Week4_Nagarjuna_Devaray

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[57]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score
from scikitplot.estimators import plot_feature_importances
```

0.1 Load dataset

[3]:
```python
df = pd.read_csv("new_churn_data.csv")
df.sample(6)
```

[3]:
```
      tenure  MonthlyCharges  TotalCharges  Churn  MonthlyCharges_log  \
6194      69          105.10       7234.80      0            4.654912
5153      23           54.15       1312.45      0            3.991758
5196      38           24.85        955.75      0            3.212858
4324      71           25.55       1898.10      0            3.240637
1147       1           18.85         18.85      0            2.936513
6588       7           70.75        450.80      1            4.259153

      TotalCharges_Tenure_Ratio  MonthlyCharges_to_TotalCharges_Ratio  \
6194                 104.852174                              0.014527
5153                  57.063043                              0.041259
5196                  25.151316                              0.026001
4324                  26.733803                              0.013461
1147                  18.850000                              1.000000
6588                  64.400000                              0.156943

      Bank transfer (automatic)  Credit card (automatic)  Electronic check  \
6194                          0                        1                 1
5153                          0                        0                 0
5196                          0                        0                 0
4324                          1                        0                 1
1147                          0                        0                 0
6588                          0                        1                 1
```

```
      Mailed check  Month-to-month  One year  Two year
6194             0               1         1         0
5153             0               0         0         0
5196             0               0         0         0
4324             0               1         0         1
1147             0               0         0         0
6588             0               0         0         0
```

0.2 Split data into features and targets

[4]:
```
X = df.drop('Churn', axis=1)
y = df['Churn']
```

0.3 Training and Test sets

[5]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
```

0.4 Fit and display model metrics

[6]:
```
dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)

print("Decision Tree:")
print("Training accuracy:", dt.score(X_train, y_train))
print("Testing accuracy:", dt.score(X_test, y_test))
```

```
Decision Tree:
Training accuracy: 0.9939555555555556
Testing accuracy: 0.7014925373134329
```

It is evident that there is presence of overfitting in the training data due to the large distinct values between the training and test accuracies

[7]:
```
dt.get_depth()
```

[7]:
```
38
```

A depth of 38 is absurd and suggests a very large discrepancy. Tuning the DT hyperparameters as below might be able to fix this.

0.5 Tune hyperparameters for the DecisionTree

[13]:
```
param_grid = {'max_depth': [2, 3, 5, 7, 10]}
dt_model = DecisionTreeClassifier()
grid_search = GridSearchCV(dt_model, param_grid, cv=5)
grid_search.fit(X_train, y_train)
```

[13]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(),
             param_grid={'max_depth': [2, 3, 5, 7, 10]})
```

[14]:
```
best_max_depth = grid_search.best_params_['max_depth']
best_max_depth
```

[14]:
```
5
```

Here we found the best max depth to be 5

0.6 Fit with the best hyperparameter

[10]:
```
dt_model_tuned = DecisionTreeClassifier(max_depth=best_max_depth)
dt_model_tuned.fit(X_train, y_train)
```

[10]:
```
DecisionTreeClassifier(max_depth=5)
```

[11]:
```
dt_model_tuned.get_depth()
```

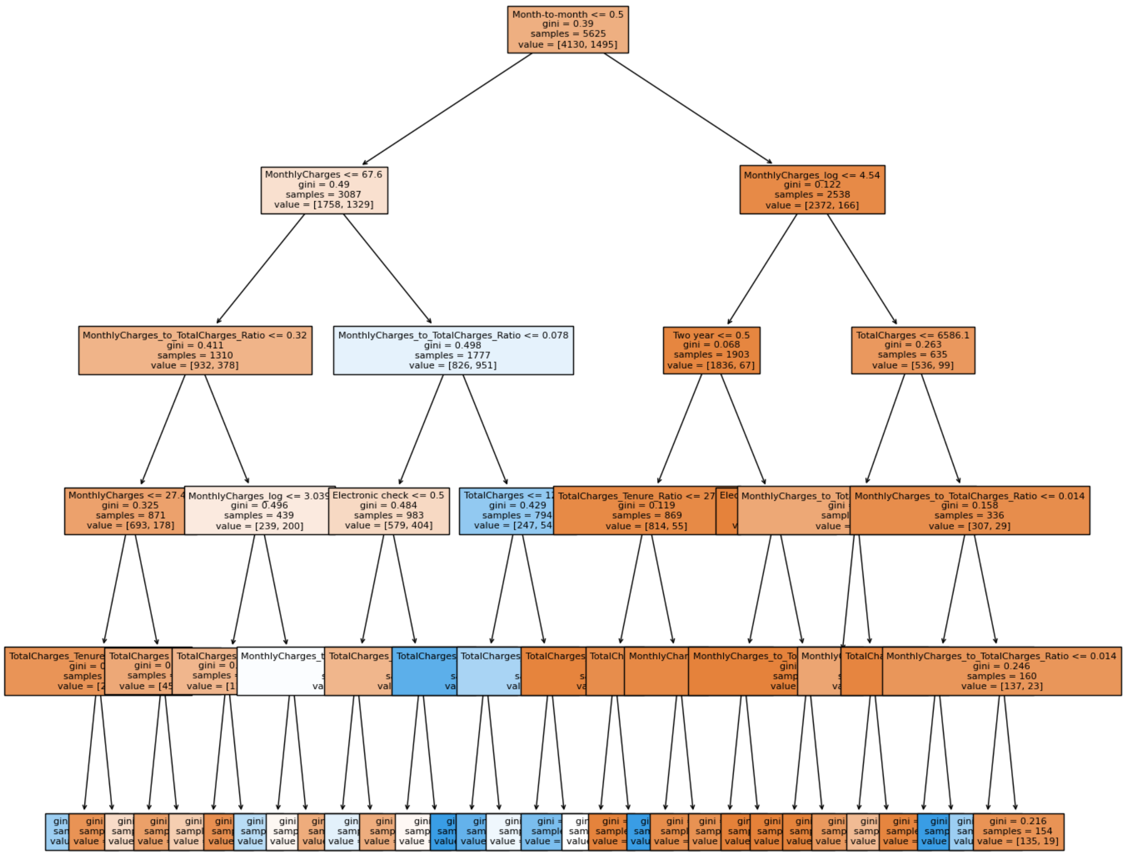
[11]:
```
5
```

[12]:
```
print("Decision Tree:")
print("Training accuracy:", dt_model_tuned.score(X_train, y_train))
print("Testing accuracy:", dt_model_tuned.score(X_test, y_test))
```

