Predicting Customer Churn in SyriaTel Telecommunications Industry

```
from PIL import Image
import IPython.display as display

# Specify the path to the image file
img_path = "C:/Users/PC/Desktop/Customer-Churn/Image3.png"

# Open the image file
img = Image.open(img_path)

# Display the image
display.display(img)
```

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NoteBook Structure

i) Business Understanding

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Business Understanding

In the telecommunications industry, customer churn poses a significant challenge for companies like SyriaTel. The objective is to develop a model that predicts whether a customer will soon terminate their services with SyriaTel. This binary classification task aims to uncover patterns in customer behavior and demographic data that may indicate a propensity to churn. The ultimate goal is to aid SyriaTel in reducing the financial impact of customer churn by implementing proactive retention strategies.

Problem Statement

SyriaTel faces the challenge of retaining its customer base amidst a competitive telecommunications landscape. Customer churn not only leads to revenue loss but also affects the company's reputation and market position. The task at hand is to develop a predictive model that accurately identifies customers likely to churn, enabling SyriaTel to intervene with targeted retention initiatives.

Objectives

To develop the best model to predict customer churn for SyriaTel, aiming to reduce the financial impact of churn by implementing proactive retention strategies.

Data Understanding

Description of Data Source

The dataset was obtained from Kaggle and consists of 21 columns and 3333 rows. It contains information relevant to predicting customer churn for SyriaTel, a telecommunications company. Each row represents a customer, and each column represents a specific feature or attribute related to customer behavior, demographics, and interactions with SyriaTel's services.

Dataset Relevance Summary

The Data has features encompassing demographics, usage patterns, interactions , the dataset offers a rich source of information for building accurate predictive models. Its real-world context and sufficient size provide ample scope for exploration and analysis, empowering the project to develop effective retention strategies and mitigate customer churn.

```
pip install imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in c:\users\pc\
anaconda3\lib\site-packages (0.12.0)
Requirement already satisfied: numpy>=1.17.3 in c:\users\pc\anaconda3\
lib\site-packages (from imbalanced-learn) (1.24.3)
Requirement already satisfied: scipy>=1.5.0 in c:\users\pc\anaconda3\
lib\site-packages (from imbalanced-learn) (1.11.1)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\pc\
anaconda3\lib\site-packages (from imbalanced-learn) (1.4.1.post1)
Requirement already satisfied: joblib>=1.1.1 in c:\users\pc\anaconda3\
lib\site-packages (from imbalanced-learn) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\pc\
anaconda3\lib\site-packages (from imbalanced-learn) (2.2.0)
Note: you may need to restart the kernel to use updated packages.

pip install xgboost

Requirement already satisfied: xgboost in c:\users\pc\anaconda3\lib\
site-packages (2.0.3)
Requirement already satisfied: numpy in c:\users\pc\anaconda3\lib\
site-packages (from xgboost) (1.24.3)
Requirement already satisfied: scipy in c:\users\pc\anaconda3\lib\
site-packages (from xgboost) (1.11.1)
Note: you may need to restart the kernel to use updated packages.
```

Data Preparation

```python
# Importing Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import xgboost as xgb



from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, confusion_matrix, roc_auc_score
from statsmodels.stats.outliers_influence import
variance_inflation_factor
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_curve
from xgboost import XGBClassifier
from imblearn.over_sampling import SMOTE
```

```
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline

# Load the dataset
df= pd.read_csv('Churn_dataset.csv')

# Cheking the first 10 rows
df.head(10)

  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
5    AL             118        510     391-8027                yes
6    MA             121        510     355-9993                 no
7    MO             147        415     329-9001                yes
8    LA             117        408     335-4719                 no
9    WV             141        415     330-8173                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
5              no                      0              223.4
98
6             yes                     24              218.2
88
7              no                      0              157.0
79
8              no                      0              184.5
97
9             yes                     37              258.6
84

   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
5            37.98  ...            101           18.75
6            37.09  ...            108           29.62
7            26.69  ...             94            8.76
8            31.37  ...             80           29.89
9            43.96  ...            111           18.87

   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
5                203.9                118                9.18
6                212.6                118                9.57
7                211.8                 96                9.53
8                215.8                 90                9.71
9                326.4                 97               14.69

   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
5                 6.3                 6               1.70
6                 7.5                 7               2.03
7                 7.1                 6               1.92
8                 8.7                 4               2.35
9                11.2                 5               3.02

   customer service calls  churn
0                       1  False
1                       1  False
2                       0  False
3                       2  False
4                       3  False
5                       0  False
6                       3  False
7                       0  False
8                       1  False
9                       0  False

[10 rows x 21 columns]
```

```
# Check the shape
df.shape
```

```
(3333, 21)
```

```python
# check data info
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
# Description of data
df.describe()
```

```
       account length    area code  number vmail messages  total day 
minutes  \
count     3333.000000  3333.000000            3333.000000       
3333.000000   
mean       101.064806   437.182418               8.099010        
179.775098   
std         39.822106    42.371290              13.688365        
54.467389   
min          1.000000   408.000000               0.000000         
0.000000   
25%         74.000000   408.000000               0.000000        
143.700000   
50%        101.000000   415.000000               0.000000        
179.400000   
75%        127.000000   510.000000              20.000000        
```

```
216.400000
max        243.000000   510.000000              51.000000
350.800000

       total day calls  total day charge  total eve minutes  total eve
calls  \
count      3333.000000       3333.000000        3333.000000
3333.000000
mean        100.435644         30.562307         200.980348
100.114311
std          20.069084          9.259435          50.713844
19.922625
min           0.000000          0.000000           0.000000
0.000000
25%          87.000000         24.430000         166.600000
87.000000
50%         101.000000         30.500000         201.400000
100.000000
75%         114.000000         36.790000         235.300000
114.000000
max         165.000000         59.640000         363.700000
170.000000

       total eve charge  total night minutes  total night calls  \
count       3333.000000          3333.000000        3333.000000
mean          17.083540           200.872037         100.107711
std            4.310668            50.573847          19.568609
min            0.000000            23.200000          33.000000
25%           14.160000           167.000000          87.000000
50%           17.120000           201.200000         100.000000
75%           20.000000           235.300000         113.000000
max           30.910000           395.000000         175.000000

       total night charge  total intl minutes  total intl calls  \
count         3333.000000         3333.000000       3333.000000
mean             9.039325           10.237294          4.479448
std              2.275873            2.791840          2.461214
min              1.040000            0.000000          0.000000
25%              7.520000            8.500000          3.000000
50%              9.050000           10.300000          4.000000
75%             10.590000           12.100000          6.000000
max             17.770000           20.000000         20.000000

       total intl charge  customer service calls
count        3333.000000             3333.000000
mean            2.764581                1.562856
std             0.753773                1.315491
min             0.000000                0.000000
25%             2.300000                1.000000
50%             2.780000                1.000000
```

```
75%              3.270000                   2.000000
max              5.400000                   9.000000
```

Data Cleaning

Check Null Values

```
# Checking for null values
df.isnull().sum()

state                     0
account length            0
area code                 0
phone number              0
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
```

Check duplicates

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

0
```

Convert Data types

```
# Convert 'churn' column to numeric (0 for False, 1 for True)
df['churn'] = df['churn'].astype(int)
df.dtypes

state                        object
account length                int64
area code                     int64
phone number                 object
```

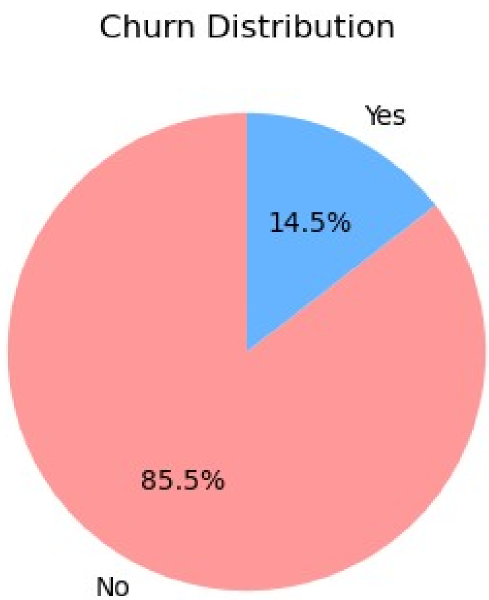
```
international plan           object
voice mail plan              object
number vmail messages         int64
total day minutes           float64
total day calls               int64
total day charge            float64
total eve minutes           float64
total eve calls               int64
total eve 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                         int32
dtype: object
```

The dataframe has no missing values and no duplicates

Exploratory data analysis

Churn Distribution

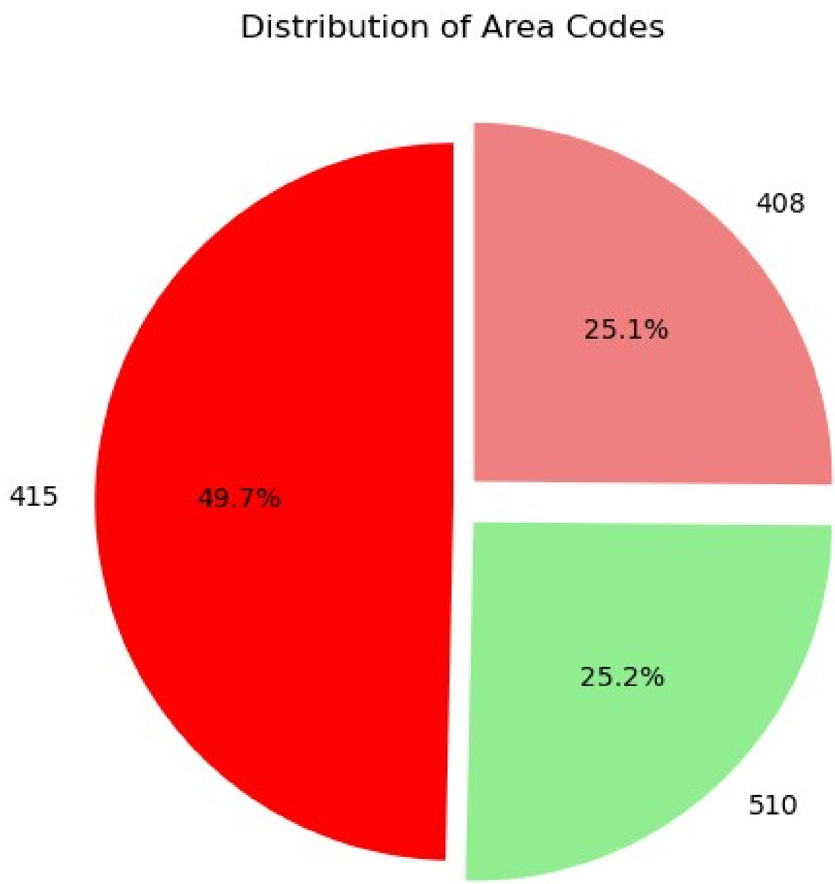
```
# Calculate churn counts
churn_counts = df['churn'].value_counts()

