Week4_Assignment

February 11, 2024

[1]:
```
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.tree import DecisionTreeClassifier, export_text
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score
import matplotlib.pyplot as plt
import seaborn as sns
```

0.1 Load dataset

[2]:
```
df = pd.read_csv("prepped_churn_data.csv")

df.index = range(1, len(df) + 1)

df.insert(0, "customerID", df.index)

df.head(5)
```

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

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

   MonthlyCharges_to_TotalCharges_Ratio
1                              1.000000
2                              0.030140
3                              0.497920
4                              0.022980
```

```
5                              0.466205
```

[3]:
```python
payment_method_dummies = pd.get_dummies(df['PaymentMethod'])
contract_dummies = pd.get_dummies(df['Contract'])

# Combine the dummy variables with the original DataFrame
df = pd.concat([df, payment_method_dummies, contract_dummies], axis=1)
df.head()
```

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

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

   MonthlyCharges_to_TotalCharges_Ratio  Bank transfer (automatic)  \
1                              1.000000                      False
2                              0.030140                      False
3                              0.497920                      False
4                              0.022980                       True
5                              0.466205                      False

   Credit card (automatic)  Electronic check  Mailed check  Month-to-month  \
1                    False              True         False            True
2                    False             False          True           False
3                    False             False          True            True
4                    False             False         False           False
5                    False              True         False            True

   One year  Two year
1     False     False
2      True     False
3     False     False
4      True     False
5     False     False
```

0.2 Convert dummies to numeric

[4]:
```
categorical_columns = ['Electronic check', 'Mailed check', 'Bank transfer␣
↪(automatic)', 'Credit card (automatic)', 'Month-to-month', 'One year', 'Two␣
↪year']

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

df.sample(5)
```

[4]:
```
      customerID  tenure  PhoneService        Contract     PaymentMethod  \
4498        4498      72             1        Two year      Mailed check
6474        6474       1             1  Month-to-month  Electronic check
6462        6462       8             1        One year      Mailed check
6426        6426       1             1  Month-to-month  Electronic check
11            11      13             1  Month-to-month      Mailed check

      MonthlyCharges  TotalCharges  Churn  \
4498           26.00       1776.00      0
6474          101.45        101.45      1
6462           43.45        345.50      0
6426           50.50         50.50      1
11             49.95        587.45      0

      MonthlyCharges_to_TotalCharges_Ratio  Bank transfer (automatic)  \
4498                              0.014640                          0
6474                              1.000000                          0
6462                              0.125760                          0
6426                              1.000000                          0
11                                0.085029                          0

      Credit card (automatic)  Electronic check  Mailed check  Month-to-month  \
4498                        0                 1             1               1
6474                        0                 0             0               0
6462                        0                 1             1               1
6426                        0                 0             0               0
11                          0                 1             1               0

      One year  Two year
4498         0         1
6474         0         0
6462         1         0
6426         0         0
11           0         0
```

[5]:
```
# Drop the original categorical columns and the customerID column
df.drop(['PaymentMethod', 'Contract', 'customerID'], axis=1, inplace=True)
df.head(5)
```

[5]:
```
   tenure  PhoneService  MonthlyCharges  TotalCharges  Churn  \
1       1             0           29.85         29.85      0
2      34             1           56.95       1889.50      0
3       2             1           53.85        108.15      1
4      45             0           42.30       1840.75      0
5       2             1           70.70        151.65      1

   MonthlyCharges_to_TotalCharges_Ratio  Bank transfer (automatic)  \
1                              1.000000                          0
2                              0.030140                          0
3                              0.497920                          0
4                              0.022980                          1
5                              0.466205                          0

   Credit card (automatic)  Electronic check  Mailed check  Month-to-month  \
1                        0                 0             0               0
2                        0                 1             1               1
3                        0                 1             1               0
4                        0                 1             0               1
5                        0                 0             0               0

   One year  Two year
1         0         0
2         1         0
3         0         0
4         1         0
5         0         0
```

