SYRIATEL PREDICTIVE ANALYSIS OF CUSTOMER CHURN

Student Name: Winny Chemusian

Student Pace: Part-time

Instructors:

1.Noah Kandie

2.William Okomba

!

1.Business Understanding

1.1 Project Overview

This project analyzes SyriaTel data and builds models that predict whether a customer will churn or not.

1.2 Introduction

SyriaTel, a telecommunications company bases in Damascus Syria, encounters a notable obstacle in curtailing customer churn, which can detrimentally affect its revenue and overall profitability. The telecommunications industry is highly competitive, with companies vying for market share and profitability. Customer retention is crucial for sustained success, as high churn rates can significantly impact revenue and profitability. Understanding its market position, customer demographics, and competitive environment is essential for devising effective churn prediction strategies.Identifying common indicators such as usage patterns, billing history, and customer service interactions is crucial for predicting and preventing churn.Different customer segments may exhibit varying churn behaviors. Understanding these differences allows for targeted retention efforts and personalized marketing strategies tailored to specific customer groups.

1.3 Business stakeholders

The primary stakeholder in this project is SyrialTel, a telecommunications company based in Damascus, Syria. Their core interest lies in understanding the patterns and reasons behind customer churn. By comprehensively understanding why customers leave, SyrialTel can take proactive measures to retain them. This includes improving service quality, enhancing customer support, and offering tailored solutions to address customer needs. By leveraging data-driven insights, SyrialTel can make informed decisions, tailor services, and allocate resources effectively to reduce churn. This proactive approach not only improves customer satisfaction but also leads to financial savings by minimizing revenue loss associated with customers discontinuing their services.

1.4 Objectives

The primary objectives of this project are as follows:

- To Build a classification model to predict customer churn for SyriaTel.
- To Identify the key factors influencing customer churn.
- To Provide insights and recommendations to SyriaTel for effective churn management.

1.5 Project Methodology

- The CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology is a widely used framework for data mining projects, and it can be effectively applied to customer churn analysis. The methodology consists of six phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment.

The processes to be undertaken in this project are:

- Data Understanding
- Data Cleaning
- Exploratory Data Analysis
- Data Preparation

- Modelling
- Evaluation
- Conclusion

1.6 Problem Statement

Our stakeholder will be SyriaTel which is a leading telecommunications company that is experiencing a significant churn rate among its customer base. Churn, the rate at which customers cease using SyriaTel's services, poses a substantial financial challenge and threatens the company's long-term sustainability. To mitigate revenue loss and improve customer retention, SyriaTel aims to develop a predictive model that can accurately identify customers at risk of churn.By addressing the problem of customer churn through predictive analytics, SyriaTel aims to secure its position in the telecommunications market and drive sustainable growth in the long term.

1.7 Success Metric

In this analysis the metric used will be ROC AUC as it measures the model's ability to discriminate between the positive class (churn) and the negative class (non-churn). This metric offesr a comprehensive assessment of a binary classifier's performance, helping stakeholders understand its ability to discriminate between churn and non-churn instances and make informed decisions regarding model deployment and optimization.

2.Data Understanding

2.1 Data Description

The data utilized for this project has been sourced from Kaggle. The dataset contains 3333 entries and 21 columns, including information about the state, account length, area code, phone number, international plan, voice mail plan, number of voice mail messages, total day minutes, total day calls, total day charge, total evening minutes, total evening calls, total evening charge, total night minutes, total night calls, total night charge, total international minutes, total international calls, total international charge, customer service calls and churn.

2.2 Importing Libraries, Loading and Checking the data set.

```
#Import required libraries
import pandas as pd
%matplotlib inline
from IPython.display import Image
import matplotlib.pyplot as mlp
import matplotlib.pyplot as plt
import numpy as np
import os
import sklearn
import seaborn as sns
from sklearn.model_selection import cross_validate
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier,
```

```
GradientBoostingClassifier, AdaBoostClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn import preprocessing
import warnings

#Loading the dataset
df=pd.read_csv('bigml_59c28831336c6604c800002a.csv')

# Creating a copy of the dataset to work with.
df_copy = df.copy()

## Checking the dataset
df.head(5)

  state  account length  area code phone number international plan  \
0    KS             128        415     382-4657                 no
1    OH             107        415     371-7191                 no
2    NJ             137        415     358-1921                 no
3    OH              84        408     375-9999                yes
4    OK              75        415     330-6626                yes

  voice mail plan  number vmail messages  total day minutes  total day
calls  \
0             yes                     25              265.1
110
1             yes                     26              161.6
123
2              no                      0              243.4
114
3              no                      0              299.4
71
4              no                      0              166.7
113

   total day charge  ...  total eve calls  total eve charge  \
0             45.07  ...               99             16.78
1             27.47  ...              103             16.62
2             41.38  ...              110             10.30
3             50.90  ...               88              5.26
4             28.34  ...              122             12.61

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01
1                254.4                103               11.45
2                162.6                104                7.32
3                196.9                 89                8.86
4                186.9                121                8.41

   total intl minutes  total intl calls  total intl charge  \
```

```
0             10.0                3               2.70
1             13.7                3               3.70
2             12.2                5               3.29
3              6.6                7               1.78
4             10.1                3               2.73

   customer service calls  churn
0                       1  False
1                       1  False
2                       0  False
3                       2  False
4                       3  False

[5 rows x 21 columns]
```

```python
# checking the shape of the data
print(f"The data has {df.shape[0]} rows and {df.shape[1]} columns")
```

```
The data has 3333 rows and 21 columns
```

```python
# checking for the information about the data Frame.
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   state                   3333 non-null   object 
 1   account length          3333 non-null   int64  
 2   area code               3333 non-null   int64  
 3   phone number            3333 non-null   object 
 4   international plan      3333 non-null   object 
 5   voice mail plan         3333 non-null   object 
 6   number vmail messages   3333 non-null   int64  
 7   total day minutes       3333 non-null   float64
 8   total day calls         3333 non-null   int64  
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64  
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64  
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64  
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64  
 20  churn                   3333 non-null   bool   
```

```
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

```python
# Check the data types of each column
print("Data types of each column:")
print(df.dtypes)
```

```
Data types of each column:
international plan           int32
voice mail plan              int32
number vmail messages        int64
total day minutes          float64
total day calls              int64
total day charge           float64
total eve minutes          float64
total eve calls              int64
total eve charge           float64
total night minutes        float64
total night calls            int64
total night charge         float64
total intl minutes         float64
total intl calls             int64
total intl charge          float64
customer service calls       int64
churn                        int64
Total Charge               float64
Total Minutes              float64
total calls                  int64
dtype: object
```

```python
# checking for the unique values in the data
for i in df.columns:
    print(f"Unique values in {i} are {df[i].nunique()}")
```

```
Unique values in state are 51
Unique values in account length are 212
Unique values in area code are 3
Unique values in phone number are 3333
Unique values in international plan are 2
Unique values in voice mail plan are 2
Unique values in number vmail messages are 46
Unique values in total day minutes are 1667
Unique values in total day calls are 119
Unique values in total day charge are 1667
Unique values in total eve minutes are 1611
Unique values in total eve calls are 123
Unique values in total eve charge are 1440
Unique values in total night minutes are 1591
Unique values in total night calls are 120
Unique values in total night charge are 933
```

```
Unique values in total intl minutes are 162
Unique values in total intl calls are 21
Unique values in total intl charge are 162
Unique values in customer service calls are 10
Unique values in churn are 2
```

```
df = df.drop(columns=['account length', 'area code', 'state', 'phone
number'])
```

3 Data Cleaning

3.1 Handling Missing Values

```
#Checking missing values
df.isna().sum()
```

```
international plan        0
voice mail plan           0
number vmail messages     0
total day minutes         0
total day calls           0
total day charge          0
total eve minutes         0
total eve calls           0
total eve charge          0
total night minutes       0
total night calls         0
total night charge        0
total intl minutes        0
total intl calls          0
total intl charge         0
customer service calls    0
churn                     0
dtype: int64
```

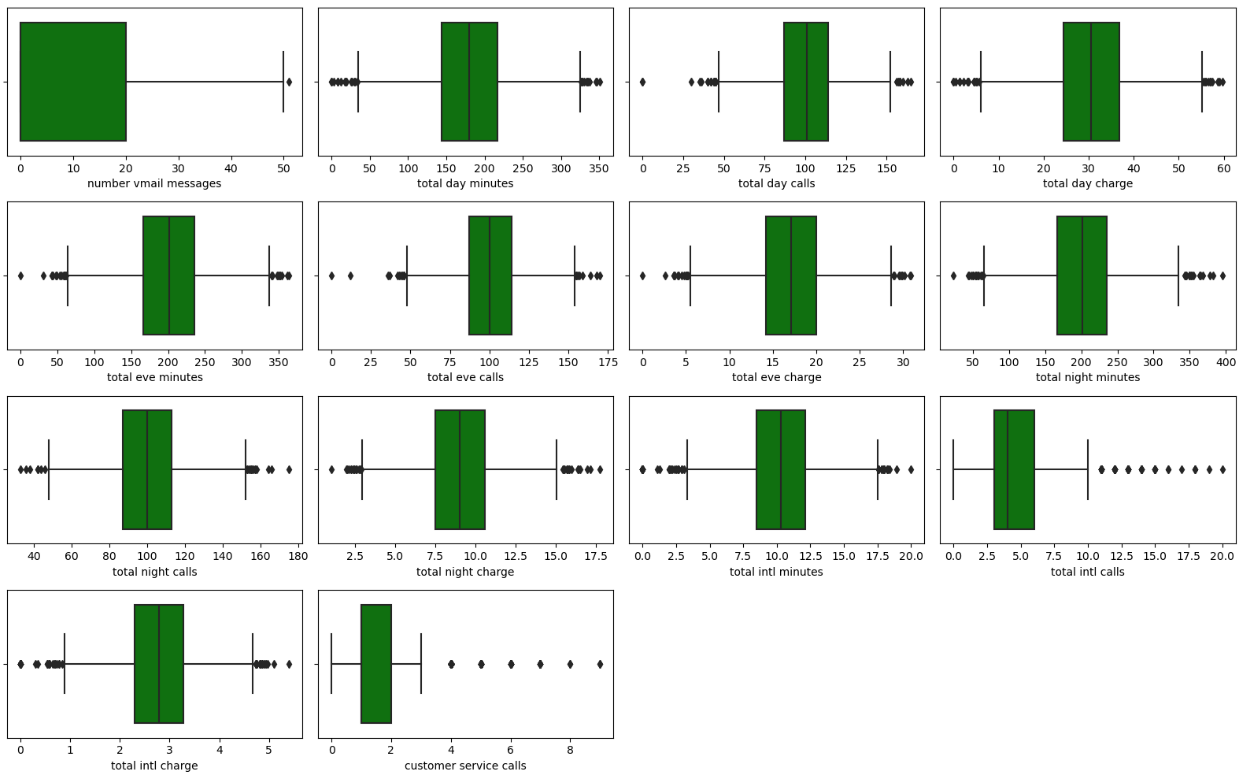
There are no missing values in our data set

```
### Analysis of the Numerical and Descriptive data
numerical_attributes = df.select_dtypes(include=['int64','float64'])
categorical_attributes = df.select_dtypes(exclude=['int64','float64'])
```

3.2 Checking for Outliers

```
#Checking for outliers
import warnings

# Ignore all warnings
warnings.filterwarnings("ignore")

# Create box plots for each numerical column
```

```
plt.figure(figsize=(16, 10))
for i, column in enumerate(numerical_attributes, 1):
    plt.subplot(4, 4, i)
    sns.boxplot(x=df[column], palette=['green'])
    plt.xlabel(column)
plt.tight_layout()
plt.show()
```



3.3 Checking for Duplicates

```
#Checking for duplicates
df.duplicated().sum()

0
```

Our data contains no duplicates

4.Exploratory Data Analysis

4.1 Summary Statistic

```
# Summary statistic
df.describe()

       international plan  voice mail plan  number vmail messages  \
count         3333.000000      3333.000000            3333.000000
```

```
mean              0.096910         0.276628                8.099010
std               0.295879         0.447398               13.688365
min               0.000000         0.000000                0.000000
25%               0.000000         0.000000                0.000000
50%               0.000000         0.000000                0.000000
75%               0.000000         1.000000               20.000000
max               1.000000         1.000000               51.000000

       total day minutes  total day calls  total day charge  \
count        3333.000000      3333.000000       3333.000000
mean          179.775098       100.435644         30.562307
std            54.467389        20.069084          9.259435
min             0.000000         0.000000          0.000000
25%           143.700000        87.000000         24.430000
50%           179.400000       101.000000         30.500000
75%           216.400000       114.000000         36.790000
max           350.800000       165.000000         59.640000

       total eve minutes  total eve calls  total eve charge  \
count        3333.000000      3333.000000       3333.000000
mean          200.980348       100.114311         17.083540
std            50.713844        19.922625          4.310668
min             0.000000         0.000000          0.000000
25%           166.600000        87.000000         14.160000
50%           201.400000       100.000000         17.120000
75%           235.300000       114.000000         20.000000
max           363.700000       170.000000         30.910000

       total night minutes  total night calls  total night charge  \
count          3333.000000        3333.000000         3333.000000
mean            200.872037         100.107711            9.039325
std              50.573847          19.568609            2.275873
min              23.200000          33.000000            1.040000
25%             167.000000          87.000000            7.520000
50%             201.200000         100.000000            9.050000
75%             235.300000         113.000000           10.590000
max             395.000000         175.000000           17.770000

       total intl minutes  total intl calls  total intl charge  \
count         3333.000000       3333.000000        3333.000000
mean            10.237294          4.479448           2.764581
std              2.791840          2.461214           0.753773
min              0.000000          0.000000           0.000000
25%              8.500000          3.000000           2.300000
50%             10.300000          4.000000           2.780000
75%             12.100000          6.000000           3.270000
max             20.000000         20.000000           5.400000

       customer service calls        churn  Total Charge  Total
Minutes  \
```

```
count                  3333.000000  3333.000000   3333.000000
3333.000000
mean                      1.562856     0.144914     59.449754
591.864776
std                       1.315491     0.352067     10.502261
89.954251
min                       0.000000     0.000000     22.930000
284.300000
25%                       1.000000     0.000000     52.380000
531.500000
50%                       1.000000     0.000000     59.470000
593.600000
75%                       2.000000     0.000000     66.480000
652.400000
max                       9.000000     1.000000     96.150000
885.000000

       total calls
count  3333.000000
mean    305.137114
std      34.448164
min     191.000000
25%     282.000000
50%     305.000000
75%     328.000000
max     416.000000
```

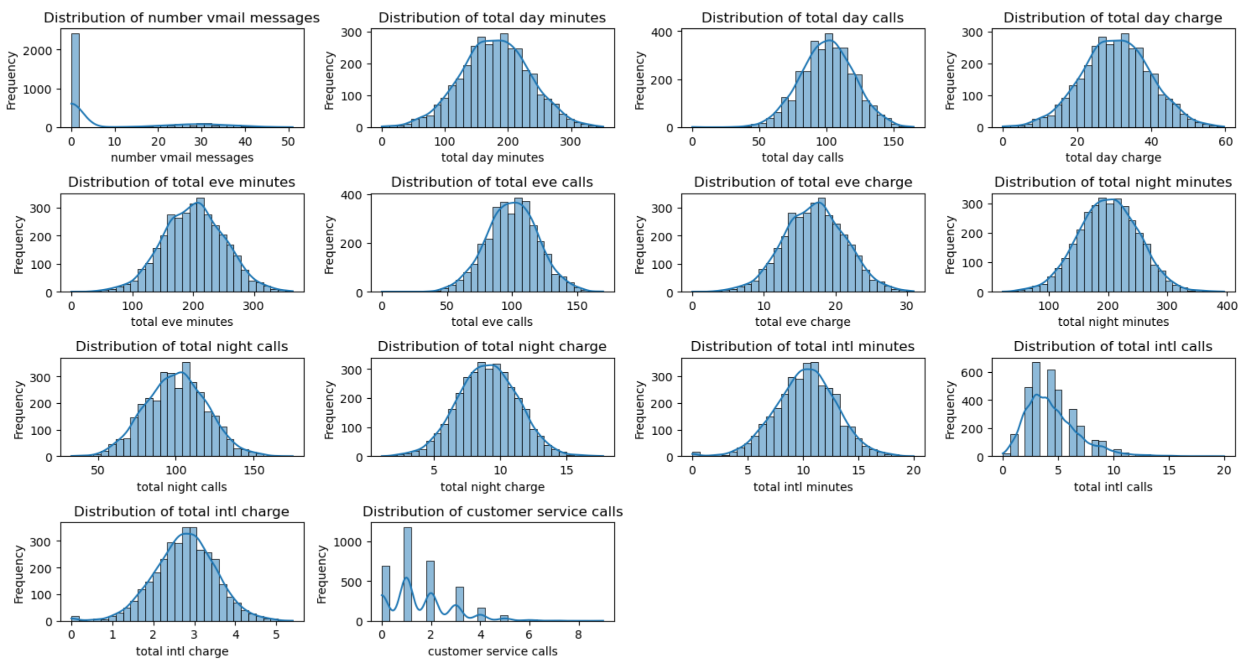
4.2 Univariate Analysis

In this section we will assess the distribution all variables

This classification problem project seeks to predict the churn of customers. The target variable is "churn" which is a binary variable. Assesing the distribution of the target variable to see if the data is balanced or not.

```python
# Plotting the distribution of numerical features
# Determine the number of rows and columns for subplots
num_plots = len(numerical_attributes)
num_rows = 4  # Adjust as needed
num_cols = num_plots // num_rows + (1 if num_plots % num_rows > 0 else
0)

# Create subplots
fig, axes = plt.subplots(num_rows, num_cols, figsize=(15, 8))

# Flatten axes if necessary
if num_plots == 1:
    axes = [axes]

# Plot histograms
```

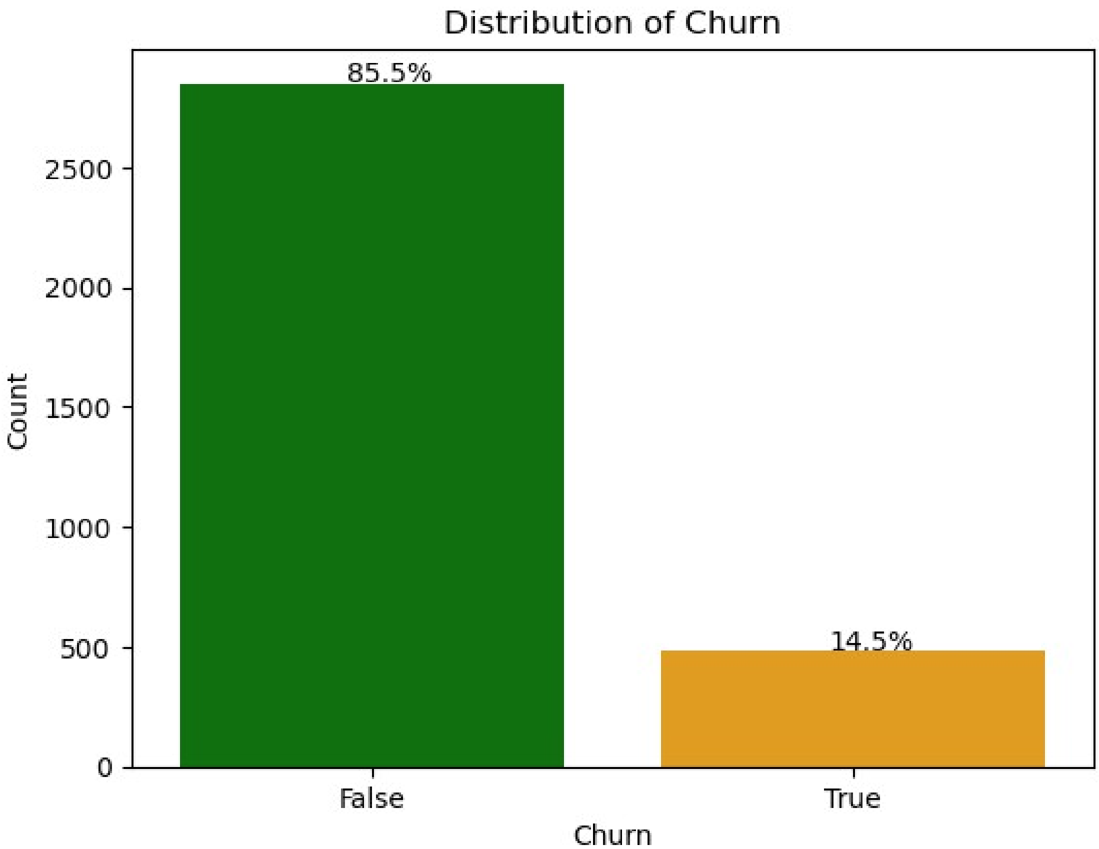
```
for i, column in enumerate(numerical_attributes):
    sns.histplot(data=df, x=column, bins=30, kde=True, ax=axes[i //
num_cols, i % num_cols])
    axes[i // num_cols, i % num_cols].set_title(f'Distribution of
{column}')
    axes[i // num_cols, i % num_cols].set_xlabel(column)
    axes[i // num_cols, i % num_cols].set_ylabel('Frequency')