# Define colors for the pie chart
colors = ['#ff9999', '#66b3ff']

# Plot pie chart with red theme
plt.figure(figsize=(4, 4))
plt.pie(churn_counts, labels=['No', 'Yes'], autopct='%1.1f%%',
startangle=90, colors=colors)
plt.title('Churn Distribution')
plt.show()
```



The pie chart indicates a higher percentage of customers staying compared to those churning. This suggests a positive state of customer retention. SyriaTel can use this insight to refine retention strategies and focus on areas for further reducing churn, ultimately enhancing customer satisfaction and long-term profitability.

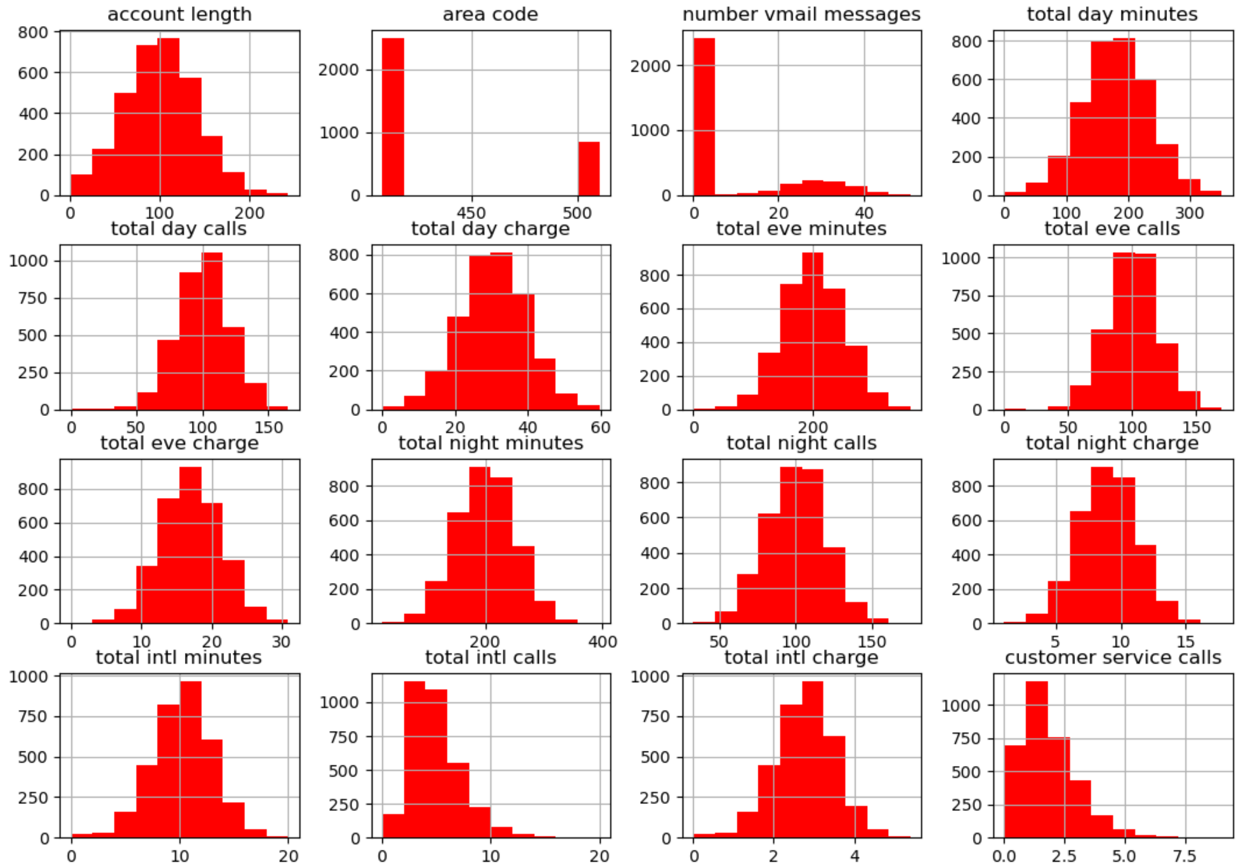
Area Code Distribution

```
# Define colors for each area code category
colors = ['red', 'lightgreen', 'lightcoral']

area_code_counts = df['area code'].value_counts()

# Plot a pie chart
plt.figure(figsize=(6, 6))
plt.pie(area_code_counts, labels=area_code_counts.index,
autopct='%1.1f%%', startangle=90, explode = (0, 0.08, 0.08),
colors=colors)
plt.title('Distribution of Area Codes')
plt.show()
```



- By leveraging insights from area code distribution, SyriaTel company can optimize their operations, improve customer satisfaction, and enhance their competitive advantage in the market.

```
# Distribution of features excluding 'churn' column

df.drop(columns='churn').hist(figsize=(13,9), color='red')
plt.show()
```

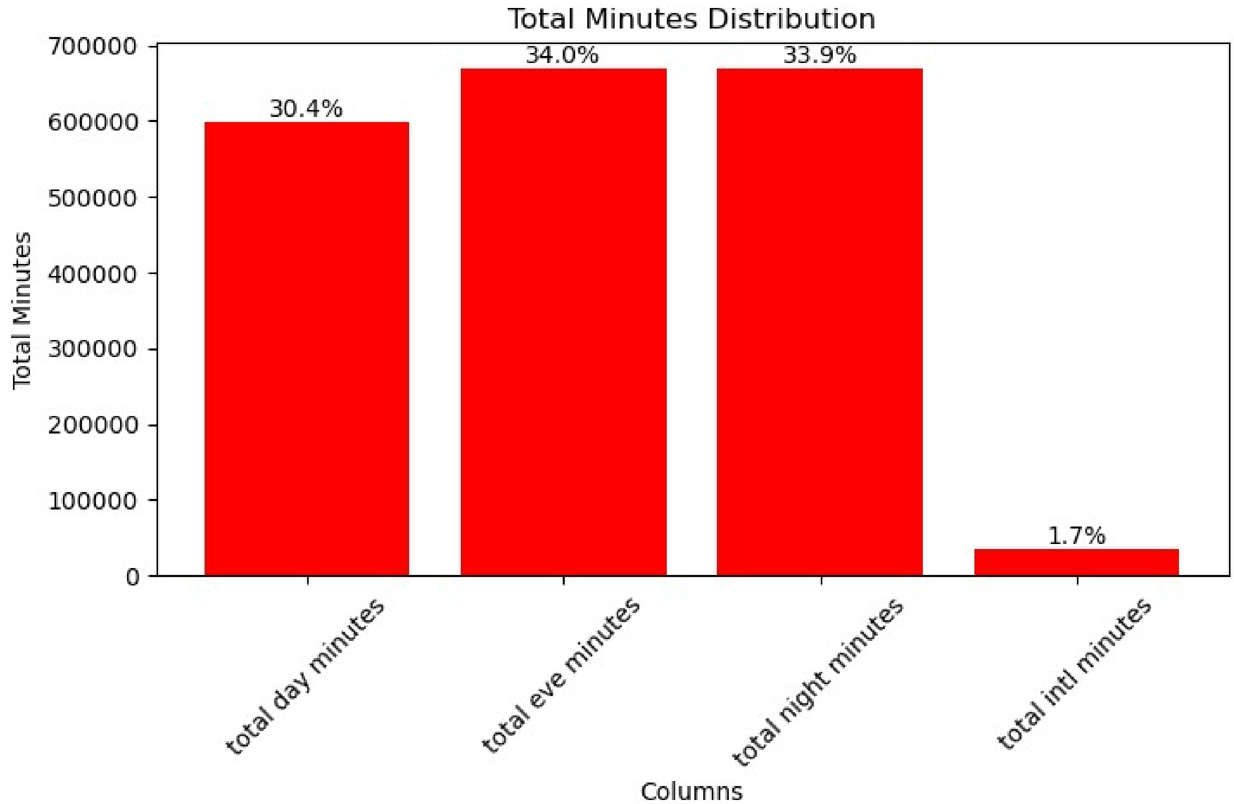


The histograms illustrate disparities in feature scaling and non-normal distributions. scaling and normalization are needed. These steps ensure consistent feature ranges and distribution, enhancing analysis and modeling effectiveness.

