Week3_Assignment

February 4, 2024

[41]:
```python
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

[13]:
```python
df = pd.read_csv("new_churn_data.csv")

df
```

[13]:
```
      tenure  PhoneService        Contract              PaymentMethod  \
0          1           NaN  Month-to-month           Electronic check
1         34           NaN        One year               Mailed check
2          2           NaN  Month-to-month               Mailed check
3         45           NaN        One year  Bank transfer (automatic)
4          2           NaN  Month-to-month           Electronic check
…        …            …               …                          …
7027      24           NaN        One year               Mailed check
7028      72           NaN        One year    Credit card (automatic)
7029      11           NaN  Month-to-month           Electronic check
7030       4           NaN  Month-to-month               Mailed check
7031      66           NaN        Two year  Bank transfer (automatic)

      MonthlyCharges  TotalCharges  Churn  MonthlyCharges_log  \
0              29.85         29.85      0            3.396185
1              56.95       1889.50      0            4.042174
2              53.85        108.15      1            3.986202
3              42.30       1840.75      0            3.744787
4              70.70        151.65      1            4.258446
…                  …             …    …                  …
7027           84.80       1990.50      0            4.440296
7028          103.20       7362.90      0            4.636669
```

```
7029          29.60        346.45       0            3.387774
7030          74.40        306.60       1            4.309456
7031         105.65       6844.50       0            4.660132

      TotalCharges_Tenure_Ratio  MonthlyCharges_to_TotalCharges_Ratio  \
0                     29.850000                              1.000000
1                     55.573529                              0.030140
2                     54.075000                              0.497920
3                     40.905556                              0.022980
4                     75.825000                              0.466205
…                           …                                   …
7027                  82.937500                              0.042602
7028                 102.262500                              0.014016
7029                  31.495455                              0.085438
7030                  76.650000                              0.242661
7031                 103.704545                              0.015436

      customerID
0              1
1              2
2              3
3              4
4              5
…            …
7027        7028
7028        7029
7029        7030
7030        7031
7031        7032

[7032 rows x 11 columns]
```

[14]:
```python
df.drop(columns=['PhoneService'], inplace=True)
df.head()
```

[14]:
```
   tenure        Contract              PaymentMethod  MonthlyCharges  \
0       1  Month-to-month           Electronic check           29.85
1      34        One year               Mailed check           56.95
2       2  Month-to-month               Mailed check           53.85
3      45        One year  Bank transfer (automatic)           42.30
4       2  Month-to-month           Electronic check           70.70

   TotalCharges  Churn  MonthlyCharges_log  TotalCharges_Tenure_Ratio  \
0         29.85      0            3.396185                  29.850000
1       1889.50      0            4.042174                  55.573529
2        108.15      1            3.986202                  54.075000
3       1840.75      0            3.744787                  40.905556
```

```
4        151.65      1            4.258446                 75.825000

   MonthlyCharges_to_TotalCharges_Ratio  customerID
0                              1.000000           1
1                              0.030140           2
2                              0.497920           3
3                              0.022980           4
4                              0.466205           5
```

0.2 Generate dummies and convert to numeric

[15]:
```python
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()
```

[15]:
```
   tenure        Contract              PaymentMethod  MonthlyCharges  \
0       1  Month-to-month           Electronic check           29.85
1      34        One year               Mailed check           56.95
2       2  Month-to-month               Mailed check           53.85
3      45        One year  Bank transfer (automatic)           42.30
4       2  Month-to-month           Electronic check           70.70

   TotalCharges  Churn  MonthlyCharges_log  TotalCharges_Tenure_Ratio  \
0         29.85      0            3.396185                  29.850000
1       1889.50      0            4.042174                  55.573529
2        108.15      1            3.986202                  54.075000
3       1840.75      0            3.744787                  40.905556
4        151.65      1            4.258446                  75.825000

   MonthlyCharges_to_TotalCharges_Ratio  customerID  \
0                              1.000000           1
1                              0.030140           2
2                              0.497920           3
3                              0.022980           4
4                              0.466205           5

   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
```

[16]:
```python
df.drop(columns=['PaymentMethod', 'Contract'], inplace=True)
df
```

[16]:
```
      tenure  MonthlyCharges  TotalCharges  Churn  MonthlyCharges_log  \
0          1           29.85         29.85      0            3.396185
1         34           56.95       1889.50      0            4.042174
2          2           53.85        108.15      1            3.986202
3         45           42.30       1840.75      0            3.744787
4          2           70.70        151.65      1            4.258446
…       …              …            …      …                 …
7027      24           84.80       1990.50      0            4.440296
7028      72          103.20       7362.90      0            4.636669
7029      11           29.60        346.45      0            3.387774
7030       4           74.40        306.60      1            4.309456
7031      66          105.65       6844.50      0            4.660132