```
Decision Tree:
Training accuracy: 0.8014222222222223
Testing accuracy: 0.7633262260127932
```

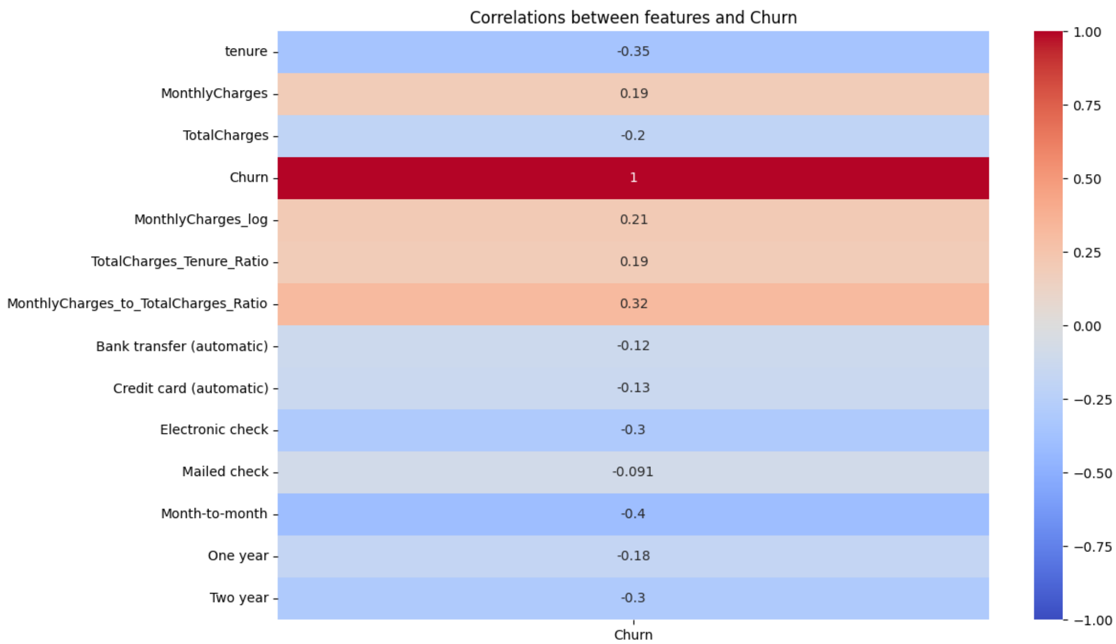
0.7 Plot the decision tree

[16]:
```
f = plt.figure(figsize = (15,15))
_ = plot_tree(dt_model_tuned,fontsize=8,feature_names = X.columns, filled=True)
```



0.8 Plot correlations between features and targets

[17]:
```
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()
```



0.9 Random Forest

[19]:
```
rf = RandomForestClassifier(random_state=42)
rf.fit(X_train,y_train)

