1. SYRIATEL PREDICTIVE ANALYSIS OF CUSTOMER CHURN

1. Business Understanding

1.1. 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. Customer churn denotes the situation where customers terminate their subscriptions with a company, frequently transitioning to competitors or discontinuing the service entirely. Notably, poor service experience and customer service are among the primary contributors to customer churn. Additionally, the ease with which customers can switch providers and encountering subpar customer experiences, such as requiring multiple contacts for issue resolution, also significantly contribute to churn rates. These factors underscore the criticality of focusing on service quality and enhancing customer satisfaction to effectively diminish the churn rate.

1.2. 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.

1.3. Main Objective

The main objective of this project is to build a predictive classifier that assists SyrialTel Telecommunication company in determining if there is a predictable pattern to customer churning.

1.4. Experimental Design

This outlines the processes to be undertaken in this project. They are:

1. Data Understanding
2. Data Cleaning
3. Exploratory Data Analysis
4. Data Preparation
5. Modelling
6. Evaluation
7. Conclusion

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.

Summary of Features in the Dataset

Each entry in the dataset represents a customer, and the attributes describe different aspects of their account and usage.

Attribute	Description
State	The state in which the customer resides.
Account Length	The number of days the customer has had the account.
Area Code	The area code of the customer's phone number.
Phone Number	The customer's phone number.
International Plan	A boolean indicating whether the customer has the international calling plan (True or False).
Voice Mail Plan	A boolean indicating whether the customer has the voicemail plan (True or False).
Number Vmail Messages	The number of voicemail messages the customer has sent.

Total Day Minutes	The total number of minutes the customer has been in calls during the day.
Total Day Calls	The total number of calls the customer has made during the day.
Total Day Charge	The total amount of money charged by the telecom company for calls during the day.
Total Eve Minutes	The total number of minutes the customer has been in calls during the evening.
Total Eve Calls	The total number of calls the customer has made during the evening.
Total Eve Charge	The total amount of money charged by the telecom company for calls during the evening.
Total Night Minutes	The total number of minutes the customer has been in calls during the night.
Total Night Calls	The total number of calls the customer has made during the night.
Total Night Charge	The total amount of money charged by the telecom company for calls during the night.
Total Intl Minutes	The total number of minutes the user has been in international calls.
Total Intl Calls	The total number of international calls the customer has made.
Total Intl Charge	The total amount of money charged by the telecom company for international calls.
Customer Service Calls	The number of calls the customer has made to customer service.
Churn	A boolean indicating whether the customer terminated their contract (True or False).

2.2. Suitability of above data in predicting customer churn

The dataset contains a variety of factors crucial for understanding customer behavior and forecasting churn for SyrialTel Company. Essential attributes include customer subscriptions like international plans and voice mail plans, as well as call usage statistics such as total day minutes and total night minutes. The 'Churn' column, which acts as the target variable, distinguishes between customers who have terminated their service ('True') and those who haven't ('False'). This comprehensive dataset lays the groundwork for building a predictive model to accurately identify churn risks and implement focused retention strategies. This aligns with the project's goal of effectively reducing customer churn.

2.3 importing the required libraries,loading and checking the data

In [ ]:

```
# 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
import xgboost as xgb
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_
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
```

In [ ]:

```
# loading the datasets
dataFrame = pd.read_csv("Dataset/bigml_59c28831336c6604c800002a.csv")
```

In [ ]:

```
# Creating a copy of the dataset to work with.
data = dataFrame.copy()
data.head()
```

Out[ ]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...	total eve calls	total eve charge	total night minutes	total night calls	total night charge	total intl minutes
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16.78	244.7	91	11.01	10.0
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16.62	254.4	103	11.45	13.7
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10.30	162.6	104	7.32	12.2
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.26	196.9	89	8.86	6.6
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12.61	186.9	121	8.41	10.1

5 rows × 21 columns

In [ ]:

```
# checking the shape of the data
(data.shape)
```

Out[ ]:

```
(3333, 21)
```

In [ ]:

```
print(f"Data has {data.shape[0]} rows and {data.shape[1]} columns")
```

```
Data has 3333 rows and 21 columns
```

In [ ]:

```
# checking for the information about the data Frame.
data.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
```

In [ ]:

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

3. Data Preparation

3.1 Data Cleaning

In [ ]:
```
# Converting area code to object as it takes no mathematical significance.
data['area code'] = data['area code'].astype('object')
```

In [ ]:
```
# Checking to confirm that the area code has been converted to object
data.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   object 
 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(7), object(5)
memory usage: 524.2+ KB
```

From the above information, phone number is best used as unique identifier as it cannot be similar to more than a person.

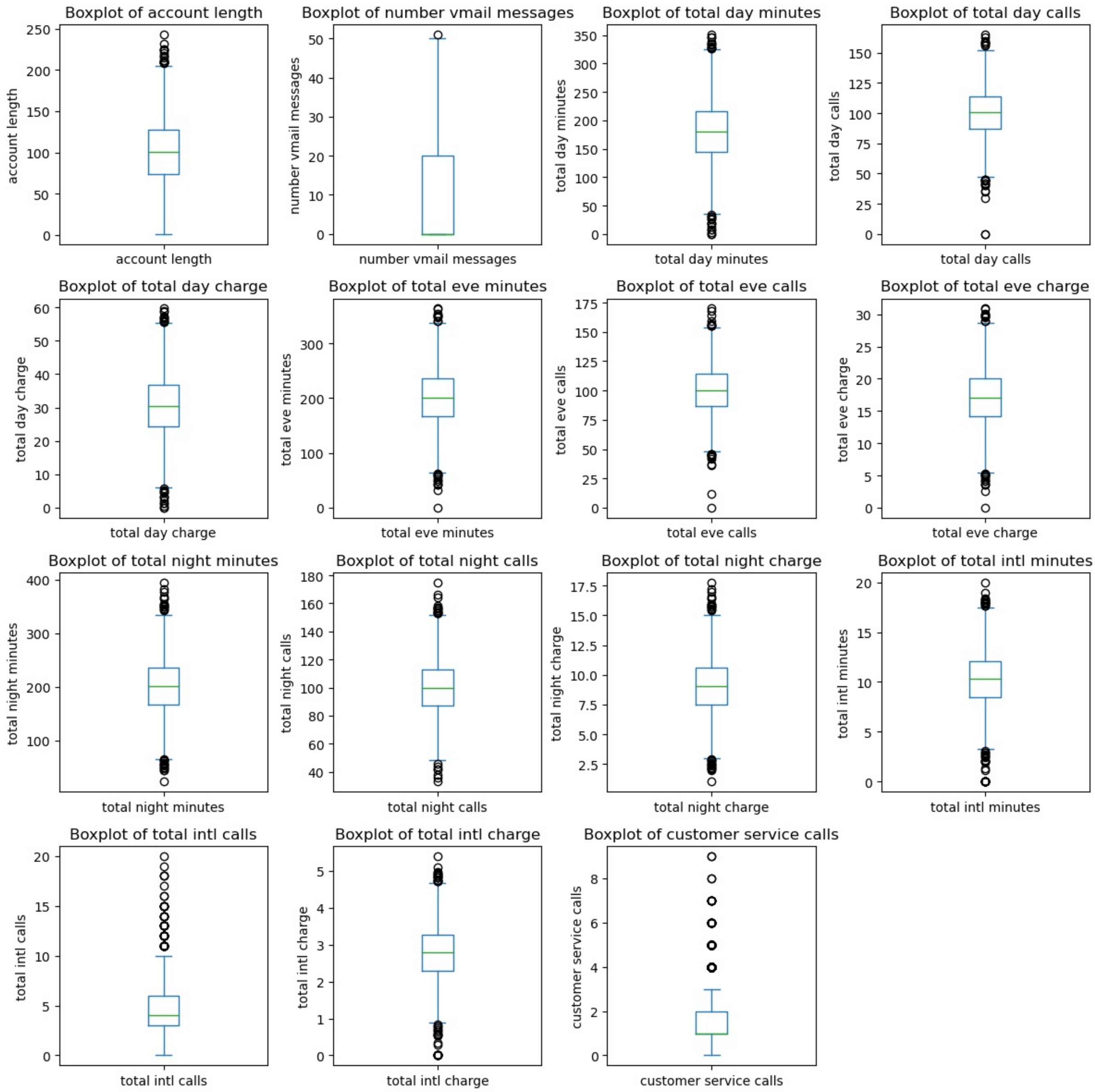
In [ ]:
```
#checking for duplicates in the data
print(data.duplicated().sum())
```

```
0
```