# Remove any empty subplots
for i in range(num_plots, num_rows * num_cols):
    axes[i // num_cols, i % num_cols].axis('off')

plt.tight_layout()
plt.show()
```



Most of the features are normally distributed except for number of voicemail messages, total intl calls and customer service calls which are left skewed.

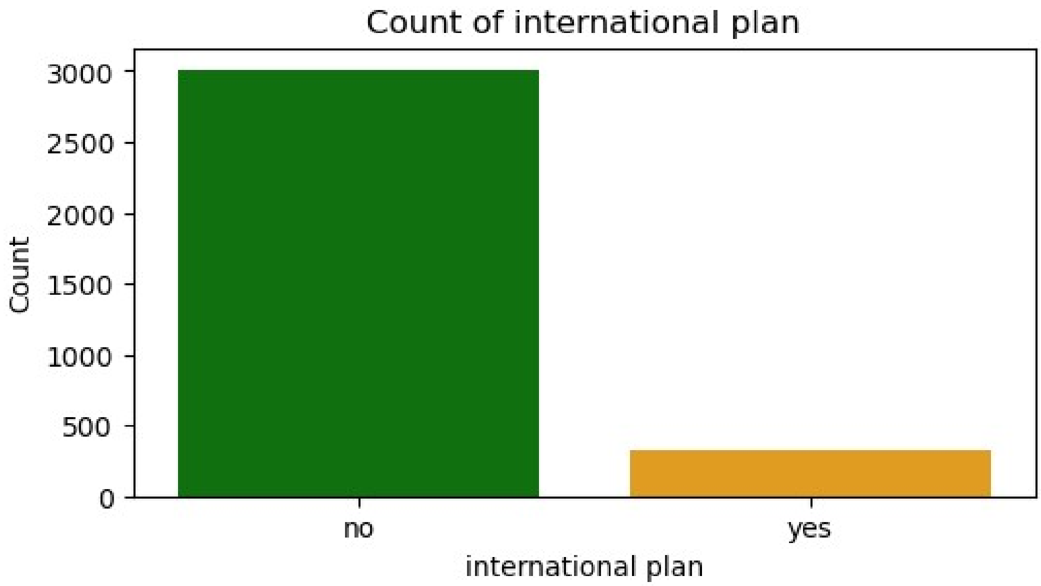
```
# Plotting the distribution of the target variable
ax = sns.countplot(x='churn', data=df, palette=['green', 'orange'])
total = len(df['churn'])
for p in ax.patches:
    percentage = '{:.1f}%'.format(100 * p.get_height() / total)
    x = p.get_x() + p.get_width() / 2 - 0.05
    y = p.get_height() + 5
    ax.annotate(percentage, (x, y), color='black')

plt.title('Distribution of Churn')
plt.xlabel('Churn')
```

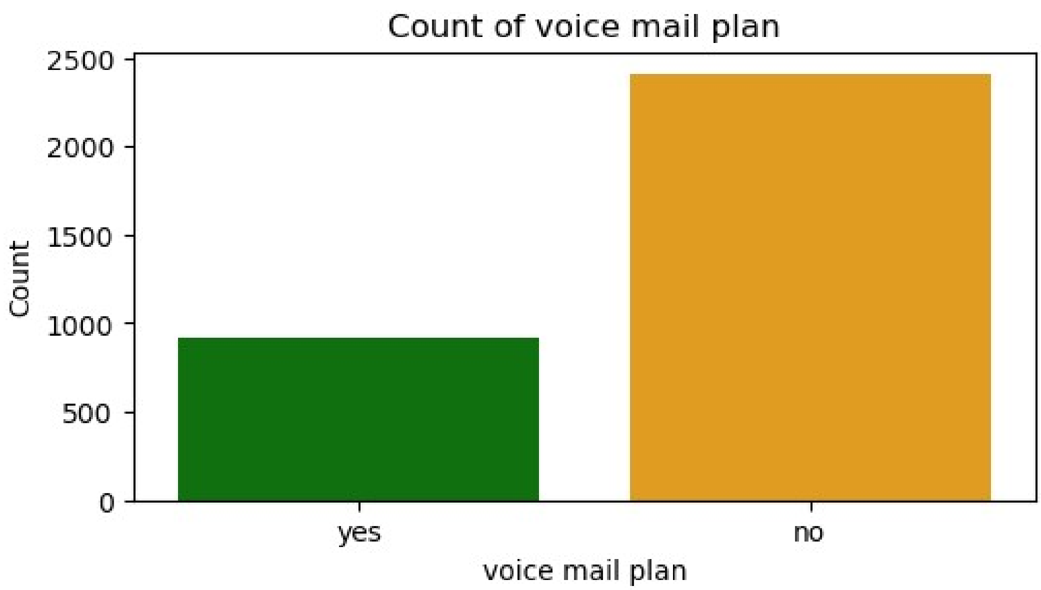
```
plt.ylabel('Count')

plt.show()
```

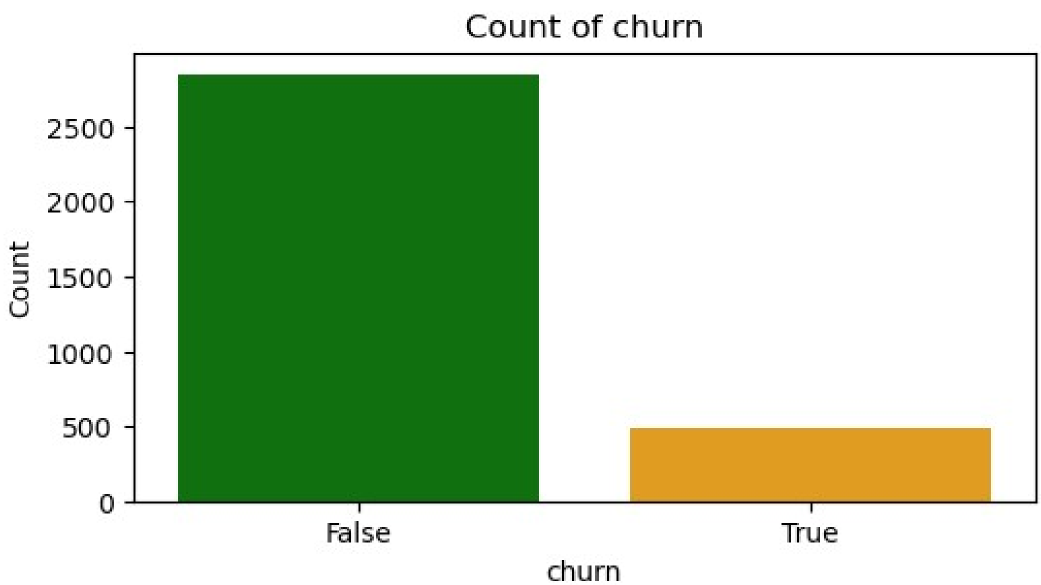


- Approximately 14.5 % of the total customers have churned from SyriaTel indicating a loss in their customer base.
- From the distribution as shown in "Distribution of churn" graph above, their is an uneven distribution of observations with 85.5% of the data belonging to the False class while 14.5% belonging to the true class.

```
# Plotting count of categorical features
for feature in categorical_attributes:
    plt.figure(figsize=(6, 3))
    sns.countplot(data=df, x=feature, palette=['green', 'orange'])
    plt.title(f'Count of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.show()
```


Count of international plan
3000
2500
2000
1500
1000
500
0
Count
no
yes
international plan


Count of voice mail plan
2500
2000
1500
1000
500
0
Count
yes
no
voice mail plan



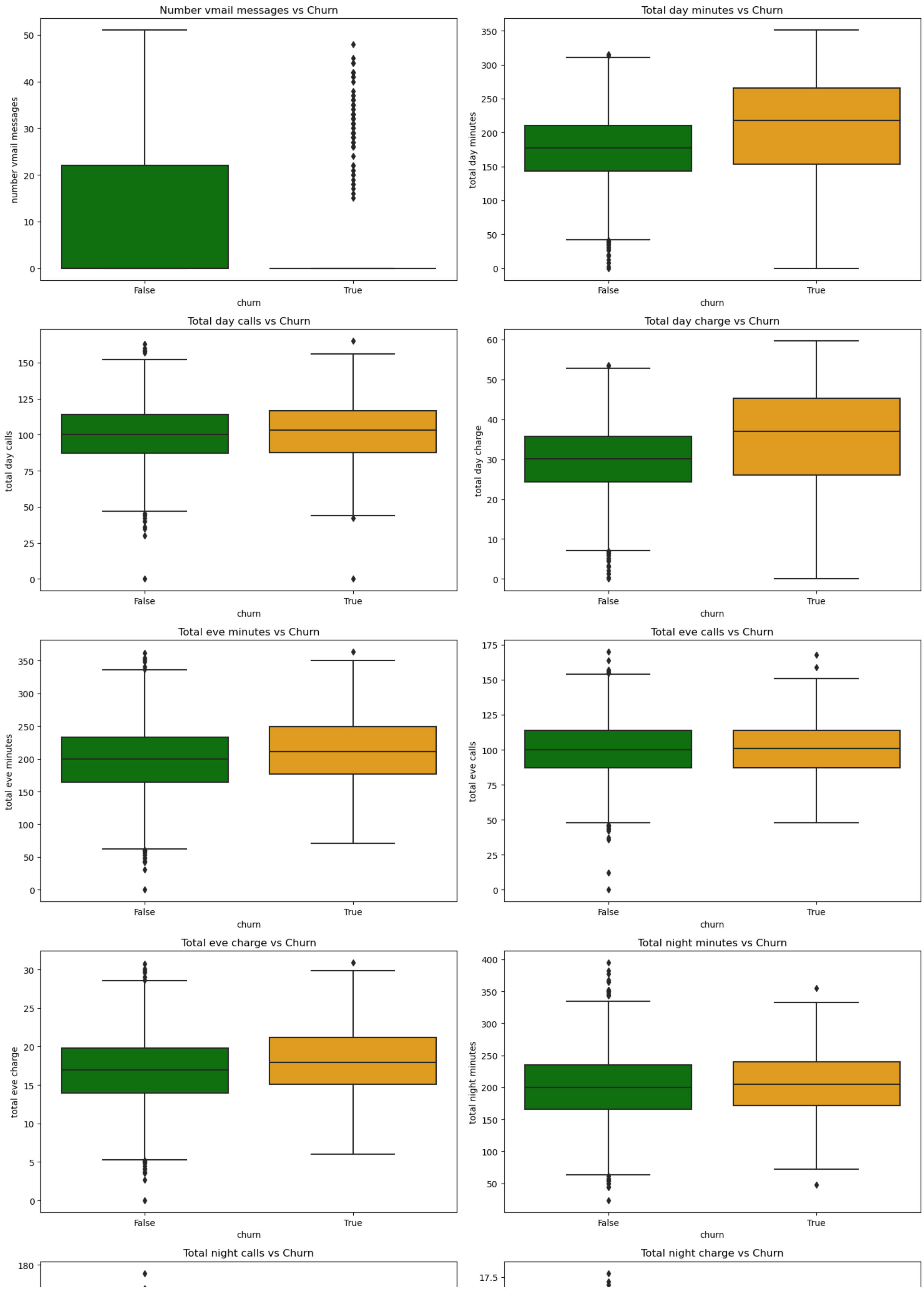
- Voice mail plan has a small effect on customer churning.
- International call plan has an effect on customer churning, as most of the customer who churn, do not have active plan subscription.

4.3 Bivariate Analysis

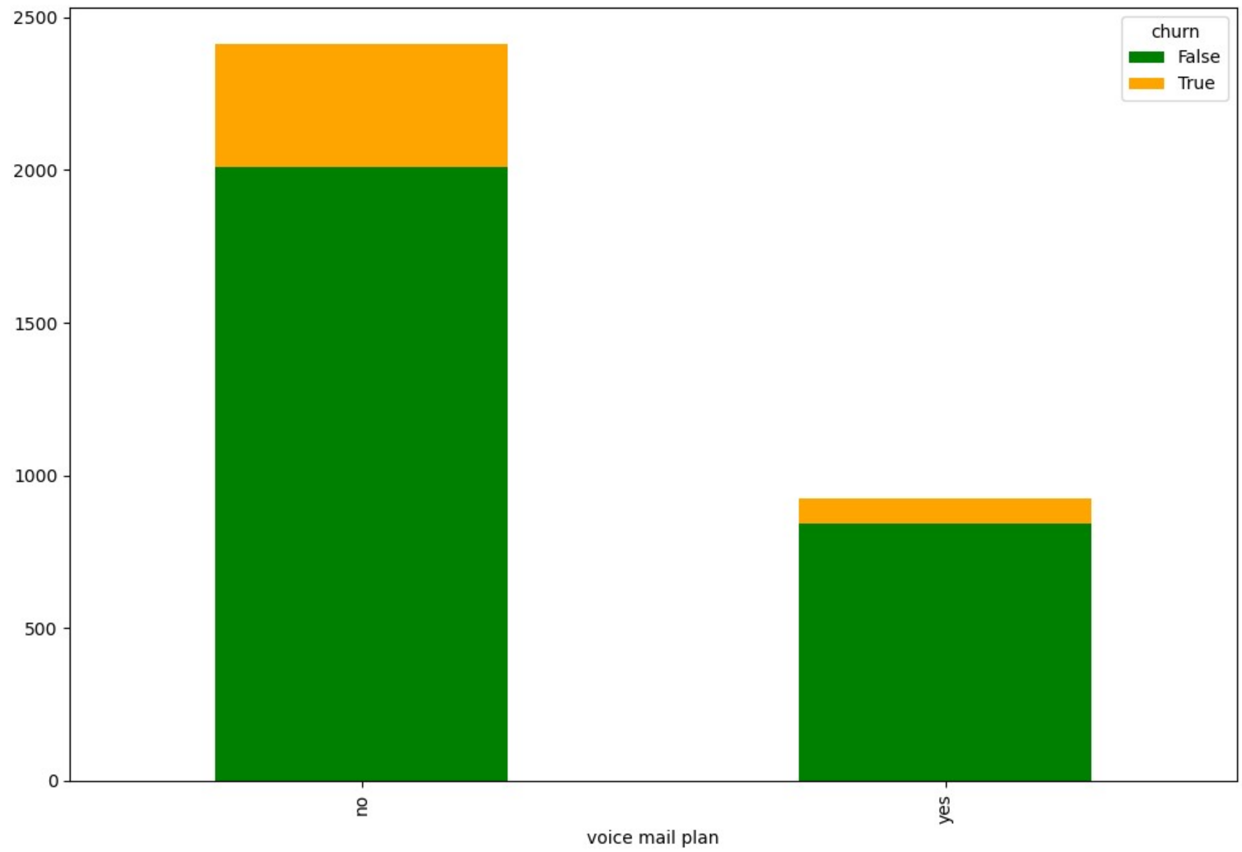
In this section we will examine the relationships between our target variable-price and other attributes in the dataset. This will help us understand how one variable affects or is affected by the other variables.

```
# Plotting bivariate analysis with the target variable (churn)
# Get numerical attributes
numerical_attributes = df.select_dtypes(include=['int64',
'float64']).columns

# Number of numerical attributes
num_numerical = len(numerical_attributes)

# Define the number of rows and columns for the subplots
num_cols = 2  # Number of columns
num_rows = (num_numerical + 1) // num_cols  # Number of rows, ensuring
enough space for all plots

# Create the subplots
fig, axes = plt.subplots(num_rows, num_cols, figsize=(15, num_rows *
5))

# Flatten axes for easy iteration
axes = axes.flatten()

# Bivariate analysis for numerical features
```

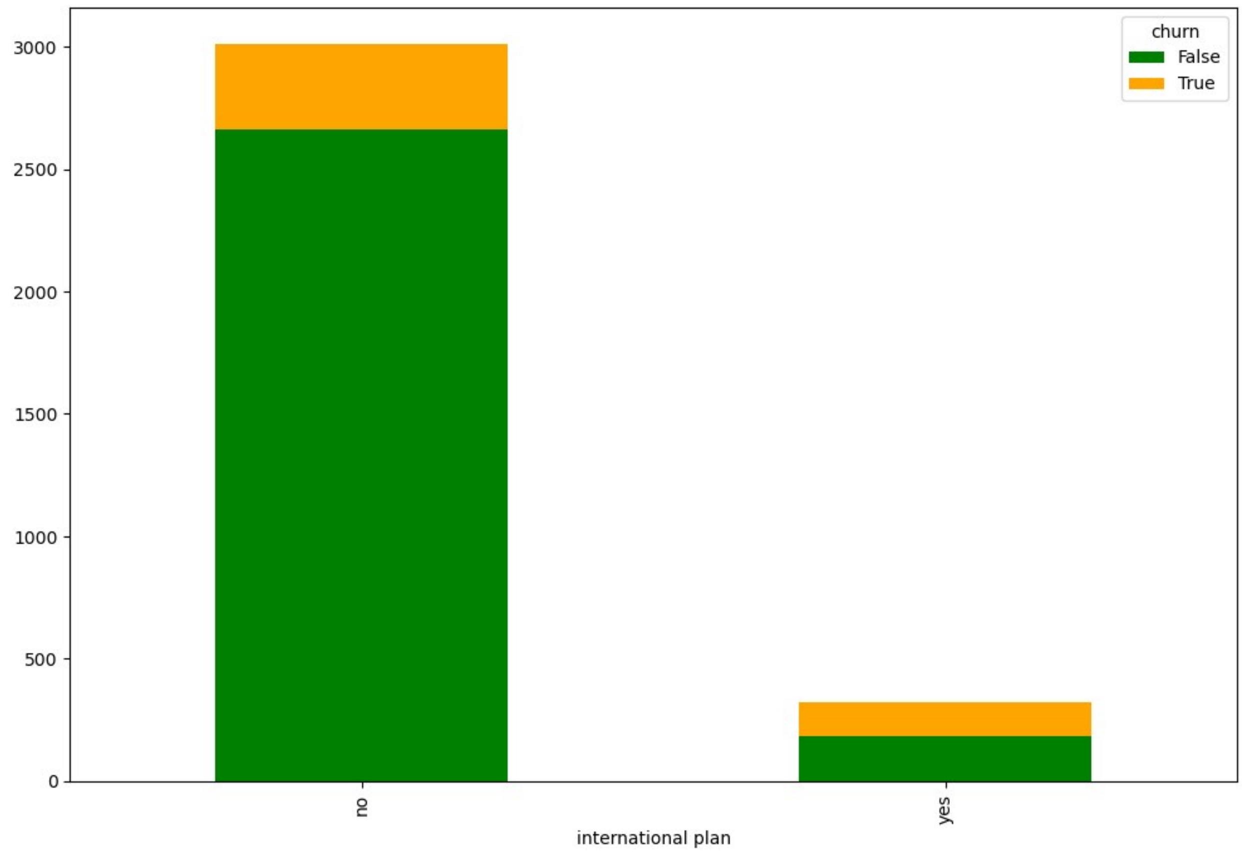
```
for i, feature in enumerate(numerical_attributes):
    sns.boxplot(x='churn', y=feature, data=df, palette=['green',
'orange'], ax=axes[i])
    axes[i].set_title(f'{feature.capitalize()} vs Churn')

