Week3_Assignment

February 6, 2024

[34]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix, ConfusionMatrixDisplay
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
```

0.1 Load dataset

[35]:
```
df = pd.read_csv("prepped_churn_data.csv")

df
```

[35]:
```
      customerID  tenure  PhoneService        Contract  \
0              1       1             0  Month-to-month
1              2      34             1        One year
2              3       2             1  Month-to-month
3              4      45             0        One year
4              5       2             1  Month-to-month
…            …       …             …             …
7038        7039      24             1        One year
7039        7040      72             1        One year
7040        7041      11             0  Month-to-month
7041        7042       4             1  Month-to-month
7042        7043      66             1        Two year

                  PaymentMethod  MonthlyCharges  TotalCharges  Churn  \
0              Electronic check        3.396185         29.85      0
1                  Mailed check        4.042174       1889.50      0
2                  Mailed check        3.986202        108.15      1
3     Bank transfer (automatic)        3.744787       1840.75      0
4              Electronic check        4.258446        151.65      1
…                           …             …           …    …
7038               Mailed check        4.440296       1990.50      0
7039    Credit card (automatic)        4.636669       7362.90      0
```

```
7040          Electronic check        3.387774        346.45      0
7041               Mailed check        4.309456        306.60      1
7042  Bank transfer (automatic)        4.660132       6844.50      0

      MonthlyCharges_Tenure_Ratio  MonthlyCharges_to_TotalCharges_Ratio
0                        3.396185                              0.113775
1                        0.118887                              0.002139
2                        1.993101                              0.036858
3                        0.083217                              0.002034
4                        2.129223                              0.028081
…                             …                                   …
7038                     0.185012                              0.002231
7039                     0.064398                              0.000630
7040                     0.307979                              0.009779
7041                     1.077364                              0.014056
7042                     0.070608                              0.000681

[7043 rows x 10 columns]
```

0.2 Generate dummies and convert to numeric

[36]:
```
payment_method_dummies = pd.get_dummies(df['PaymentMethod'])
contract_dummies = pd.get_dummies(df['Contract'])

df = pd.concat([df, payment_method_dummies, contract_dummies], axis=1)
df.head()
```

[36]:
```
   customerID  tenure  PhoneService        Contract  \
0           1       1             0  Month-to-month
1           2      34             1        One year
2           3       2             1  Month-to-month
3           4      45             0        One year
4           5       2             1  Month-to-month

               PaymentMethod  MonthlyCharges  TotalCharges  Churn  \
0           Electronic check        3.396185         29.85      0
1               Mailed check        4.042174       1889.50      0
2               Mailed check        3.986202        108.15      1
3  Bank transfer (automatic)        3.744787       1840.75      0
4           Electronic check        4.258446        151.65      1

   MonthlyCharges_Tenure_Ratio  MonthlyCharges_to_TotalCharges_Ratio  \
0                     3.396185                              0.113775
1                     0.118887                              0.002139
2                     1.993101                              0.036858
3                     0.083217                              0.002034
4                     2.129223                              0.028081
```

```
   Bank transfer (automatic)  Credit card (automatic)  Electronic check  \
0                      False                    False              True
1                      False                    False             False
2                      False                    False             False
3                       True                    False             False
4                      False                    False              True

   Mailed check  Month-to-month  One year  Two year
0         False            True     False     False
1          True           False      True     False
2          True            True     False     False
3         False           False      True     False
4         False            True     False     False
```

[37]:
```python
dummy_columns = ['Electronic check', 'Mailed check', 'Bank transfer␣
↪(automatic)', 'Credit card (automatic)', 'Month-to-month', 'One year', 'Two␣
↪year']

for column in dummy_columns:
    df[column] = pd.factorize(df[column])[0]

df.sample(5)
```

[37]:
```
      customerID  tenure  PhoneService        Contract  \
1048        1049      29             1        One year
871          872      57             1        One year
1225        1226      16             0  Month-to-month
6120        6121       6             1  Month-to-month
5415        5416      18             1  Month-to-month