In [ ]:
```
# checking for missing values in the data
print(data.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
```

In [ ]:
```
# checking for outliers in numerical columns
numeric_cols = data.select_dtypes(include=['int64', 'float64'])
num_plots = len(numeric_cols.columns)
num_rows = (num_plots + 3) // 4 # 4 columns
num_cols = min(num_plots, 4)

plt.figure(figsize=(12, 3 * num_rows))

for i, col in enumerate(numeric_cols.columns):
    plt.subplot(num_rows, num_cols, i + 1)
    data[col].plot(kind='box')
    plt.title(f'Boxplot of {col}')  # Set title
    plt.ylabel(col)  # Set y-label

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



In [ ]:
```
# Given that the data has no missing values,the phone number column was dropped as it was only significant as a
data.drop('phone number', axis=1, inplace=True)
```

From the above, it is evident that the data above is clean; contains no duplicates and have no missing data.

Justification for data Cleaning

The data cleaning process has been performed to build the foundation for meaningful and accurate exploratory analysis by ensuring that the data is accurate, reliable, consistent, complete, and ready for analysis.

3.2. Explotarory Data Analysis

In [ ]:
```
# Summary statistic
data.describe()
```

Out[ ]:

	account length	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	total eve charge	total night minutes	total night calls
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000
mean	101.064806	8.099010	179.775098	100.435644	30.562307	200.980348	100.114311	17.083540	200.872037	100.107711
std	39.822106	13.688365	54.467389	20.069084	9.259435	50.713844	19.922625	4.310668	50.573847	19.568609
min	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	23.200000	33.000000
25%	74.000000	0.000000	143.700000	87.000000	24.430000	166.600000	87.000000	14.160000	167.000000	87.000000
50%	101.000000	0.000000	179.400000	101.000000	30.500000	201.400000	100.000000	17.120000	201.200000	100.000000
75%	127.000000	20.000000	216.400000	114.000000	36.790000	235.300000	114.000000	20.000000	235.300000	113.000000
max	243.000000	51.000000	350.800000	165.000000	59.640000	363.700000	170.000000	30.910000	395.000000	175.000000

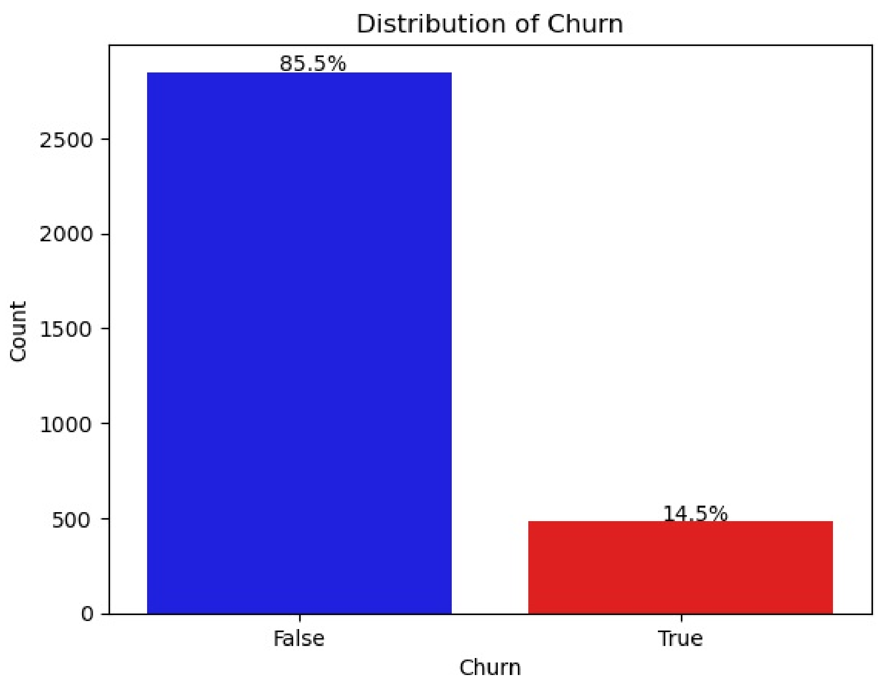
Univariate Analysis

These 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.

In [ ]:
```
# checking for the distribution of the target variable "churn"
data['churn'].value_counts()
```

Out[ ]:
```
churn
False    2850
True      483
Name: count, dtype: int64
```

In [ ]:
```
# Plotting the distribution of the target variable
ax = sns.countplot(x='churn', data=data, palette=['blue', 'red'])
total = len(data['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()
```



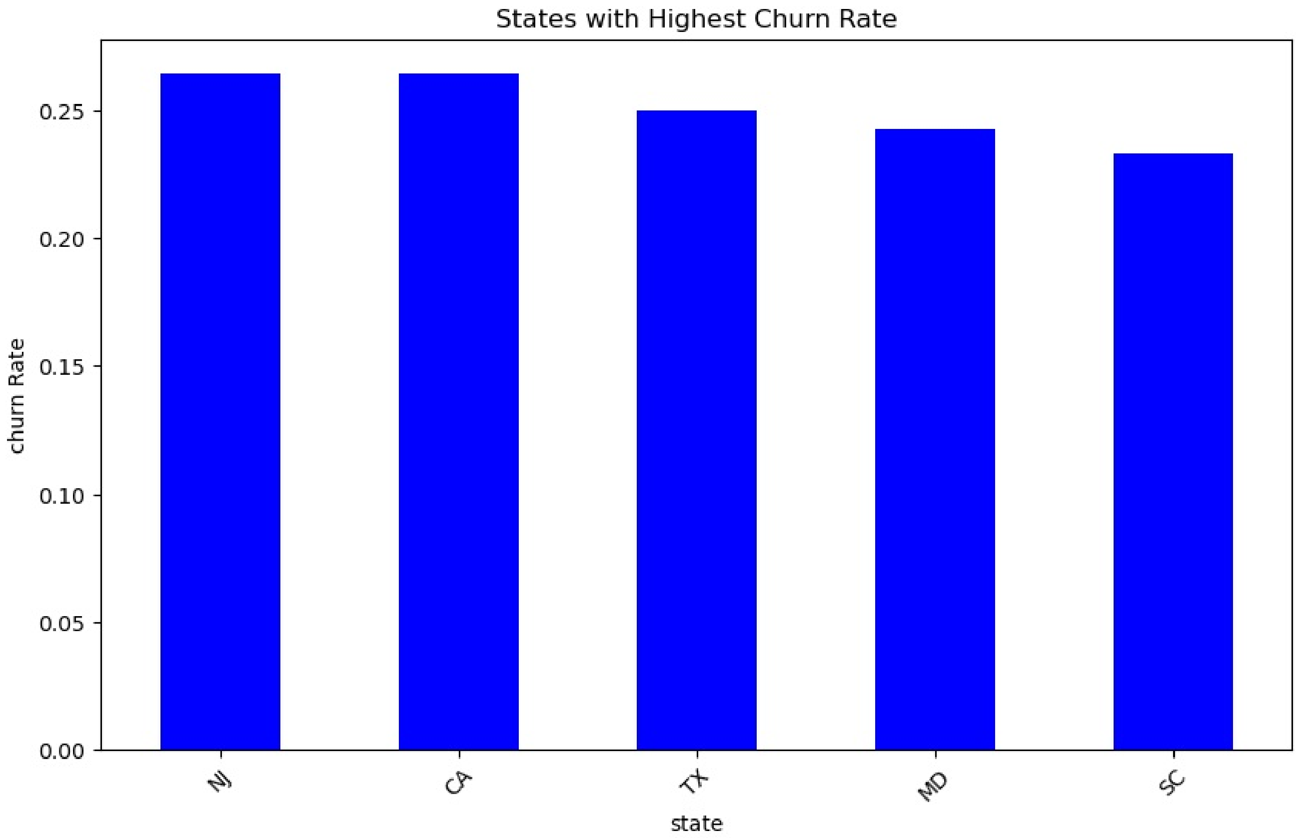
It is evident that from the 3,333 customers, 483 customers have churned from SyriaTel. This is approximately 14.5 % of the total customers indicating a loss in their customer base.

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.

Top 5 States with the highest churn rate

In [ ]:
```
# Calculate churn rate for each state
```