```
# unique values of categorical features

categorical_cols = df.drop('phone number',
axis=1).select_dtypes(include='object').columns
for col in categorical_cols:
    print(col)
    print(df[col].unique())

state
['KS' 'OH' 'NJ' 'OK' 'AL' 'MA' 'MO' 'LA' 'WV' 'IN' 'RI' 'IA' 'MT' 'NY'
 'ID' 'VT' 'VA' 'TX' 'FL' 'CO' 'AZ' 'SC' 'NE' 'WY' 'HI' 'IL' 'NH' 'GA'
 'AK' 'MD' 'AR' 'WI' 'OR' 'MI' 'DE' 'UT' 'CA' 'MN' 'SD' 'NC' 'WA' 'NM'
 'NV' 'DC' 'KY' 'ME' 'MS' 'TN' 'PA' 'CT' 'ND']
international plan
['no' 'yes']
voice mail plan
['yes' 'no']
```

Minutes Distributiion

```
# Define the column names
col_sum = ['total day minutes', 'total eve minutes', 'total night
minutes', 'total intl minutes']

# Calculate the sum for each column
sums = df[col_sum].sum()

plt.figure(figsize=(8, 4))

# Plot the histogram bars
bars = plt.bar(sums.index, sums, color='red')

plt.xlabel('Columns')
plt.ylabel('Total Minutes')
plt.title('Total Minutes Distribution')

# Add percentage labels
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2., height + 10,
f"{height/sum(sums)*100:.1f}%", ha='center', va='bottom')

plt.xticks(rotation=45)
plt.show()
```

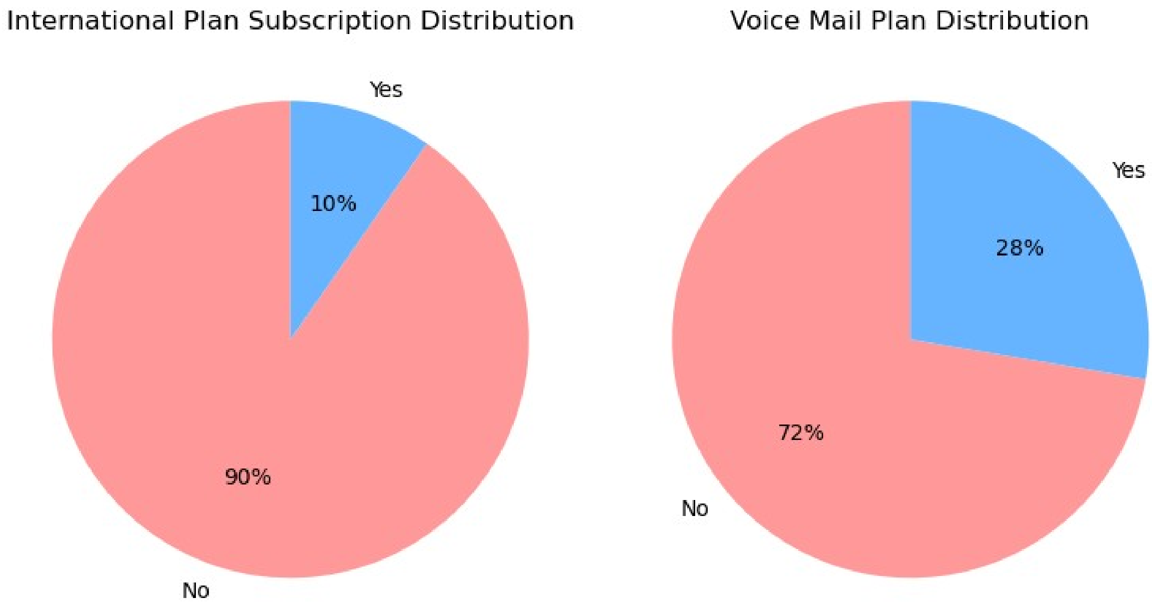


This histogram illustrates the distribution of total minutes across different call categories. Each bar represents the total sum of minutes for a specific call category, enabling visualization of the relative contribution of each call category to the overall total minutes. The observation from the histogram indicates that the total evening minutes have the highest sum compared to other call categories.

Subscription plan distribution

```
#  colors for the pie charts
colors = ['#ff9999', '#66b3ff']

# Create a figure with two subplots
plt.figure(figsize=(8, 5))

# Plot first pie chart (International Plan Subscription Distribution)
plt.subplot(1, 2, 1)
plt.pie(df['international plan'].value_counts(), labels=['No', 'Yes'],
autopct='%.0f%%', startangle=90, colors=colors)
plt.title('International Plan Subscription Distribution')

# Plot the second pie chart (Voice Mail Plan Distribution)
plt.subplot(1, 2, 2)
plt.pie(df['voice mail plan'].value_counts(), labels=['No', 'Yes'],
autopct='%.0f%%', startangle=90, colors=colors)
plt.title('Voice Mail Plan Distribution')
```

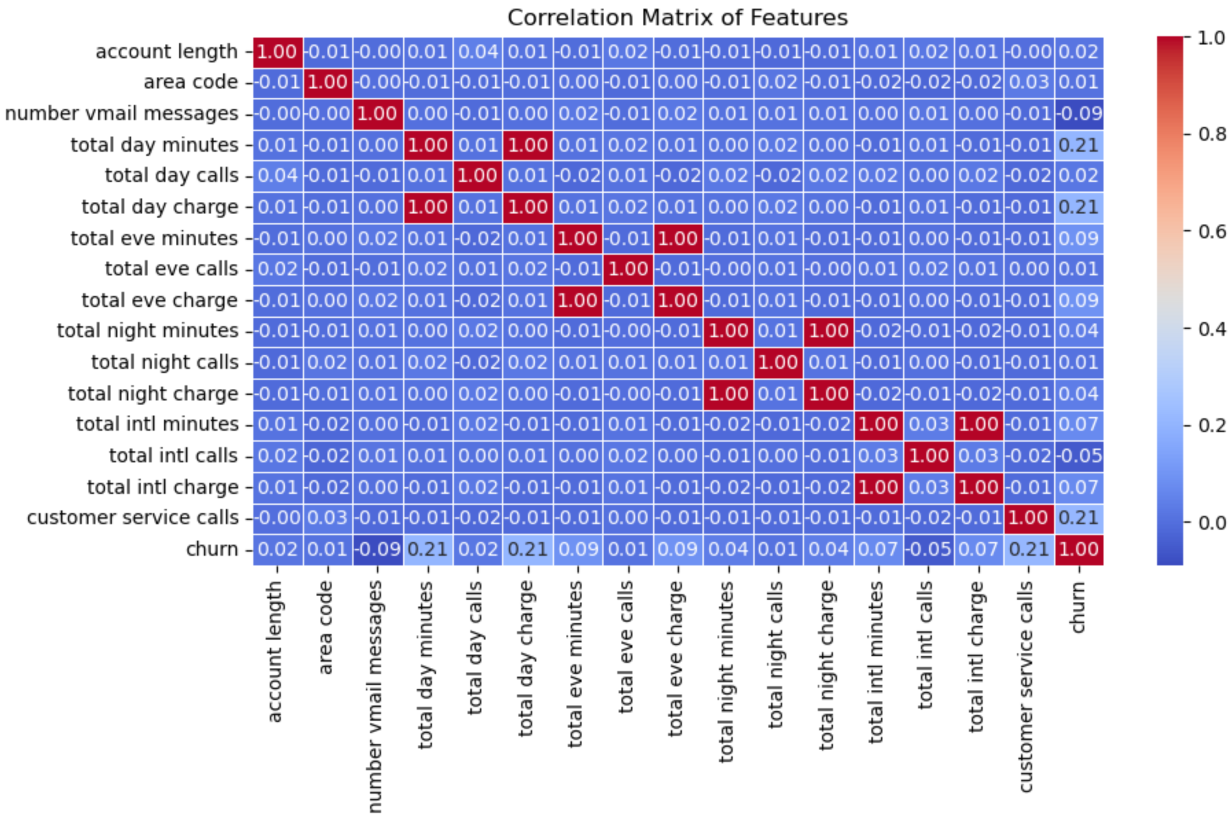
```
# Adjust layout for better spacing
plt.tight_layout()

# Show the plot
plt.show()
```



Based on these observations, it can be inferred that there is a higher demand for voicemail services compared to international calling services among SyriaTel customers. This information can help the company tailor its marketing strategies and service offerings to better meet the needs and preferences of its customer base.

Correlation of features

```
# Excluding non-numeric columns
numeric_df = df.select_dtypes(include=['number'])

# Calculate the correlation matrix
corr_matrix = numeric_df.corr()

# Plot the heatmap
plt.figure(figsize=(10, 5))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f",
linewidths=0.5)
plt.title('Correlation Matrix of Features')
plt.show()
```



- Most features show very low correlation with each other.
- Perfect positive correlations exist between total evening charge and total evening minutes, total day charge and total day minutes, total night charge and total night minutes, and total international charge and total international minutes, which is expected as call charges depend on call duration.
- Weak positive correlations are observed between total day minutes, total day charge, and customer service calls with churn.
- Other features exhibit negligible correlations with churn, approximately 0.

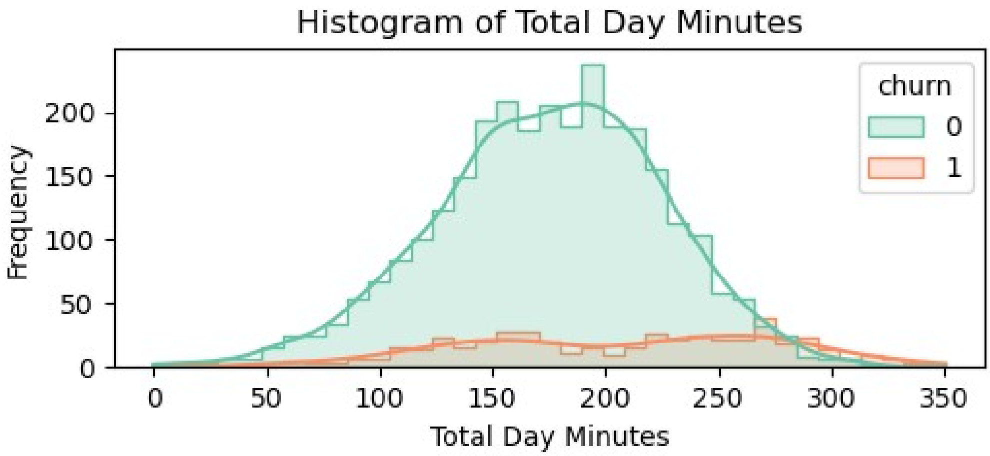
```
# Remove non-numeric columns
numeric_df = df.select_dtypes(include=['number'])