                  PaymentMethod  MonthlyCharges  TotalCharges  Churn  \
1048               Mailed check        2.985682         572.2      0
871     Credit card (automatic)        4.580365        5598.0      0
1225           Electronic check        3.911023         810.2      1
6120           Electronic check        4.085136         357.6      0
5415           Electronic check        3.918005         913.3      0

      MonthlyCharges_Tenure_Ratio  MonthlyCharges_to_TotalCharges_Ratio  \
1048                     0.102955                              0.005218
871                      0.080357                              0.000818
1225                     0.244439                              0.004827
6120                     0.680856                              0.011424
5415                     0.217667                              0.004290

      Bank transfer (automatic)  Credit card (automatic)  Electronic check  \
1048                          0                        0                 1
```

```
871                               0                         1                 1
1225                              0                         0                 0
6120                              0                         0                 0
5415                              0                         0                 0

      Mailed check  Month-to-month  One year  Two year
1048             1               1         1         0
871              0               1         1         0
1225             0               0         0         0
6120             0               0         0         0
5415             0               0         0         0
```

0.3 Drop original cat columns

[38]:
```python
df.drop(columns=['PaymentMethod', 'Contract', 'customerID'], inplace=True)
df
```

[38]:
```
      tenure  PhoneService  MonthlyCharges  TotalCharges  Churn  \
0          1             0        3.396185         29.85      0
1         34             1        4.042174       1889.50      0
2          2             1        3.986202        108.15      1
3         45             0        3.744787       1840.75      0
4          2             1        4.258446        151.65      1
…        …            …             …           …     …
7038      24             1        4.440296       1990.50      0
7039      72             1        4.636669       7362.90      0
7040      11             0        3.387774        346.45      0
7041       4             1        4.309456        306.60      1
7042      66             1        4.660132       6844.50      0

      MonthlyCharges_Tenure_Ratio  MonthlyCharges_to_TotalCharges_Ratio  \
0                        3.396185                              0.113775
1                        0.118887                              0.002139
2                        1.993101                              0.036858
3                        0.083217                              0.002034
4                        2.129223                              0.028081
…                             …                                   …
7038                     0.185012                              0.002231
7039                     0.064398                              0.000630
7040                     0.307979                              0.009779
7041                     1.077364                              0.014056
7042                     0.070608                              0.000681

      Bank transfer (automatic)  Credit card (automatic)  Electronic check  \
0                             0                        0                 0
1                             0                        0                 1
2                             0                        0                 1
```

```
3                             1                        0                 1
4                             0                        0                 0
…                          …                      …               …
7038                          0                        0                 1
7039                          0                        1                 1
7040                          0                        0                 0
7041                          0                        0                 1
7042                          1                        0                 1

      Mailed check  Month-to-month  One year  Two year
0                0               0         0         0
1                1               1         1         0
2                1               0         0         0
3                0               1         1         0
4                0               0         0         0
…            …             …       …       …
7038             1               1         1         0
7039             0               1         1         0
7040             0               0         0         0
7041             1               0         0         0
7042             0               1         0         1

[7043 rows x 14 columns]
```

[39]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 14 columns):
 #   Column                                 Non-Null Count  Dtype
---  ------                                 --------------  -----
 0   tenure                                 7043 non-null   int64
 1   PhoneService                           7043 non-null   int64
 2   MonthlyCharges                         7043 non-null   float64
 3   TotalCharges                           7043 non-null   float64
 4   Churn                                  7043 non-null   int64
 5   MonthlyCharges_Tenure_Ratio            7043 non-null   float64
 6   MonthlyCharges_to_TotalCharges_Ratio   7043 non-null   float64
 7   Bank transfer (automatic)              7043 non-null   int64
 8   Credit card (automatic)                7043 non-null   int64
 9   Electronic check                       7043 non-null   int64
 10  Mailed check                           7043 non-null   int64
 11  Month-to-month                         7043 non-null   int64
 12  One year                               7043 non-null   int64
 13  Two year                               7043 non-null   int64
dtypes: float64(4), int64(10)
memory usage: 770.5 KB
```