```
state_churn_rate = data.groupby('state')['churn'].mean().sort_values(ascending=False)

# Get the top states with the highest churn rate
top_states_churn = state_churn_rate.head(5)

# Plot the top states with the highest churn rate
plt.figure(figsize=(10, 6))
top_states_churn.plot(kind='bar', color='blue')
plt.title('States with Highest Churn Rate')
plt.xlabel('state')
plt.ylabel('churn Rate')
plt.xticks(rotation=45)
plt.show()
```

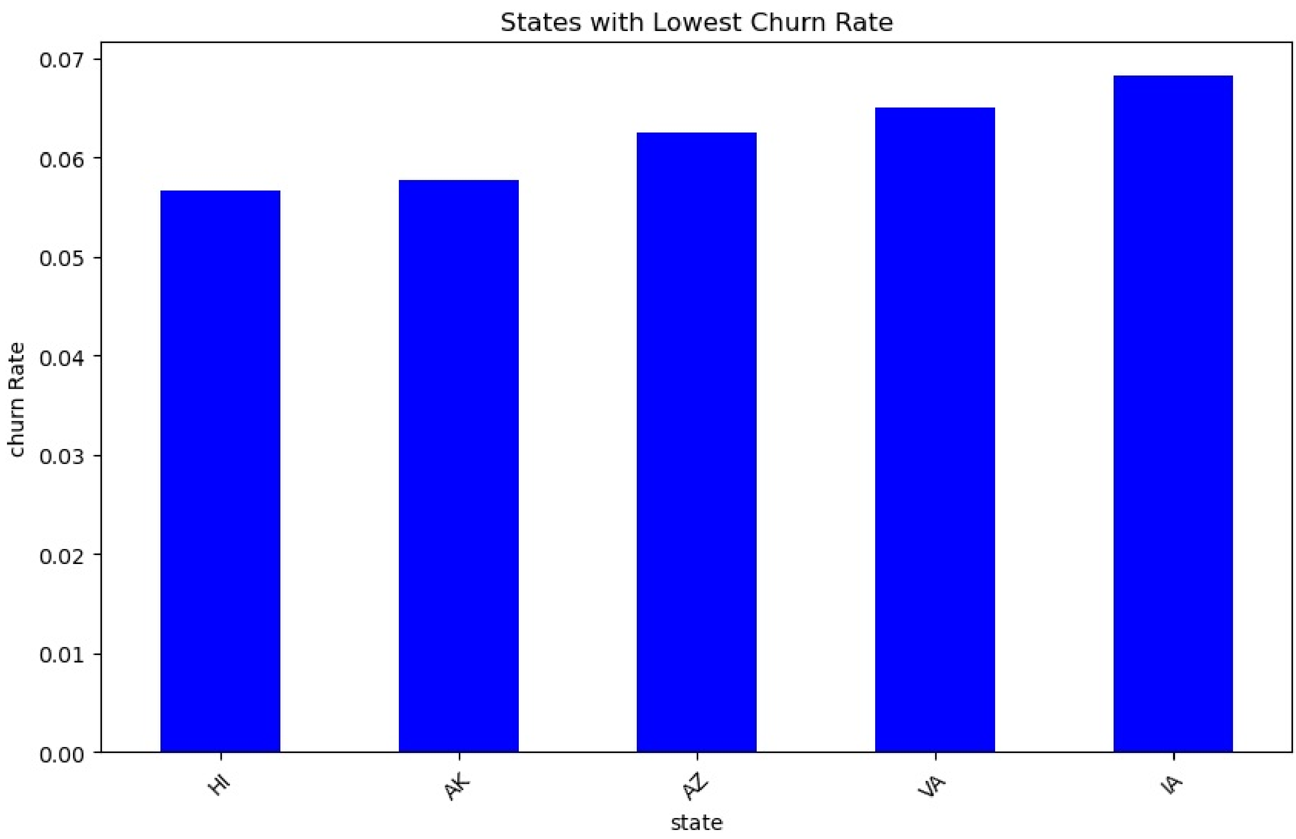


The top 5 states with the highest churn rate are:

- NJ: New Jersey
- CA: California
- TX: Texas
- MD: Maryland
- SC: South Carolina

Top 5 States with the lowest churn rate

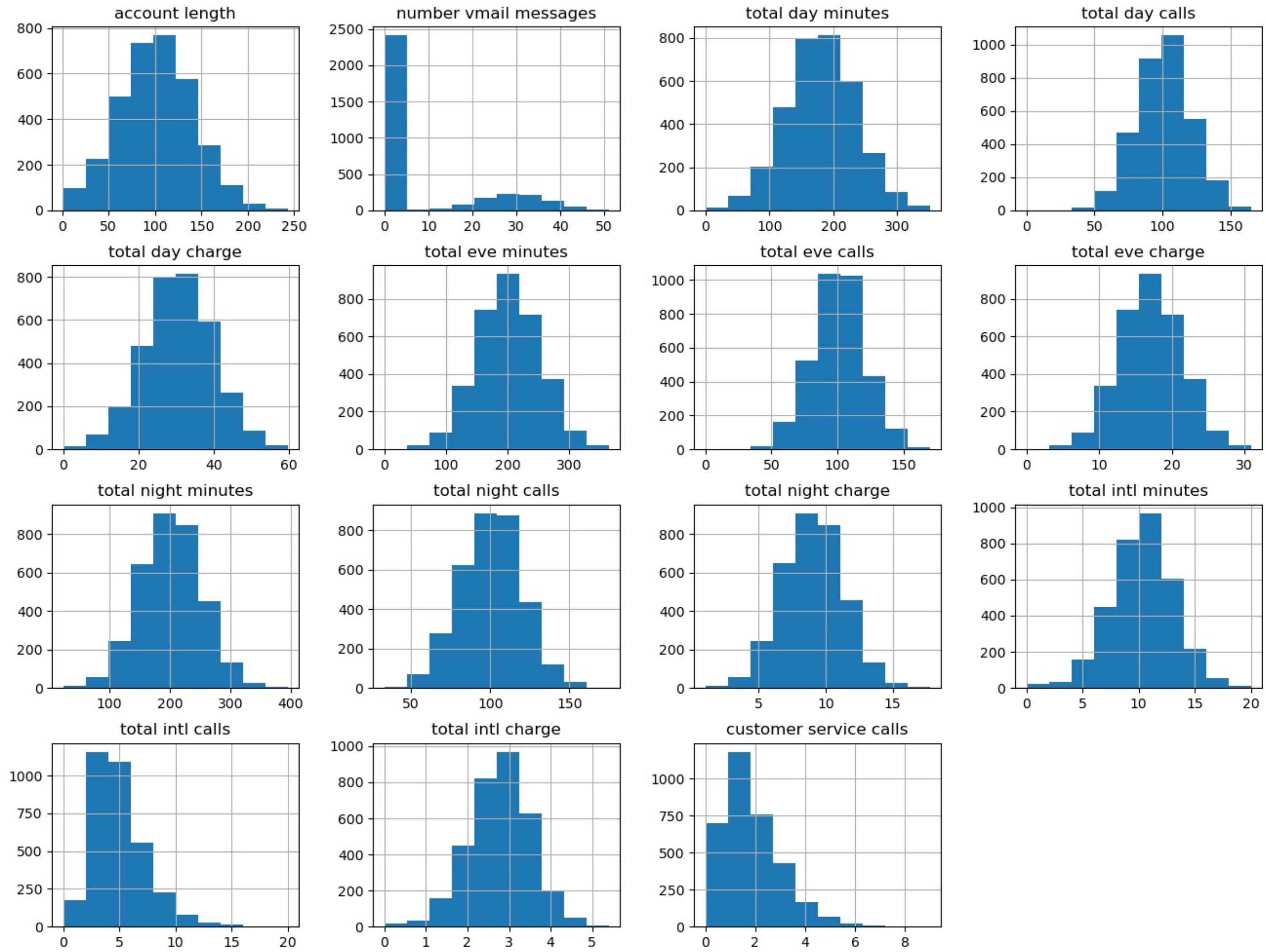
In [ ]:
```
# Calculate churn rate for each state
state_churn_rate = data.groupby('state')['churn'].mean().sort_values()