print(rf.score(X_train,y_train))
print(rf.score(X_test,y_test))
```

```
0.9939555555555556
0.7668798862828714
```

The large deviation in accuracies prove that there is overfitting

0.10 Define hyperparameters for tuning

[26]:
```
param_grid = {
    'max_depth': [2, 5, 10]
}
```

0.11 Perform GridSearchCV for hyperparameter tuning

[27]:
```
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5)
grid_search.fit(X_train, y_train)
```

[27]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(random_state=42),
             param_grid={'max_depth': [2, 5, 10]})
```

0.12 Get best parameters

[28]:
```
best_params = grid_search.best_params_
print("Best parameters:", best_params)
```

```
Best parameters: {'max_depth': 5}
```

0.13 Evaluate RFC with best parameters

[29]:
```
rf_best = RandomForestClassifier(random_state=42, **best_params)
rf_best.fit(X_train, y_train)
```

[29]:
```
RandomForestClassifier(max_depth=5, random_state=42)
```

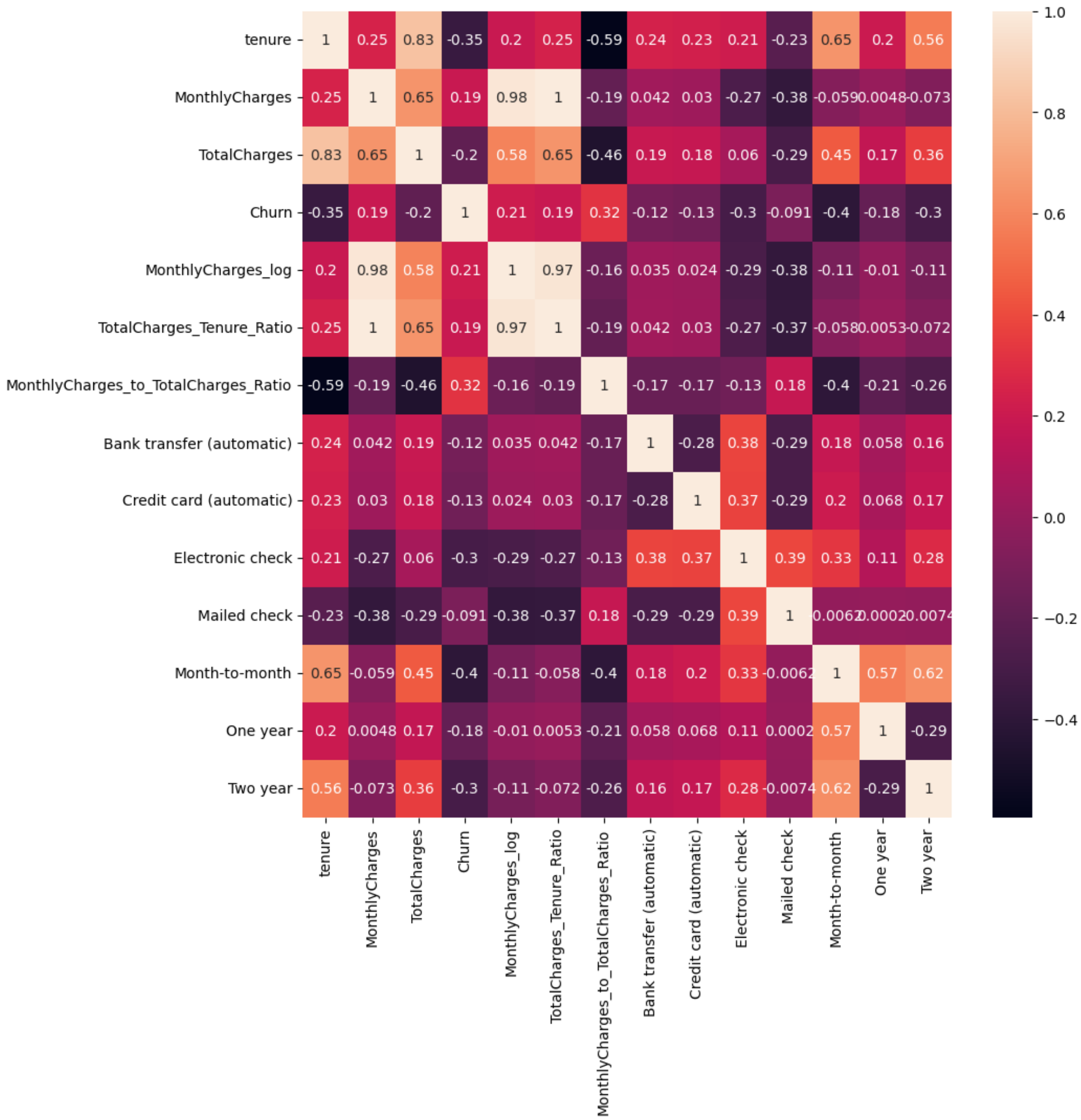
[30]:
```
print("Random Forest:")
print("Training accuracy:", rf_best.score(X_train, y_train))
print("Testing accuracy:", rf_best.score(X_test, y_test))
```

```
Random Forest:
Training accuracy: 0.8060444444444445
Testing accuracy: 0.7867803837953091
```