# Remove any empty subplots
for j in range(i + 1, num_rows * num_cols):
    fig.delaxes(axes[j])

plt.tight_layout()
plt.show()
```


Number vmail messages vs Churn
number vmail messages
Total day minutes vs Churn
total day minutes
Total day calls vs Churn
total day calls
Total day charge vs Churn
total day charge
Total eve minutes vs Churn
total eve minutes
Total eve calls vs Churn
total eve calls
Total eve charge vs Churn
total eve charge
Total night minutes vs Churn
total night minutes
Total night calls vs Churn
Total night charge vs Churn
churn
False
True

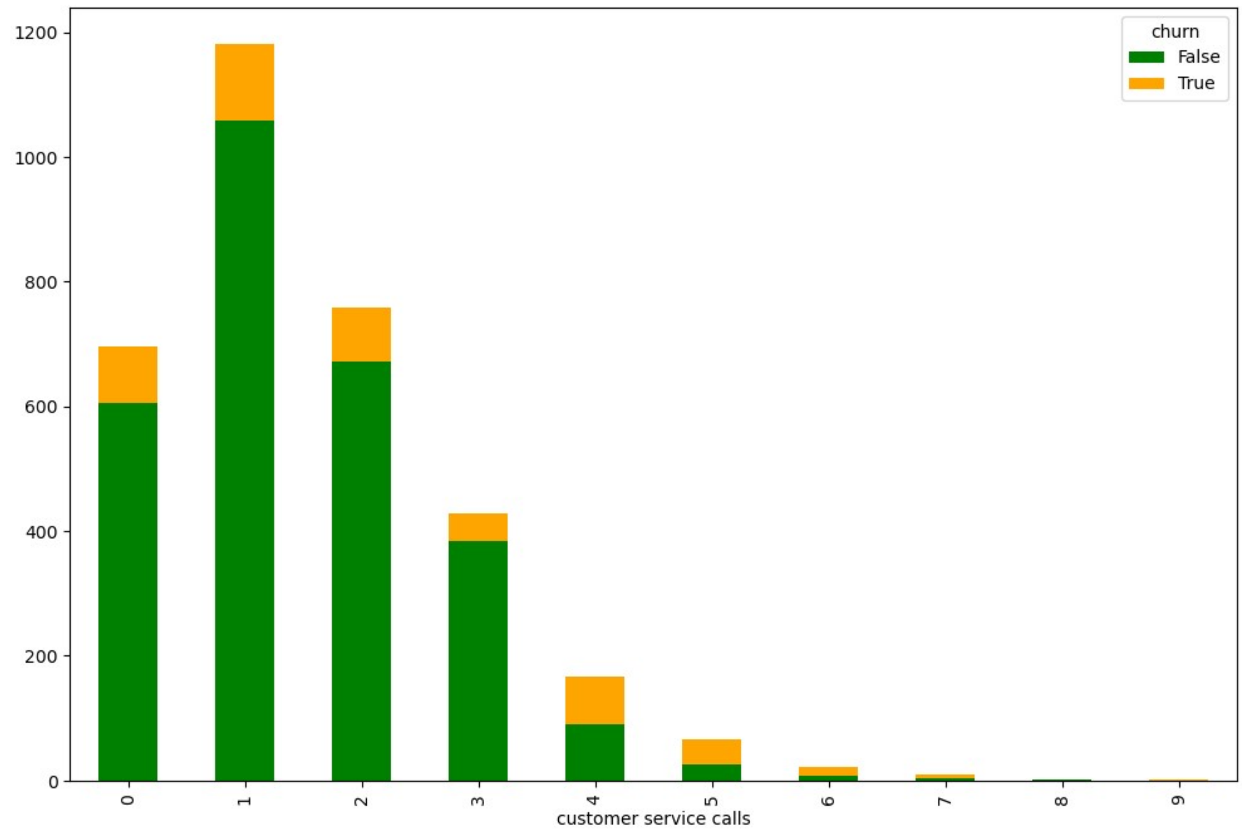
```
#Checking for the impact of the voice mail plan on churn

# Function to take different plans
def plot_churn_vs_plan(df, plan_column):
    # Plotting the churn vs plan with blue and red bars
    df.groupby([plan_column, 'churn']).size().unstack().plot(
        kind='bar', stacked=True, figsize=(12,8), color=['green',
'orange'])
    plt.show()

    # Calculating the percentage of customers subscribed to the plan
    total_customers = len(df)
    total_subscribed = sum(df[plan_column] == 'yes')
    percentage_subscribed = (total_subscribed / total_customers) * 100
    print('The number of customers subscribed to the {} : {:.2f}
%'.format(plan_column, percentage_subscribed))

    # Calculating the percentage of churned customers among those
subscribed to the plan
    churned_with_plan = sum((df[plan_column] == 'yes') & (df['churn']
== True))
    percentage_churned_with_plan = (churned_with_plan /
total_subscribed) * 100
    print('The number of subscribed customers who churned with {} :
{:.2f}%'.format(plan_column, percentage_churned_with_plan))

# Plot churn vs plan for 'voice mail plan'
plot_churn_vs_plan(df, 'voice mail plan')
```




```
The number of customers subscribed to the voice mail plan : 27.66%
The number of subscribed customers who churned with voice mail plan :
8.68%

plot_churn_vs_plan(df,'international plan')
```




```
The number of customers subscribed to the international plan : 9.69%
The number of subscribed customers who churned with international plan
: 42.41%

# Ignore all warnings
warnings.filterwarnings("ignore")

plot_churn_vs_plan(df,'customer service calls')
```

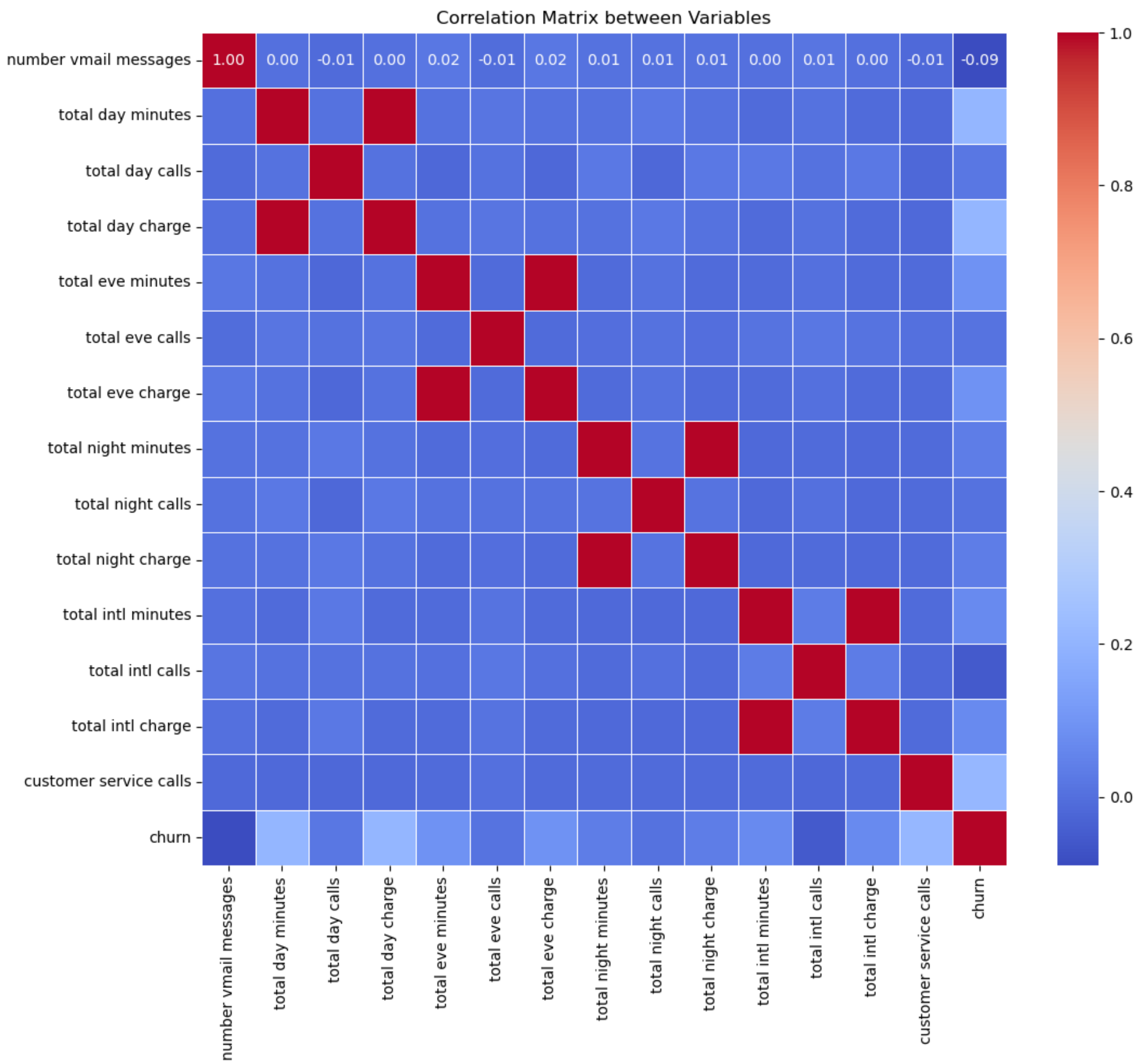



```
The number of customers subscribed to the customer service calls :
0.00%

---------------------------------------------------------------------------
ZeroDivisionError                         Traceback (most recent call last)
Cell In[44], line 4
      1 # Ignore all warnings
      2 warnings.filterwarnings("ignore")
----> 4 plot_churn_vs_plan(df,'customer service calls')

Cell In[41], line 18, in plot_churn_vs_plan(df, plan_column)
     16 # Calculating the percentage of churned customers among those subscribed to the plan
     17 churned_with_plan = sum((df[plan_column] == 'yes') & (df['churn'] == True))
---> 18 percentage_churned_with_plan = (churned_with_plan / total_subscribed) * 100
     19 print('The number of subscribed customers who churned with {} : {:.2f}%'.format(plan_column, percentage_churned_with_plan))

ZeroDivisionError: division by zero
```

4.4 Multivariate analysis

We check for multicollinearity of features to enhance accuracy during modeling.

```
from sklearn.preprocessing import LabelEncoder

# Assuming you have a DataFrame named 'df' containing your dataset

# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Define the columns to be label encoded
columns_to_encode = ['international plan', 'voice mail plan', 'churn']

# Apply label encoding to each column
for column in columns_to_encode:
    df[column] = label_encoder.fit_transform(df[column])

# Compute the correlation matrix for the numerical columns
numerical_attributes = df.select_dtypes(include=['float64',
'int64']).columns.tolist()
corr_matrix = df[numerical_attributes].corr()

# Generate the correlation heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f",
linewidths=0.5)
plt.title('Correlation Matrix between Variables')
plt.show()
```




```python
# Print correlation coefficients
corr_matrix
```

```
                        number vmail messages  total day minutes  \
number vmail messages                1.000000           0.000778
total day minutes                    0.000778           1.000000
total day calls                     -0.009548           0.006750
total day charge                     0.000776           1.000000
total eve minutes                    0.017562           0.007043
total eve calls                     -0.005864           0.015769
total eve charge                     0.017578           0.007029
total night minutes                  0.007681           0.004323
total night calls                    0.007123           0.022972
total night charge                   0.007663           0.004300
total intl minutes                   0.002856          -0.010155
```

```
total intl calls                     0.013957          0.008033
total intl charge                    0.002884         -0.010092
customer service calls              -0.013263         -0.013423
churn                               -0.089728          0.205151

                        total day calls  total day charge  total eve
minutes  \
number vmail messages         -0.009548          0.000776
0.017562
total day minutes              0.006750          1.000000
0.007043
total day calls                1.000000          0.006753          -
0.021451
total day charge               0.006753          1.000000
0.007050
total eve minutes             -0.021451          0.007050
1.000000
total eve calls                0.006462          0.015769          -
0.011430
total eve charge              -0.021449          0.007036
1.000000
total night minutes            0.022938          0.004324          -
0.012584
total night calls             -0.019557          0.022972
0.007586
total night charge             0.022927          0.004301          -
0.012593
total intl minutes             0.021565         -0.010157          -
0.011035
total intl calls               0.004574          0.008032
0.002541
total intl charge              0.021666         -0.010094          -
0.011067
customer service calls        -0.018942         -0.013427          -
0.012985
churn                          0.018459          0.205151
0.092796

                        total eve calls  total eve charge  \
number vmail messages         -0.005864          0.017578
total day minutes              0.015769          0.007029
total day calls                0.006462         -0.021449
total day charge               0.015769          0.007036
total eve minutes             -0.011430          1.000000
total eve calls                1.000000         -0.011423
total eve charge              -0.011423          1.000000
total night minutes           -0.002093         -0.012592
total night calls              0.007710          0.007596
total night charge            -0.002056         -0.012601
```

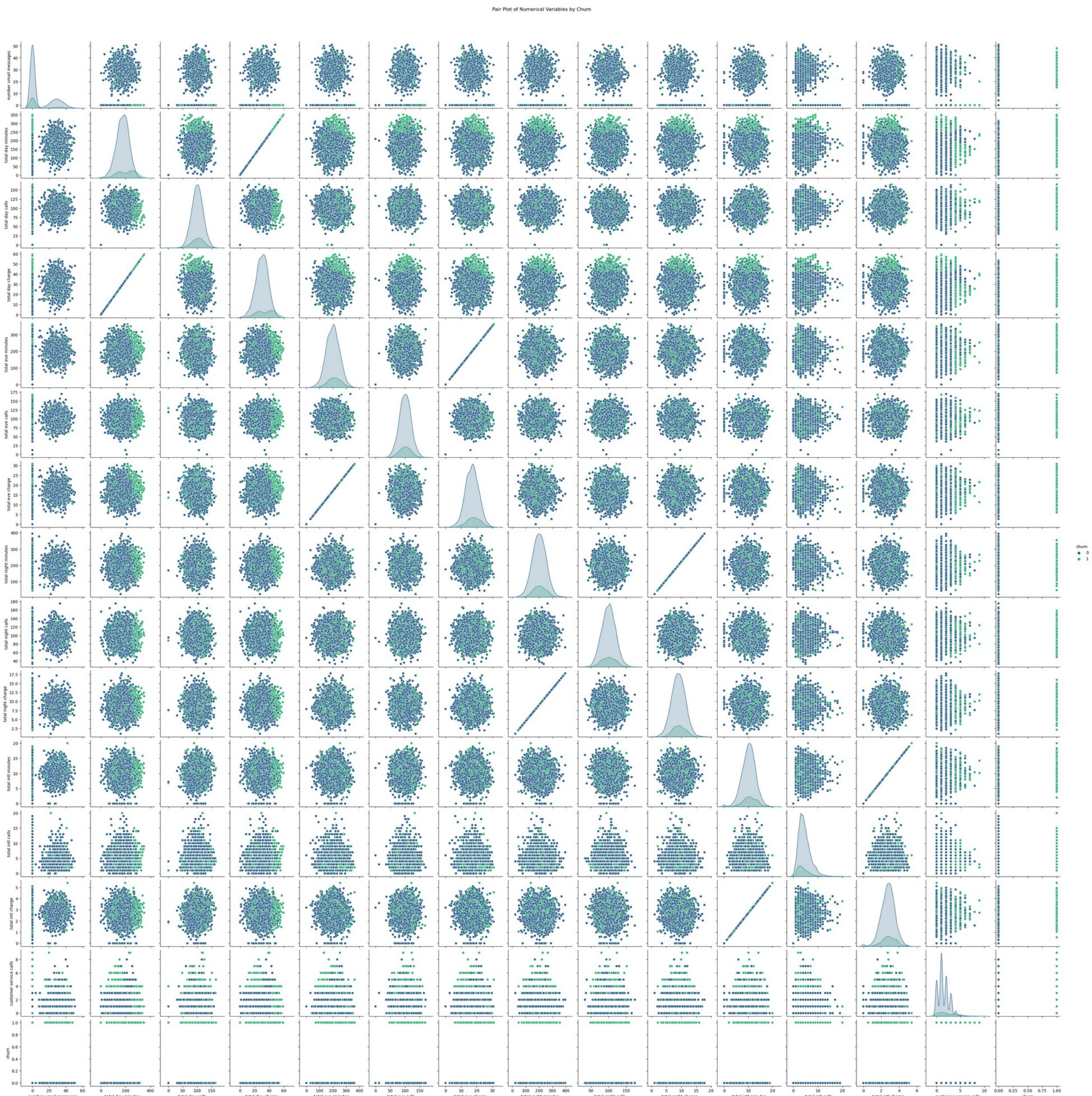
```
total intl minutes              0.008703        -0.011043
total intl calls                0.017434         0.002541
total intl charge               0.008674        -0.011074
customer service calls          0.002423        -0.012987
churn                           0.009233         0.092786

                        total night minutes  total night calls  \
number vmail messages              0.007681           0.007123
total day minutes                  0.004323           0.022972
total day calls                    0.022938          -0.019557
total day charge                   0.004324           0.022972
total eve minutes                 -0.012584           0.007586
total eve calls                   -0.002093           0.007710
total eve charge                  -0.012592           0.007596
total night minutes                1.000000           0.011204
total night calls                  0.011204           1.000000
total night charge                 0.999999           0.011188
total intl minutes                -0.015207          -0.013605
total intl calls                  -0.012353           0.000305
total intl charge                 -0.015180          -0.013630
customer service calls            -0.009288          -0.012802
churn                              0.035493           0.006141

                        total night charge  total intl minutes  \
number vmail messages             0.007663            0.002856
total day minutes                 0.004300           -0.010155
total day calls                   0.022927            0.021565
total day charge                  0.004301           -0.010157
total eve minutes                -0.012593           -0.011035
total eve calls                  -0.002056            0.008703
total eve charge                 -0.012601           -0.011043
total night minutes               0.999999           -0.015207
total night calls                 0.011188           -0.013605
total night charge                1.000000           -0.015214
total intl minutes               -0.015214            1.000000
total intl calls                 -0.012329            0.032304
total intl charge                -0.015186            0.999993
customer service calls           -0.009277           -0.009640
churn                             0.035496            0.068239

                        total intl calls  total intl charge  \
number vmail messages           0.013957           0.002884
total day minutes               0.008033          -0.010092
total day calls                 0.004574           0.021666
total day charge                0.008032          -0.010094
total eve minutes               0.002541          -0.011067
total eve calls                 0.017434           0.008674
total eve charge                0.002541          -0.011074
total night minutes            -0.012353          -0.015180
total night calls               0.000305          -0.013630
```

```
total night charge             -0.012329          -0.015186
total intl minutes              0.032304           0.999993
total intl calls                1.000000           0.032372
total intl charge               0.032372           1.000000
customer service calls         -0.017561          -0.009675
churn                          -0.052844           0.068259

                        customer service calls      churn
number vmail messages                -0.013263 -0.089728
total day minutes                    -0.013423  0.205151
total day calls                      -0.018942  0.018459
total day charge                     -0.013427  0.205151
total eve minutes                    -0.012985  0.092796
total eve calls                       0.002423  0.009233
total eve charge                     -0.012987  0.092786
total night minutes                  -0.009288  0.035493
total night calls                    -0.012802  0.006141
total night charge                   -0.009277  0.035496
total intl minutes                   -0.009640  0.068239
total intl calls                     -0.017561 -0.052844
total intl charge                    -0.009675  0.068259
customer service calls                1.000000  0.208750
churn                                 0.208750  1.000000
```

While most of the features in the dataset do not show significant correlation, there are some pairs of features that exhibit perfect positive correlation. This are:

- Total day charge and Total day minutes,
- Total eve charge and Total eve minutes,
- Total night charge and Total night minutes,
- Total int charge and Total int minutes.