# Get the top states with the lowest churn rate
bottom_states_churn = state_churn_rate.head(5)

# Plot the top states with the lowest churn rate
plt.figure(figsize=(10, 6))
bottom_states_churn.plot(kind='bar', color='blue')
plt.title('States with Lowest Churn Rate')
plt.xlabel('state')
plt.ylabel('churn Rate')
plt.xticks(rotation=45)
plt.show()
```



The top 5 states with the lowest churn rate are:

- HI: Hawaii
- AK: Alaska
- AZ: Arizona
- VA: Virginia
- LA: Louisiana

In [ ]:
```
# distribution of features
data.drop(columns='churn').hist(figsize=(16,12));
```

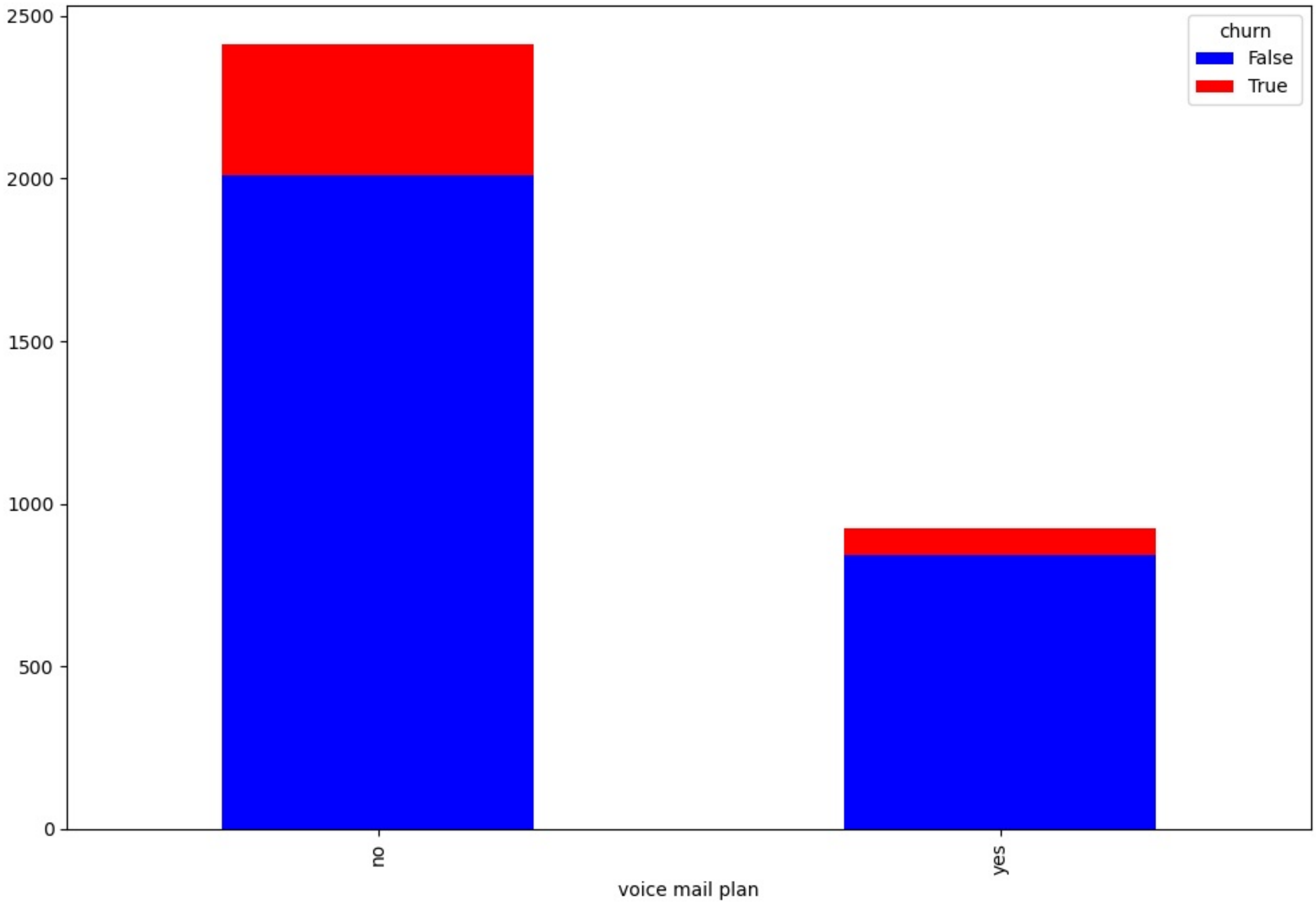


Most of the features are normally distributed. However, a few of the features have to be scaled and normalized.

Voice mail plan effect on churn

In [ ]:

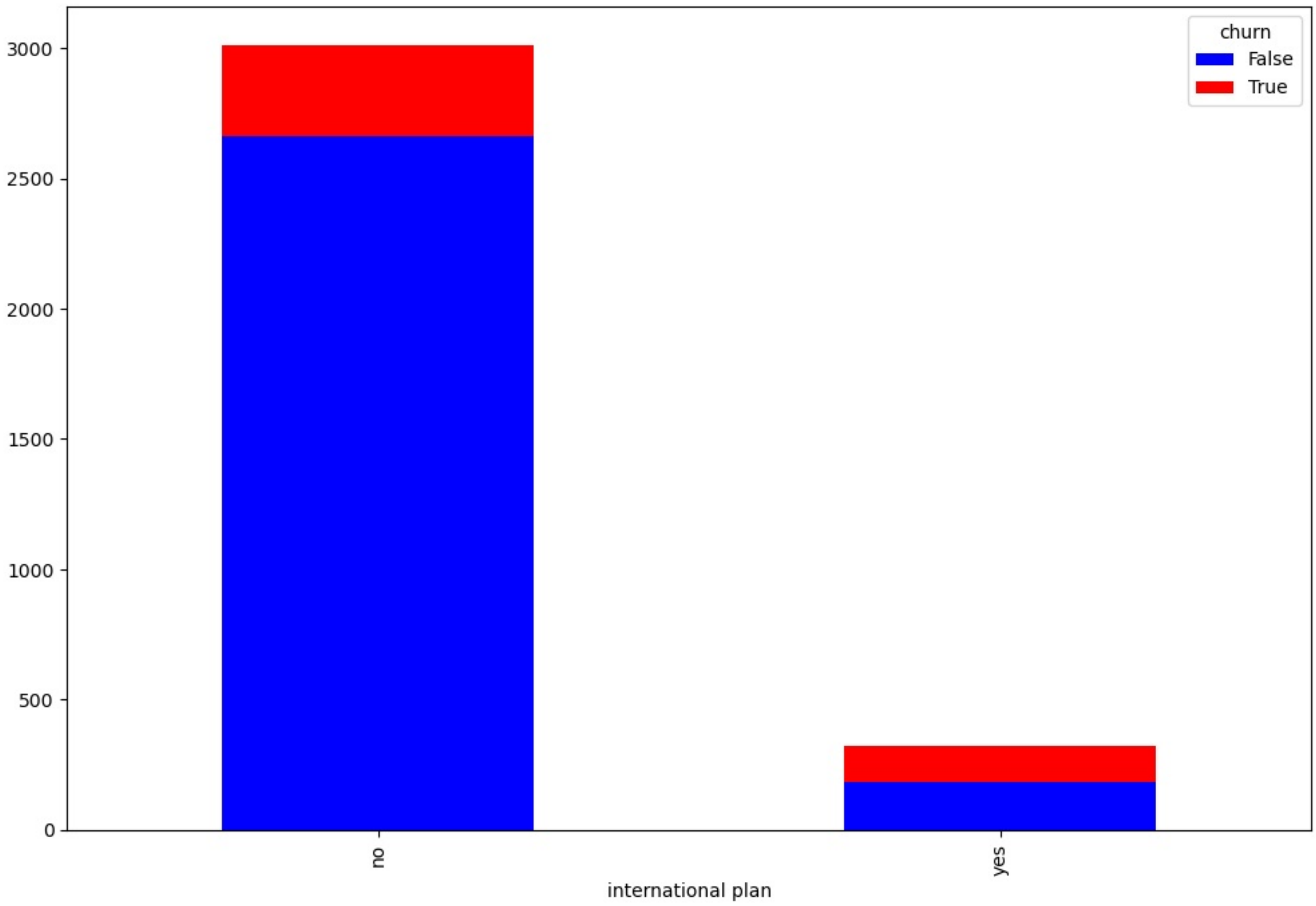
```
#Checking for the impact of the voice mail plan on churn