      TotalCharges_Tenure_Ratio  MonthlyCharges_to_TotalCharges_Ratio  \
0                     29.850000                              1.000000
1                     55.573529                              0.030140
2                     54.075000                              0.497920
3                     40.905556                              0.022980
4                     75.825000                              0.466205
…                           …                                   …
7027                  82.937500                              0.042602
7028                 102.262500                              0.014016
7029                  31.495455                              0.085438
7030                  76.650000                              0.242661
7031                 103.704545                              0.015436

      customerID  Bank transfer (automatic)  Credit card (automatic)  \
0              1                      False                    False
1              2                      False                    False
2              3                      False                    False
3              4                       True                    False
4              5                      False                    False
…            …                        …                      …
7027        7028                      False                    False
7028        7029                      False                     True
7029        7030                      False                    False
7030        7031                      False                    False
7031        7032                       True                    False
```

```
      Electronic check  Mailed check  Month-to-month  One year  Two year
0                 True         False            True     False     False
1                False          True           False      True     False
2                False          True            True     False     False
3                False         False           False      True     False
4                 True         False            True     False     False
…                    …             …               …         …         …
7027             False          True           False      True     False
7028             False         False           False      True     False
7029              True         False            True     False     False
7030             False          True            True     False     False
7031             False         False           False     False      True

[7032 rows x 15 columns]
```

[17]:
```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)
```

[17]:
```
      tenure  MonthlyCharges  TotalCharges  Churn  MonthlyCharges_log  \
2606      10           70.30        738.20      1            4.252772
4054      14           50.10        709.50      0            3.914021
6461       8           43.45        345.50      0            3.771611
5114      27           49.85       1336.15      0            3.909018
4381      30          100.40       2936.25      0            4.609162

      TotalCharges_Tenure_Ratio  MonthlyCharges_to_TotalCharges_Ratio  \
2606                  73.820000                              0.095232
4054                  50.678571                              0.070613
6461                  43.187500                              0.125760
5114                  49.487037                              0.037309
4381                  97.875000                              0.034193

      customerID  Bank transfer (automatic)  Credit card (automatic)  \
2606        2607                          0                        0
4054        4055                          1                        0
6461        6462                          0                        0
5114        5115                          0                        0
4381        4382                          1                        0

      Electronic check  Mailed check  Month-to-month  One year  Two year
2606                 0             0               0         0         0
```

```
4054                     1             0               0         0         0
6461                     1             1               1         1         0
5114                     1             1               0         0         0
4381                     1             0               0         0         0
```

0.3 Check for missing values

[18]:
```
df.isna().sum()
```

[18]:
```
tenure                                   0
MonthlyCharges                           0
TotalCharges                             0
Churn                                    0
MonthlyCharges_log                       0
TotalCharges_Tenure_Ratio                0
MonthlyCharges_to_TotalCharges_Ratio     0
customerID                               0
Bank transfer (automatic)                0
Credit card (automatic)                  0
Electronic check                         0
Mailed check                             0
Month-to-month                           0
One year                                 0
Two year                                 0
dtype: int64
```

0.4 Data Modellling

0.4.1 Split data into features(X) and targets (y)

[20]:
```
features = df.drop('Churn', axis=1)
targets = df['Churn']
```

[21]:
```
X = features
y = targets
```

[23]:
```
X.sample(6)
```

[23]:
```
      tenure  MonthlyCharges  TotalCharges  MonthlyCharges_log  \
392        2           44.30         89.30            3.790985
5075      40           71.35       2847.20            4.267597
3175       3           20.00         63.60            2.995732
6287      31           50.40       1580.10            3.919991
1145      13           96.65       1162.85            4.571096
5232      55           64.20       3627.30            4.162003

      TotalCharges_Tenure_Ratio  MonthlyCharges_to_TotalCharges_Ratio  \
392                   44.650000                              0.496081
```

```
5075                      71.180000                                 0.025060
3175                      21.200000                                 0.314465
6287                      50.970968                                 0.031897
1145                      89.450000                                 0.083115
5232                      65.950909                                 0.017699

      customerID  Bank transfer (automatic)  Credit card (automatic)  \
392          393                          0                        0
5075        5076                          0                        0
3175        3176                          0                        0
6287        6288                          0                        1
1145        1146                          0                        0
5232        5233                          0                        0