0.4 Removing outliers

[40]:
```
numerical_columns = df.select_dtypes(include=[np.number]).columns

# IQR-based function to remove outliers
def remove_outliers_iqr(data_frame, columns):
    for column in columns:
        Q1 = data_frame[column].quantile(0.25)
        Q3 = data_frame[column].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        data_frame = data_frame[(data_frame[column] >= lower_bound) &␣
 ↪(data_frame[column] <= upper_bound)]
    return data_frame

df_clean = remove_outliers_iqr(df, numerical_columns)
df_clean
```

[40]:
```
      tenure  PhoneService  MonthlyCharges  TotalCharges  Churn  \
5          8             1        4.601664        820.50      1
6         22             1        4.489759       1949.40      0
8         28             1        4.652054       3046.05      1
11        16             1        2.941804        326.80      0
13        49             1        4.641502       5036.30      1
…        …             …             …            …     …
7033      38             1        4.241327       2625.25      0
7034      67             1        4.634243       6886.25      1
7035      19             1        4.365643       1495.10      0
7037      72             1        3.051640       1419.40      0
7042      66             1        4.660132       6844.50      0

      MonthlyCharges_Tenure_Ratio  MonthlyCharges_to_TotalCharges_Ratio  \
5                        0.575208                              0.005608
6                        0.204080                              0.002303
8                        0.166145                              0.001527
11                       0.183863                              0.009002
13                       0.094725                              0.000922
…                             …                                   …
7033                     0.111614                              0.001616
7034                     0.069168                              0.000673
7035                     0.229771                              0.002920
7037                     0.042384                              0.002150
7042                     0.070608                              0.000681

      Bank transfer (automatic)  Credit card (automatic)  Electronic check  \
5                             0                        0                 0
```

```
6                                 0                        1                 1
8                                 0                        0                 0
11                                0                        1                 1
13                                1                        0                 1
…                             …                      …                …
7033                              0                        1                 1
7034                              0                        1                 1
7035                              1                        0                 1
7037                              1                        0                 1
7042                              1                        0                 1

      Mailed check  Month-to-month  One year  Two year
5                0               0         0         0
6                0               0         0         0
8                0               0         0         0
11               0               1         0         1
13               0               0         0         0
…            …             …        …       …
7033             0               0         0         0
7034             0               0         0         0
7035             0               0         0         0
7037             0               1         0         1
7042             0               1         0         1

[3026 rows x 14 columns]
```

0.5 Data Modelling

[41]:
```python
X = df_clean.drop('Churn', axis=1)
y = df_clean['Churn']
```

[42]:
```python
X.sample()
```

[42]:
```
      tenure  PhoneService  MonthlyCharges  TotalCharges  \
7024      44             1        4.440296       3626.35

      MonthlyCharges_Tenure_Ratio  MonthlyCharges_to_TotalCharges_Ratio  \
7024                     0.100916                              0.001224

      Bank transfer (automatic)  Credit card (automatic)  Electronic check  \
7024                          0                        1                 1

      Mailed check  Month-to-month  One year  Two year
7024             0               0         0         0
```

0.6 Split data into training and testing sets

[43]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

0.7 Fit model into training data

[44]:
```
rf_model = RandomForestClassifier(random_state=42)

# Train the model
rf_model.fit(X_train, y_train)
```

[44]:
```
RandomForestClassifier(random_state=42)
```

[45]:
```
df['Churn'].value_counts(normalize=True)
```

[45]:
```
Churn
0    0.73463
1    0.26537
Name: proportion, dtype: float64
```

The frequency of each unique value in the Churn column is calculated. Setting normalize=True returns the relative frequencies proportions instead of raw counts. The proportion of the two unique values are as,

```
Yes: 0.26537
No : 0.73463
```