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

    # Calculating the percentage of customers subscribed to the plan
    total_customers = len(data)
    total_subscribed = sum(data[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((data[plan_column] == 'yes') & (data['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_chu

# Plot churn vs plan for 'voice mail plan'
plot_churn_vs_plan(data, '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%
```

International call plan to churn

In [ ]:
```
plot_churn_vs_plan(data,'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%
```

Findings

1. Voice mail plan has a small notable effect on customer churning.

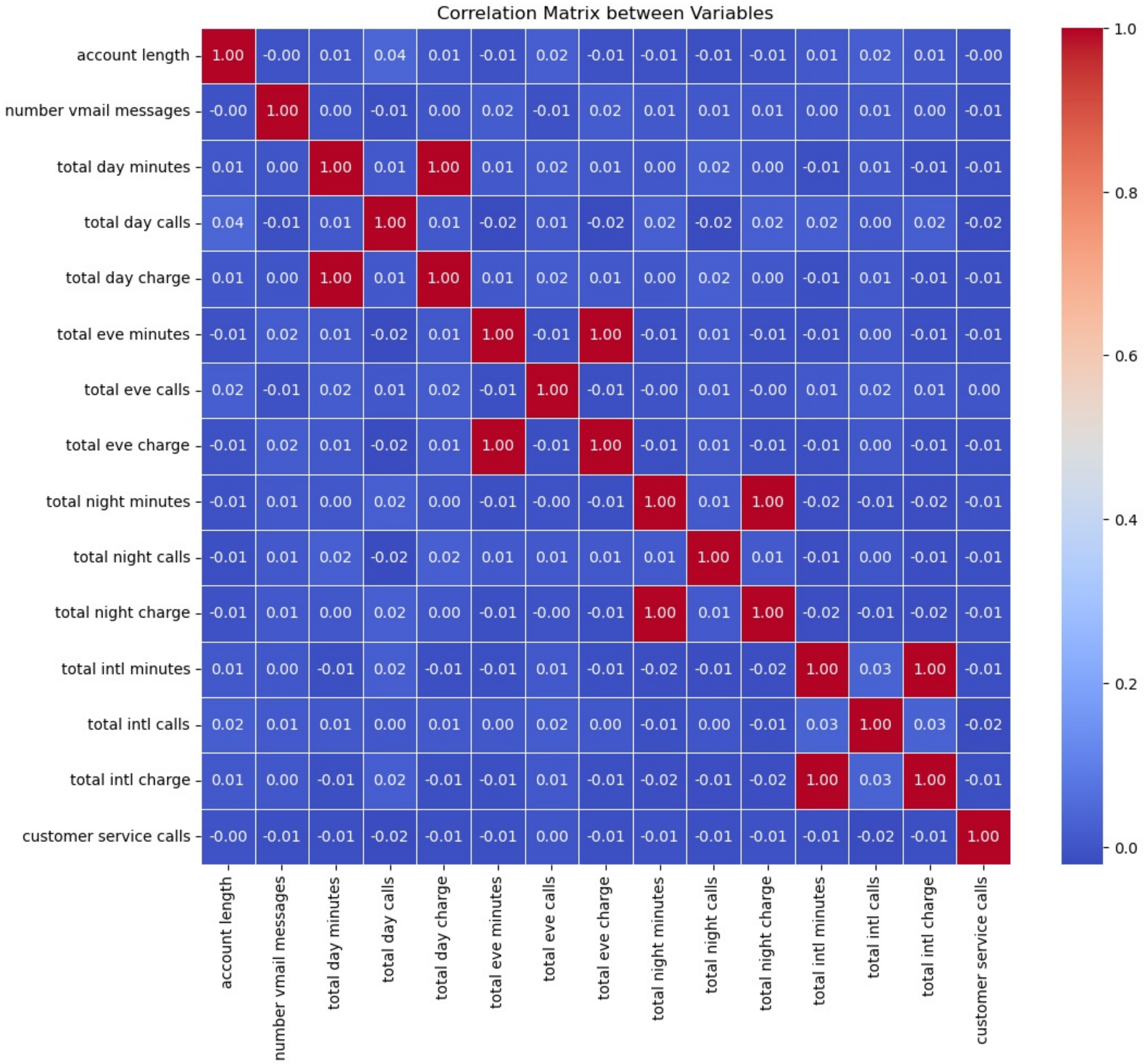
2. International call plan has an effect on customer churning, as most of the customer who churn, do not have active plan subscription. Of the 9.7% with subsription, 42.1% of those do churn.

Multivariate analysis

In this analysis, we check for multicollinearity of features to enhance accuracy during modeling.

In [ ]:

```
# Compute the correlation matric for the numerical columns
numeric_columns = data.select_dtypes(include=['float64', 'int64']).columns.tolist()
corr_matrix = data[numeric_columns].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()
```



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:

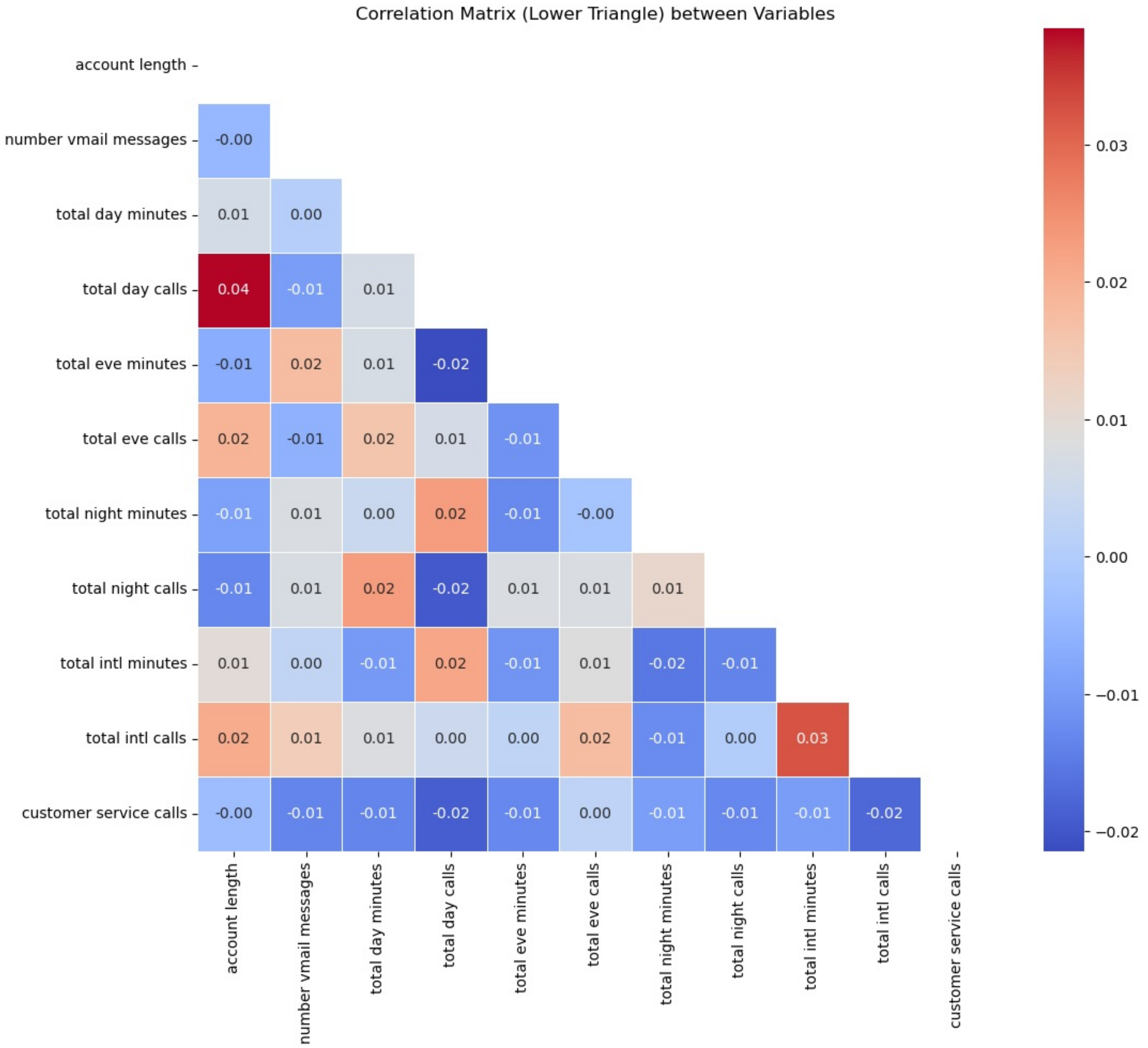
- Total day charge and Total day minutes,
- Total eve charge and Total eve minutes,
- Total night charge and Total night minutes,
- Total int charge and Total int minutes.

3.3 Data pre-preprocessing

we drop the columns with multicollinearity

In [ ]:
```python
# Dropping columns with multicollinearity.
columns_to_drop = ['total day charge', 'total eve charge', 'total night charge', 'total intl charge']
data = data.drop(columns=[col for col in columns_to_drop if col in data.columns])
```

In [ ]:
```python
# Computing the correlation matrix
numeric_columns = data.select_dtypes(include=['float64', 'int64']).columns.tolist()
corr_matrix = data[numeric_columns].corr()
mask = np.triu(np.ones_like(corr_matrix, dtype=bool))

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



Checking the multicollinearity of the data, it is evident that the correlation between the variables are now acceptable as they are negligible. This will ensure that the model interpretation, feature importance, Model performance, Dimensionality reduction and Model stability are enhanced.

Train-test split

Splitting data into training and testing datasets before applying any preprocessing steps is crucial to prevent data leakage and maintain the integrity of the evaluation process. This ensures that the test data remains untouched and accurately represents unseen data.

Using a fixed random_state value, 42, is essential for code reproducibility. By setting the random_state parameter to a specific value, we ensure that the data split remains consistent across different runs of the code, which is important for reproducibility purposes.

In [ ]:
```python
# Defining the target variable(y) and the independent variables(x).
y = data['churn']
X = data.drop(['churn','area code'], axis=1)

# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)
```

In [ ]:
```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2499 entries, 367 to 3174
Data columns (total 14 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   state                   2499 non-null   object 
 1   account length          2499 non-null   int64  
 2   international plan      2499 non-null   object 
 3   voice mail plan         2499 non-null   object 
 4   number vmail messages   2499 non-null   int64  
 5   total day minutes       2499 non-null   float64
 6   total day calls         2499 non-null   int64  
 7   total eve minutes       2499 non-null   float64
 8   total eve calls         2499 non-null   int64  
 9   total night minutes     2499 non-null   float64
 10  total night calls       2499 non-null   int64  
 11  total intl minutes      2499 non-null   float64
 12  total intl calls        2499 non-null   int64  
 13  customer service calls  2499 non-null   int64  
dtypes: float64(4), int64(7), object(3)
memory usage: 292.9+ KB
```

Encoding Categorical feature

In ensuring data suitability for prediction, it becomes important to format it correctly. Categorical inputs pose a challenge for Machine Learning models. The project thus use one-hot encoding to convert categorical variables in the dataset into numerical values.

In [ ]:
```
# Specifying the categorical columns to be encoded
categorical_columns = ['international plan', 'voice mail plan' , 'state']

# Initializing the OneHotEncoder with the desired parameters
ohe = OneHotEncoder(drop='first')

# Encoding the categorical columns in the training set
X_train_encoded = pd.DataFrame(ohe.fit_transform(X_train[categorical_columns]))

# Encoding the categorical columns in the test set using the fitted encoder
X_test_encoded = pd.DataFrame(ohe.transform(X_test[categorical_columns]))
```

In [ ]:
```
# Setting the index of the encoded training dataframe to match the original training data
X_train_encoded.index = X_train.index

# Setting the index of the encoded test dataframe to match the original test data
X_test_encoded.index = X_test.index
```

In [ ]:
```
# Removing the original categorical columns from the training data
X_train.drop(categorical_columns, axis=1, inplace=True)

# Removing the original categorical columns from the test data
X_test.drop(categorical_columns, axis=1, inplace=True)
```

In [ ]:
```
# Initializing the MinMaxScaler
scaler = MinMaxScaler()

# Scaling and transform the training data
X_train_scaled = pd.DataFrame(scaler.fit_transform(X_train), index=X_train.index, columns=X_train.columns)

# Scaling and transform the test data
X_test_scaled = pd.DataFrame(scaler.transform(X_test), index=X_test.index, columns=X_test.columns)
```