      Electronic check  Mailed check  Month-to-month  One year  Two year
392                  0             0               0         0         0
5075                 1             1               0         0         0
3175                 1             1               0         0         0
6287                 1             0               1         1         0
1145                 1             1               0         0         0
5232                 0             0               1         1         0
```

0.5 Split data into training and testing sets

[24]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[25]:
```
X_train.shape
```

[25]: (5625, 14)

[26]:
```
X_test.shape
```

[26]: (1407, 14)

[27]:
```
y_train.shape
```

[27]: (5625,)

[28]:
```
y_test.shape
```

[28]: (1407,)

0.6 Fit model into training data

[29]:
```
rf_model = RandomForestClassifier(random_state=42)

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

[29]:
```
RandomForestClassifier(random_state=42)
```

The output indicates that the RandomForestClassifier object has been created with random_state=42. This parameter is used to set the random seed for reproducibility.

[30]:
```
df['Churn'].value_counts(normalize=True)
```

[30]:
```
Churn
0    0.734215
1    0.265785
Name: proportion, dtype: float64
```

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

```
Yes: 0.265785
No : 0.734215
```

[31]:
```
print(rf_model.score(X_train, y_train))
print(rf_model.score(X_test, y_test))
```

```
1.0
0.7718550106609808
```

The accuracy score on the training set is 1.0, which means the model predicts all training data points correctly. This could suggest that the model might be overfitting the training data.

The accuracy score on the test set is approximately 0.772, indicating that the model performs less accurately on test data compared to the training data. This discrepancy suggests that the model might not generalize well to new data points, supporting the suspicion of overfitting.

0.7 Evaluate performance on the training set

[32]:
```
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
```

0.8 Evaluate performance on the test set

[33]:
```
test_predictions = rf_model.predict(X_test)
test_accuracy = accuracy_score(y_test, test_predictions)
print(f'Test Accuracy: {test_accuracy}')
```

```
Test Accuracy: 0.7718550106609808
```

0.9 Comparison with No information rate

[34]:
```
no_info_rate = max(y_train.value_counts(normalize=True))
print(f'No Information Rate: {no_info_rate}')
```

```
No Information Rate: 0.7342222222222222
```

Training Accuracy (1.0)

This indicates that the model achieved perfect accuracy on the training data, correctly predicting all churn outcomes. This might suggest a potential risk of overfitting, where the model may have memorized the training data too well, making it less generalizable to unseen data.

Test Accuracy (0.772)

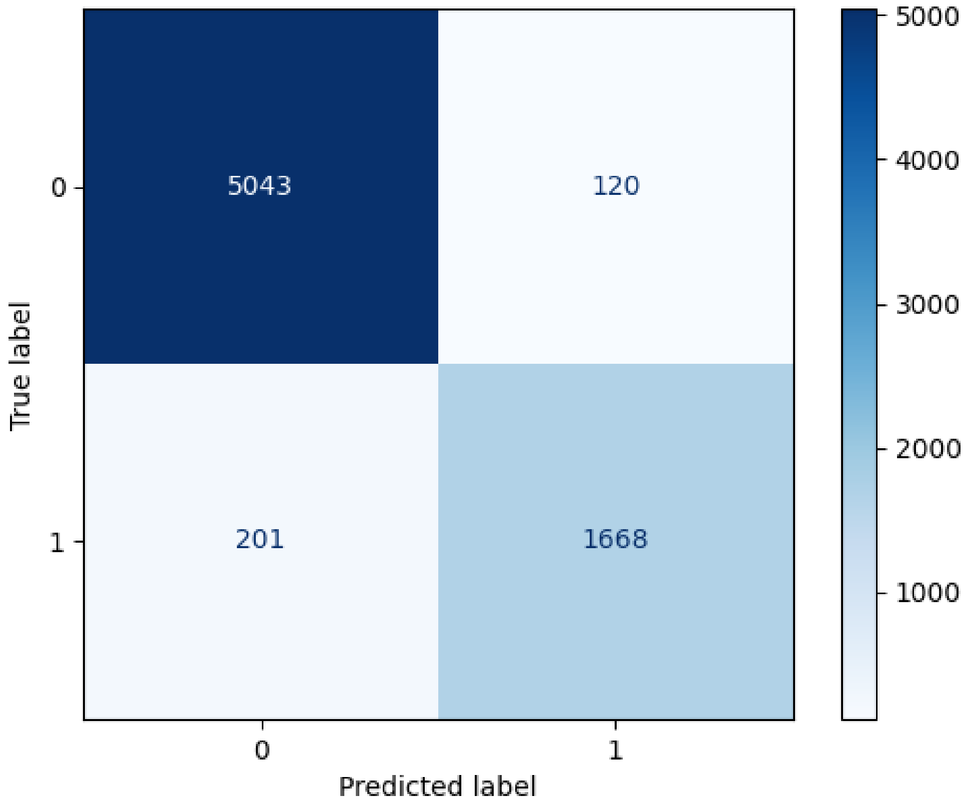
The model's accuracy on the test data is approximately 77.2%, meaning it correctly predicted churn outcomes for about 77.2% of the customers in the test set. This performance is slightly better than random chance, but it's not exceptional. It suggests that the model is moderately effective in predicting churn based on the given features.