```
# Create a pair plot (scatterplot matrix)
sns.pairplot(df, vars=numerical_attributes, hue='churn',
palette='viridis')
plt.suptitle('Pair Plot of Numerical Variables by Churn', y=1.02)
plt.show()
```



4.5 Feature Engineering

Feature engineering involves creating new features from existing ones to improve model performance or extract more meaningful information from the data. In this case, i have added two columns ('Total Charge', Total calls and 'Total Minutes') by combining existing columns related to charges and minutes.

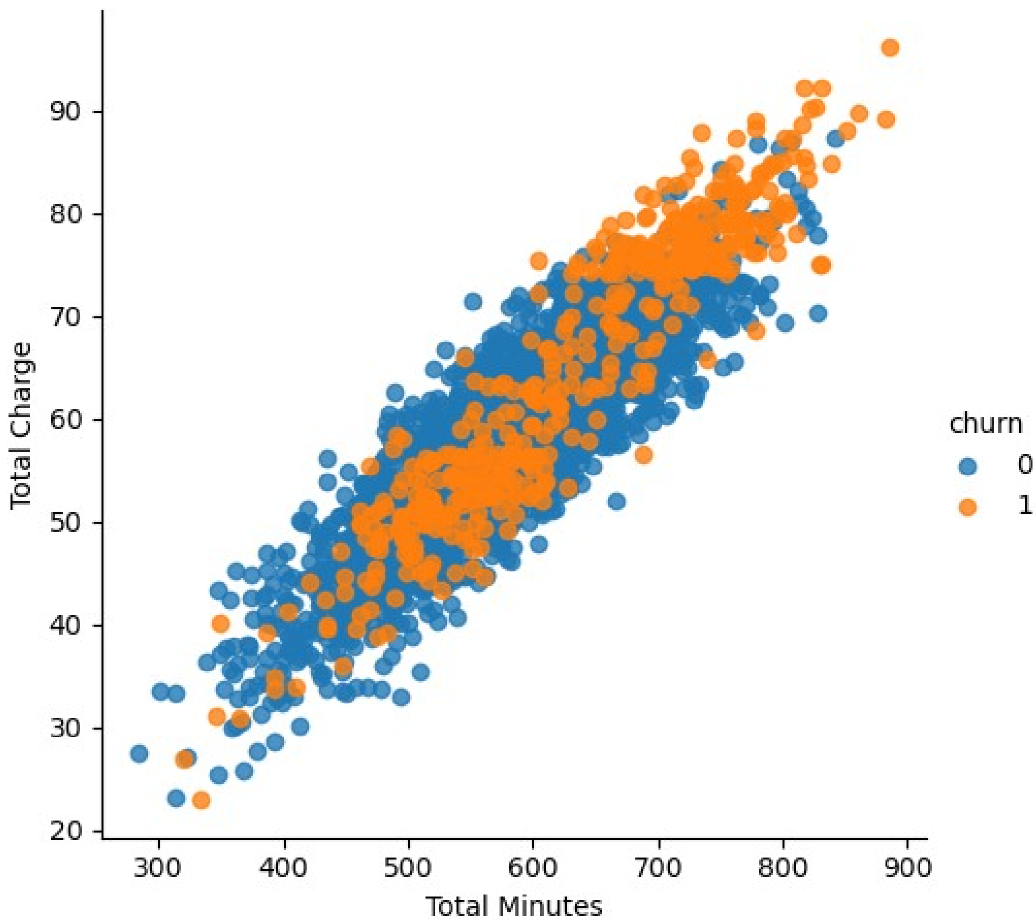
```
# Add columns for charges and create a new colums for totals
df['Total Charge'] = df['total day charge'] + df['total eve charge'] +
df['total night charge'] + df['total intl charge']
df['Total Minutes'] = df['total day minutes'] + df['total eve
minutes'] + df['total night minutes'] + df['total intl minutes']
```

```python
df['total calls'] = df['total day calls'] + df['total eve calls'] +
df['total night calls']+ df['total intl calls']

# Display the updated DataFrame
df.head(3)
```

```
   international plan  voice mail plan  number vmail messages  \
0                   0                1                     25
1                   0                1                     26
2                   0                0                      0

   total day minutes  total day calls  total day charge  total eve
minutes  \
0              265.1              110             45.07
197.4
1              161.6              123             27.47
195.5
2              243.4              114             41.38
121.2

   total eve calls  total eve charge  total night minutes  total night
calls  \
0               99             16.78                244.7
91
1              103             16.62                254.4
103
2              110             10.30                162.6
104

   total night charge  total intl minutes  total intl calls  \
0               11.01                10.0                 3
1               11.45                13.7                 3
2                7.32                12.2                 5

   total intl charge  customer service calls  churn  Total Charge  \
0               2.70                       1      0         75.56
1               3.70                       1      0         59.24
2               3.29                       0      0         62.29

   Total Minutes  total calls
0          717.2          303
1          625.2          332
2          539.4          333
```

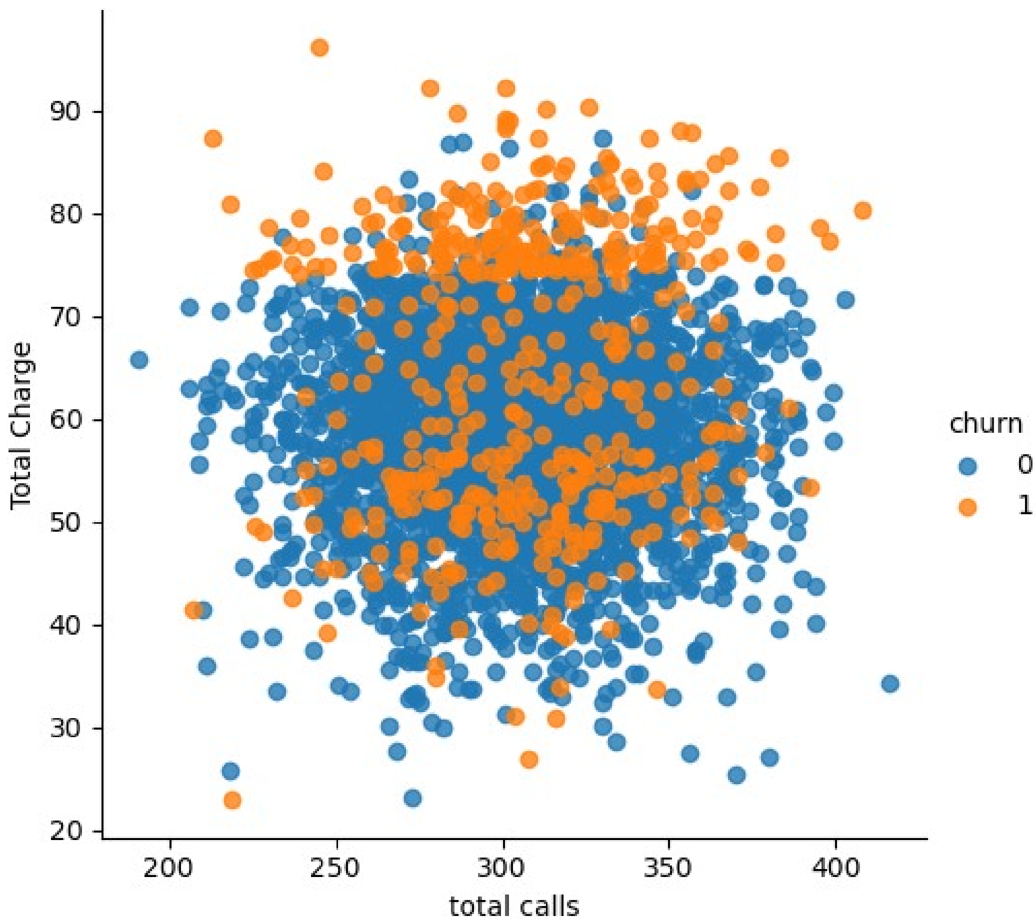
```python
sns.lmplot(x='Total Minutes', y='Total Charge', data=df, hue='churn',
fit_reg=False)
```

```
<seaborn.axisgrid.FacetGrid at 0x22fad499050>
```

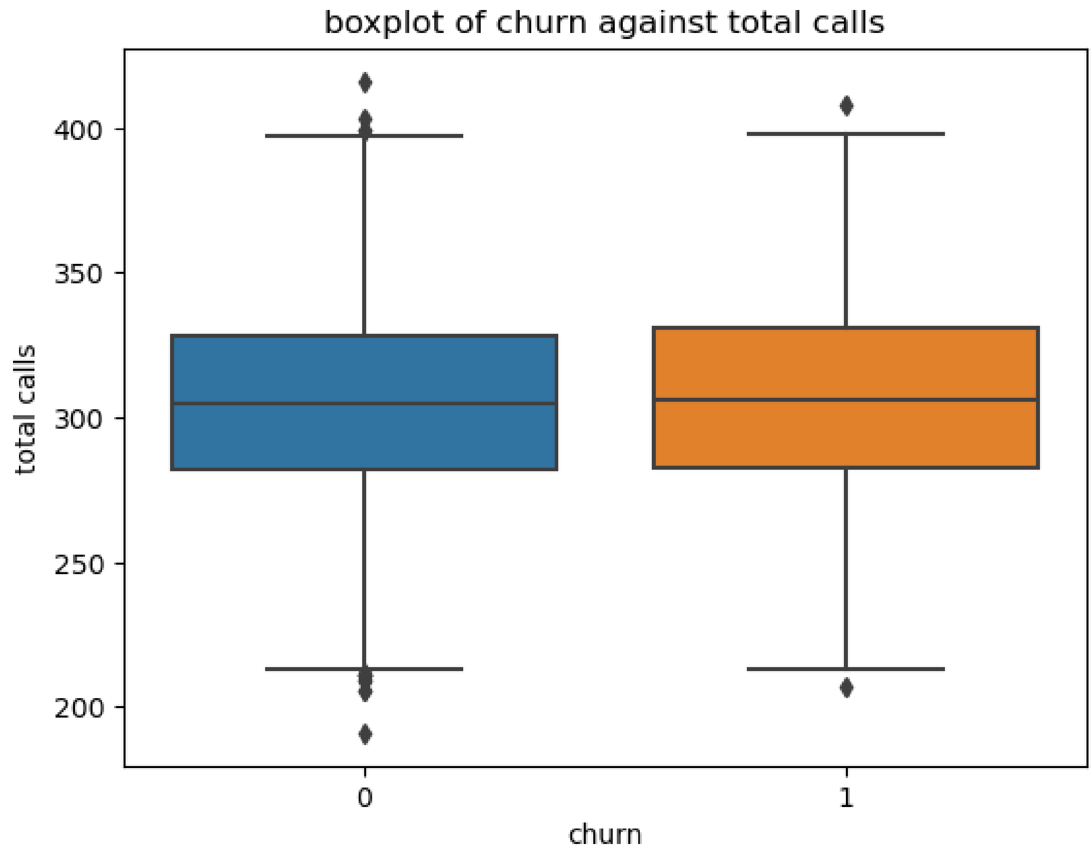



```
sns.lmplot(x='total calls', y='Total Charge', data=df, hue='churn', fit_reg=False)
```

```
<seaborn.axisgrid.FacetGrid at 0x22fad755050>
```




```
# total calls made against churn
sns.boxplot(x='churn', y='total calls', data=df).set(title='boxplot of churn against total calls')

[Text(0.5, 1.0, 'boxplot of churn against total calls')]
```



5 MODELLING

5.1 Data preparation

```
#import libraries
# Importing the relevant libraries for the project
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import joblib
import warnings

warnings.filterwarnings('ignore')

from sklearn.utils import resample
from sklearn.metrics import precision_score, recall_score,
accuracy_score, f1_score, make_scorer, auc
from sklearn.metrics import
roc_auc_score,ConfusionMatrixDisplay,confusion_matrix ,
classification_report, roc_curve
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import
train_test_split,GridSearchCV,cross_val_score
from sklearn.preprocessing import
StandardScaler,OneHotEncoder,LabelEncoder,OrdinalEncoder,MinMaxScaler
from sklearn.ensemble import
RandomForestClassifier,GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.pipeline import Pipeline
from sklearn.feature_selection import RFECV
from xgboost import XGBClassifier

# Dropping columns with multicollinearity.
columns_to_drop = ['total day minutes', 'total eve minutes', 'total
night minutes', 'total intl minutes']
df_1 = df.drop(columns=[col for col in columns_to_drop if col in
df.columns])
df_1.head(2)
```

```
   international plan  voice mail plan  number vmail messages  \
0                   0                1                     25
1                   0                1                     26

   total day calls  total day charge  total eve calls  total eve
charge  \
0              110             45.07               99
16.78
1              123             27.47              103
16.62

   total night calls  total night charge  total intl calls  total intl
charge  \
0                 91               11.01                 3
2.7
1                103               11.45                 3
3.7

   customer service calls  churn  Total Charge  Total Minutes  total
calls
0                       1      0         75.56          717.2
303
1                       1      0         59.24          625.2
332
```

```
# Defining the target variable(y) and the independent variables(x).
y = df_1['churn']
X = df_1.drop(['churn','Total Charge','Total Minutes','total
calls'],axis=1)
```

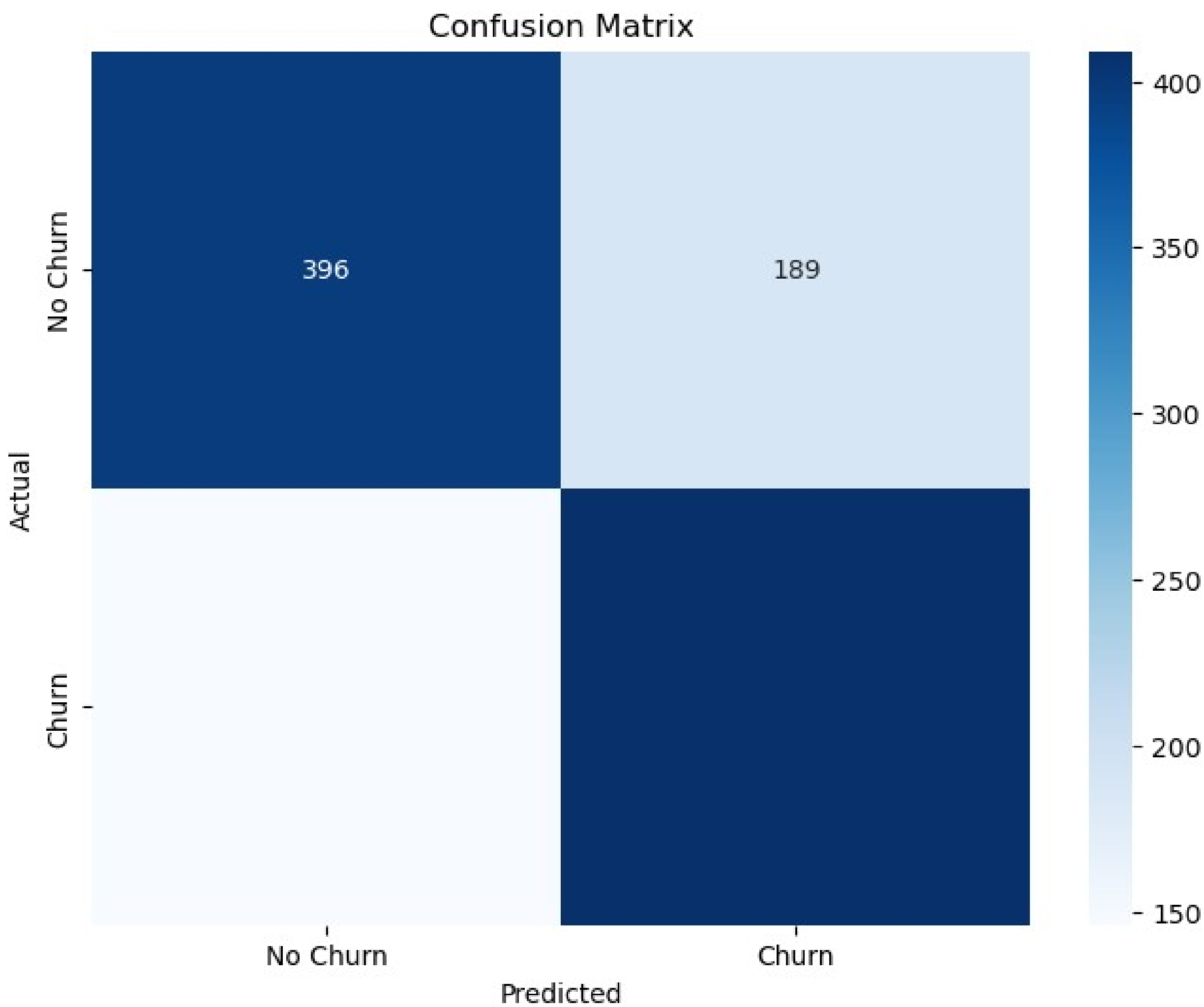
```python
from imblearn.over_sampling import SMOTE
oversample = SMOTE(random_state=42)
X_smote, y_smote = oversample.fit_resample(X, y)

#Splitting data

X_train, X_test, y_train, y_test = train_test_split(X_smote, y_smote,
test_size=0.2, random_state=42)

# Feature scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

MODEL 1:Baseline Model (Logistic Regression)

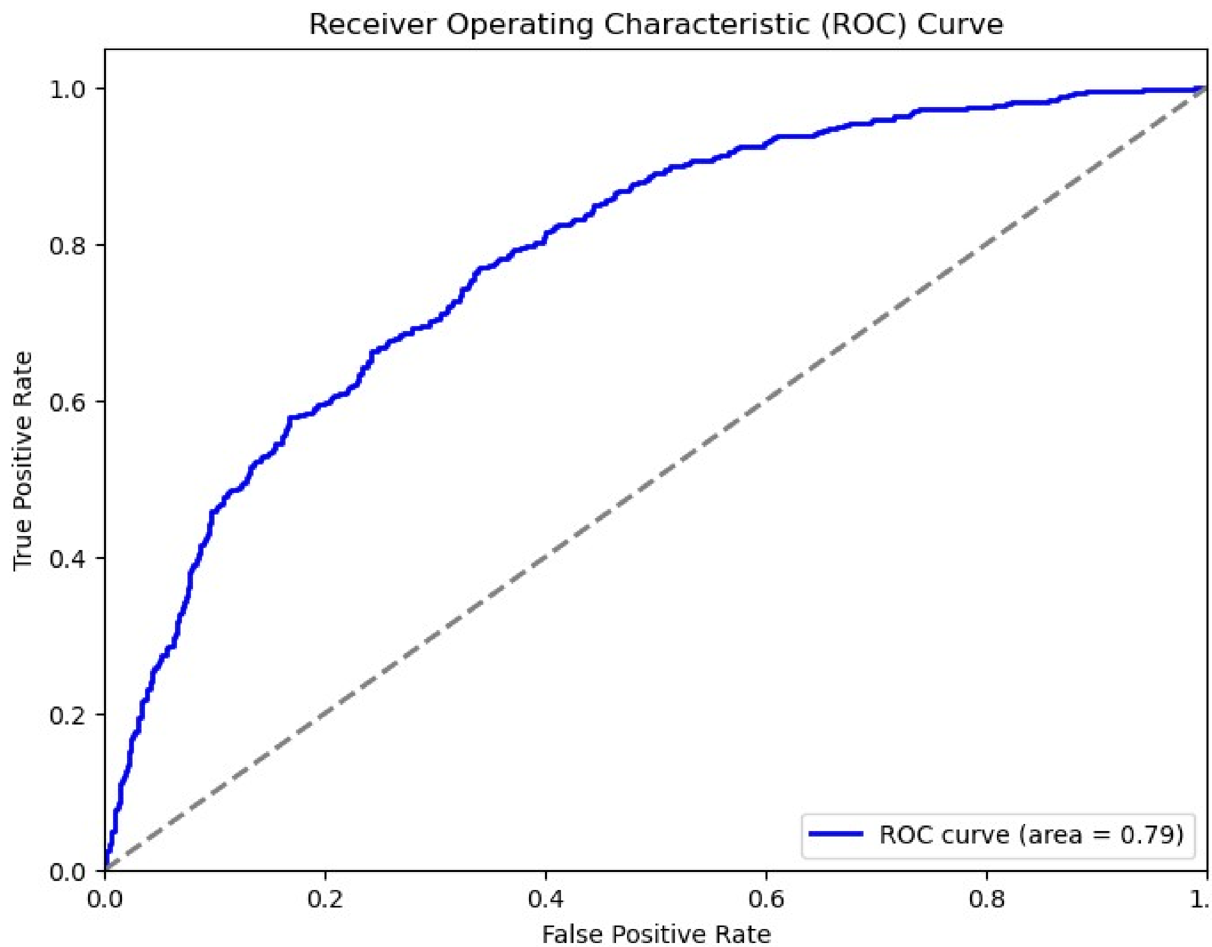
```python
# Instantiate the model
log_reg = LogisticRegression()

# Fit the model
log_reg.fit(X_train, y_train)

# Generate predictions
y_hat_train = log_reg.predict(X_train)
y_hat_test = log_reg.predict(X_test)

# Make predictions on the test set
y_pred = log_reg.predict(X_test)
y_pred_proba = log_reg.predict_proba(X_test)[:, 1]

# Generate classification report
class_report = classification_report(y_test, y_pred)
print("Classification Report:\n", class_report)

# Compute confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", conf_matrix)

# Compute ROC AUC score
roc_auc = roc_auc_score(y_test, y_pred_proba)
print("ROC AUC Score:", roc_auc)

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=['No Churn', 'Churn'], yticklabels=['No Churn', 'Churn'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

```python
# Plot ROC curve
fpr, tpr, _ = roc_curve(y_test, y_pred_proba)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (area =
%0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.73      0.68      0.70       585
           1       0.68      0.74      0.71       555

    accuracy                           0.71      1140
   macro avg       0.71      0.71      0.71      1140
weighted avg       0.71      0.71      0.71      1140