Now the data is ready for Modelling

0.3 Break data into features and targets

[6]:
```
X = df.drop('Churn', axis=1)
y = df['Churn']
```

0.4 Split data into Training and Test sets

[7]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

0.5 Fit a decision tree to the training data

[8]:
```
dt_model = DecisionTreeClassifier(max_depth=3)
dt_model.fit(X_train, y_train)
```

[8]:
```
DecisionTreeClassifier(max_depth=3)
```

0.6 Plot the decision tree

[9]:
```
tree_rules = export_text(dt_model, feature_names=list(X.columns))
print(tree_rules)
```

```
|--- Month-to-month <= 0.50
|   |--- MonthlyCharges <= 67.60
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.32
|   |   |   |--- class: 0
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.32
|   |   |   |--- class: 0
|   |--- MonthlyCharges >  67.60
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.08
|   |   |   |--- class: 0
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.08
|   |   |   |--- class: 1
|--- Month-to-month >  0.50
|   |--- MonthlyCharges <= 93.67
|   |   |--- Two year <= 0.50
|   |   |   |--- class: 0
|   |   |--- Two year >  0.50
|   |   |   |--- class: 0
|   |--- MonthlyCharges >  93.67
|   |   |--- TotalCharges <= 6586.10
|   |   |   |--- class: 0
|   |   |--- TotalCharges >  6586.10
|   |   |   |--- class: 0
```

Root Node

Month-to-month is the first feature used for splitting the data.

If Month-to-month is less than or equal to 0.50, it goes to the left branch; otherwise, it goes to the right branch.

First Split (Left Branch)

If Month-to-month is less than or equal to 0.50, it further checks MonthlyCharges.

If MonthlyCharges is less than or equal to 67.60, it checks MonthlyCharges_to_TotalCharges_Ratio.

If MonthlyCharges_to_TotalCharges_Ratio is less than or equal to 0.32, the predicted class is 0.

If MonthlyCharges_to_TotalCharges_Ratio is greater than 0.32, the predicted class is 0.

If MonthlyCharges is greater than 67.60, it checks MonthlyCharges_to_TotalCharges_Ratio.

If MonthlyCharges_to_TotalCharges_Ratio is less than or equal to 0.08, the predicted class is 0.

If MonthlyCharges_to_TotalCharges_Ratio is greater than 0.08, the predicted class is 1.

Second Split (Right Branch)

If Month-to-month is greater than 0.50, it checks MonthlyCharges.

If MonthlyCharges is less than or equal to 93.67, it checks One year.

If One year is less than or equal to 0.50, the predicted class is 0.

If One year is greater than 0.50, the predicted class is 0.

If MonthlyCharges is greater than 93.67, it checks TotalCharges.

If TotalCharges is less than or equal to 6586.10, the predicted class is 0.

If TotalCharges is greater than 6586.10, the predicted class is 0.

0.6.1 Interpretation

Root Node (Month-to-month

The first split is based on the contract type, specifically if a customer is on a month-to-month contract or not.

This aligns with business understanding as month-to-month contracts might be more prone to churn due to their shorter commitment.

First Split (Left Branch - Month-to-month Contract)

Further decisions are made based on monthly charges and the ratio of monthly charges to total charges.

Lower values of these features are associated with a predicted class of 0 (no churn), indicating that customers with lower charges and a reasonable ratio are less likely to churn.

First Split (Right Branch - Other Contracts)

For customers on contracts other than month-to-month, decisions are made based on monthly charges, the duration of the contract (One year), and total charges.

Similar to the left branch, lower values are associated with a predicted class of 0 (no churn).

0.6.2 Business Insights

The model suggests that customers with longer-term contracts are less likely to churn.

For month-to-month customers, lower monthly charges and a reasonable ratio of monthly charges to total charges indicate lower churn risk.

