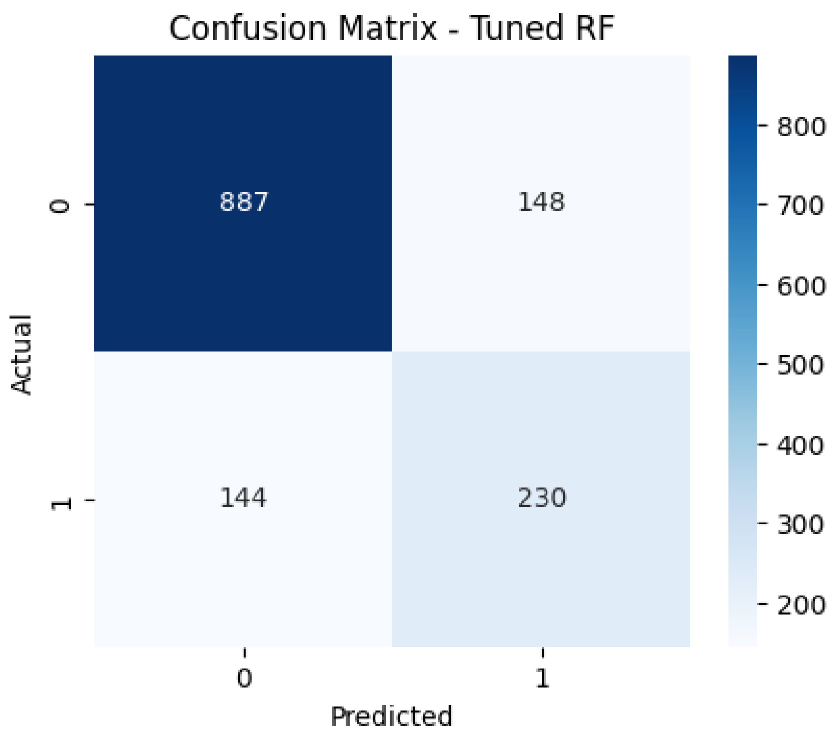
[92]:
```
# 8.1 Classification Report of Tuned Random Forest
y_pred_best = best_rf.predict(X_test)
print("\nTuned Random Forest:\n", classification_report(y_test, y_pred_best))
```

```

Tuned Random Forest:
               precision    recall  f1-score   support

           0       0.86      0.86      0.86      1035
           1       0.61      0.61      0.61       374

    accuracy                           0.79      1409
   macro avg       0.73      0.74      0.74      1409
```

```
weighted avg       0.79      0.79      0.79      1409
```

[93]:

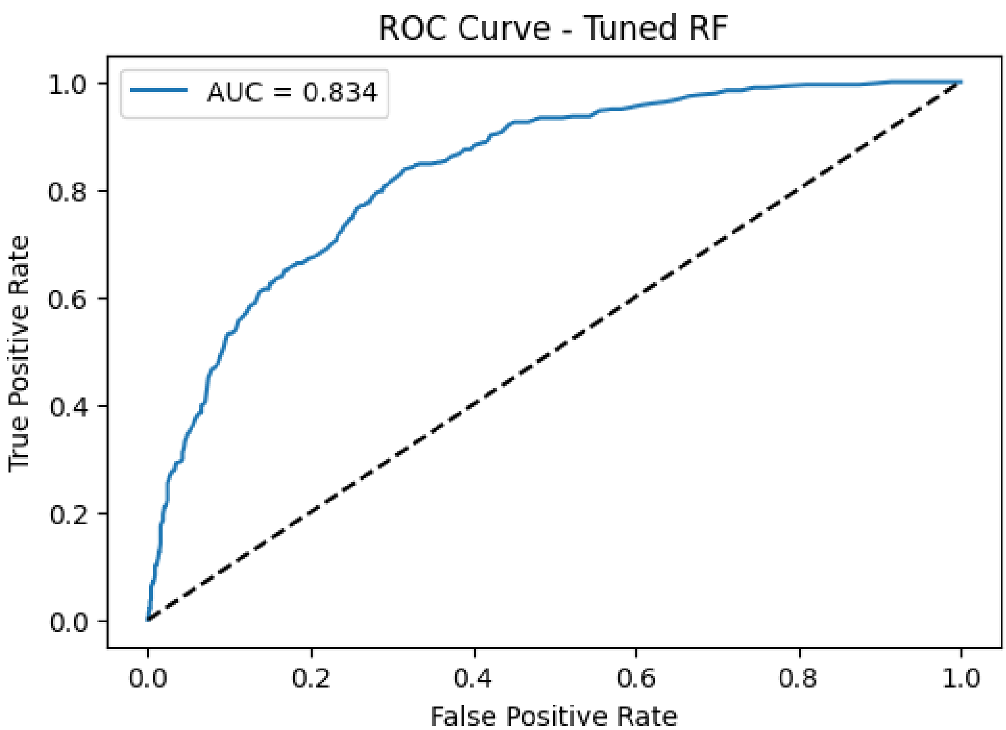
```
# 8.2 Confusion Matrix of Tuned Random Forest
cm = confusion_matrix(y_test, y_pred_best)
plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confusion Matrix - Tuned RF")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



[94]:

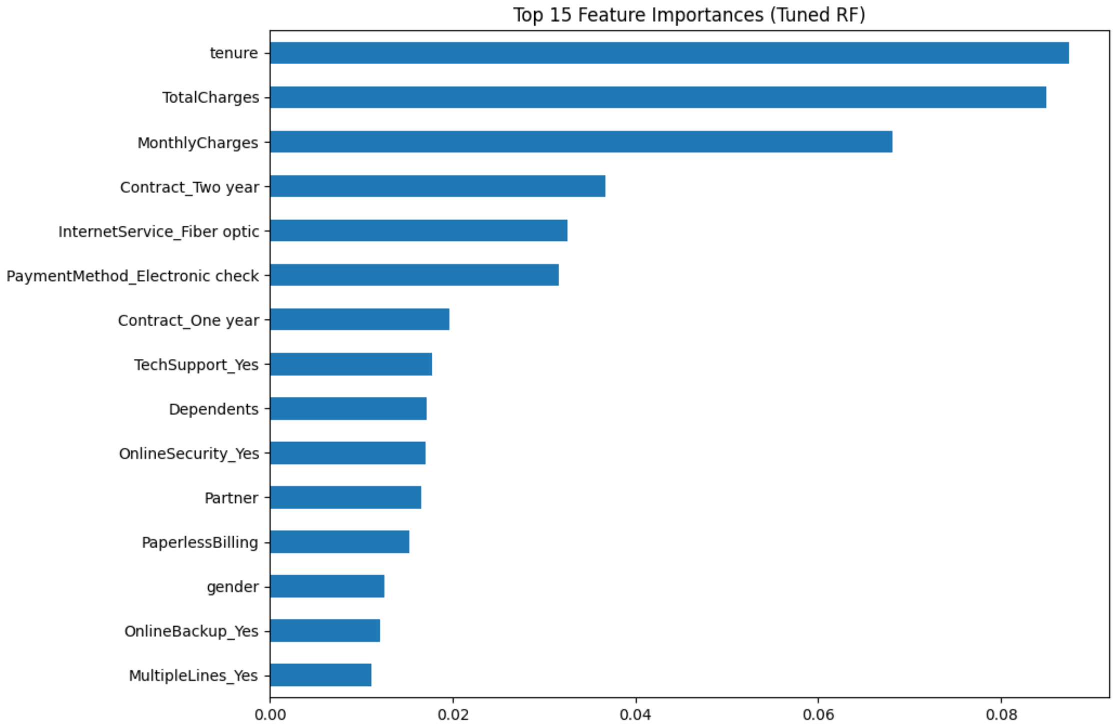
```
# 8.3 ROC Curve and AUC Score
from sklearn.metrics import roc_curve, roc_auc_score

y_prob = best_rf.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
auc = roc_auc_score(y_test, y_prob)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, label=f"AUC = {auc:.3f}")
plt.plot([0,1],[0,1],'k--')
plt.title("ROC Curve - Tuned RF")
plt.xlabel("False Positive Rate")
```

```
plt.ylabel("True Positive Rate")
plt.legend()
plt.show()
```



9 9. Feature Importance

[95]:
```
# Feature Importance (Random Forest)

importances = pd.Series(best_rf.feature_importances_, index=X.columns)
top_imp = importances.sort_values(ascending=False).head(15)
plt.figure(figsize=(10,8))
top_imp.plot(kind='barh')
plt.gca().invert_yaxis()
plt.title("Top 15 Feature Importances (Tuned RF)")
plt.show()
```



10 10. Final comparison table

[96]:
```python
# 10. Final comparison

def evaluate(name, y_true, y_pred):
    print(f"\n{name}")
    print("Accuracy :", accuracy_score(y_true, y_pred))
    print("Precision:", precision_score(y_true, y_pred, zero_division=0))
    print("Recall   :", recall_score(y_true, y_pred, zero_division=0))
    print("F1 Score :", f1_score(y_true, y_pred, zero_division=0))

evaluate("Logistic Regression", y_test, y_pred_log)
evaluate("Decision Tree", y_test, y_pred_tree)
evaluate("Random Forest (baseline)", y_test, y_pred_rf)
evaluate("Random Forest (tuned)", y_test, y_pred_best)
```

```
Logistic Regression
Accuracy : 0.7757274662881476
Precision: 0.5714285714285714
Recall   : 0.6203208556149733
F1 Score : 0.5948717948717949
```

```
Decision Tree
Accuracy : 0.7735982966643009
Precision: 0.569620253164557
Recall   : 0.6016042780748663
F1 Score : 0.5851755526657998

Random Forest (baseline)
Accuracy : 0.7927608232789212
Precision: 0.6084656084656085
Recall   : 0.6149732620320856
F1 Score : 0.6117021276595744

Random Forest (tuned)
Accuracy : 0.7927608232789212
Precision: 0.6084656084656085
Recall   : 0.6149732620320856
F1 Score : 0.6117021276595744
```