No-Information Rate (0.734)

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

0.10 Plot confusion matrix

[40]:
```
# Combine train and test predictions
predictions = np.concatenate((train_predictions, test_predictions))

# Combine train and test true labels
y_true = pd.concat([y_train, y_test])

# Calculate confusion matrix
cm = confusion_matrix(y_true, predictions, labels=rf_model.classes_)

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



By combining the predictions and the targets, we calculate the confusion matrix based on all the predictions made by the model, whether they are from the training set or the test set. This provides a comprehensive view of the model's performance across the entire dataset, allowing us to better assess its overall effectiveness in making predictions.

True negatives (TN): 5043 instances where the true label is 0 (no churn) are correctly predicted. This signifies the number of customers who were correctly identified as not churning.

False negatives (FN): The model incorrectly predicted 0 (no churn) when the true label is 1 (churn) in 201 instances. This signifies the number of customers who were incorrectly identified as not churning, leading to missed opportunities for intervention. These are customers who churned despite the model predicting otherwise.

True positives (TP): The model correctly predicted 1668 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 120 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 Model Tuning

[42]:
```
rf_model.predict_proba(X_test)
```

[42]:
```
array([[1.  , 0.  ],
       [0.82, 0.18],
       [0.38, 0.62],
       …,
       [0.97, 0.03],
       [0.75, 0.25],
       [1.  , 0.  ]])
```

The first column represents the probability that the sample belongs to class 0 (no churn). The model is very confident that it belongs to class 0 (no churn) because it assigns a probability of 1.0 to class 0 and 0.0 to class 1

The second column represents the probability that the sample belongs to class 1 (churn). The model predicts a probability of 0.82 for class 0 and 0.18 for class 1, suggesting that the sample is more likely to belong to class 0 but with less certainty compared to the first sample.

[43]:
```
# Define the hyperparameter grid
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)
```

[43]:
```
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')
```

1 Print the best hyperparameters

[44]:
```
print(f'Best hyperparameters: {grid_search.best_params_}')
```

```
Best hyperparameters: {'max_depth': 20, 'min_samples_leaf': 4,
'min_samples_split': 10, 'n_estimators': 100}
```

1.1 Evaluate performance on the test set using the best model

[45]:
```
best_model = grid_search.best_estimator_
test_predictions = best_model.predict(X_test)
```

1.2 Print accuracy and other metrics

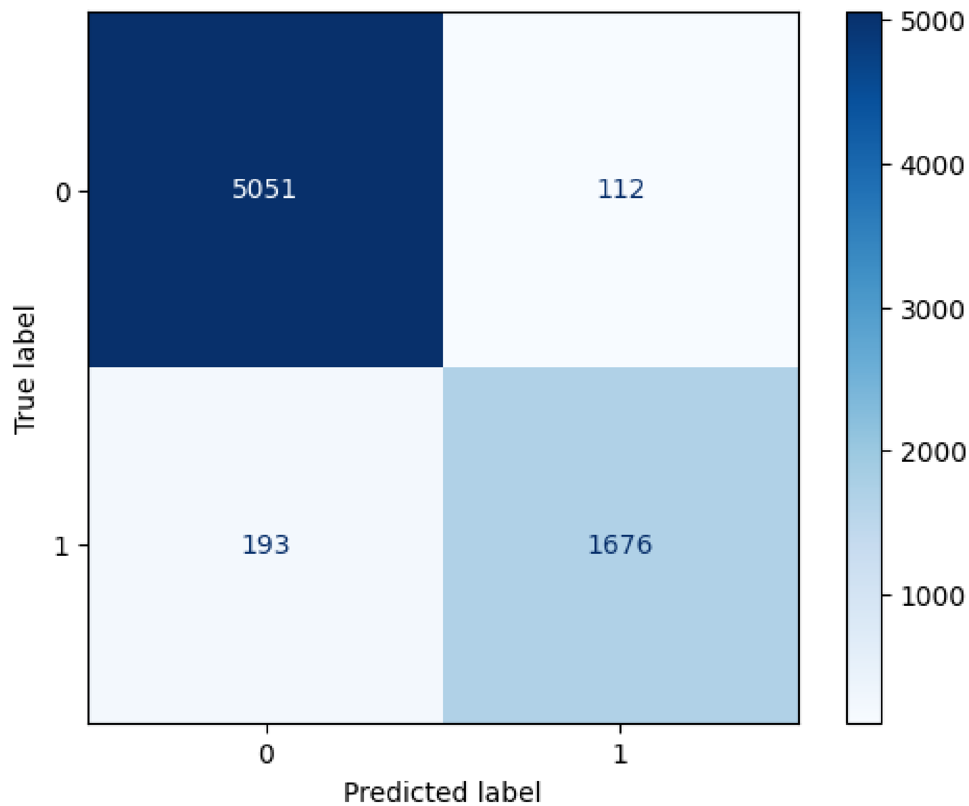
[46]:
```
test_accuracy = accuracy_score(y_test, test_predictions)
print(f'Test Accuracy: {test_accuracy}')
```