Higher monthly charges and a higher ratio in month-to-month customers increase the likelihood of churn.

The tree doesn't seem to heavily rely on the features One year and TotalCharges for the non-month-to-month contracts.

0.7 Hyperparameter tuning for decision tree

[10]:
```
param_grid = {'max_depth': [3, 5, 7, 10]}
dt_model = DecisionTreeClassifier()
grid_search = GridSearchCV(dt_model, param_grid, cv=5)
grid_search.fit(X_train, y_train)
```

[10]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(),
             param_grid={'max_depth': [3, 5, 7, 10]})
```

[11]:
```
# Best hyperparameters
best_max_depth = grid_search.best_params_['max_depth']
best_max_depth
```

[11]:
```
5
```

0.8 Fit a decision tree with the best hyperparameter

[12]:
```
dt_model_tuned = DecisionTreeClassifier(max_depth=best_max_depth)
dt_model_tuned.fit(X_train, y_train)
```

[12]:
```
DecisionTreeClassifier(max_depth=5)
```

0.9 Plot the decision tree

[13]:
```
tree_rules_tuned = export_text(dt_model_tuned, feature_names=list(X.columns))
print(tree_rules_tuned)
```

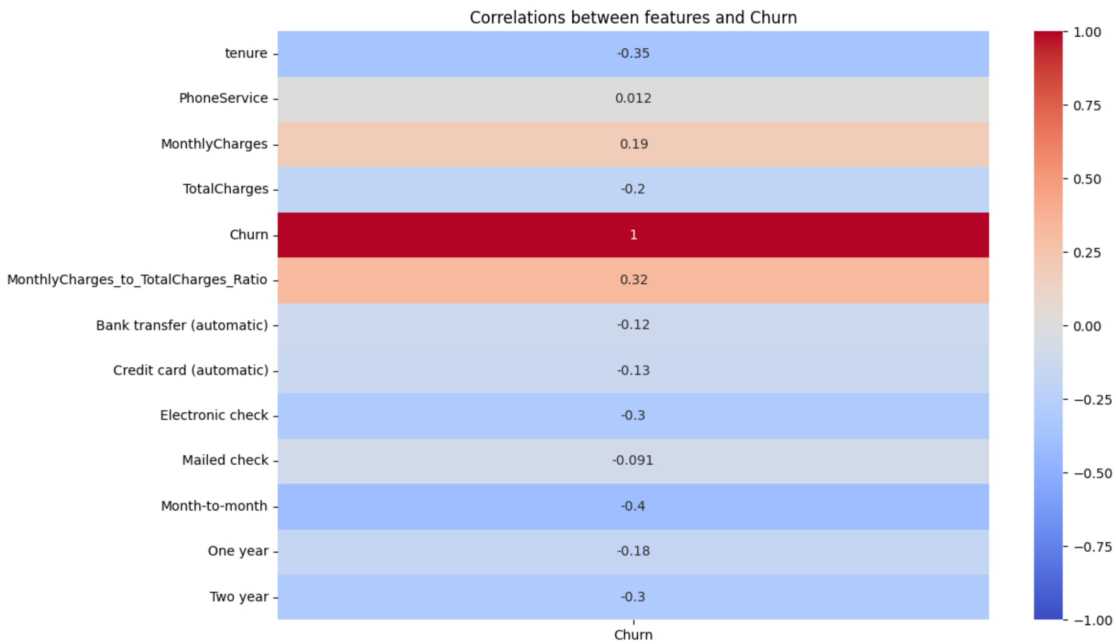
```
|--- Month-to-month <= 0.50
|   |--- MonthlyCharges <= 67.60
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.32
|   |   |   |--- PhoneService <= 0.50
|   |   |   |   |--- TotalCharges <= 352.20
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- TotalCharges >  352.20
|   |   |   |   |   |--- class: 0
|   |   |   |--- PhoneService >  0.50
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.06
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.06
|   |   |   |   |   |--- class: 0
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.32
|   |   |   |--- MonthlyCharges <= 20.88
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.61
|   |   |   |   |   |--- class: 0
```