These values have a relatively lesser difference therefore it can be noted that overfitting was dealt with

0.14 Feature selection

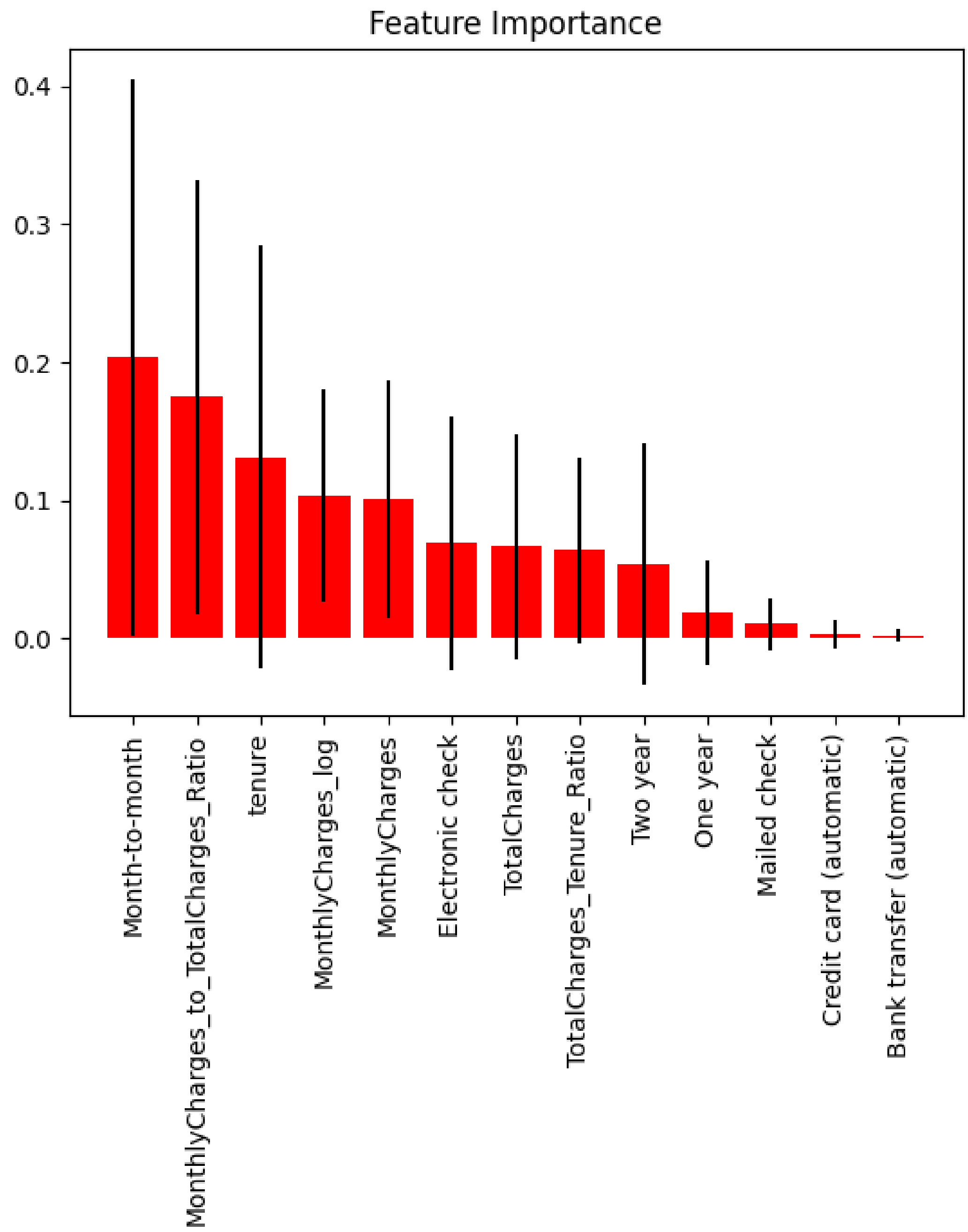
[31]:
```
plt.figure(figsize=(10, 10))
sns.heatmap(df.corr(), annot=True)
plt.show()
```