# Calculate the correlation matrix
corr_matrix = numeric_df.corr()

# Sort  values for 'churn' column in descending order
churn_corr = corr_matrix['churn'].sort_values(ascending=False)

# Display the sorted correlation values
churn_corr
```

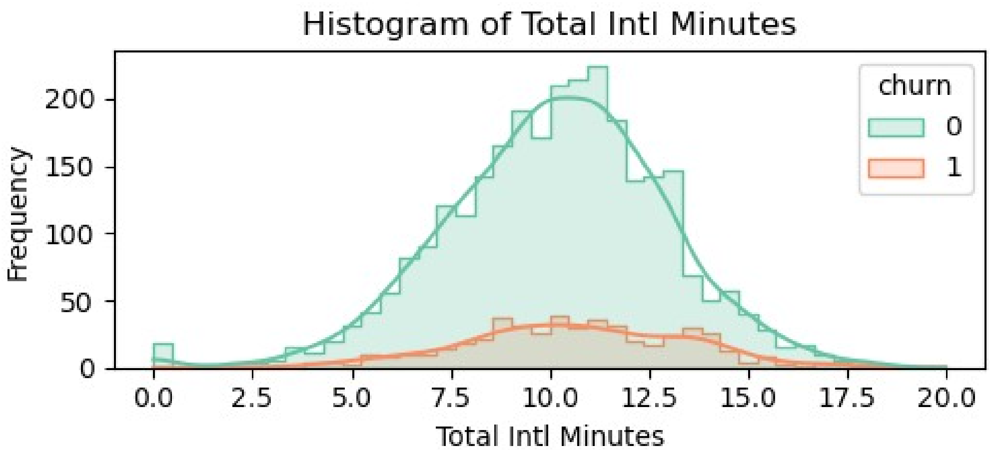
```
churn                     1.000000
customer service calls    0.208750
total day minutes         0.205151
total day charge          0.205151
```

```
total eve minutes         0.092796
total eve charge          0.092786
total intl charge         0.068259
total intl minutes        0.068239
total night charge        0.035496
total night minutes       0.035493
total day calls           0.018459
account length            0.016541
total eve calls           0.009233
area code                 0.006174
total night calls         0.006141
total intl calls         -0.052844
number vmail messages    -0.089728
Name: churn, dtype: float64
```

Histogram Plot of Total Day Minutes vs Total Intl Minutes

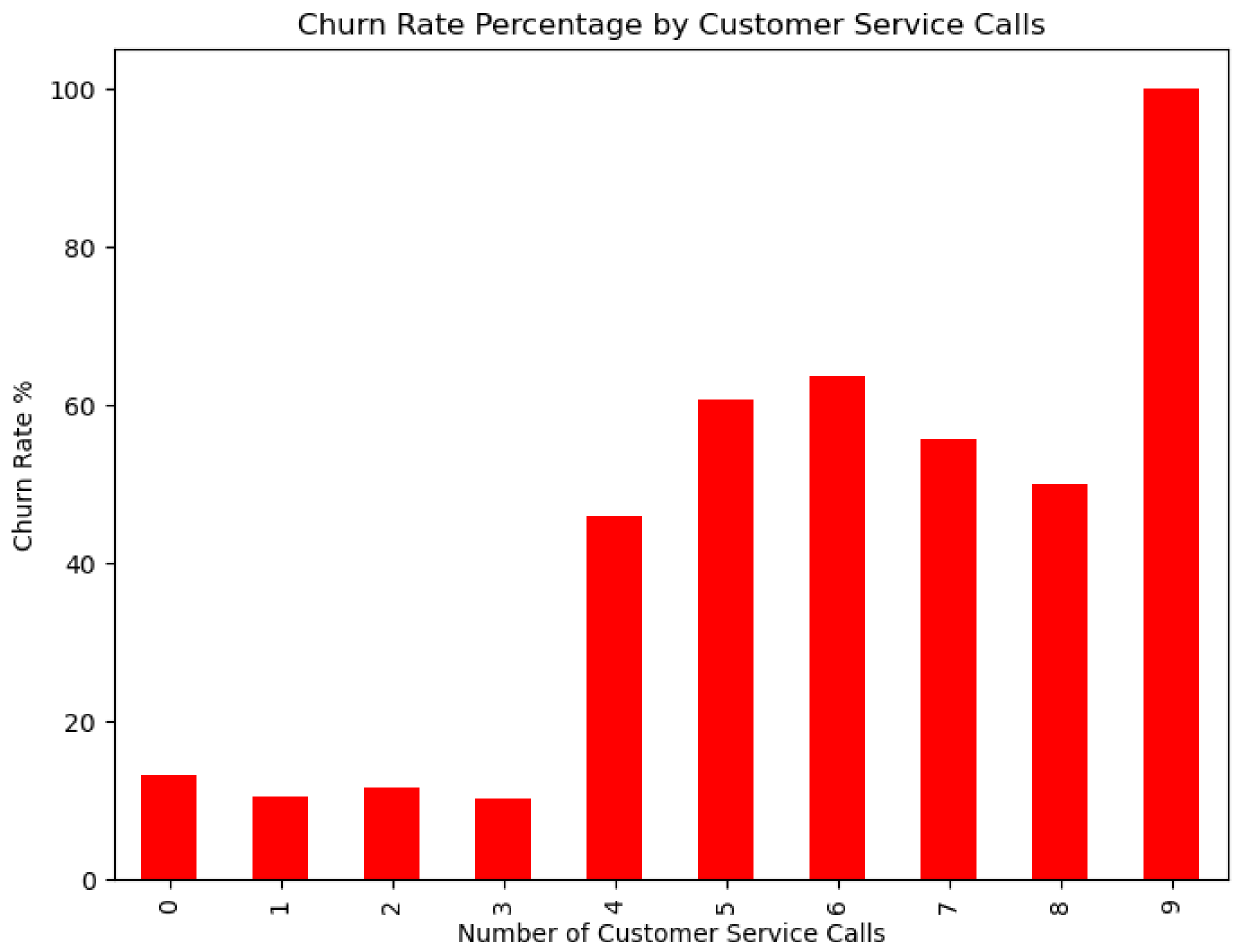
```
plt.figure(figsize=(10, 5))


# Histogram of Total Day Minutes
plt.subplot(2, 2, 2)
sns.histplot(data=df, x='total day minutes', hue='churn', kde=True,
palette='Set2', element='step', fill=True)
plt.title('Histogram of Total Day Minutes')
plt.xlabel('Total Day Minutes')
plt.ylabel('Frequency')


# Histogram of Total Intl Minutes
plt.subplot(2, 2, 4)
sns.histplot(data=df, x='total intl minutes', hue='churn', kde=True,
palette='Set2', element='step', fill=True)
plt.title('Histogram of Total Intl Minutes')
plt.xlabel('Total Intl Minutes')
plt.ylabel('Frequency')


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





Customer service vs Churn

```
# Calculate churn rate percentage for each number of customer service calls
churn_rate = df.groupby('customer service calls')['churn'].mean() * 100

# Plotting a bar plot
churn_rate.plot(kind='bar', figsize=(8, 6), color='Red')

# Adding title and labels
plt.title('Churn Rate Percentage by Customer Service Calls')
plt.xlabel('Number of Customer Service Calls')
plt.ylabel('Churn Rate %')

# Display the plot
plt.show()
```



- A clear positive correlation emerges between the number of customer service calls and the likelihood of churn.
- There's a consistent rise in churn as the number of calls increases.
- However, an increase in churn becomes evident after the 6th call, suggesting a potential turning point.
- The sudden increase in churn after the 6th call suggests a crucial point where more interactions could make customers more unhappy, causing more people to leave.
- While the overall trend indicates a higher likelihood of churn with more service calls, the sudden increase at the 6th call underscores its significance in influencing customer retention.

Data Preparation for Machine Learning

Multicollinearity of features

```
# independent variables  to check multicollinearity
```

```
X = df[['total day minutes', 'total eve minutes', 'total night
minutes', 'total intl minutes']]

# Calculate VIF for each variable
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns
vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in
range(len(X.columns))]

vif_data
```

```
              feature        VIF
0    total day minutes   9.673057
1    total eve minutes  12.026619
2  total night minutes  12.000415
3   total intl minutes  10.844008
```