```
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.61
|   |   |   |   |   |--- class: 0
|   |   |   |--- MonthlyCharges >  20.88
|   |   |   |   |--- PhoneService <= 0.50
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- PhoneService >  0.50
|   |   |   |   |   |--- class: 0
|   |--- MonthlyCharges >  67.60
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.08
|   |   |   |--- Electronic check <= 0.50
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.02
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.02
|   |   |   |   |   |--- class: 1
|   |   |   |--- Electronic check >  0.50
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.02
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.02
|   |   |   |   |   |--- class: 0
|   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.08
|   |   |   |--- TotalCharges <= 120.00
|   |   |   |   |--- MonthlyCharges <= 69.88
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- MonthlyCharges >  69.88
|   |   |   |   |   |--- class: 1
|   |   |   |--- TotalCharges >  120.00
|   |   |   |   |--- MonthlyCharges <= 83.40
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- MonthlyCharges >  83.40
|   |   |   |   |   |--- class: 1
|--- Month-to-month >  0.50
|   |--- MonthlyCharges <= 93.67
|   |   |--- One year <= 0.50
|   |   |   |--- Electronic check <= 0.50
|   |   |   |   |--- PhoneService <= 0.50
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- PhoneService >  0.50
|   |   |   |   |   |--- class: 0
|   |   |   |--- Electronic check >  0.50
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.02
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.02
|   |   |   |   |   |--- class: 0
|   |   |--- One year >  0.50
|   |   |   |--- MonthlyCharges <= 41.38
|   |   |   |   |--- TotalCharges <= 37.08
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- TotalCharges >  37.08
```

```
|   |   |   |   |   |--- class: 0
|   |   |   |--- MonthlyCharges >  41.38
|   |   |   |   |--- MonthlyCharges <= 43.77
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- MonthlyCharges >  43.77
|   |   |   |   |   |--- class: 0
|   |--- MonthlyCharges >  93.67
|   |   |--- TotalCharges <= 6586.10
|   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.01
|   |   |   |   |--- class: 1
|   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.01
|   |   |   |   |--- MonthlyCharges <= 103.22
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- MonthlyCharges >  103.22
|   |   |   |   |   |--- class: 0
|   |   |--- TotalCharges >  6586.10
|   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.01
|   |   |   |   |--- TotalCharges <= 8678.62
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- TotalCharges >  8678.62
|   |   |   |   |   |--- class: 1
|   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.01
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio <= 0.01
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- MonthlyCharges_to_TotalCharges_Ratio >  0.01
|   |   |   |   |   |--- class: 0
```

0.10 Plot correlations between features and targets

[14]:
```python
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr()[['Churn']], annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title("Correlations between features and Churn")
plt.show()
```



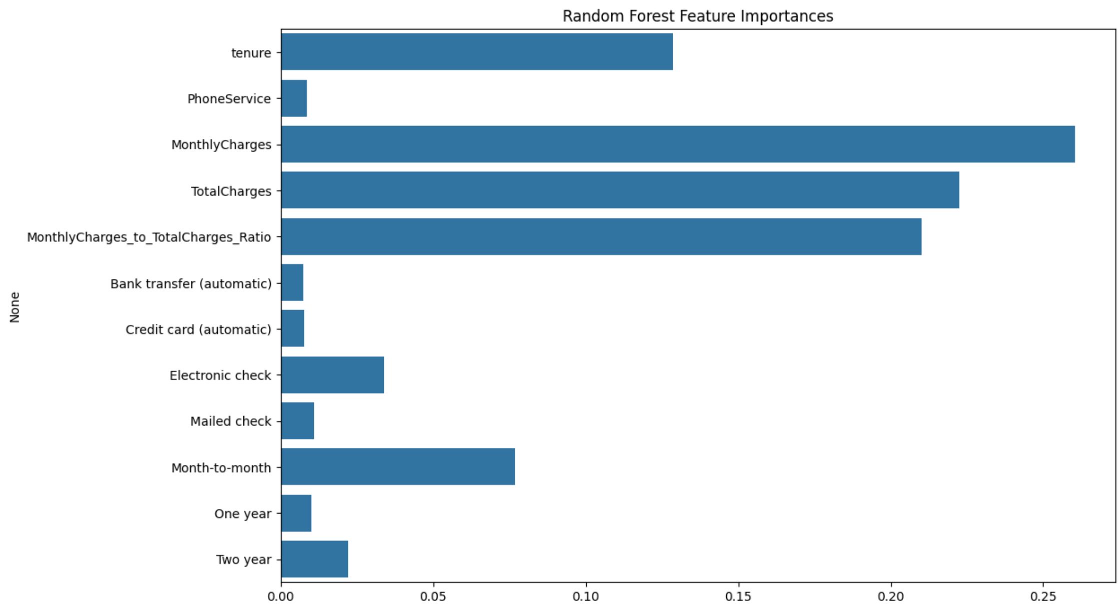
0.11 Fit a random forest model

[15]:
```
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
```

[15]:
```
RandomForestClassifier(random_state=42)
```

0.12 Plot feature importances from the RF

[16]:
```
plt.figure(figsize=(12, 8))
sns.barplot(x=rf_model.feature_importances_, y=X.columns)
plt.title("Random Forest Feature Importances")
plt.show()
```



0.13 Remove less-important features

[17]:
```
less_important_features = ['PhoneService', 'Bank transfer (automatic)', 'Credit␣
↪card (automatic)', 'Mailed check', 'One year']