```
Test Accuracy: 0.783226723525231
```

[47]:
```
no_info_rate = max(y_train.value_counts(normalize=True))
print(f'No Information Rate: {no_info_rate}')
```

```
No Information Rate: 0.7342222222222222
```

[48]:
```
# Combine train and test predictions
predictions = np.concatenate((train_predictions, test_predictions))

# Combine train and test true labels
y_true = pd.concat([y_train, y_test])

# Calculate confusion matrix
cm = confusion_matrix(y_true, predictions, labels=rf_model.classes_)

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



The output suggests that the tuned RandomForestClassifier has achieved a test accuracy of approximately 78.32%, and this performance is better than predicting the majority class based on the no information rate of approximately 73.42%.

1.3 Feature imporatnces for RFC

[53]:
```
feature_importances = rf_model.feature_importances_
feature_importances
```

[53]:
```
array([0.09565127, 0.1276828 , 0.11934591, 0.12266915, 0.12452515,
       0.13594701, 0.11683536, 0.00802883, 0.00797538, 0.02915635,
       0.00866748, 0.0726516 , 0.01151357, 0.01935016])
```

Each number in the array corresponds to the importance of a specific feature.

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.

1.4 DataFrame to display feature importances

[55]:
```
importance_df = pd.DataFrame({'Feature': X_train.columns, 'Importance':␣
    ↪feature_importances})
importance_df.head(5)
```

[55]:
```
                     Feature  Importance
0                     tenure    0.095651
1             MonthlyCharges    0.127683
2               TotalCharges    0.119346
3         MonthlyCharges_log    0.122669
4  TotalCharges_Tenure_Ratio    0.124525
```

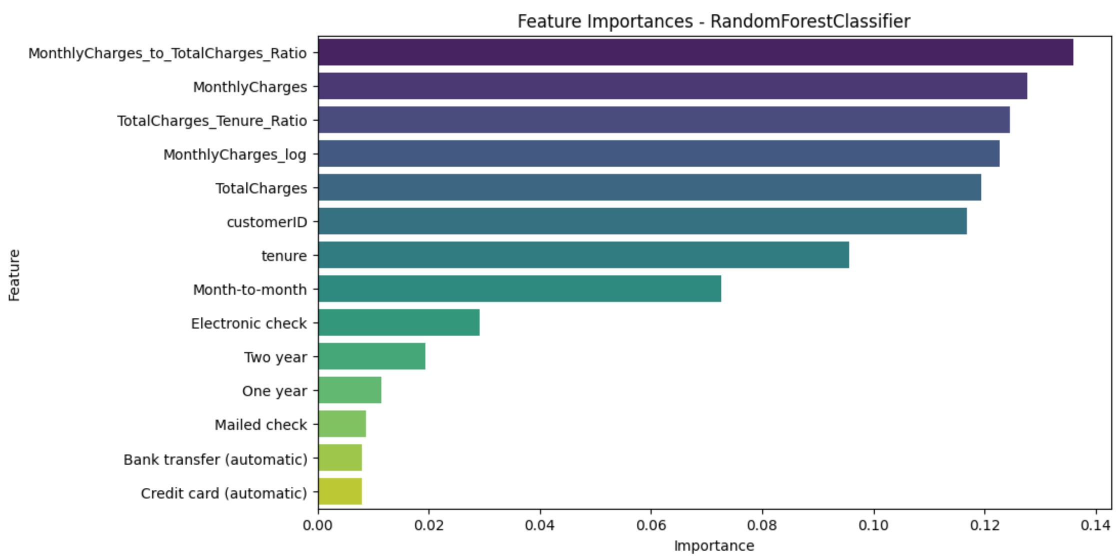
Significant features include MonthlyCharges (0.127683), TotalCharges_Tenure_Ratio (0.124525), TotalCharges (0.119346), and MonthlyCharges_log (0.122669).