Drop the columns with a high correlation (total day minutes and total day charge), (total eve minutes and total eve charge), (total night minutes and total night charge), (total intl minutes and total intl charge)

```
# drop the columns with high correlation
cols_drop = ['total day charge', 'total eve charge', 'total night
charge', 'total intl charge']
df = df.drop(cols_drop, axis=1)
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 eve minutes  total eve calls  total night minutes  total
night calls  \
0              197.4               99                244.7
```

```
91
1               195.5               103                 254.4
103
2               121.2               110                 162.6
104
3                61.9                88                 196.9
89
4               148.3               122                 186.9
121

   total intl minutes  total intl calls  customer service calls  churn

0                10.0                 3                       1      0

1                13.7                 3                       1      0

2                12.2                 5                       0      0

3                 6.6                 7                       2      0

4                10.1                 3                       3      0
```

```
df.dtypes
```

```
state                      object
account length              int64
area code                   int64
phone number               object
international plan         object
voice mail plan            object
number vmail messages       int64
total day minutes         float64
total day calls             int64
total eve minutes         float64
total eve calls             int64
total night minutes       float64
total night calls           int64
total intl minutes        float64
total intl calls            int64
customer service calls      int64
churn                       int32
dtype: object
```

```
# Dummy variables
df = pd.get_dummies(df, columns=['state', 'international plan', 'voice
mail plan'], drop_first = True)

df.drop('phone number', axis=1, inplace=True)

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 65 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   account length          3333 non-null   int64
 1   area code               3333 non-null   int64
 2   number vmail messages   3333 non-null   int64
 3   total day minutes       3333 non-null   float64
 4   total day calls         3333 non-null   int64
 5   total eve minutes       3333 non-null   float64
 6   total eve calls         3333 non-null   int64
 7   total night minutes     3333 non-null   float64
 8   total night calls       3333 non-null   int64
 9   total intl minutes      3333 non-null   float64
 10  total intl calls        3333 non-null   int64
 11  customer service calls  3333 non-null   int64
 12  churn                   3333 non-null   int32
 13  state_AL                3333 non-null   bool
 14  state_AR                3333 non-null   bool
 15  state_AZ                3333 non-null   bool
 16  state_CA                3333 non-null   bool
 17  state_CO                3333 non-null   bool
 18  state_CT                3333 non-null   bool
 19  state_DC                3333 non-null   bool
 20  state_DE                3333 non-null   bool
 21  state_FL                3333 non-null   bool
 22  state_GA                3333 non-null   bool
 23  state_HI                3333 non-null   bool
 24  state_IA                3333 non-null   bool
 25  state_ID                3333 non-null   bool
 26  state_IL                3333 non-null   bool
 27  state_IN                3333 non-null   bool
 28  state_KS                3333 non-null   bool
 29  state_KY                3333 non-null   bool
 30  state_LA                3333 non-null   bool
 31  state_MA                3333 non-null   bool
 32  state_MD                3333 non-null   bool
 33  state_ME                3333 non-null   bool
 34  state_MI                3333 non-null   bool
 35  state_MN                3333 non-null   bool
 36  state_MO                3333 non-null   bool
 37  state_MS                3333 non-null   bool
 38  state_MT                3333 non-null   bool
 39  state_NC                3333 non-null   bool
 40  state_ND                3333 non-null   bool
 41  state_NE                3333 non-null   bool
 42  state_NH                3333 non-null   bool
 43  state_NJ                3333 non-null   bool
 44  state_NM                3333 non-null   bool
```

```
 45  state_NV                 3333 non-null   bool
 46  state_NY                 3333 non-null   bool
 47  state_OH                 3333 non-null   bool
 48  state_OK                 3333 non-null   bool
 49  state_OR                 3333 non-null   bool
 50  state_PA                 3333 non-null   bool
 51  state_RI                 3333 non-null   bool
 52  state_SC                 3333 non-null   bool
 53  state_SD                 3333 non-null   bool
 54  state_TN                 3333 non-null   bool
 55  state_TX                 3333 non-null   bool
 56  state_UT                 3333 non-null   bool
 57  state_VA                 3333 non-null   bool
 58  state_VT                 3333 non-null   bool
 59  state_WA                 3333 non-null   bool
 60  state_WI                 3333 non-null   bool
 61  state_WV                 3333 non-null   bool
 62  state_WY                 3333 non-null   bool
 63  international plan_yes  3333 non-null   bool
 64  voice mail plan_yes     3333 non-null   bool
dtypes: bool(52), float64(4), int32(1), int64(8)
memory usage: 494.9 KB
```

Train Test Split

```
# Splitting the dataset into features (X) and target variable (y)

y = df['churn']
X = df.drop(columns=['churn'])



# Split the data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

Scaling

```
# Create StandardScaler object
scaler = StandardScaler()

# Fit and transform the features
X_scaled = scaler.fit_transform(X)

# Convert the scaled features back to a DataFrame
X_scaled = pd.DataFrame(X_scaled, columns=X.columns)

X_scaled.head()
```

```
   account length  area code  number vmail messages  total day minutes  \
0        0.676489  -0.523603               1.234883           1.566767

1        0.149065  -0.523603               1.307948          -0.333738

2        0.902529  -0.523603              -0.591760           1.168304

3       -0.428590  -0.688834              -0.591760           2.196596

4       -0.654629  -0.523603              -0.591760          -0.240090


   total day calls  total eve minutes  total eve calls  total night
minutes  \
0         0.476643          -0.070610        -0.055940
0.866743
1         1.124503          -0.108080         0.144867
1.058571
2         0.675985          -1.573383         0.496279            -
0.756869
3        -1.466936          -2.742865        -0.608159            -
0.078551
4         0.626149          -1.038932         1.098699            -
0.276311

   total night calls  total intl minutes  ...  state_TX  state_UT
state_VA  \
0          -0.465494           -0.085008  ...  -0.14859  -0.14859 -
0.153781
1           0.147825            1.240482  ...  -0.14859  -0.14859 -
0.153781
2           0.198935            0.703121  ...  -0.14859  -0.14859 -
0.153781
3          -0.567714           -1.303026  ...  -0.14859  -0.14859 -
0.153781
4           1.067803           -0.049184  ...  -0.14859  -0.14859 -
0.153781

   state_VT  state_WA  state_WI  state_WV  state_WY  international
plan_yes  \
0 -0.149642 -0.142134   -0.1548  -0.18124 -0.153781                -
0.327580
1 -0.149642 -0.142134   -0.1548  -0.18124 -0.153781                -
0.327580
2 -0.149642 -0.142134   -0.1548  -0.18124 -0.153781                -
0.327580
3 -0.149642 -0.142134   -0.1548  -0.18124 -0.153781
3.052685
4 -0.149642 -0.142134   -0.1548  -0.18124 -0.153781
```

```
3.052685

   voice mail plan_yes
0             1.617086
1             1.617086
2            -0.618396
3            -0.618396
4            -0.618396

[5 rows x 64 columns]
```

Using MinMaxScaler, the features are scaled to a range between 0 and 1 to ensure uniformity and enhance model performance.

To check for model imbalance

```
# Calculate the distribution of the target variable
class_distribution = df['churn'].value_counts()

# Check if the dataset is imbalanced
if class_distribution[0] / class_distribution[1] > 2 or
class_distribution[1] / class_distribution[0] > 2:
    print("The dataset is imbalanced.")
else:
    print("The dataset is balanced.")

The dataset is imbalanced.
```

Handle Imbalance SMOTE

```
#initialize SMOTE object

smote = SMOTE(random_state=42)

#Apply SMOTE to training Data

X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)

# Initialize the logistic regression model

model = LogisticRegression()

#Train  model on the resampled data

model.fit(X_train_smote, y_train_smote)

LogisticRegression()
```

Data Modeling

1. Logistic Regression Model

Linear regression aims to establish a linear relationship between the independent and dependent variables to predict the target variable.

```
# Create a logistic regression model
logreg = LogisticRegression(fit_intercept=False, C=1e12,
solver='liblinear')

# Fit the model on the training data
logreg.fit(X_train, y_train)
```

```
LogisticRegression(C=1000000000000.0, fit_intercept=False,
solver='liblinear')
```

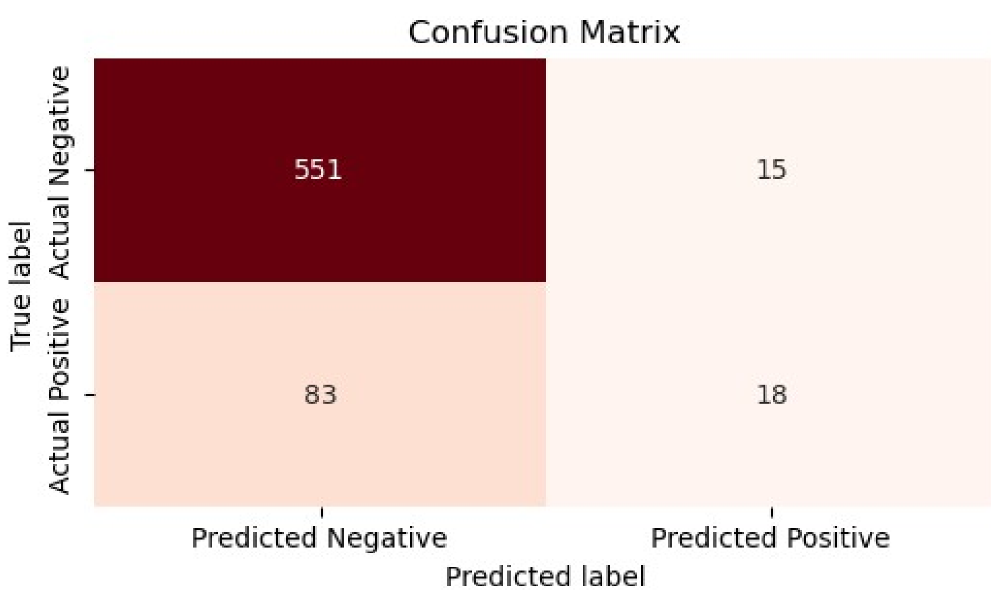
```
# Generate predictions on the test set
y_pred = logreg.predict(X_test)

# Calulate the performance metrics

# Accuracy
accuracy = accuracy_score(y_test, y_pred)

# Precision
precision = precision_score(y_test, y_pred)

# Recall
recall = recall_score(y_test, y_pred)

# F1-score
f1 = f1_score(y_test, y_pred)

# Calculate AUC for Logistic Regression
auc_lr = roc_auc_score(y_test, y_pred)



print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1-score:", f1)
print("auc_lr:", auc_lr)
```

```
Accuracy: 0.8530734632683659
Precision: 0.5454545454545454
Recall: 0.1782178217821782
```

```
F1-score: 0.26865671641791045
auc_lr: 0.575858027498863
```

- Accuracy: The logistic regression model achieved an accuracy of 85.31%, indicating its ability to correctly classify instances.
- Precision: With a precision of 54.55%, the model shows a considerable rate of false positives, suggesting that it incorrectly predicts churn for a significant number of non-churn customers.
- Recall: At 17.82%, the model exhibits a relatively low recall, implying its struggle to capture all actual positive cases of churn.
- F1-score: The F1-score stands at 26.87%, highlighting the need for improvement to strike a better balance between precision and recall.