X_train_filtered = X_train.drop(less_important_features, axis=1)
X_test_filtered = X_test.drop(less_important_features, axis=1)

X_train_filtered.shape
```

[17]: (5625, 7)

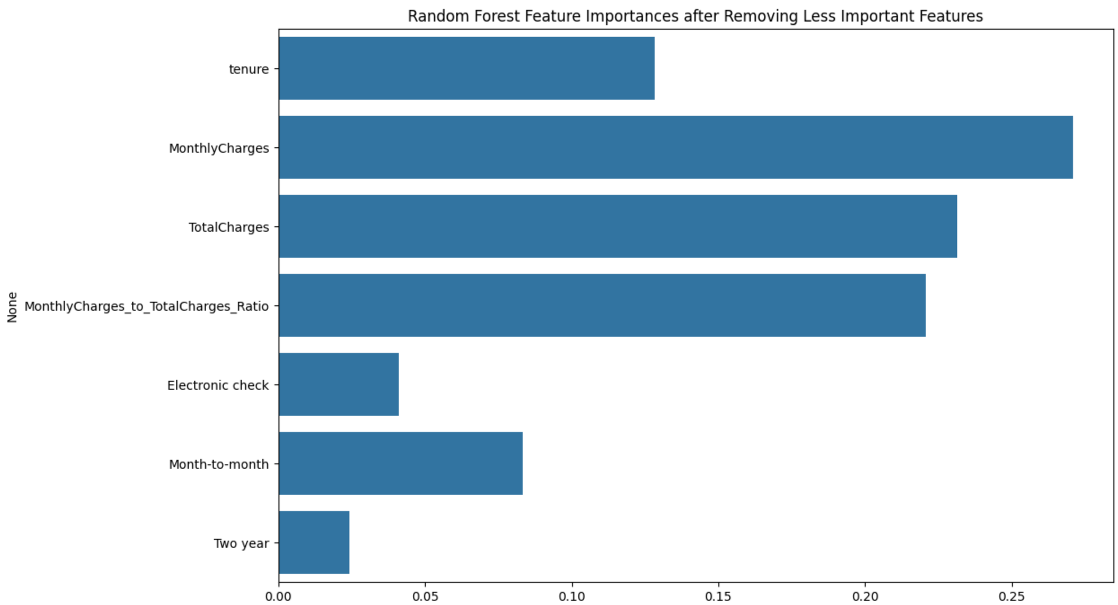
0.14 Fit RF to new data

[18]:
```
rf_model_filtered = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model_filtered.fit(X_train_filtered, y_train)
```

[18]: RandomForestClassifier(random_state=42)

0.15 Plot feature imporatnces

[19]:
```
plt.figure(figsize=(12, 8))
sns.barplot(x=rf_model_filtered.feature_importances_, y=X_train_filtered.
↪columns)
plt.title("Random Forest Feature Importances after Removing Less Important␣
↪Features")
plt.show()
```



0.16 Evaluate Model performance

[20]:
```python
def evaluate_model(model, X, y_true):
    y_pred = model.predict(X)
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred)
    recall = recall_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred)
    print(f"Accuracy: {accuracy:.4f}, Precision: {precision:.4f}, Recall:␣
 ↪{recall:.4f}, F1 Score: {f1:.4f}")
```

0.17 The earlier dt

[21]:
```python
print("Evaluation of Tuned Decision Tree Model:")
evaluate_model(dt_model_tuned, X_test, y_test)
```