Features with lower importances, such as Bank transfer (automatic), and Credit card (automatic), contribute less to the model's predictive capability.

[56]:
```
# Sort the DataFrame by importance values
importance_df = importance_df.sort_values(by='Importance', ascending=False)
```

1.5 Bar chart to visualize feature importances

[58]:
```
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()
```



Interpretation

The graph provides a visual representation of the importance of each feature in descending order.

It helps in identifying which features have the most influence on the model's predictions.

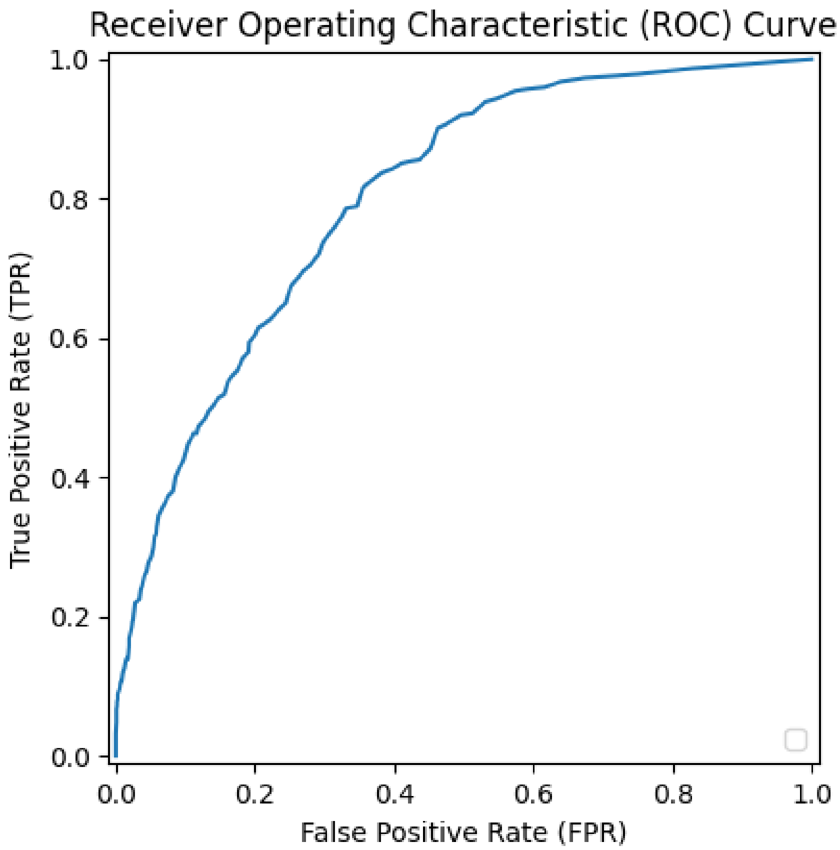
Features with taller bars like MonthlyCharges, MonthlyCharges_log, TotalCharges_to_Tenure_ratio e.t.c., have higher importances and contribute more to the model's decision-making.

1.6 ROC Curve

[60]:
```
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.

[61]:
```
y_pred = rf_model.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.88      0.85      1033
           1       0.59      0.46      0.52       374

    accuracy                           0.77      1407
   macro avg       0.71      0.67      0.68      1407
weighted avg       0.76      0.77      0.76      1407
```

Classification Report

Precision: Precision measures the proportion of true positive predictions among all positive predictions. A precision of 0.59 for class 1 suggests that among all instances predicted as churn (positive cases), approximately 59% 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 0.46 for class 1 indicates that the model correctly identified approximately 46% 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 0.77 indicates that approximately 77% of all predictions made by the model on the test set are correct.

2 Deployment

2.1 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.

2.2 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.