```
# Generate predictions on the test set
y_pred = logreg.predict(X_test)

# Build confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

#Visualize the Matrix
plt.figure(figsize=(6,3))
sns.heatmap(conf_matrix, annot=True, cmap='Reds', fmt='g', cbar=False,

            xticklabels=['Predicted Negative', 'Predicted Positive'],
            yticklabels=['Actual Negative', 'Actual Positive'])
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.title('Confusion Matrix')
plt.show()
```



- True Negative (TN): 551 instances were correctly predicted as non-churn customers.

- False Positive (FP): 15 instances were incorrectly predicted as churn customers when they were actually non-churn customers.
- False Negative (FN): 83 instances were incorrectly predicted as non-churn customers when they were actually churn customers.
- True Positive (TP): 18 instances were correctly predicted as churn customers.

Conclusion

- While the model performs reasonably well in predicting non-churn instances, it struggles with identifying churn instances accurately.
- Addressing the high false negative rate is crucial to improve the model's effectiveness in identifying customers at risk of churn and implementing targeted retention strategies.

2. Decision Tree Model

```
# Create an instance of DecisionTreeClassifier

dt = DecisionTreeClassifier(random_state=42)

# Fit the model to the training data
dt.fit(X_train, y_train)
```

```
DecisionTreeClassifier(random_state=42)
```

```
# Generate predictions on the test set

y_pred_dt = dt.predict(X_test)

# Calculate the performance metrics

accuracy_dt = accuracy_score(y_test, y_pred_dt)

precision_dt = precision_score(y_test, y_pred_dt)

recall_dt = recall_score(y_test, y_pred_dt)

f1_dt = f1_score(y_test, y_pred_dt)

# Calculate AUC for  Decision Tree
auc_dt = roc_auc_score(y_test, y_pred_dt)



# Print the performance metrics


print("Accuracy:", accuracy_dt)
print("Precision:", precision_dt)
print("Recall:", recall_dt)
```

```
print("F1-score:", f1_dt)
print("auc_dt:", auc_dt)
```

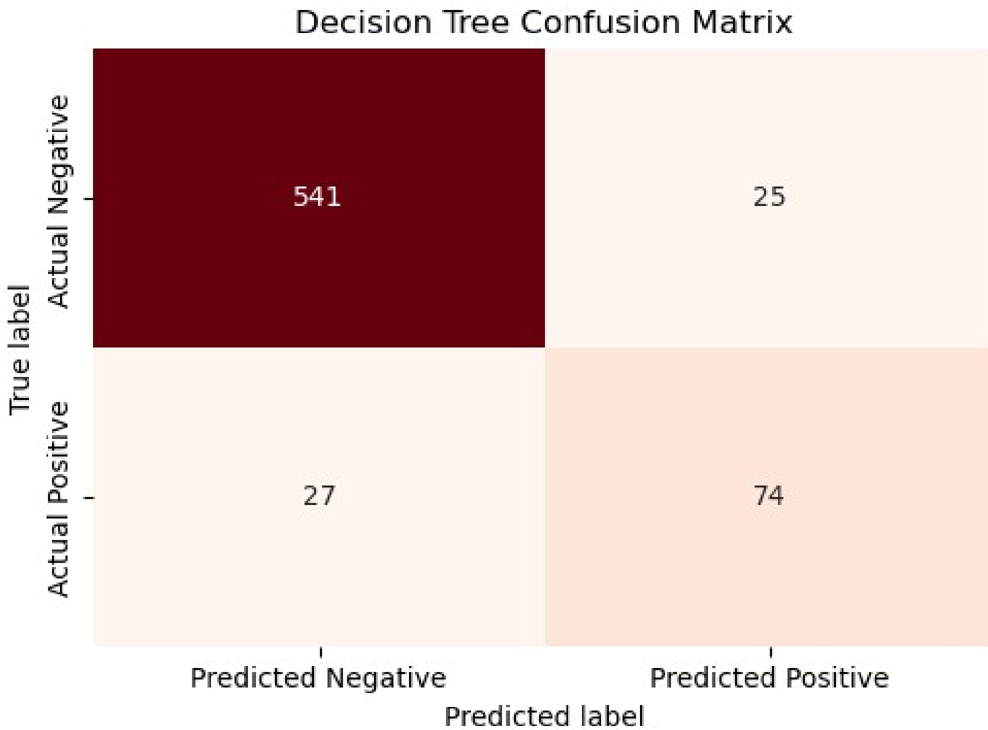
```
Accuracy: 0.9220389805097451
Precision: 0.7474747474747475
Recall: 0.7326732673267327
F1-score: 0.74
auc_dt: 0.844251828009656
```

- Accuracy: The decision tree model achieved a higher accuracy of 92.20% compared to the logistic regression model's accuracy of 55.47%.
- Precision: The decision tree model exhibited a higher precision of 74.75%, indicating a lower rate of false positives, compared to the logistic regression model's precision of 21.01%.
- Recall: The decision tree model had a slightly lower recall of 73.27% compared to the logistic regression model's recall of 70.30%.
- F1-score: The decision tree model showed a higher F1-score of 74.00%, reflecting a better balance between precision and recall, compared to the logistic regression model's F1-score of 32.35%.

In overall the decision tree model outperformed the logistic regression model across all metrics, suggesting that it may be a better choice for this classification task.

Confusion Matrix

```
# Generate predictions on the test set
y_pred_dt = dt.predict(X_test)

# Build confusion matrix
conf_matrix_dt = confusion_matrix(y_test, y_pred_dt)

# Visualize the Matrix
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix_dt, annot=True, cmap='Reds', fmt='g',
cbar=False,
            xticklabels=['Predicted Negative', 'Predicted Positive'],
            yticklabels=['Actual Negative', 'Actual Positive'])
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.title('Decision Tree Confusion Matrix')
plt.show()
```



- The decision tree model correctly identified 74 instances as positive (churn) out of the actual positive instances.
- It correctly classified 541 instances as negative (non-churn) out of the actual negative instances.
- There were 25 instances incorrectly classified as positive (false alarms).
- Additionally, there were 27 instances incorrectly classified as negative (missed opportunities).

3. Random Forest

```
#Initializing the Random Forest model

rf_model = RandomForestClassifier(random_state=42)


#Train the Random Forest model on the training data

rf_model.fit(X_train, y_train)

RandomForestClassifier(random_state=42)


#Generate predictions on the test data

y_pred_rf = rf_model.predict(X_test)

# Calculate the accuracy
accuracy_rf = accuracy_score(y_test, y_pred_rf)
```

```
# Calculate the precision
precision_rf = precision_score(y_test, y_pred_rf)

# Calculate the recall
recall_rf = recall_score(y_test, y_pred_rf)

# Calculate the F1-score
f1_rf = f1_score(y_test, y_pred_rf)

# Calculate the ROC AUC score
roc_auc_rf = roc_auc_score(y_test, y_pred_rf)

# Print the performance metrics

print("Random Forest Metrics:")
print("Accuracy:", accuracy_rf)
print("Precision:", precision_rf)
print("Recall:", recall_rf)
print("F1-score:", f1_rf)
print("ROC AUC Score:", roc_auc_rf)
```

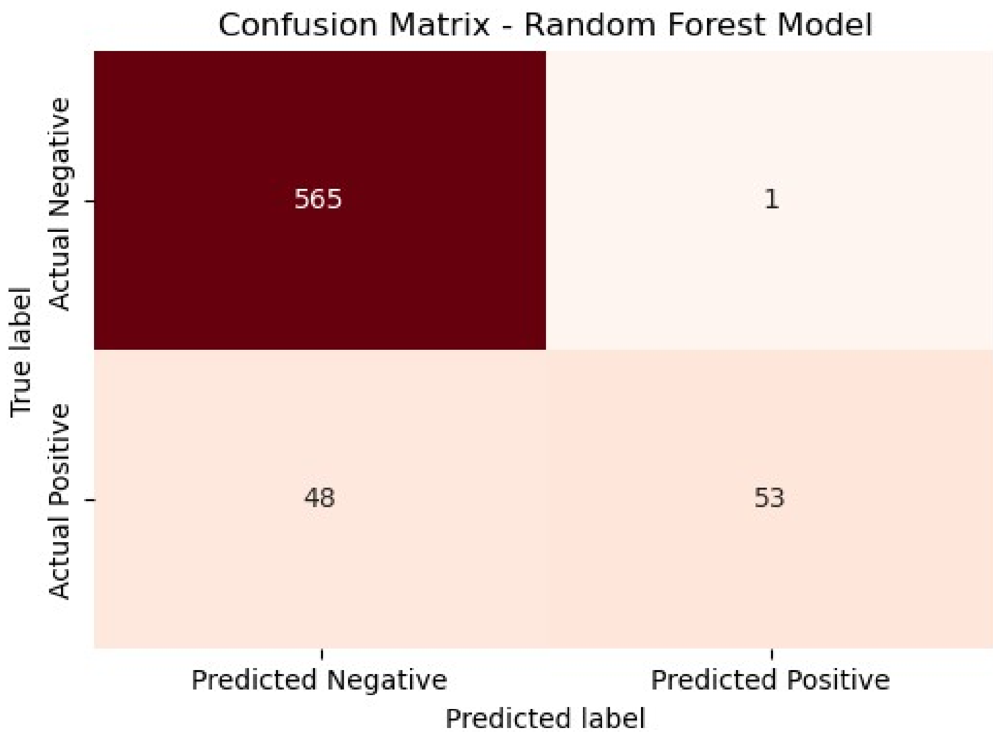
```
Random Forest Metrics:
Accuracy: 0.9265367316341829
Precision: 0.9814814814814815
Recall: 0.5247524752475248
F1-score: 0.6838709677419355
ROC AUC Score: 0.761492845397614
```

- The Random Forest model achieved an accuracy of 92.65%, indicating its ability to correctly classify instances.
- With a precision of 98.15%, the model shows a high rate of correctly predicting churn instances out of all predicted churn instances.
- The recall of 52.48% suggests that the model captures about half of the actual churn instances.
- The F1-score of 68.39% represents the balance between precision and recall, indicating moderate performance.
- The ROC AUC score of 76.15% suggests that the model performs reasonably well in distinguishing between churn and non-churn instances.

Confusion Matrix