[46]:
```
print(rf_model.score(X_train, y_train))
print(rf_model.score(X_test, y_test))
```

```
1.0
0.7442244224422442
```

0.8 Performance Evaluation on the training and testing set

[47]:
```
train_predictions = rf_model.predict(X_train)
train_accuracy = accuracy_score(y_train, train_predictions)
print(f'Training Accuracy: {train_accuracy}')
```

```
Training Accuracy: 1.0
```

[48]:
```
test_predictions = rf_model.predict(X_test)
test_accuracy = accuracy_score(y_test, test_predictions)
print(f'Test Accuracy: {test_accuracy}')
```

```
Test Accuracy: 0.7442244224422442
```

0.9 Comparison with NO IR

[49]:
```
no_info_rate = max(y_train.value_counts(normalize=True))
print(f'No Information Rate: {no_info_rate}')
```

```
No Information Rate: 0.7442148760330578
```

Training Accuracy (1.0)

This indicates that the model achieved perfect accuracy on the training data, correctly predicting all churn outcomes.

Test Accuracy (0.746)

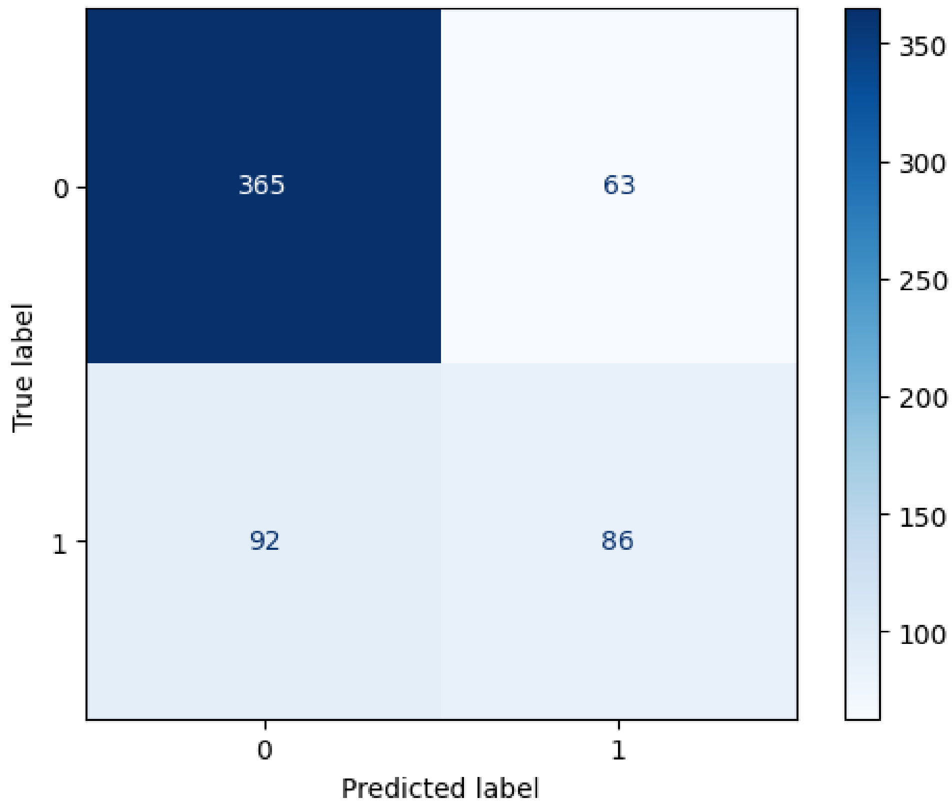
The model's accuracy on the test data is approximately 74.6%, meaning it correctly predicted churn outcomes for about 74.6% of the customers in the test set. It suggests that the model is moderately effective in predicting churn based on the given features.