Confusion Matrix:
 [[396 189]
 [146 409]]
ROC AUC Score: 0.7866112266112266
```



Confusion Matrix
396
189
No Churn
Churn
Actual
No Churn
Churn
Predicted
400
350
300
250
200
150



The model has a balanced precision and recall for both churn and non-churn classes, resulting in an F1-score of 0.70 and 0.71 for class churn and non-churnrespectively. The accuracy of 0.71 indicates that the model is correctly predicting churn status for most customers. The ROC AUC score of 0.79 suggests that the model has a good discriminatory ability between churn and non-churn customers.

MODEL 2: Decision Tree Model

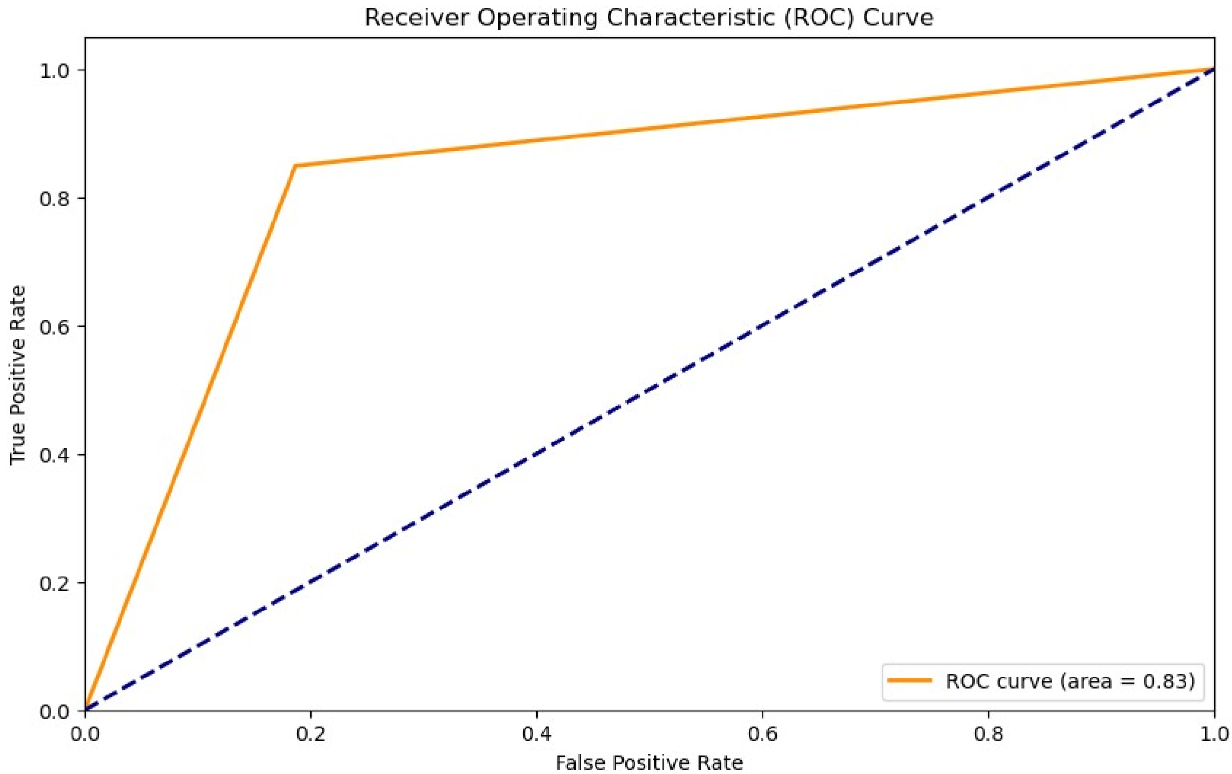
```
# Initialize and train the decision tree classifier
tree_clf = DecisionTreeClassifier(random_state=42)
tree_clf.fit(X_train, y_train)

# Make predictions on the test set
y_test_pred = tree_clf.predict(X_test)
y_train_pred = tree_clf.predict(X_train)

# Evaluate the model
accuracy = accuracy_score(y_test, y_test_pred)
f1 = f1_score(y_test, y_pred)

# Generate classification report
```

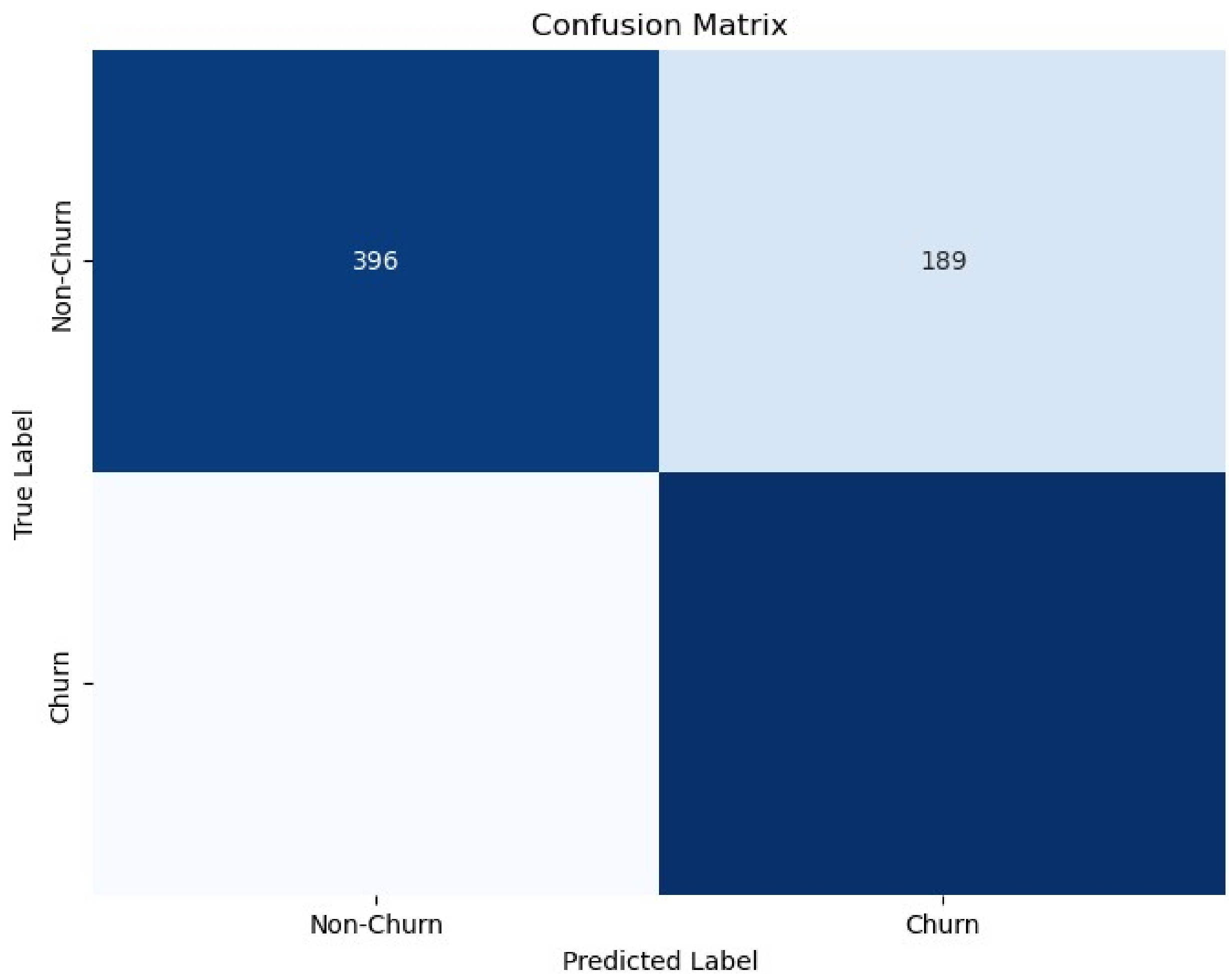
```python
class_report = classification_report(y_test, y_test_pred)

# Compute ROC AUC score
y_pred_proba = tree_clf.predict_proba(X_test)[:, 1]
roc_auc = roc_auc_score(y_test, y_pred_proba)

print("Decision Tree - Accuracy:", accuracy)
print("Decision Tree - F1 Score:", f1)
print("\nClassification Report:\n", class_report)
print("ROC AUC Score:", roc_auc)
```

```
Decision Tree - Accuracy: 0.8307017543859649
Decision Tree - F1 Score: 0.7094535993061578

Classification Report:
               precision    recall  f1-score   support

           0       0.85      0.81      0.83       585
           1       0.81      0.85      0.83       555

    accuracy                           0.83      1140
   macro avg       0.83      0.83      0.83      1140
weighted avg       0.83      0.83      0.83      1140

ROC AUC Score: 0.8311619311619312
```

```python
# Visualize the ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

plt.figure(figsize=(10, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area =
{roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()

# Visualize the Confusion Matrix
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['Non-Churn', 'Churn'], yticklabels=['Non-
Churn', 'Churn'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
```

```
plt.title('Confusion Matrix')
plt.show()
```





- The decision tree model performs very well with an accuracy of 0.87.
- The precision, recall, and F1 scores for both classes (non-churn and churn) are balanced around 0.83, indicating that the model performs equally well on both classes.
- The ROC AUC score of 0.83 further confirms the model's excellent discriminatory power between churn and non-churn customers.
- Overall, the model demonstrates a high level of performance and reliability in predicting customer churn as compared to the baseline model.

Checking for decision tree model overfitting

```
# Evaluate the model on the training data
train_accuracy = accuracy_score(y_train, y_train_pred)
train_f1 = f1_score(y_train, y_train_pred)
train_class_report = classification_report(y_train, y_train_pred)

# Evaluate the model on the test data
test_accuracy = accuracy_score(y_test, y_test_pred)
test_f1 = f1_score(y_test, y_test_pred)
test_class_report = classification_report(y_test, y_test_pred)
```

```
print("Training Set Performance:")
print("Accuracy:", train_accuracy)
print("F1 Score:", train_f1)
print("\nClassification Report:\n", train_class_report)

print("Test Set Performance:")
print("Accuracy:", test_accuracy)
print("F1 Score:", test_f1)
print("\nClassification Report:\n", test_class_report)

# Check for overfitting
if train_accuracy > test_accuracy:
    print("The model might be overfitting.")
else:
    print("The model does not appear to be overfitting.")
```

```
Training Set Performance:
Accuracy: 1.0
F1 Score: 1.0

Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      2265
           1       1.00      1.00      1.00      2295

    accuracy                           1.00      4560
   macro avg       1.00      1.00      1.00      4560
weighted avg       1.00      1.00      1.00      4560

Test Set Performance:
Accuracy: 0.8307017543859649
F1 Score: 0.8299559471365638

Classification Report:
               precision    recall  f1-score   support

           0       0.85      0.81      0.83       585
           1       0.81      0.85      0.83       555

    accuracy                           0.83      1140
   macro avg       0.83      0.83      0.83      1140
weighted avg       0.83      0.83      0.83      1140

The model might be overfitting.
```

Hypeparameter Tuning

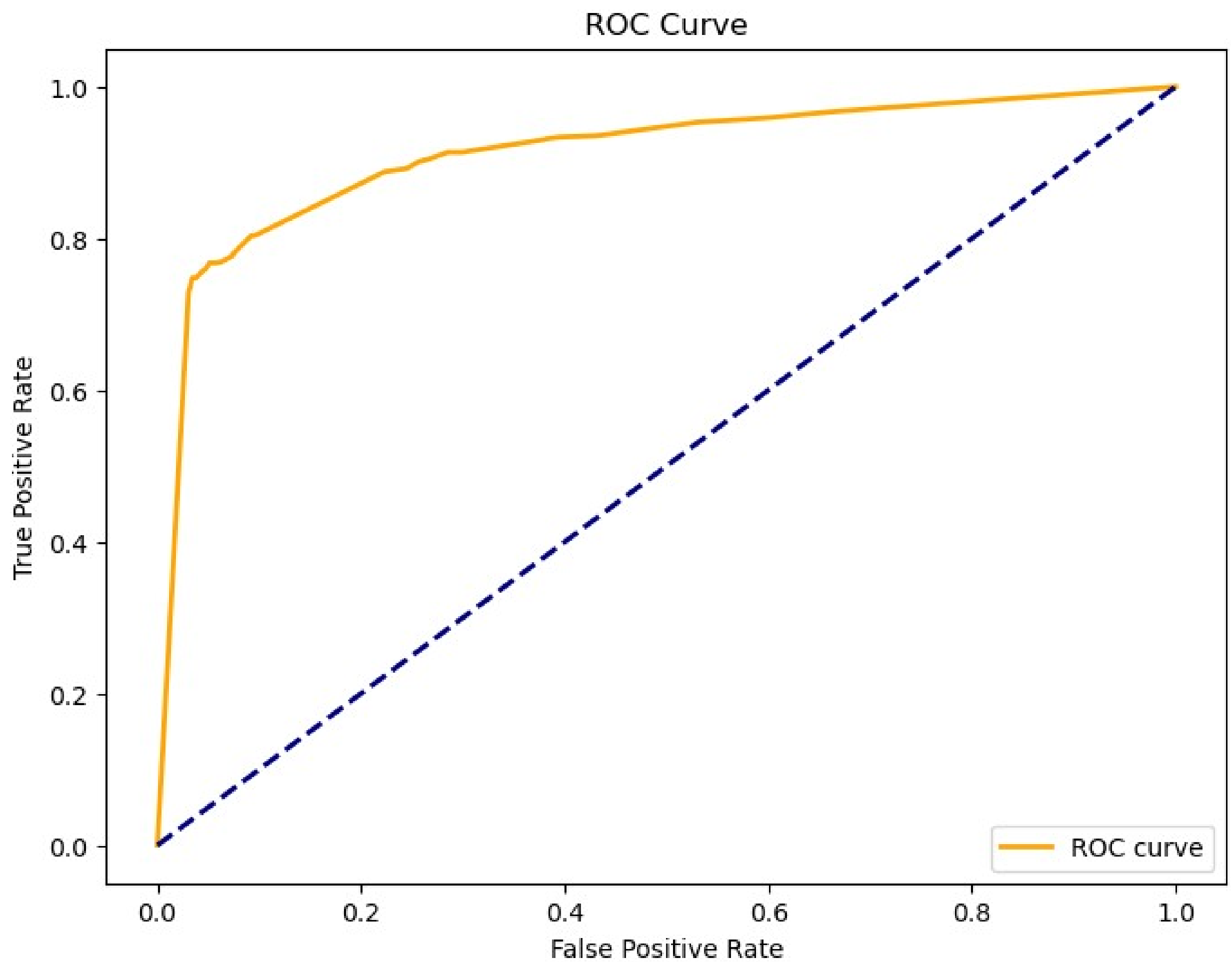
To regularize the decision tree and mitigate overfitting,we will set hyperparameters, so as to reduce the complexity of the decision tree and prevent it from overfitting the training data. The model will generalize better to new, unseen data, improving its performance on the test set.

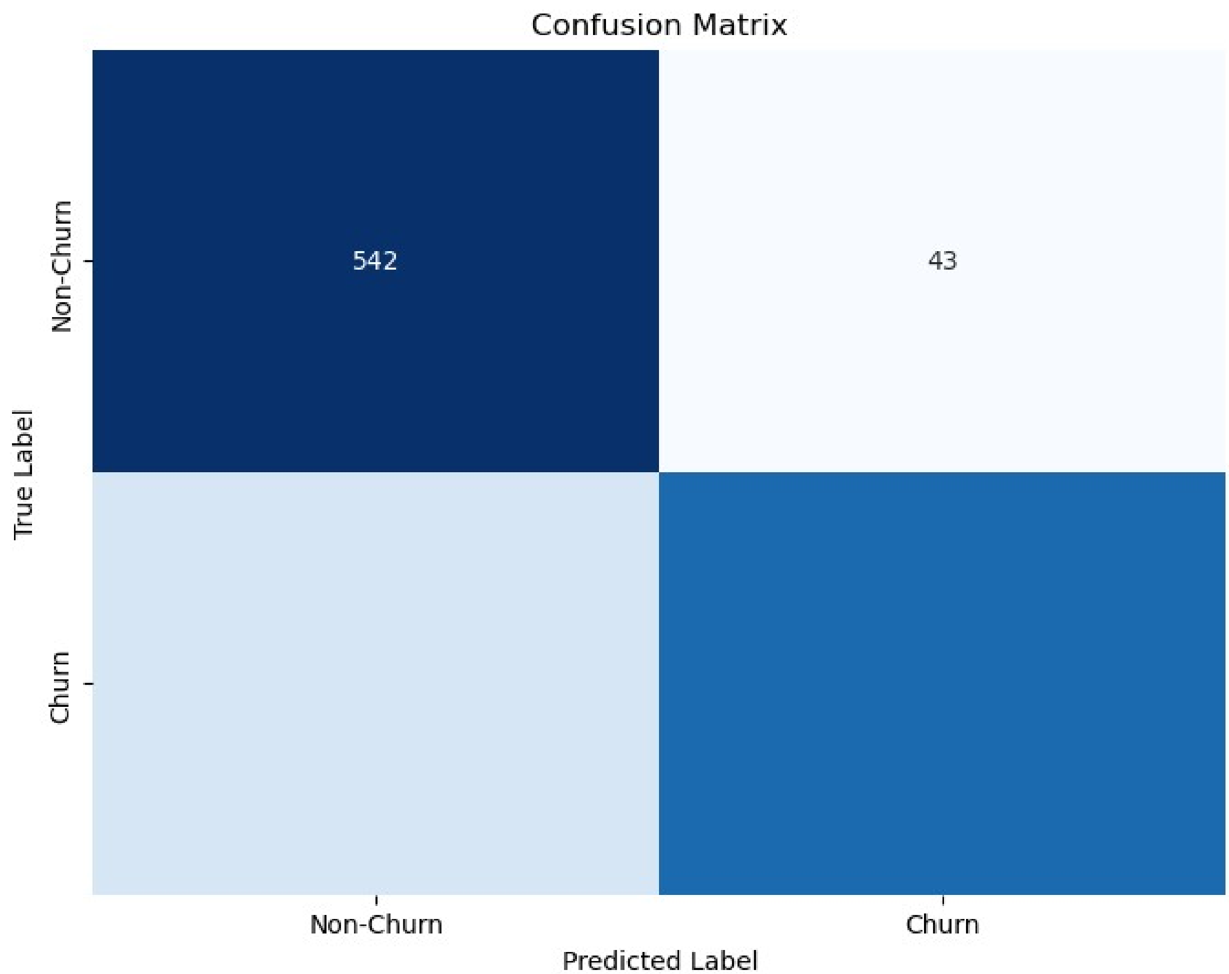
```python
from sklearn.model_selection import GridSearchCV
# Define the parameter grid
param_grid = {
    'max_depth': [10, 20, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Setup the GridSearchCV
grid_search = GridSearchCV(tree_clf, param_grid, cv=5,
scoring='roc_auc', n_jobs=-1)