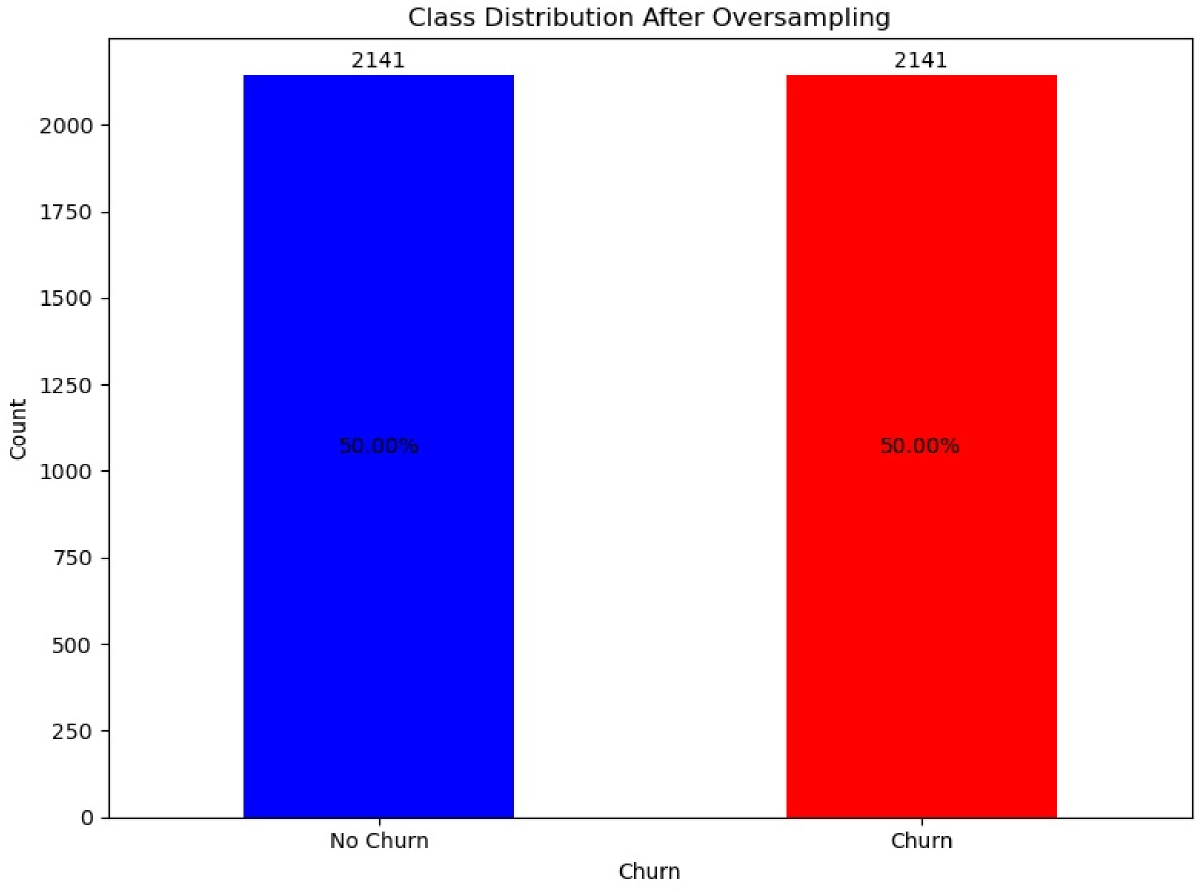
In [ ]:
```
# Concatenating the scaled numeric features and encoded categorical features for the training data
X_train_processed = pd.concat([X_train_scaled, X_train_encoded], axis=1)

# Concatenating the scaled numeric features and encoded categorical features for the test data
X_test_processed = pd.concat([X_test_scaled, X_test_encoded], axis=1)
```

Dealing with class imbalance by applying oversampling

In [ ]:
```
# Combine X_train_processed and y_train into a single DataFrame
train_data = pd.concat([X_train_processed, y_train], axis=1)

# Separate majority and minority classes
majority_class = train_data[train_data['churn'] == 0]
minority_class = train_data[train_data['churn'] == 1]

# Upsample minority class to match the number of samples in the majority class
minority_upsampled = resample(minority_class,
                              replace=True,
                              n_samples=len(majority_class),
                              random_state=0)

# Combine majority class with upsampled minority class
upsampled_data = pd.concat([majority_class, minority_upsampled])
```

```
# Separate features (X) and target (y) from upsampled data
X_train_processed_upsampled = upsampled_data.drop('churn', axis=1)
y_train_upsampled = upsampled_data['churn']
```

In [ ]:
```
# Calculate class distribution after oversampling
after_counts = upsampled_data['churn'].value_counts()
after_total = after_counts.sum()

# Plot class distribution after oversampling
plt.figure(figsize=(8, 6))
bars = after_counts.plot(kind='bar', color=['blue', 'red'])
for bar in bars.patches:
    x = bar.get_x() + bar.get_width() / 2
    y = bar.get_height()
    percentage = f"{y / after_total * 100:.2f}%"
    plt.text(x, y/2, percentage, ha='center', va='center')
    plt.text(x, y + 10, str(int(y)), ha='center', va='bottom')
plt.title('Class Distribution After Oversampling')
plt.xlabel('Churn')
plt.ylabel('Count')
plt.xticks([0, 1], ['No Churn', 'Churn'], rotation=0)
plt.tight_layout()
plt.show()
```



In [ ]:
```
# Drop the last column (index 11)
X_train_processed_upsampled.drop(X_train_processed_upsampled.columns[11], axis=1, inplace=True)
```

In [ ]:
```
# checking the X_train_processed_upsampled
X_train_processed_upsampled
```

Out[ ]:

	account length	number vmail messages	total day minutes	total day calls	total eve minutes	total eve calls	total night minutes	total night calls	total intl minutes	total intl calls	customer service calls
367	0.190476	0.000000	0.217117	0.718519	0.696728	0.635294	0.623453	0.471831	0.900	0.166667	0.111111
3103	0.493506	0.000000	0.555141	0.600000	0.624141	0.635294	0.779989	0.563380	0.660	0.055556	0.222222
549	0.519481	0.607843	0.673464	0.244444	0.565301	0.688235	0.466649	0.366197	0.505	0.277778	0.444444
2531	0.774892	0.000000	0.404078	0.770370	0.496288	0.664706	0.433029	0.380282	0.505	0.222222	0.111111
2378	0.480519	0.000000	0.584721	0.681481	0.452296	0.552941	0.314954	0.478873	0.630	0.388889	0.333333
...	...	...	...	...	...	...	...	...	...	...	...
2664	0.809524	0.509804	0.563469	0.629630	0.458070	0.394118	0.471490	0.598592	0.720	0.166667	0.111111
832	0.372294	0.000000	0.918725	0.562963	0.562552	0.547059	0.438408	0.669014	0.470	0.222222	0.222222
1122	0.683983	0.000000	0.535612	0.555556	0.676657	0.864706	0.588488	0.514085	0.520	0.277778	0.111111
1651	0.272727	0.000000	0.639575	0.770370	0.297498	0.511765	0.313072	0.697183	0.865	0.500000	0.111111
1337	0.415584	0.000000	0.672889	0.570370	0.433324	0.617647	0.585799	0.612676	0.365	0.111111	0.000000

4282 rows × 11 columns

Justification of above

- Normalizing data: Normalization to change the values of numeric columns in the dataset to a common scale, without distorting differences in the ranges of values.
- Dealing with class imbalance: Dealing with class imbalance is crucial for building reliable machine learning models. Imbalanced classes introduce bias, leading to inaccurate predictions. This was dealt with through upsampling.