No-Information Rate (0.744)

This rate serves as a baseline metric, indicating the accuracy achieved by always predicting the majority class (i.e., No churn).

0.10 Confusion matrix

[50]:
```
cm = confusion_matrix(y_test, test_predictions, labels=rf_model.classes_)

# format and display the confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=rf_model.
 ↪classes_)
disp.plot(cmap=plt.cm.Blues)
plt.show()
```



True negatives (TN) The model correctly predicted 369 instances where the true label is 0 (no churn). This signifies the number of customers who were correctly identified as not churning.

False negatives (FN) The model incorrectly predicted no churn when the true label is 1 (churn) in 95 instances. These are customers who churned despite the model predicting otherwise.

True positives (TP) The model correctly predicted 83 instances where the true label is 1 (churn). This signifies the number of customers who were correctly identified as churning. These are customers who actually churned, and the model successfully flagged them for attention or intervention.

False positives (FP) The model incorrectly predicted 1 (churn) when the true label is 0 (no churn) in 59 instances. This signifies the number of customers who were incorrectly identified as churning, leading to unnecessary intervention or resources being allocated to customers who were not at risk of churning.

0.11 Tuning the model

[51]:
```
rf_model.predict_proba(X_test)
```

[51]: array([[1. , 0.],
        [0.4 , 0.6],
        [0.79, 0.21],
        …,
        [0.76, 0.24],
        [0.7 , 0.3],
        [0.73, 0.27]])

0.12 Hyperparameter grid

[52]:
```
param_grid = {
    'n_estimators': [10, 50, 100],
    'max_depth': [None, 5, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Create the GridSearchCV object
grid_search = GridSearchCV(rf_model, param_grid=param_grid, cv=3,␣
 ↪scoring='accuracy')

# Fit the model to the training data with grid search
grid_search.fit(X_train, y_train)
```

[52]:
```
GridSearchCV(cv=3, estimator=RandomForestClassifier(random_state=42),
             param_grid={'max_depth': [None, 5, 10, 20],
                         'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10],
                         'n_estimators': [10, 50, 100]},
             scoring='accuracy')
```

0.13 Best hyperparameters

[53]:
```
print(f'Best hyperparameters: {grid_search.best_params_}')
```

Best hyperparameters: {'max_depth': 5, 'min_samples_leaf': 1,
'min_samples_split': 2, 'n_estimators': 100}

[54]:
```
best_model = grid_search.best_estimator_
test_predictions = best_model.predict(X_test)
```

[55]:
```
test_accuracy = accuracy_score(y_test, test_predictions)
print(f'Test Accuracy: {test_accuracy}')
```

Test Accuracy: 0.7656765676567657

0.14 Comparing with No information rate

[56]:
```
no_info_rate = max(y_train.value_counts(normalize=True))
print(f'No Information Rate: {no_info_rate}')
```

```
No Information Rate: 0.7442148760330578
```

0.15 Feature Importances

[57]:
```
feature_importances = rf_model.feature_importances_
feature_importances
```

[57]:
```
array([0.11909002, 0.        , 0.21096741, 0.16718326, 0.20039006,
       0.16038264, 0.00860197, 0.00808315, 0.02888944, 0.        ,
       0.05754082, 0.        , 0.03887124])
```

The values represent the proportion of impurity reduction that each feature contributes to the model.

Higher values indicate features that are more influential in making predictions.

0.16 Display feature importances

[58]:
```
importance_df = pd.DataFrame({'Feature': X_train.columns, 'Importance':␣
↪feature_importances})
importance_df.head(5)
```

[58]:

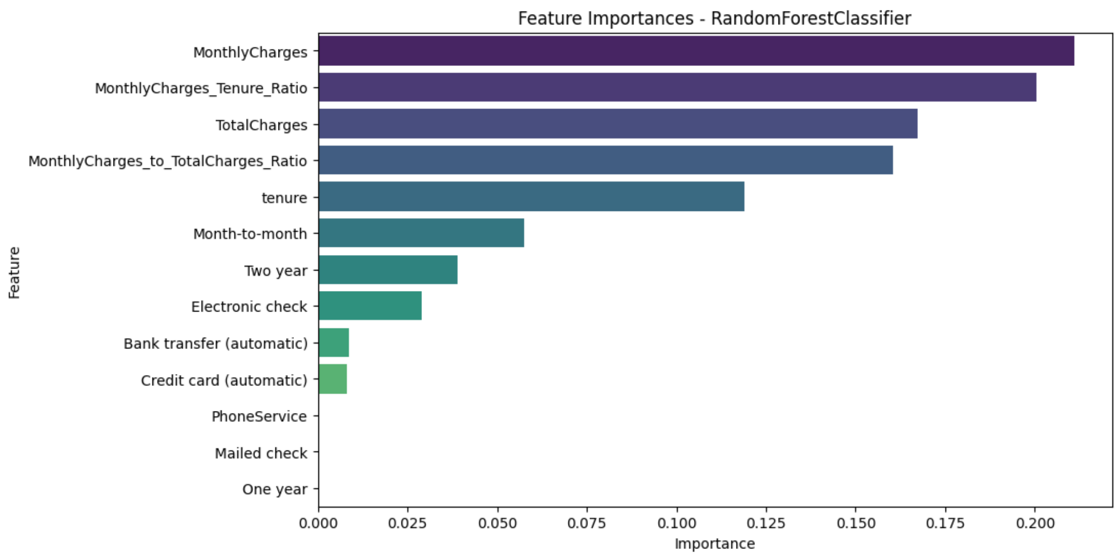
	Feature	Importance
0	tenure	0.119090
1	PhoneService	0.000000
2	MonthlyCharges	0.210967
3	TotalCharges	0.167183
4	MonthlyCharges_Tenure_Ratio	0.200390

0.17 Sort df by Importance

[59]:
```
importance_df = importance_df.sort_values(by='Importance', ascending=False)
```

0.18 Bar cahrt to visualize feature importances

[60]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=importance_df, hue='Feature',␣
↪palette='viridis', legend=False)
plt.title('Feature Importances - RandomForestClassifier')
plt.show()
```



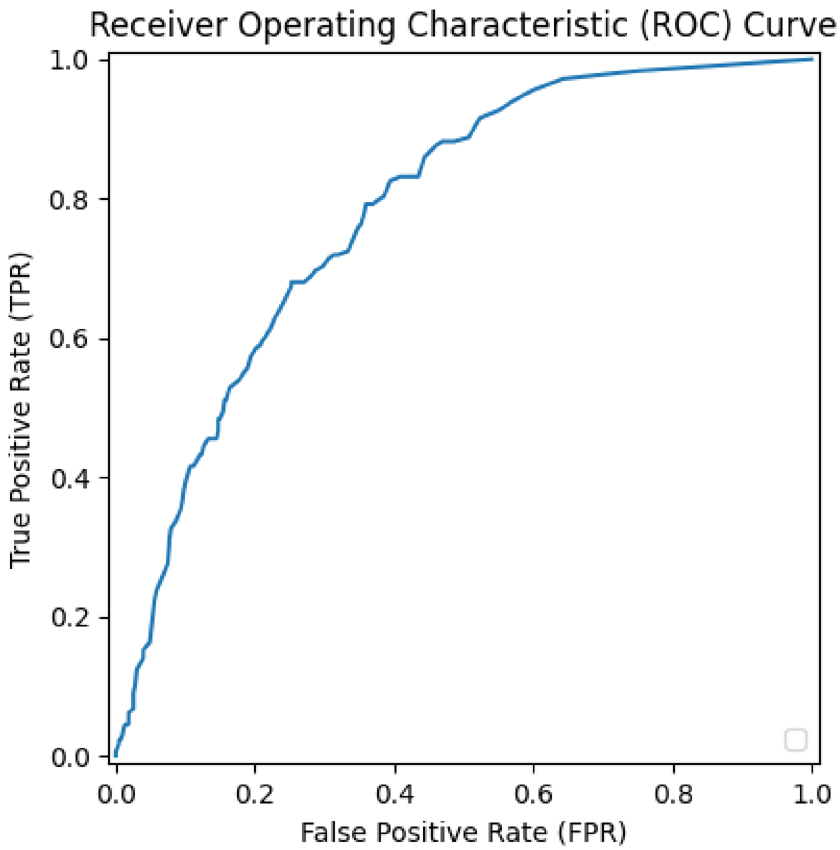
Features with taller bars like MonthlyCharges, MonthlyCharges_tenure_ratio e.t.c., have higher importances and contribute more to the model's decision-making.

0.19 ROC Curve

[61]:
```
from sklearn.metrics import roc_curve, RocCurveDisplay