```
Evaluation of Tuned Decision Tree Model:
Accuracy: 0.7676, Precision: 0.5732, Recall: 0.4920, F1 Score: 0.5295
```

0.18 Earlier RF

[22]:
```python
print("\nEvaluation of Random Forest Model:")
evaluate_model(rf_model, X_test, y_test)
```

```
Evaluation of Random Forest Model:
Accuracy: 0.7626, Precision: 0.5667, Recall: 0.4545, F1 Score: 0.5045
```

0.19 RF with no less important features

[23]:
```
print("\nEvaluation of Random Forest Model after Removing Less Important␣
↪Features:")
evaluate_model(rf_model_filtered, X_test_filtered, y_test)
```

```
Evaluation of Random Forest Model after Removing Less Important Features:
Accuracy: 0.7647, Precision: 0.5754, Recall: 0.4385, F1 Score: 0.4977
```

0.20 Interpretation of the Results

Tuned Decision Tree vs. Original Random Forest

The tuned decision tree shows slightly better performance across all metrics compared to the original random forest.

Random Forest Model with and without Feature Removal

Removing less important features had a modest impact on the random forest model's performance. The accuracy and precision slightly improved, but there is a trade-off with a decrease in recall and F1 score.

0.21 Summary of Plots and Interpretation:

Decision Tree Rules

The decision tree, especially after tuning, provides a clear set of rules for predicting churn. Key factors include contract type (month-to-month), monthly charges, and the ratio of monthly charges to total charges.

Correlation Heatmap

The heatmap visually represents the correlations between features and the target variable (Churn). Features with higher absolute correlations are more influential in predicting churn.

Random Forest Feature Importances

The bar plot displays feature importances from the random forest model. Features like 'Month-to-month', 'MonthlyCharges', and 'MonthlyCharges_to_TotalCharges_Ratio' show higher importance.

Random Forest Feature Importances after Removing Less Important Features

After removing less important features, the bar plot reflects updated feature importances. Features like 'Month-to-month' and 'MonthlyCharges' continue to play a significant role.

0.22 Summary

In this analysis, we began by preprocessing the churn data, including the creation of dummy variables for categorical features and factorization of selected columns. We trained decision tree and random forest models, initially evaluating their performance using accuracy, precision, recall, and F1 score metrics. The decision tree model was further refined through hyperparameter tuning using GridSearchCV to optimize the max_depth parameter. Upon identifying less important features, a modified random forest model was created after their removal. In model evaluation, we assessed the tuned decision tree, the original random forest, and the modified random forest, observing moderate accuracy across all models. Notably, the removal of less important features had a modest impact on overall model performance.