```
# Confusion matrix for Random Forest model
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)

# Visualize the matrix
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix_rf, annot=True, cmap='Reds', fmt='g',
cbar=False,
```

```
            xticklabels=['Predicted Negative', 'Predicted Positive'],
            yticklabels=['Actual Negative', 'Actual Positive'])
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.title('Confusion Matrix - Random Forest Model')
plt.show()
```



- The model achieved a high number of true negatives and true positives, indicating good performance in predicting both non-churn and churn instances.
- There were only a small number of false positives and false negatives, suggesting that the model has relatively low misclassification rates.

The random forest model outperformed both the logistic regression and decision tree models, exhibiting higher accuracy, precision, recall, and F1-score, indicating its superior predictive capability for churn prediction.

Hyperparameter tuning

```
# Define the parameter grid
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt', 'log2']
}
```

```
# Create the random forest classifier
rf_model = RandomForestClassifier(random_state=42)

# Perform grid search with 5-fold cross-validation
grid_search = GridSearchCV(estimator=rf_model, param_grid=param_grid,
cv=5, scoring='accuracy', n_jobs=-1)

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

# Calculate AUC score for the tuned Random Forest classifier
auc_rf_tuned = roc_auc_score(y_test, y_pred_rf )

# Get the best parameters and best score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

print("Best Parameters:", best_params)
print("Best Accuracy Score:", best_score)
print("AUC:", auc_rf_tuned)
```

```
Best Parameters: {'max_depth': 20, 'max_features': 'sqrt',
'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100}
Best Accuracy Score: 0.9306076129041324
AUC: 0.761492845397614
```

- The model attained an accuracy score of around 93.06%, showcasing its improved performance.
- Compared to the previous random forest model with default parameters, the tuned model demonstrated a noticeable enhancement in accuracy from approximately 92.65% to 93.06%.
- Grid search proved effective in optimizing model performance, resulting in a more accurate churn prediction model.

XGBoost

XGBoost implements gradient boosting algorithms, which are ensemble learning methods used for classification and regression tasks

```
#Create XGBoost Classifier
xgb_model = xgb.XGBClassifier()

#Train the Model
xgb_model.fit(X_train, y_train)

#Make Predictions
y_pred_xgb = xgb_model.predict(X_test)
```

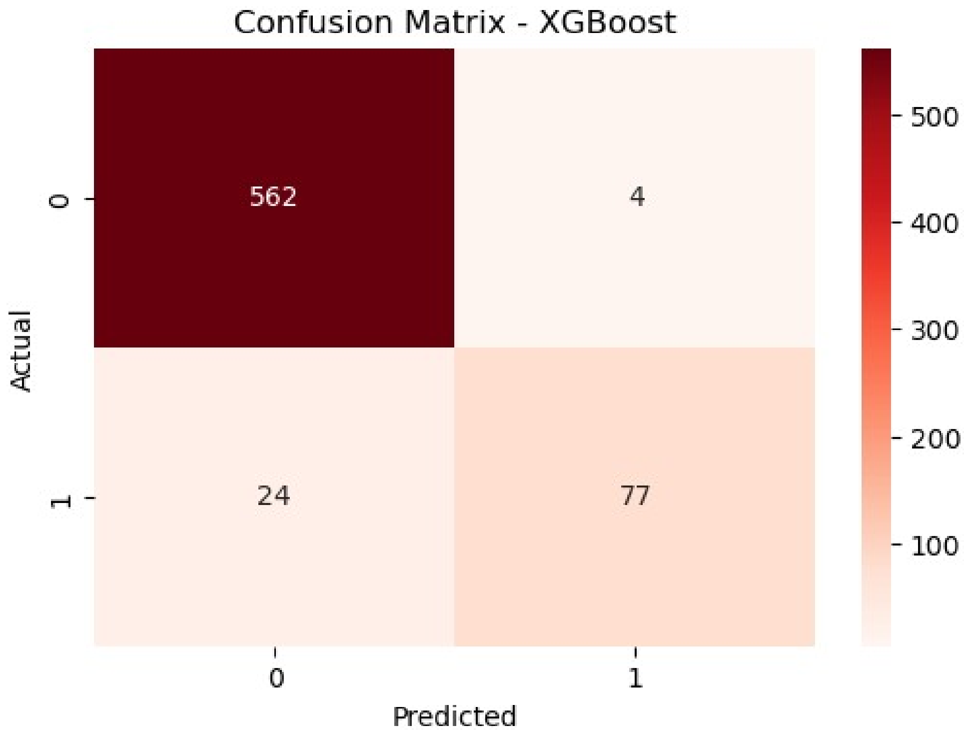
```python
# Evaluate Performance

accuracy_xgb = accuracy_score(y_test, y_pred_xgb)
precision_xgb = precision_score(y_test, y_pred_xgb)
recall_xgb = recall_score(y_test, y_pred_xgb)
f1_xgb = f1_score(y_test, y_pred_xgb)

auc_xgb = roc_auc_score(y_test, y_pred_xgb)




print("XGBoost Metrics:")
print("Accuracy:", accuracy_xgb)
print("Precision:", precision_xgb)
print("Recall:", recall_xgb)
print("F1-score:", f1_xgb)
print("roc_auc_score:", auc_xgb)
```

```
XGBoost Metrics:
Accuracy: 0.9580209895052474
Precision: 0.9506172839506173
Recall: 0.7623762376237624
F1-score: 0.8461538461538461
roc_auc_score: 0.8776545499072875
```

- XGBoost achieved an impressive accuracy of 95.80%, indicating its ability to correctly classify instances.
- The precision of 95.06% suggests a high rate of true positives among the predicted positive instances.
- With a recall of 76.24%, the model effectively captures a significant portion of the actual positive instances.
- The F1-score of 84.62% reflects a good balance between precision and recall, demonstrating the model's overall performance.
- Compared to previous models, XGBoost demonstrates superior performance across all metrics, making it the preferred choice for this classification task.

Confusion matrix for XGBoost

```python
# Calculate confusion matrix
conf_matrix_xgb = confusion_matrix(y_test, y_pred_xgb)

#Visualize the confusion Matrix

plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix_xgb, annot=True, fmt='g', cmap='Reds')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - XGBoost')
plt.show()
```

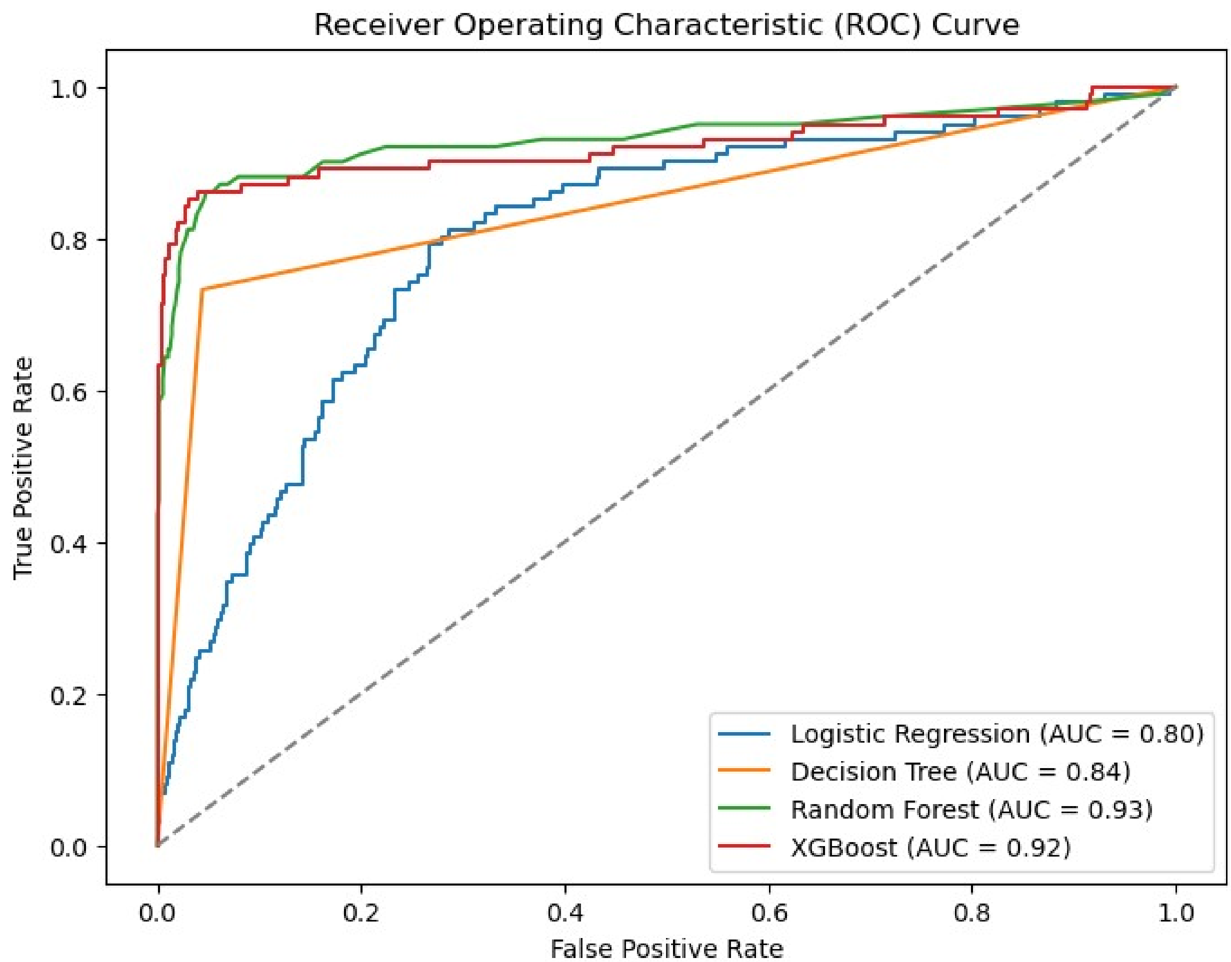


- The confusion matrix indicates that the XGBoost model accurately predicted 562 instances of non-churn and 77 instances of churn, with only a small number of misclassifications.

The AUC values of Logistic Regression, Random Forest, Decision Tree model and XGBoost