# Make predictions on the test set
y_pred_prob = rf_model.predict_proba(X_test)[:, 1]

# Compute ROC curve and ROC area for each class
fpr, tpr, _ = roc_curve(y_test, y_pred_prob)

# Plot ROC curve
plt.figure(figsize=(8, 8))
RocCurveDisplay(fpr=fpr, tpr=tpr).plot()
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.xlabel('False Positive Rate (FPR)')
plt.ylabel('True Positive Rate (TPR)')
plt.show()
```

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```

```
<Figure size 800x800 with 0 Axes>
```



The ROC curve is a graphical representation of the trade-off between true positive rate (sensitivity) and false positive rate (1 - specificity) across different threshold values.

True Positive Rate (TPR) / Sensitivity

This is the y-axis. It represents the proportion of actual positive instances (churn cases) correctly predicted by the model.

False Positive Rate (FPR) / 1 - Specificity

This is the x-axis. It represents the proportion of actual negative instances incorrectly predicted as positive by the model.

Interpretation

Curve Shape

The curve is generally upward-sloping, indicating that as the true positive rate increases, there is a corresponding increase in the false positive rate.

Thresholds

The curve represents different classification thresholds for the model. It shows how the TPR and FPR change as the decision threshold is varied.

[62]:
```
y_pred = rf_model.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.80      0.85      0.82       428
           1       0.58      0.48      0.53       178

    accuracy                           0.74       606
   macro avg       0.69      0.67      0.68       606
weighted avg       0.73      0.74      0.74       606
```

Classification Report

Precision: Precision measures the proportion of true positive predictions among all positive predictions. A precision of 0.58 for class 1 suggests that among all instances predicted as churn (positive cases), approximately 58% are actually churned customers.

Recall: Recall, also known as sensitivity, measures the proportion of actual positive cases that were correctly identified by the model. A recall of 0.48 for class 1 indicates that the model correctly identified approximately 48% of all churned customers.

F1-score: The F1-score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance. A higher F1-score indicates better balance between precision and recall.

Accuracy: Accuracy represents the overall correctness of the model's predictions, regardless of class. An accuracy of `0.74` indicates that approximately 74% of all predictions made by the model on the test set are correct.

0.20 Deployment

0.21 Microservice Architecture

Deploying the model as a microservice within a microservices architecture offers several benefits. It enables the model to be containerized, facilitating independent deployment and scalability. This approach aligns with the principles of modularity and flexibility promoted by microservices architecture, allowing the model to seamlessly integrate into the existing customer management system without disrupting other functionalities.

Additionally, containerization provides isolation, ensuring that any changes or updates to the model can be made independently of the larger system, enhancing maintainability and reliability.

0.22 Application

It can be deployed in the business to automate the identification of customers at a high risk of churning.

By integrating it into the business's customer management system, it can provide real-time predictions.

The business can use these predictions to trigger targeted and personalized interventions, such as special offers, proactive customer support, or tailored communication. This approach enables the business to address potential churners, optimize resource allocation, and foster stronger customer retention strategies.