# Fit the grid search
grid_search.fit(X_train, y_train)

# Best parameters
print("Best parameters for Decision Tree:")
print(grid_search.best_params_)

# Best estimator
best_decision_tree = grid_search.best_estimator_

# Predictions and evaluation
y_pred = best_decision_tree.predict(X_test)
y_pred_prob = best_decision_tree.predict_proba(X_test)[:, 1]

print("Classification Report:")
print(classification_report(y_test, y_pred))
print("ROC AUC Score:", roc_auc_score(y_test, y_pred_prob))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

```
Best parameters for Decision Tree:
{'max_depth': 10, 'min_samples_leaf': 4, 'min_samples_split': 10}
Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.87      0.84       585
           1       0.86      0.79      0.82       555

    accuracy                           0.83      1140
   macro avg       0.84      0.83      0.83      1140
weighted avg       0.84      0.83      0.83      1140

ROC AUC Score: 0.8968091168091168
Confusion Matrix:
[[511  74]
 [115 440]]
```

```python
# Predictions and evaluation
y_pred = best_decision_tree.predict(X_test)
```

```python
y_pred_prob = best_decision_tree.predict_proba(X_test)[:, 1]

# ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='orange', lw=2, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['Non-Churn', 'Churn'], yticklabels=['Non-
Churn', 'Churn'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```


ROC Curve
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve



The tuned decision tree model, tuned with the best parameters (max_depth=10, min_samples_leaf=4, min_samples_split=2), performs well with an overall accuracy of 0.83. The high precision for class 1 (0.82) and high recall for class 0 (0.87) indicate the model is good at identifying both classes correctly, with a slightly higher ability to correctly identify class 0 instances. The ROC AUC score of 0.896 signifies strong discriminative ability of the model. The confusion matrix further shows that misclassifications are relatively low. This model performs better than the baseline model in terms of all metrics i.e recall, precision, accuracy, f1 score and ROC score.

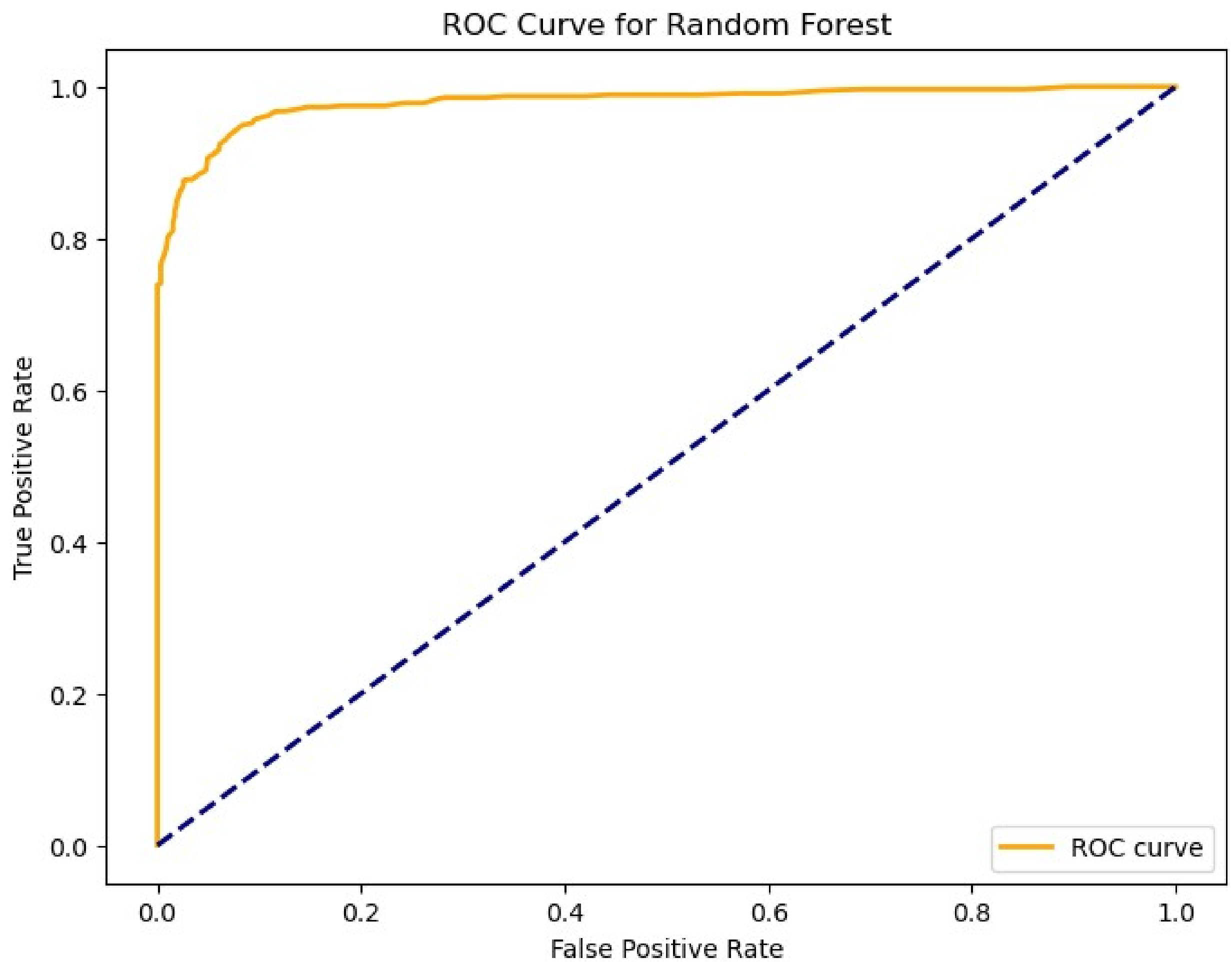
MODEL 3: Random Forest

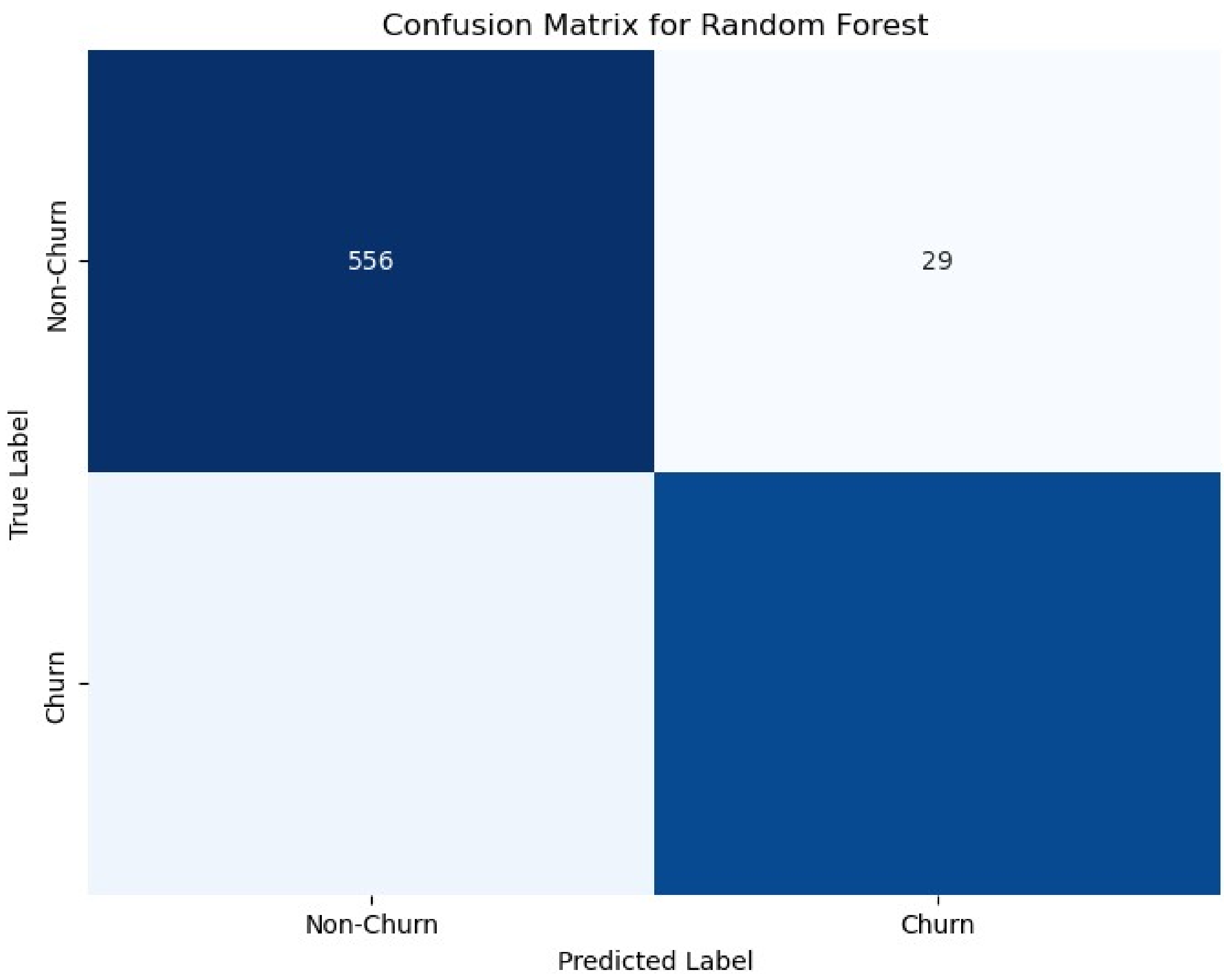
```
from sklearn.ensemble import RandomForestClassifier

# Initialize and train model
random_forest = RandomForestClassifier(random_state=42)
random_forest.fit(X_train, y_train)

# Predictions
y_pred = random_forest.predict(X_test)
y_pred_prob = random_forest.predict_proba(X_test)[:, 1]
```

```python
# Evaluation
print("\nRandom Forest")
print("Classification Report:")
print(classification_report(y_test, y_pred))
print("ROC AUC Score:", roc_auc_score(y_test, y_pred_prob))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

```
Random Forest
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.92      0.92       585
           1       0.92      0.91      0.92       555

    accuracy                           0.92      1140
   macro avg       0.92      0.92      0.92      1140
weighted avg       0.92      0.92      0.92      1140

ROC AUC Score: 0.9716516516516518
Confusion Matrix:
[[539  46]
 [ 48 507]]
```

```python
# ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='orange', lw=2, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Random Forest')
plt.legend(loc='lower right')
plt.show()

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['Non-Churn', 'Churn'], yticklabels=['Non-
Churn', 'Churn'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix for Random Forest')
plt.show()
```


ROC Curve for Random Forest
True Positive Rate
False Positive Rate
ROC curve
0.0
0.2
0.4
0.6
0.8
1.0



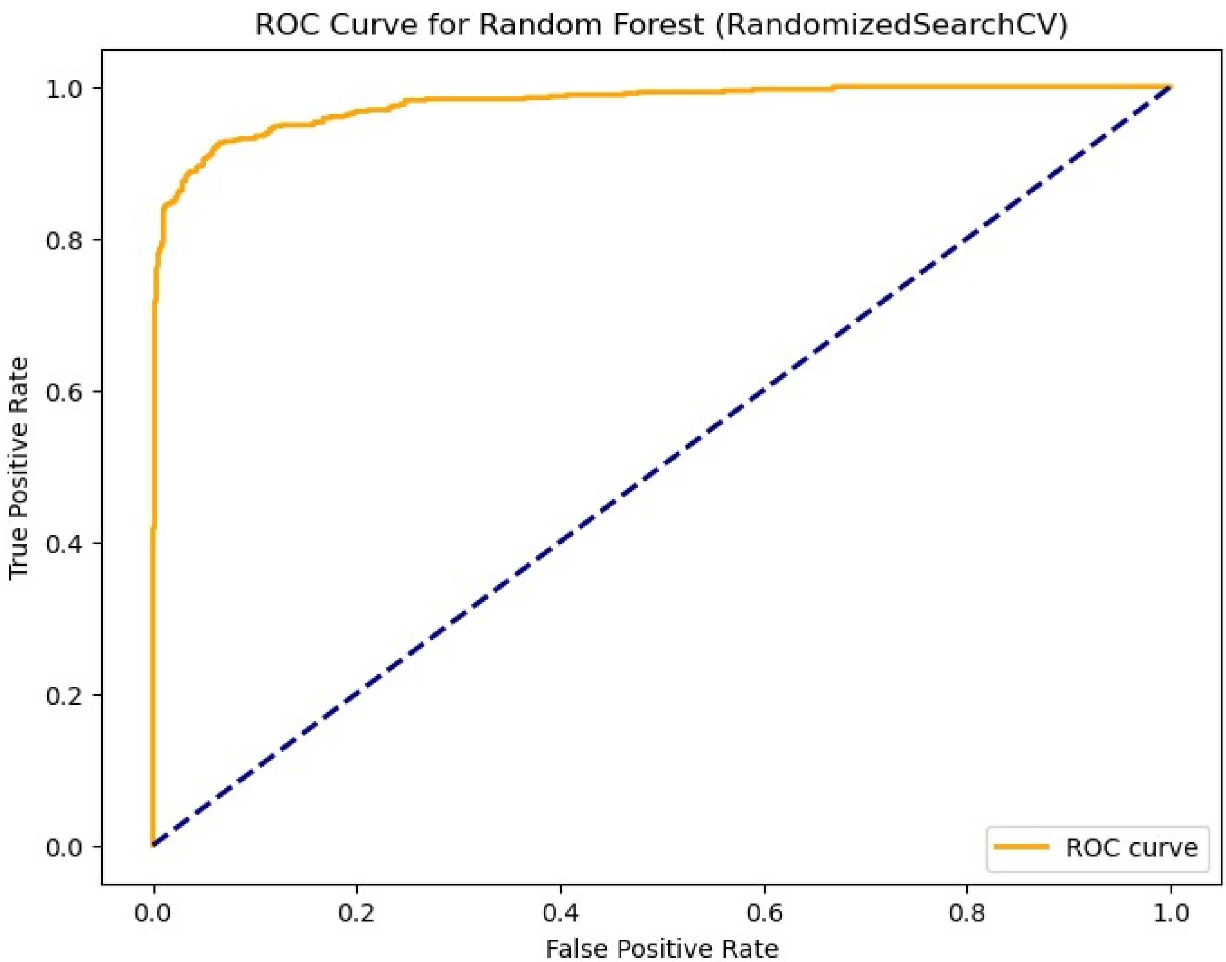

```
from sklearn.model_selection import RandomizedSearchCV
# Define the parameter grid
param_distributions = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 20, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False]
}

# Setup the RandomizedSearchCV
random_search = RandomizedSearchCV(random_forest, param_distributions,
n_iter=50, cv=5, scoring='roc_auc', n_jobs=-1, random_state=42)

# Fit the random search
random_search.fit(X_train, y_train)

# Best parameters
print("Best parameters for Random Forest:")
print(random_search.best_params_)
```

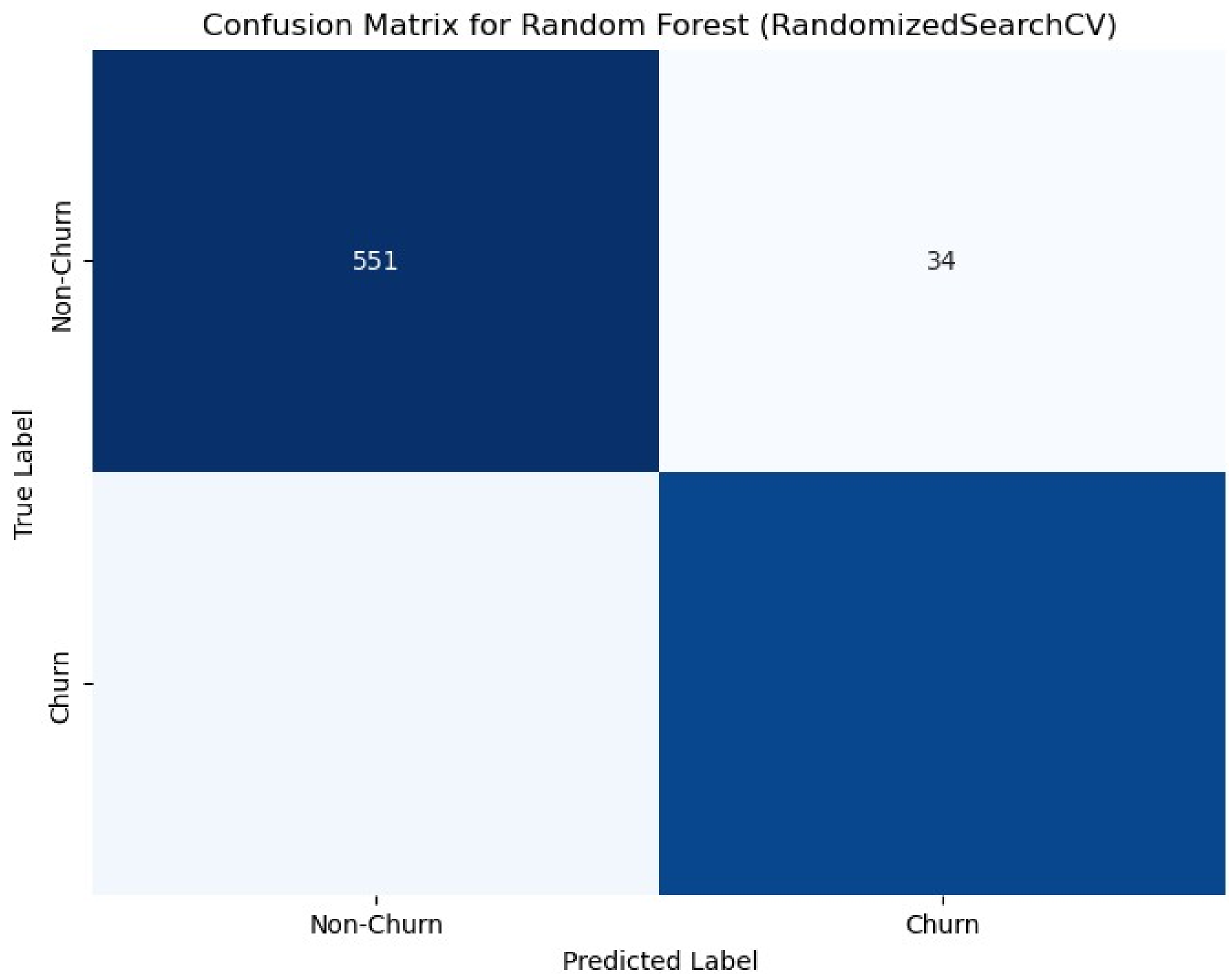
```
# Best estimator
best_random_forest = random_search.best_estimator_

# Predictions and evaluation
y_pred = best_random_forest.predict(X_test)
y_pred_prob = best_random_forest.predict_proba(X_test)[:, 1]

print("Classification Report:")
print(classification_report(y_test, y_pred))
print("ROC AUC Score:", roc_auc_score(y_test, y_pred_prob))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

```
Best parameters for Random Forest:
{'n_estimators': 200, 'min_samples_split': 2, 'min_samples_leaf': 1,
'max_depth': 20, 'bootstrap': False}
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.94      0.93       585
           1       0.94      0.91      0.92       555

    accuracy                           0.93      1140
   macro avg       0.93      0.93      0.93      1140
weighted avg       0.93      0.93      0.93      1140

ROC AUC Score: 0.9775452375452374
Confusion Matrix:
[[551  34]
 [ 50 505]]
```

```
# ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='orange', lw=2, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Random Forest (RandomizedSearchCV)')
plt.legend(loc='lower right')
plt.show()

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['Non-Churn', 'Churn'], yticklabels=['Non-
Churn', 'Churn'])
```

```
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix for Random Forest (RandomizedSearchCV)')
plt.show()
```





The tuned Random Forest model, tuned with the best parameters (n_estimators=200, min_samples_split=2, min_samples_leaf=1, max_depth=20, bootstrap=False), performs exceptionally well with an overall accuracy of 0.93. The model demonstrates high precision and recall for both classes, with an F1-score of 0.93 and 0.92 for both classes, indicating balanced performance. The ROC AUC score of 0.9775 signifies the model's excellent ability to distinguish between classes.

Model 4: Gradient Boosting Model

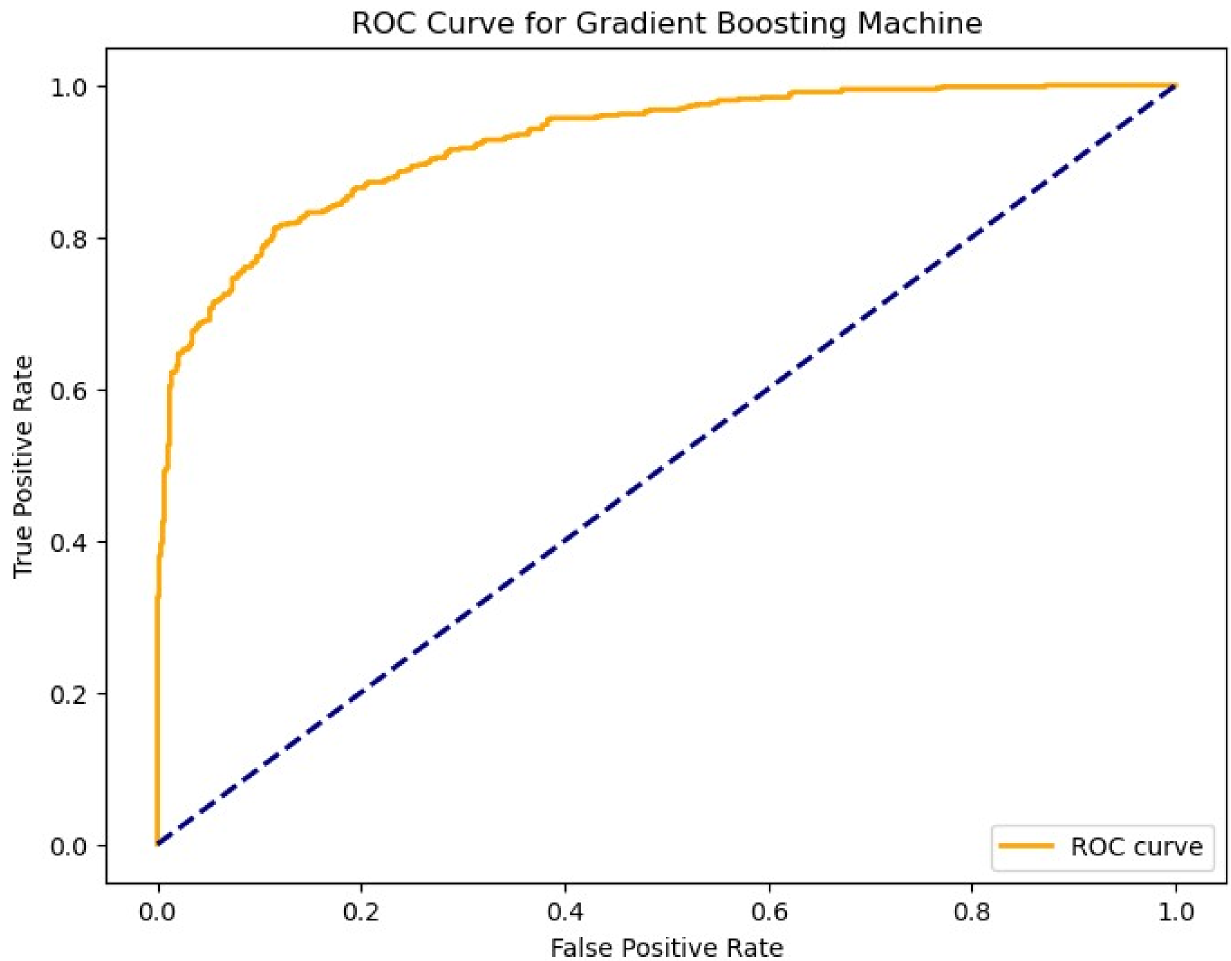
```
from sklearn.ensemble import GradientBoostingClassifier