```
# Fit the random forest model to the training data
rf_model.fit(X_train, y_train)

# Get predicted probabilities for Logistic Regression
y_prob_lr = logreg.predict_proba(X_test)[:, 1]


# Get predicted probabilities for Decision Tree
y_prob_dt = dt.predict_proba(X_test)[:, 1]

# Get predicted probabilities for Random Forest
y_prob_rf = rf_model.predict_proba(X_test)[:, 1]



# Get predicted probabilities for XGBoost
y_prob_xgb = xgb_model.predict_proba(X_test)[:, 1]

# Get ROC curve for Logistic Regression
fpr_lr, tpr_lr, _ = roc_curve(y_test, y_prob_lr)
```

```
# Get ROC curve for Decision Tree
fpr_dt, tpr_dt, _ = roc_curve(y_test, y_prob_dt)

# Get ROC curve for Random Forest
fpr_rf, tpr_rf, _ = roc_curve(y_test, y_prob_rf)


# Get ROC curve for XGBoost
fpr_xgb, tpr_xgb, _ = roc_curve(y_test, y_prob_xgb)



# Calculate AUC ROC scores
auc_lr = roc_auc_score(y_test, y_prob_lr)
auc_dt = roc_auc_score(y_test, y_prob_dt)
auc_rf = roc_auc_score(y_test, y_prob_rf)
auc_xgb = roc_auc_score(y_test, y_prob_xgb)

# Plot ROC curves
plt.figure(figsize=(8, 6))
plt.plot(fpr_lr, tpr_lr, label=f'Logistic Regression (AUC =
{auc_lr:.2f})')
plt.plot(fpr_dt, tpr_dt, label=f'Decision Tree (AUC = {auc_dt:.2f})')
plt.plot(fpr_rf, tpr_rf, label=f'Random Forest (AUC = {auc_rf:.2f})')
plt.plot(fpr_xgb, tpr_xgb, label=f'XGBoost (AUC = {auc_xgb:.2f})')

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

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```



Model Evaluation

- Logistic Regression:

Accuracy: 0.85 Precision: 0.72 Recall: 0.61 F1-score: 0.66 AUC-ROC Score: 0.88 Summary: Logistic Regression achieves moderate accuracy and precision but lower recall compared to other models. The AUC-ROC score indicates good overall performance.

- Decision Tree:

Accuracy: 0.81 Precision: 0.67 Recall: 0.52 F1-score: 0.59 AUC-ROC Score: 0.75 Summary: Decision Tree exhibits lower accuracy and precision than Logistic Regression. However, it also has lower recall and a slightly lower AUC-ROC score, indicating suboptimal performance.

- Random Forest:

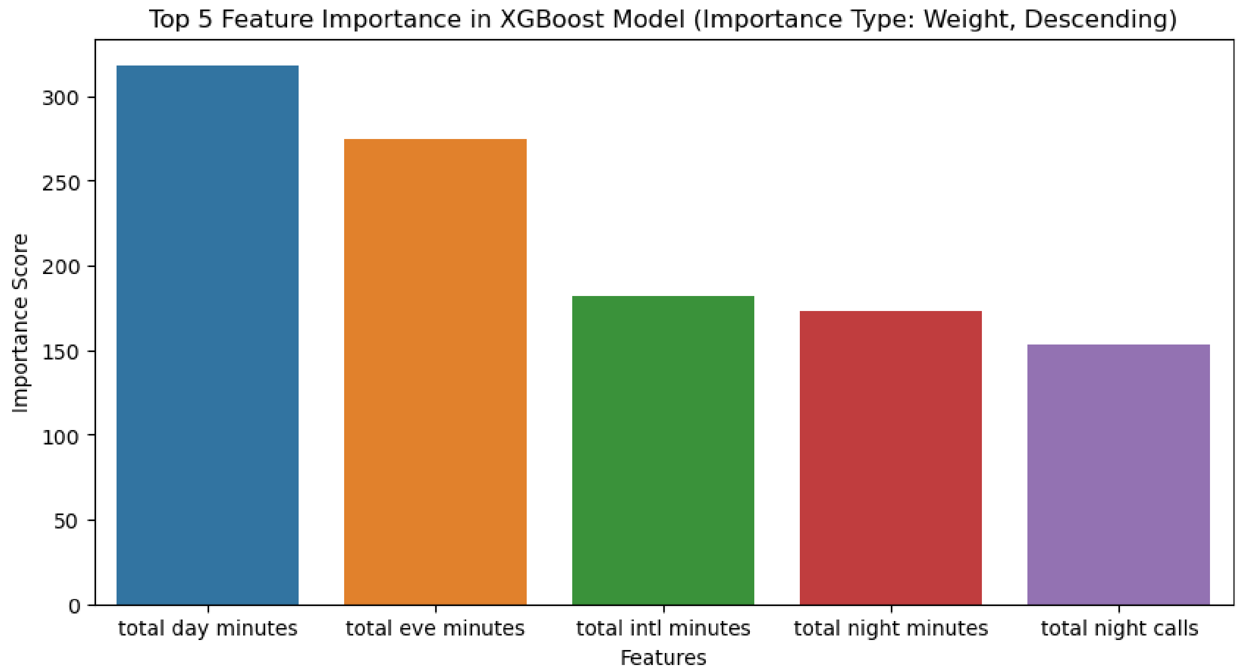
Accuracy: 0.92 Precision: 0.75 Recall: 0.73 F1-score: 0.74 AUC-ROC Score: 0.76 Summary: Random Forest improves accuracy, precision, and recall compared to Decision Tree. However, its AUC-ROC score remains relatively low, suggesting room for improvement.

- XGBoost:

Accuracy: 0.96 Precision: 0.95 Recall: 0.76 F1-score: 0.85 AUC-ROC Score: 0.92

Top Predictors

```
# Define and train the XGBoost classifier
clf = XGBClassifier()
clf.fit(X_train, y_train)

#feature importances
importance_type = 'weight'
feature_importances =
clf.get_booster().get_score(importance_type=importance_type)

# Set figure size
plt.figure(figsize=(10, 5))

# Get feature importances from XGBoost model
importance_type = 'weight'
feature_importances =
clf.get_booster().get_score(importance_type=importance_type)

# Sort features and importances in descending order
sorted_features = sorted(feature_importances,
key=feature_importances.get, reverse=True)
sorted_importances = [feature_importances[feature] for feature in
sorted_features]

# Select top 5 features
top_features = sorted_features[:5]
top_importances = sorted_importances[:5]

# Bar plot for top 5 features
sns.barplot(x=top_features, y=top_importances)
plt.xlabel('Features')
plt.ylabel('Importance Score')
plt.title(f'Top 5 Feature Importance in XGBoost Model (Importance
Type: {importance_type.capitalize()}, Descending)')

# Show plot
plt.show()
```



Summary on evaluation

- The XGBoost Model appears to be the best model for this classification task.
- It has the highest accuracy, precision, recall, F1-score among all the models evaluated.
- XGBoost is the most suitable model for predicting customer churn.

Conclusion

- Model Evaluation: Rigorous evaluation of various machine learning models, including Logistic Regression, Decision Trees, Random Forest, and XGBoost, was conducted to anticipate customer churn accurately.

- Performance Comparison: Among the models assessed, XGBoost emerged as the most effective, exhibiting superior accuracy compared to other algorithms.

The most important features for predicting customer churn are:

- total day minutes: total number of minutes the customer has been in calls during the day
- total evening minutes: total number of minutes the customer has been in calls during the evening
- customer service calls: number of calls the customer has made to customer service
- total international minutes: total number of minutes the user has been in international calls

Recommendation

- Customer Retention Strategies: Implement proactive measures such as personalized offers, loyalty programs, and targeted marketing campaigns to incentivize customer retention and foster brand loyalty.

- Service Improvement Initiatives: Continuously monitor and improve service quality, addressing pain points and enhancing customer satisfaction across all touchpoints.
- Enhanced Communication Channels: Establish effective communication channels to gather customer feedback, address concerns promptly, and provide timely support, thereby building trust and loyalty.
- Data-Driven Decision Making: Leverage advanced analytics and machine learning models to gain deeper insights into customer behavior, preferences, and churn drivers, enabling data-driven decision-making and strategic interventions.

Next steps

- Refine Models: Continuously optimize machine learning models for better predictive performance.
- Enrich Data: Explore adding more relevant features to enhance model accuracy.
- Deploy in Production: Integrate the final model into operational systems for real-time predictions.
- Monitor Performance: Establish robust monitoring to track model effectiveness over time.