0.15 Plot feature importances

[32]:
```
plt.figure(figsize=(10, 6))
plot_feature_importances(rf_best, feature_names=X.columns, x_tick_rotation=90)
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```



Features from Electronic check to the left side of the plot seem to be less important

[54]:
```
less_important_features =['Electronic check', 'TotalCharges',␣
 ↪'TotalCharges_Tenure_Ratio','Two year','One year','Mailed check','Credit␣
 ↪card (automatic)', 'Bank transfer (automatic)']
```

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

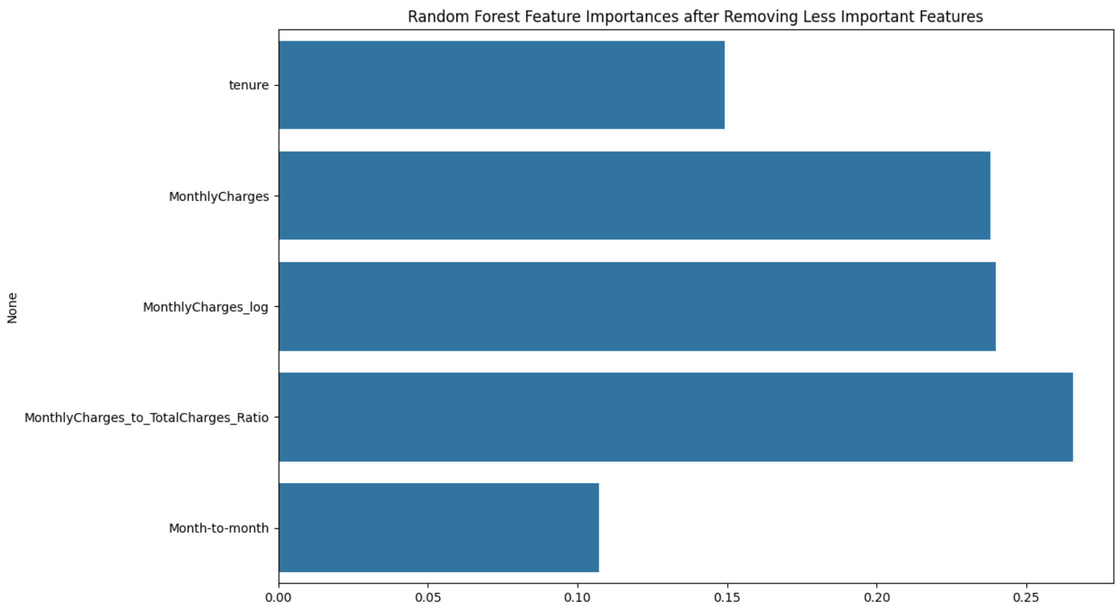
[55]:
```
# Verify the shapes of X_train and y_train
print("Shape of X_train:", X_train_filtered.shape)
print("Shape of y_train:", y_train.shape)

# Fit the RandomForestClassifier
rf_model_filtered = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model_filtered.fit(X_train_filtered, y_train)
```

```
Shape of X_train: (5625, 5)
Shape of y_train: (5625,)
```

[55]:
```
RandomForestClassifier(random_state=42)
```

[56]:
```
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

[58]:
```
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 RF with no less important features

[60]:
```
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: 0.7548, Precision: 0.5469, Recall: 0.4519, F1 Score: 0.4949
```

0.18 Summary

We conduct a comprehensive analysis of churn data using Decision Trees and Random Forest. Initially, the data is loaded and divided into features and the target variable.

Following this, the dataset is split into training and testing sets. The analysis begins with Decision Trees, where an initial model is trained and evaluated for accuracy on both the training and testing sets. Subsequently, hyperparameter tuning is performed using GridSearchCV to optimize the max_depth parameter, enhancing the model's performance. Similar steps are followed for Random Forests, where an initial model is trained and evaluated, followed by hyperparameter tuning to optimize the max_depth. Feature selection techniques are then employed, visualizing feature correlations and identifying important features using plot_feature_importances.

Less important features are removed, and a new Random Forest model is trained on the filtered dataset. Finally, the performance of the filtered model is evaluated using metrics such as accuracy, precision, recall, and F1-score, aiming to build an accurate predictive model for identifying potential churners in the dataset.