# Initialize and train model
gbm = GradientBoostingClassifier(random_state=42)
gbm.fit(X_train, y_train)

# Predictions
y_pred = gbm.predict(X_test)
y_pred_prob = gbm.predict_proba(X_test)[:, 1]

# Evaluation
```

```
print("\nGradient Boosting Machine")
print("Classification Report:")
print(classification_report(y_test, y_pred))
print("ROC AUC Score:", roc_auc_score(y_test, y_pred_prob))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

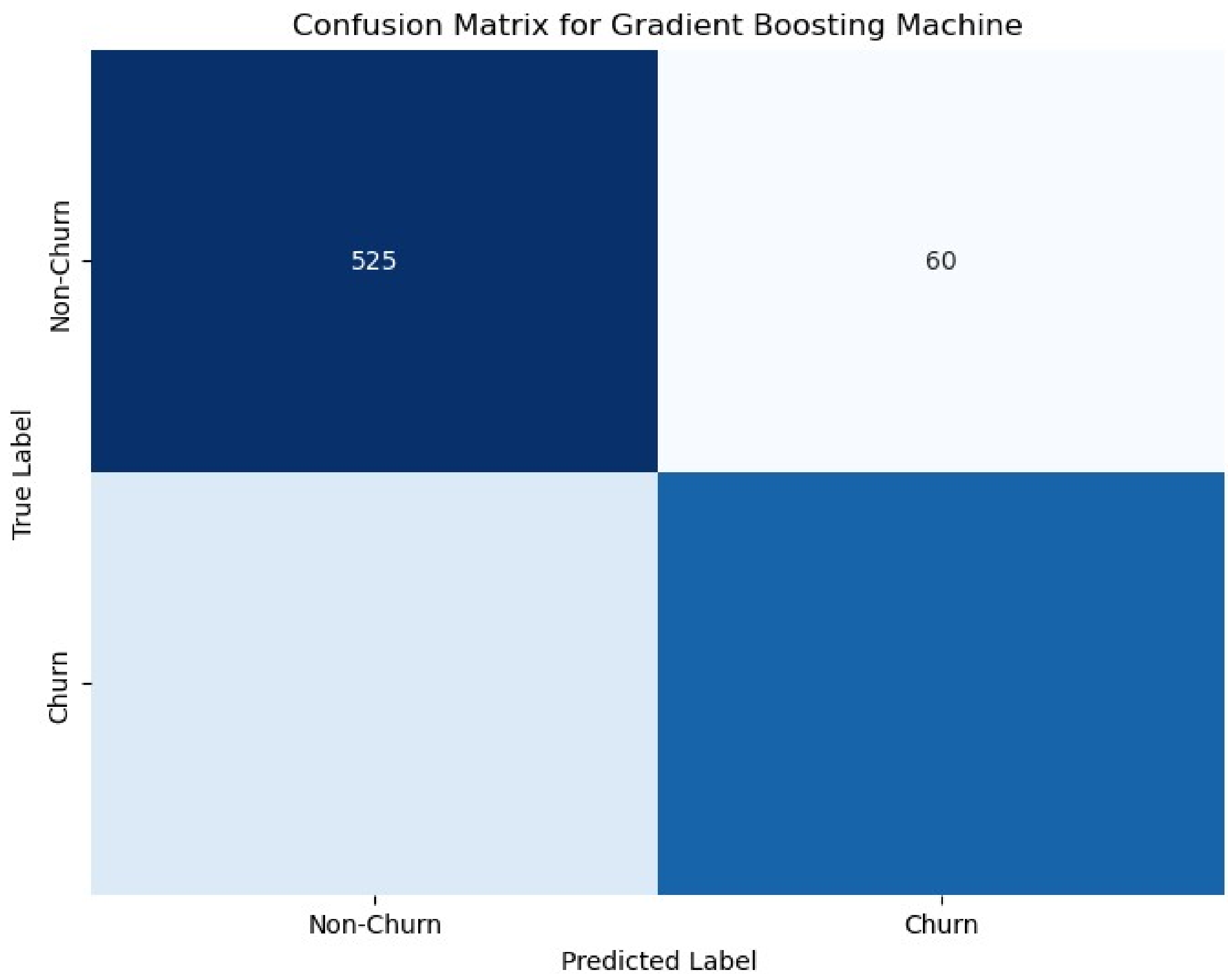
```
Gradient Boosting Machine
Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.90      0.85       585
           1       0.88      0.78      0.82       555

    accuracy                           0.84      1140
   macro avg       0.84      0.84      0.84      1140
weighted avg       0.84      0.84      0.84      1140

ROC AUC Score: 0.9248202048202048
Confusion Matrix:
[[525  60]
 [124 431]]
```

```
# ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='orange', lw=2, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Gradient Boosting Machine')
plt.legend(loc='lower right')
plt.show()

# ROC AUC Score
roc_auc = roc_auc_score(y_test, y_pred_prob)
print("ROC AUC Score:", roc_auc)

# Confusion Matrix
y_pred = gbm.predict(X_test)
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['Non-Churn', 'Churn'], yticklabels=['Non-
Churn', 'Churn'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
```

```
plt.title('Confusion Matrix for Gradient Boosting Machine')
plt.show()
```




```
ROC AUC Score: 0.9248202048202048
```



Hyperparameter tuned Gradient Boosting Model

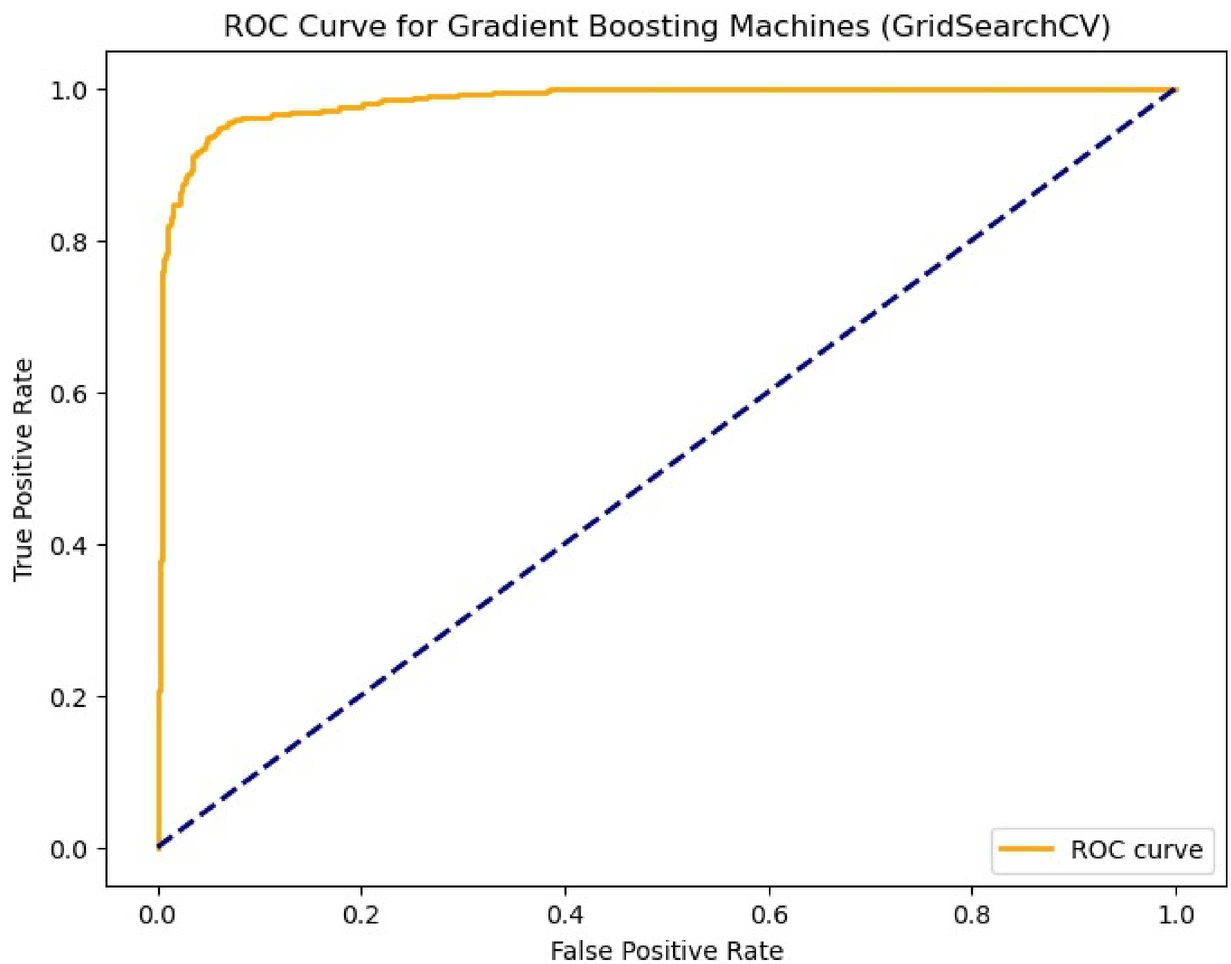
```
# Define the parameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 5, 7]
}

# Setup the GridSearchCV
grid_search = GridSearchCV(gbm, param_grid, cv=5, scoring='roc_auc',
n_jobs=-1)

# Fit the grid search
grid_search.fit(X_train, y_train)

# Best parameters
print("Best parameters for Gradient Boosting Machines:")
print(grid_search.best_params_)

# Best estimator
```

```
best_gbm = grid_search.best_estimator_

# Predictions and evaluation
y_pred = best_gbm.predict(X_test)
y_pred_prob = best_gbm.predict_proba(X_test)[:, 1]

print("Classification Report:")
print(classification_report(y_test, y_pred))
print("ROC AUC Score:", roc_auc_score(y_test, y_pred_prob))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

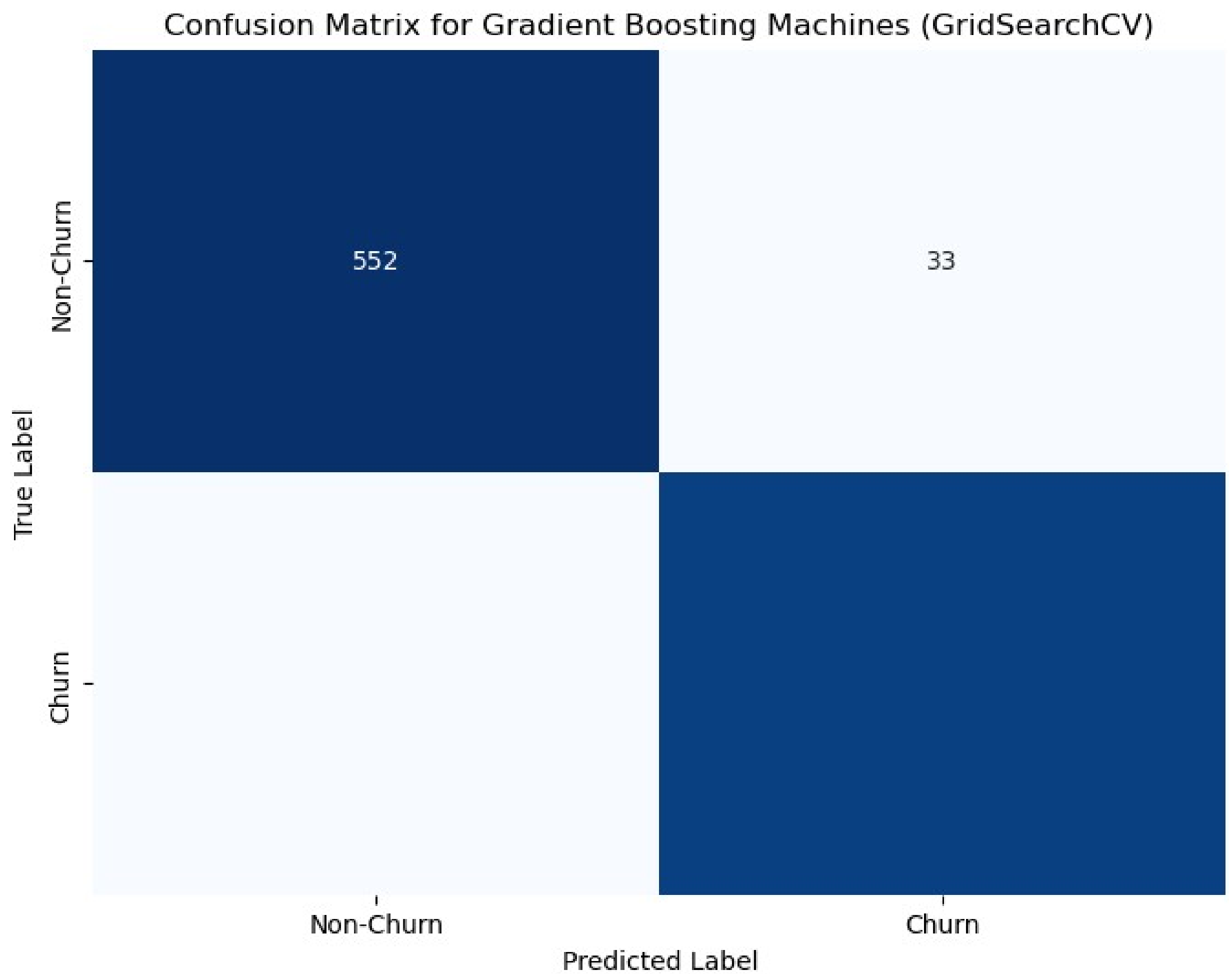
```
Best parameters for Gradient Boosting Machines:
{'learning_rate': 0.2, 'max_depth': 7, 'n_estimators': 300}
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.94      0.94       585
           1       0.94      0.94      0.94       555

    accuracy                           0.94      1140
   macro avg       0.94      0.94      0.94      1140
weighted avg       0.94      0.94      0.94      1140

ROC AUC Score: 0.9839069839069838
Confusion Matrix:
[[552  33]
 [ 35 520]]
```

```
# ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='orange', lw=2, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Gradient Boosting Machines (GridSearchCV)')
plt.legend(loc='lower right')
plt.show()

# ROC AUC Score
roc_auc = roc_auc_score(y_test, y_pred_prob)
print("ROC AUC Score:", roc_auc)

# Confusion Matrix
y_pred = best_gbm.predict(X_test)
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
```

```
            xticklabels=['Non-Churn', 'Churn'], yticklabels=['Non-
Churn', 'Churn'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix for Gradient Boosting Machines
(GridSearchCV)')
plt.show()
```




```
ROC AUC Score: 0.9839069839069838
```



- The tuned Gradient Boosting Machine (GBM) model, tuned with the best parameters (learning_rate=0.2, max_depth=7, n_estimators=300), performs exceptionally well with an overall accuracy of 0.94. The model shows high precision and recall for both classes, with F1-scores of 0.94 for class 0 and 0.94 for class 1, indicating balanced and reliable performance. The ROC AUC score of 0.98 signifies the model's excellent ability to distinguish between the classes. The confusion matrix shows minimal misclassifications, with only 10 false positives and 31 false negatives, highlighting the model's robustness and accuracy.
- The accuracy of the model has improved after tuning the hyperparameters from 0.87 to 0.94 with the tuned model.
- Overall, the GBM classifier with the specified hyperparameters demonstrates outstanding performance, achieving high accuracy, precision, recall, and ROC AUC score.

MODEL 5: K NEAREST NEIGHBOURS MODEL

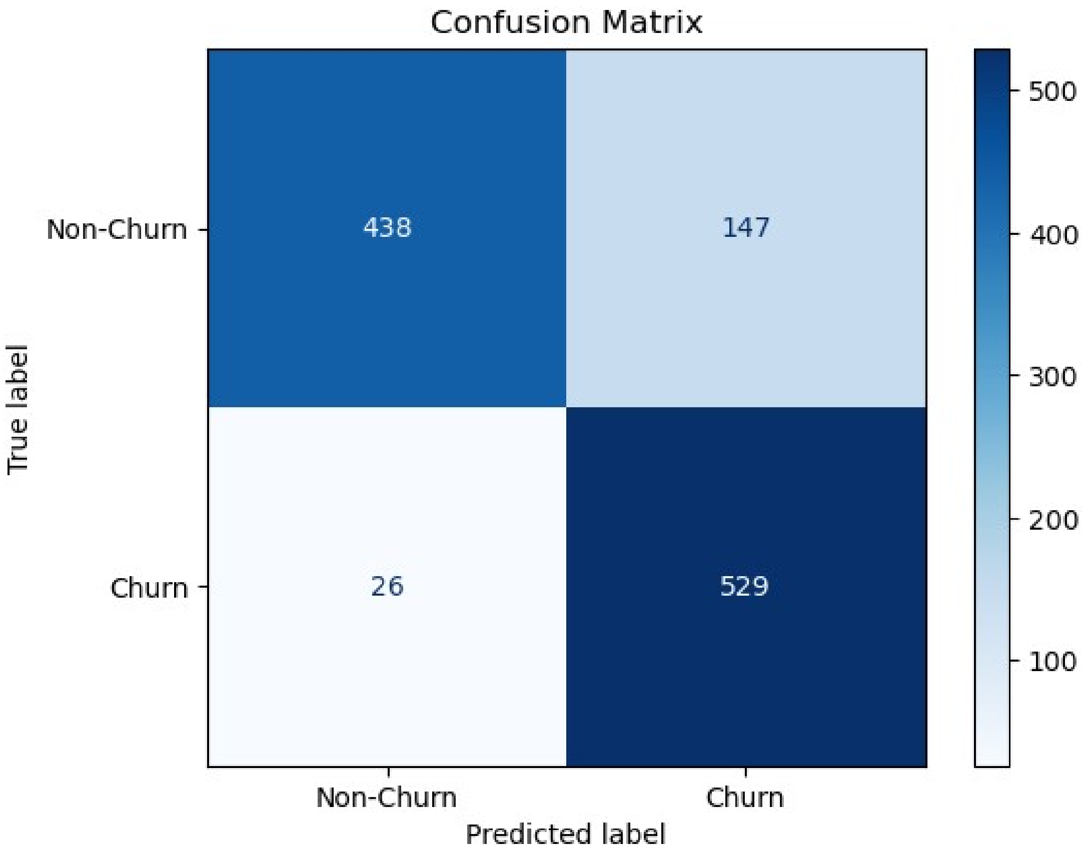
```
# Initialize the KNN classifier
k = 5  # Number of neighbors to consider
knn = KNeighborsClassifier(n_neighbors=k)

# Train the classifier
```

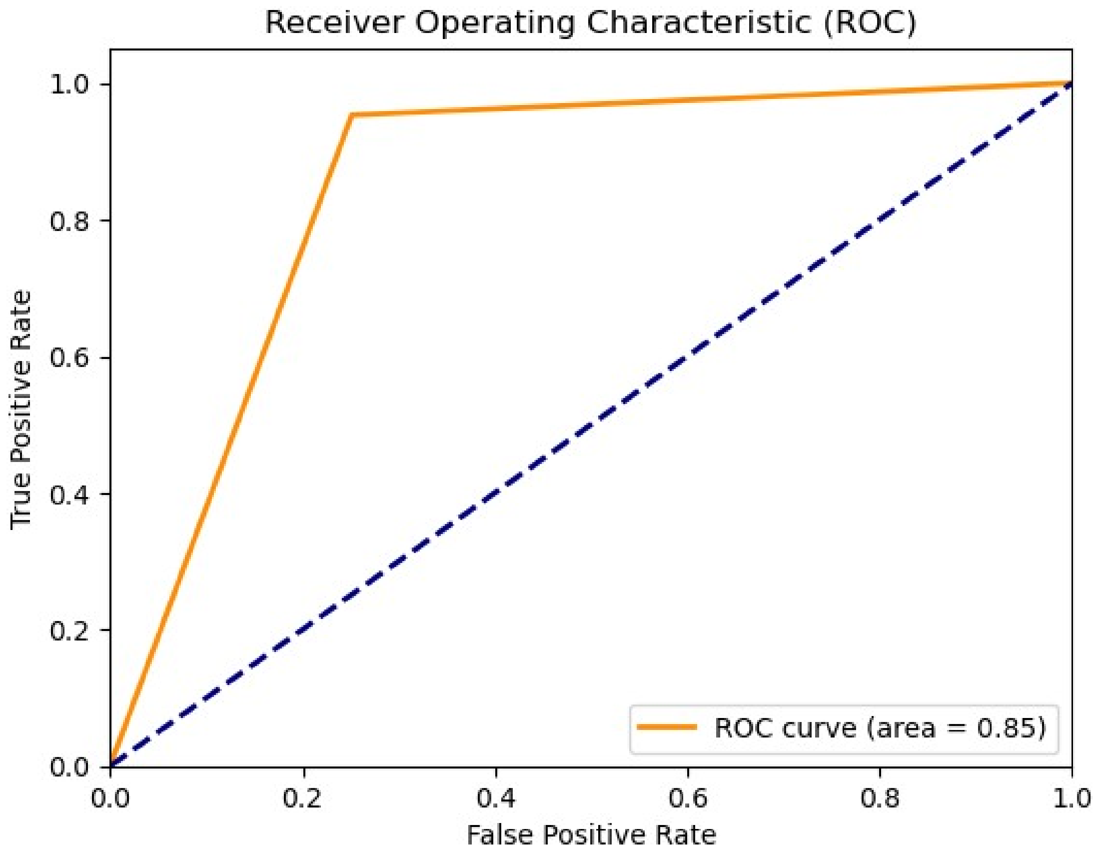
```python
knn.fit(X_train, y_train)

# Make predictions
y_pred = knn.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

# Generate classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))
print("ROC AUC Score:", roc_auc_score(y_test, y_pred))
```

```
Accuracy: 0.8482456140350877
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.75      0.84       585
           1       0.78      0.95      0.86       555

    accuracy                           0.85      1140
   macro avg       0.86      0.85      0.85      1140
weighted avg       0.87      0.85      0.85      1140

ROC AUC Score: 0.850935550935551
```

```python
# Calculate confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Plot confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=["Non-Churn", "Churn"])
disp.plot(cmap=plt.cm.Blues)
plt.title("Confusion Matrix")
plt.show()

# Plot ROC curve
fpr, tpr, _ = roc_curve(y_test, y_pred)
roc_auc = auc(fpr, tpr)

plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area =
%0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
```

```python
plt.legend(loc="lower right")
plt.show()
```





- The KNN classifier with an accuracy of approximately 0.85 and ROC score of 0.8509 performs well on the test data. The classification report shows that:
- For Class 0: High precision (0.94) but somewhat lower recall (0.75), indicating the model is very precise but misses some actual class 0 instances.
- For Class 1: High recall (0.78) but slightly lower precision (0.95), indicating the model captures most actual class 1 instances but includes some false positives.
- Overall, the model exhibits balanced performance with a slight emphasis on capturing the positive class (class 1) accurately, as evidenced by the high recall for class 1. The macro and weighted averages confirm that the model maintains a good balance between precision and recall across both classes.

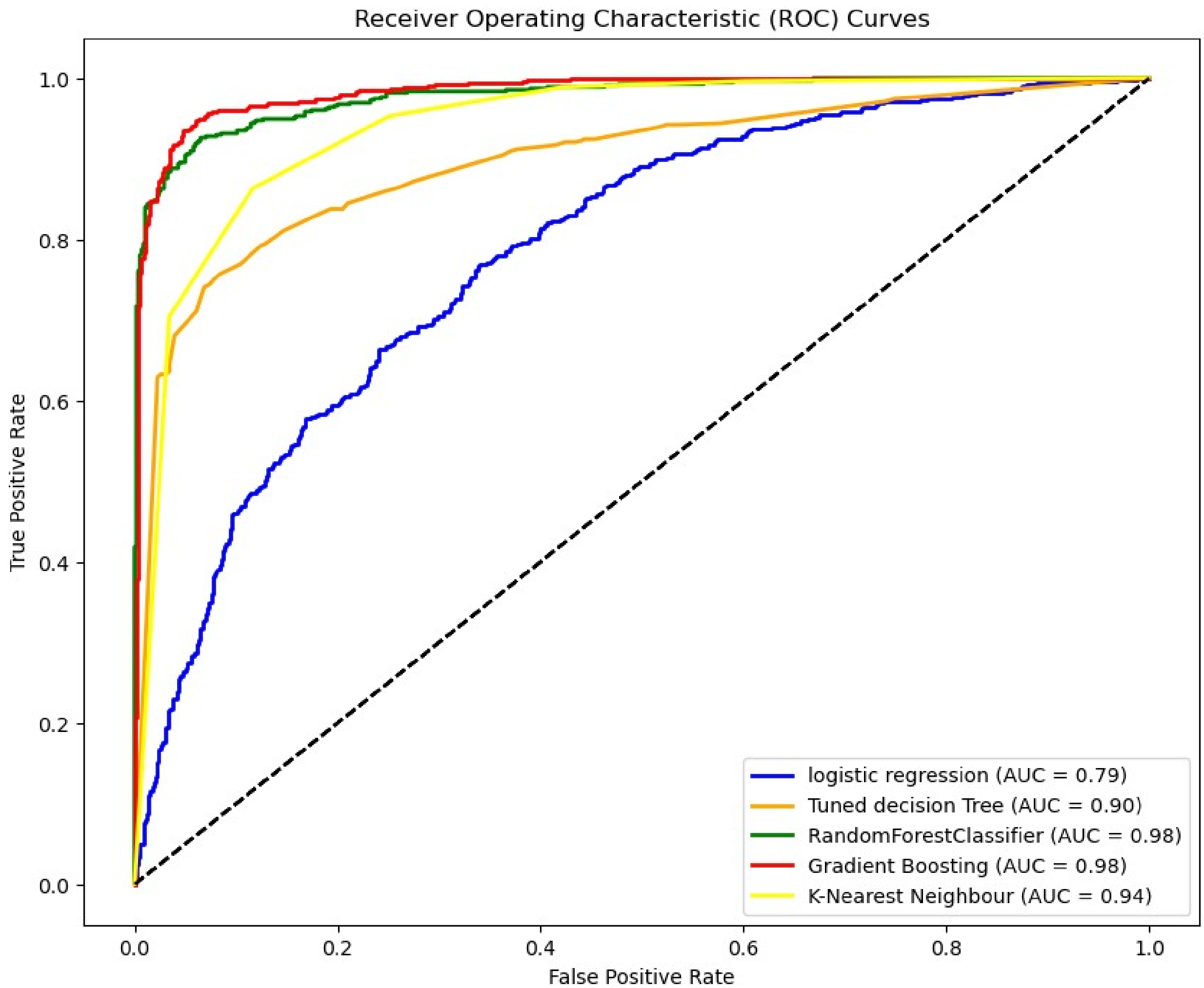
6. EVALUATION

```
# Define and tune the model
xgb_classifier_tuned = XGBClassifier()
with open ("customer_churn_model.pkl","wb") as f:
    joblib.dump(xgb_classifier_tuned,f)
```

Best Overal Model

```
# Define models and their labels
models = [log_reg, best_decision_tree, random_search, grid_search,
knn]
model_labels = ['logistic regression', 'Tuned decision
Tree','RandomForestClassifier', 'Gradient Boosting', 'K-Nearest
Neighbour']

# Convert y_test to integer values
y_test_int = y_test.astype(int)

# Plot ROC curves for all models
plt.figure(figsize=(10, 8))

# Calculate ROC curves and AUC scores for each model
for model, label, color in zip(models, model_labels, ['blue',
'orange', 'green', 'red', "yellow"]):
    # Generate model predictions
    y_score = model.predict_proba(X_test)[:, 1]

    # Calculate ROC curve and AUC
    fpr, tpr, _ = roc_curve(y_test_int, y_score, pos_label=1)
    roc_auc = auc(fpr, tpr)

    # Plot ROC curve
    plt.plot(fpr, tpr, lw=2, label='{} (AUC = {:.2f})'.format(label,
roc_auc), color=color)

    # Plot the ROC curve for random guessing
    random_guess_fpr = [0, 1]
    random_guess_tpr = [0, 1]
    plt.plot(random_guess_fpr, random_guess_tpr, linestyle='--',
color='black')


    # Print ROC AUC score
    print(f'{label} ROC AUC Score: {roc_auc:.4f}')

# Set labels and title
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curves')
plt.legend(loc='lower right')
plt.show()
```

```
logistic regression ROC AUC Score: 0.7866
Tuned decision Tree ROC AUC Score: 0.8968
RandomForestClassifier ROC AUC Score: 0.9775
Gradient Boosting ROC AUC Score: 0.9839
K-Nearest Neighbour ROC AUC Score: 0.9408
```



Interpretation:

Best Model: The Gradient Boosting model is the best performer with an ROC AUC score of 0.9832, indicating the highest accuracy in distinguishing between churners and non-churners

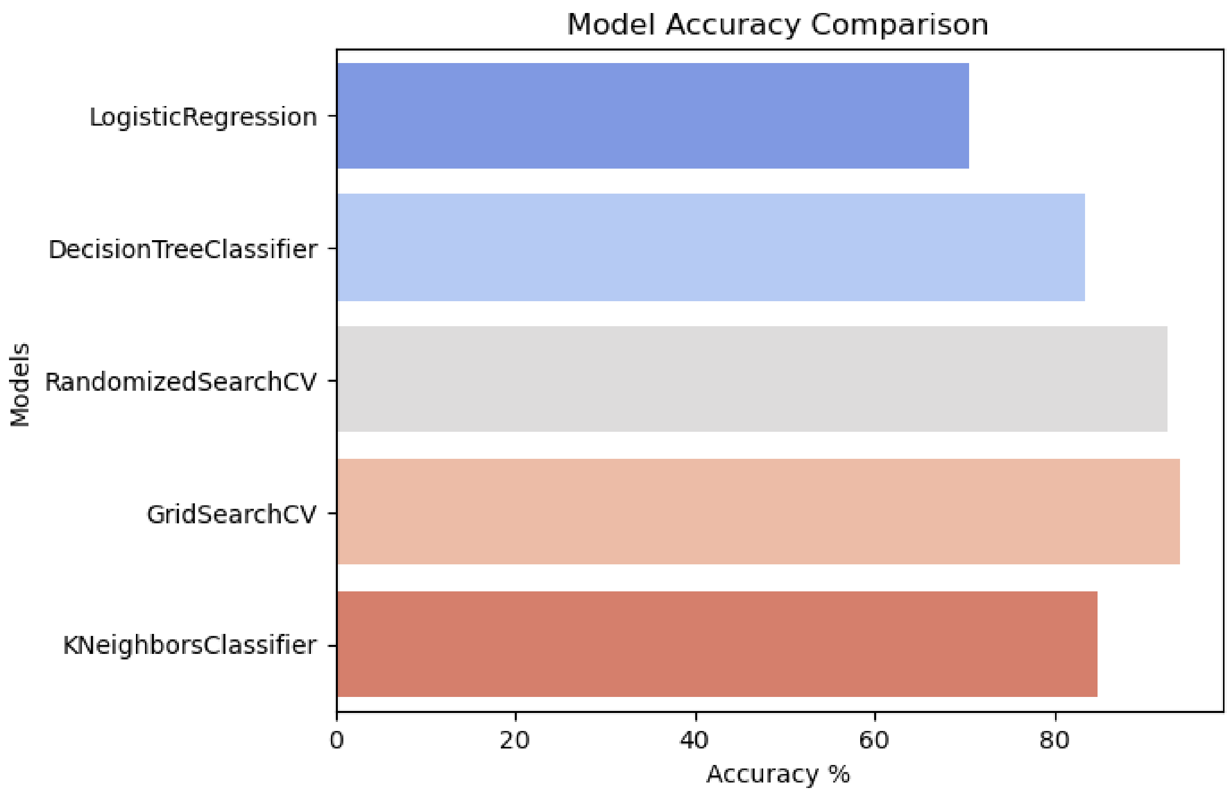
r. These scores suggest that ensemble methods like Gradient Boosting and Random Forest are highly effective for the customer churn prediction task, offering superior performance compared to individual models like logistic regression and decision trees.ves.

```
# Initialize an empty list to store the results
results = []

# Evaluate each model
for model, label in zip(models, model_labels):
    # Predict the test set
    y_pred = model.predict(X_test)
    y_pred_proba = model.predict_proba(X_test)[:, 1]

    # Calculate metrics
```

```
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    accuracy = accuracy_score(y_test, y_pred)
    roc_auc = roc_auc_score(y_test, y_pred_proba)

    # Append the results to the list
    results.append([label, precision, recall, f1, accuracy, roc_auc])

# Create a DataFrame from the results
results_df = pd.DataFrame(results, columns=['Model', 'Precision',
'Recall', 'F1 Score', 'Accuracy', 'ROC AUC Score'])

# Display the DataFrame
print(results_df)
```

```
                    Model  Precision    Recall  F1 Score  Accuracy  \
0     logistic regression   0.683946  0.736937  0.709454  0.706140
1     Tuned decision Tree   0.856031  0.792793  0.823199  0.834211
2  RandomForestClassifier   0.936920  0.909910  0.923218  0.926316
3       Gradient Boosting   0.940325  0.936937  0.938628  0.940351
4     K-Nearest Neighbour   0.782544  0.953153  0.859464  0.848246

   ROC AUC Score
0       0.786611
1       0.896809
2       0.977545
3       0.983907
4       0.940756
```

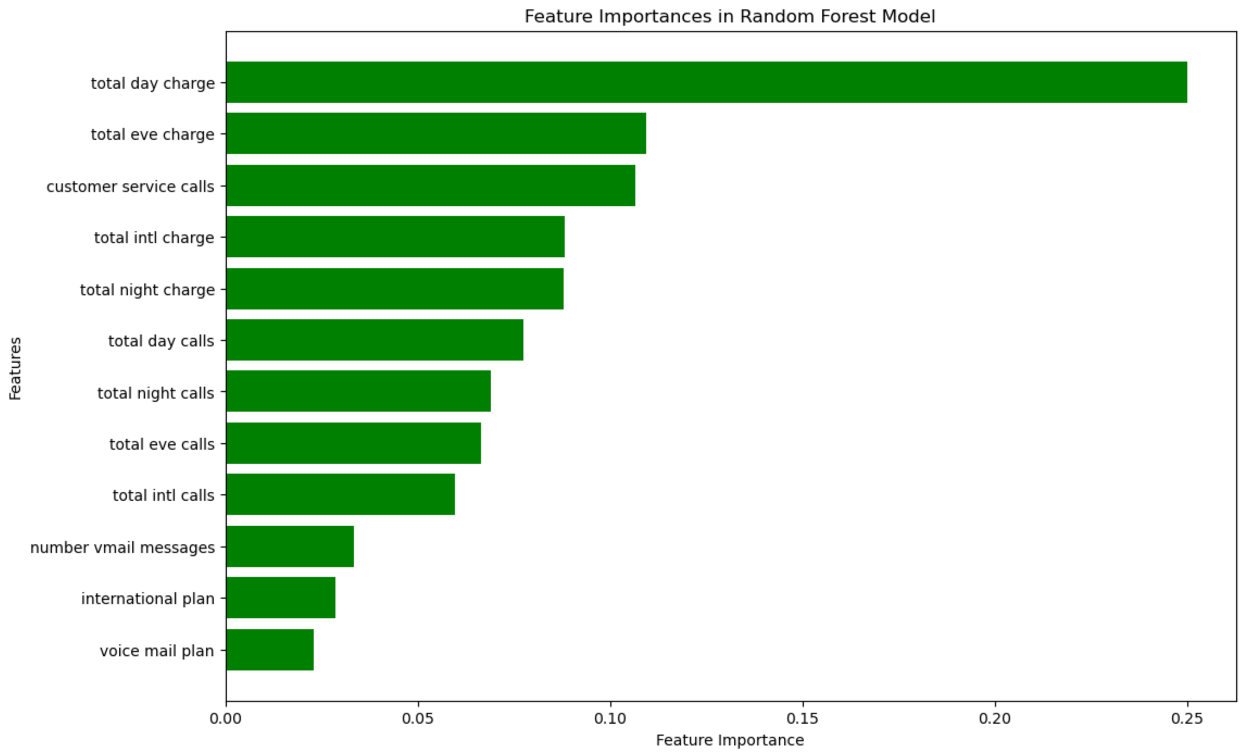
```
# Initialize the results DataFrame
results = pd.DataFrame(columns=["Models", "Accuracy"])

# Loop through models to calculate accuracy and append results
for model in models:
    names = model.__class__.__name__
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred) * 100
    result = pd.DataFrame([[names, accuracy]], columns=["Models",
"Accuracy"])
    results = pd.concat([results, result], ignore_index=True)

# Plot the results
sns.barplot(x='Accuracy', y='Models', data=results,
palette="coolwarm")
plt.xlabel('Accuracy %')
plt.title('Model Accuracy Comparison')
plt.show()
```



Feature importance based on the best model

```
# Get the best estimator (the trained Random Forest model)
best_rf_classifier = random_search.best_estimator_

# Extract feature importances
feature_importances = best_rf_classifier.feature_importances_
features = X.columns

# Create a DataFrame for better visualization
import pandas as pd

feature_importance_df = pd.DataFrame({
    'Feature': features,
    'Importance': feature_importances
})

# Sort the DataFrame by importance
feature_importance_df =
feature_importance_df.sort_values(by='Importance', ascending=False)

# Plot the feature importances
plt.figure(figsize=(12, 8))
plt.barh(feature_importance_df['Feature'],
feature_importance_df['Importance'], color='green')
```

```
plt.xlabel('Feature Importance')
plt.ylabel('Features')
plt.title('Feature Importances in Random Forest Model')
plt.gca().invert_yaxis()  # To display the most important feature at
the top
plt.show()
```



Top five features

The top five features that were also crucial in determining the churn of customers were:

- **Total day charge:** The total amount of money charged by the telecom company for calls during the day.
- **Customer Service calls:** The number of calls the customer has made to customer service.
- **Total eve charge:** The total amount of money charged by the telecom company for calls during the evening.
- **Total intl charge:** The total amount of money charged by the telecom company for international calls..
- **Total night charge:** The total amount of money charged by the telecom company for calls during the night.

Conclusion

Recommendations

- Focus retention strategies on high-usage customers and those with frequent customer service interactions. e.g offering discounts and incentives.

- Investigate the low adoption of international and voice mail plans to understand customer needs and improve these offerings e.g offering more affordable international plans, or by making it easier for customers to sign up for international plans .

- Provide proactive support to customers making frequent customer service calls to improve their experience and satisfactio

n.

- Continuously monitor and analyze usage patterns to detect early signs of potential churn and act accordingly.

Next Steps

- Deploying the model: Implement the churn prediction model into the operational environment to start making real-time predictions on customer churn, enabling proactive retention strategies.

- Monitor and update the model: Continuously track the model's performance and accuracy over time, ensuring it remains effective in predicting churn, and regularly update it with new data to maintain relevance and accuracy.

- Interpreting the model insights: Analyze the model's predictions and identify the key factors influencing customer churn, providing valuable insights for targeted retention efforts and strategic decision-making.

- Collecting more diverse data: Expand the dataset by gathering a wider range of customer attributes, behaviors, and interactions to enhance the model's predictive capabilities and capture more nuanced patterns of churn behavior.