6. MODELLING

6.1. BASELINE MODEL: Logistic regression

In [ ]:
```
# Instantiate the model
logreg = LogisticRegression(fit_intercept=False, C=1e12, solver='liblinear')

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

Out[ ]:
```
LogisticRegression
LogisticRegression(C=1000000000000.0, fit_intercept=False, solver='liblinear')
```

In [ ]:
```
# Generate predictions
y_hat_train = logreg.predict(X_train)
y_hat_test = logreg.predict(X_test)
```

In [ ]:
```
# Checking the classifier accuracy on training set.
residuals = np.abs(y_train ^ y_hat_train)
print(pd.Series(residuals).value_counts())
print('-----------------------------------')
print(pd.Series(residuals).value_counts(normalize=True))
```

```
churn
False    2134
True      365
Name: count, dtype: int64
-----------------------------------
churn
False    0.853942
True     0.146058
Name: proportion, dtype: float64
```

In [ ]:
```
# Checking the classifier accuracy on test set.
residuals = np.abs(y_test ^ y_hat_test)
print(pd.Series(residuals).value_counts())
print('-----------------------------------')
print(pd.Series(residuals).value_counts(normalize=True))
```

```
churn
False    707
True     127
Name: count, dtype: int64
-----------------------------------
churn
False    0.847722
True     0.152278
Name: proportion, dtype: float64
```

In [ ]:
```
# Confusion matrix
```

```
def conf_matrix(y_true, y_pred):
    cm = {'TP': 0, 'TN': 0, 'FP': 0, 'FN': 0}

    for ind, label in enumerate(y_true):
        pred = y_pred[ind]
        if label == 1:
            # CASE: TP
            if label == pred:
                cm['TP'] += 1
            # CASE: FN
            else:
                cm['FN'] += 1
        else:
            # CASE: TN
            if label == pred:
                cm['TN'] += 1
            # CASE: FP
            else:
                cm['FP'] += 1
    return cm

conf_matrix(y_test, y_hat_test)
```

Out[ ]:

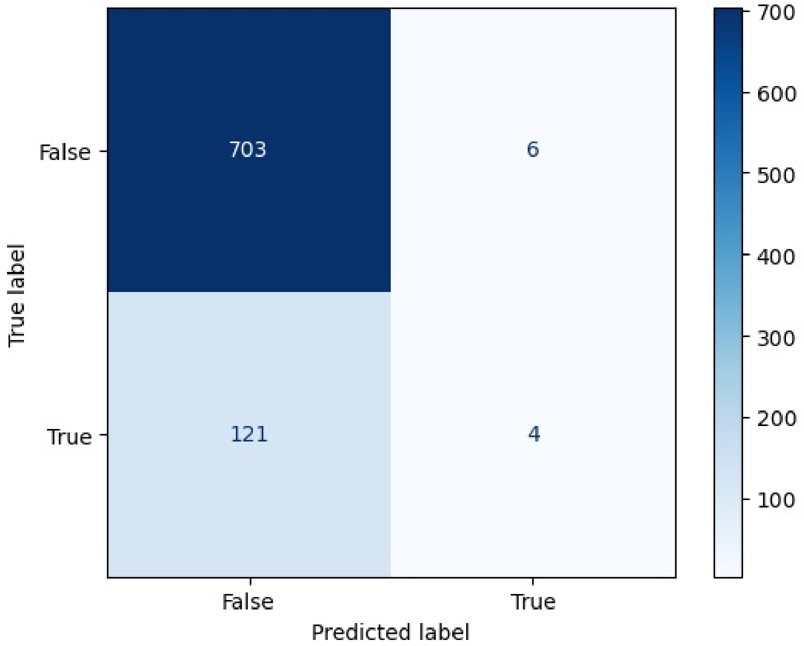
```
{'TP': 4, 'TN': 703, 'FP': 6, 'FN': 121}
```

In [ ]:

```
# Visualizing the confusion matrix
cnf_matrix = confusion_matrix(y_test, y_hat_test)
disp = ConfusionMatrixDisplay(confusion_matrix=cnf_matrix, display_labels=logreg.classes_)
disp.plot(cmap=plt.cm.Blues)
```

Out[ ]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2397d12c690>
```



In [ ]:

```
# Compute predicted probabilities for the positive class
y_prob_train = logreg.predict_proba(X_train)[:, 1]
y_prob_test = logreg.predict_proba(X_test)[:, 1]

# Predict classes based on the highest probability
y_hat_train = (y_prob_train > 0.5).astype(int)
y_hat_test = (y_prob_test > 0.5).astype(int)

# Calculate evaluation metrics
train_accuracy = accuracy_score(y_train, y_hat_train)
train_precision = precision_score(y_train, y_hat_train)
train_recall = recall_score(y_train, y_hat_train)
train_f1_score = f1_score(y_train, y_hat_train)
train_roc_auc = roc_auc_score(y_train, y_prob_train)

test_accuracy = accuracy_score(y_test, y_hat_test)
test_precision = precision_score(y_test, y_hat_test)
test_recall = recall_score(y_test, y_hat_test)
test_f1_score = f1_score(y_test, y_hat_test)
test_roc_auc = roc_auc_score(y_test, y_prob_test)
```

In [ ]:

```
# Print evaluation metrics
print('Training Accuracy: ', train_accuracy)
print('Training Precision: ', train_precision)
print('Training Recall: ', train_recall)
print('Training F1-Score: ', train_f1_score)
print('Training ROC AUC: ', train_roc_auc)
print('\n')
```

```
print('Testing Accuracy: ', test_accuracy)
print('Testing Precision: ', test_precision)
print('Testing Recall: ', test_recall)
print('Testing F1-Score: ', test_f1_score)
print('Testing ROC AUC: ', test_roc_auc)
```

```
Training Accuracy:  0.8539415766306523
Training Precision:  0.40540540540540543
Training Recall:  0.041899441340782122
Training F1-Score:  0.0759493670886076
Training ROC AUC:  0.7089870811686702


Testing Accuracy:  0.8477218225419664
Testing Precision:  0.4
Testing Recall:  0.032
Testing F1-Score:  0.05925925925925926
Testing ROC AUC:  0.7305726375176304
```

With a training accuracy of approximately 85.4% and a testing accuracy of about 84.8%, the model demonstrates relatively consistent performance across both training and testing datasets, suggesting reasonable generalization to unseen data. However, upon closer examination, it's apparent that the model's ability to predict churn is relatively low. This is evident from the low precision scores of around 40% on both the training and testing sets, indicating that only about 40% of the customers identified as churners by the model are actually churning. Similarly, the recall scores are quite low, indicating that the model is only capturing a small percentage of actual churn cases, approximately 4.2% on the training set and 3.2% on the testing set. Consequently, the F1-scores are also low, indicating an imbalance between precision and recall, with the model struggling to achieve both simultaneously. Further refining of the model's weakness can be achieved by evaluating other model as this is the baseline model.

MODEL 2: K - Nearest Neighbors

In [ ]:
```
# Instantiate KNeighborsClassifier
knn_classifier = KNeighborsClassifier()

# Fit the classifier
knn_classifier.fit(X_train_scaled, y_train)

# Predict on the test set
test_preds = knn_classifier.predict(X_test)

# Predict on the training set
train_preds = knn_classifier.predict(X_test)

# Predict on the training set
train_preds = knn_classifier.predict(X_train_scaled)
```

In [ ]:
```
#Evaluating the model

def print_metrics(labels, preds):
    print("Precision Score: {}".format(precision_score(labels, preds)))
    print("Recall Score: {}".format(recall_score(labels, preds)))
    print("Accuracy Score: {}".format(accuracy_score(labels, preds)))
    print("F1 Score: {}".format(f1_score(labels, preds)))

print("Training Set Metrics:")
print_metrics(y_train, train_preds)
print("\nTesting Set Metrics:")
print_metrics(y_test, test_preds)
```

```
Training Set Metrics:
Precision Score: 0.9136690647482014
Recall Score: 0.3547486033519553
Accuracy Score: 0.9027611044417767
F1 Score: 0.5110663983903421

Testing Set Metrics:
Precision Score: 0.17857142857142858
Recall Score: 0.8
Accuracy Score: 0.4184652278177458
F1 Score: 0.291970802919708
```

The churn prediction model demonstrates high precision on the training set, correctly identifying 91.4% of predicted churn cases, though its recall is lower at 35.5%. Despite this, it achieves an overall accuracy of 90.3%, with a balanced F1 score. However, on the testing set, while maintaining a high recall of 80.0%, precision drops significantly to 17.9%, leading to an accuracy of 41.8%. This decline indicates a challenge in generalizing to unseen data. Further refinement through feature parameter tuning may improve its predictive reliability('Using optimal k').

Finding the optimal K

In [ ]:
```
def find_best_k(X_train_scaled, y_train, X_test_scaled, y_test, min_k=1, max_k=25):
    best_k = 0
    best_score = 0.0
    for k in range(min_k, max_k+1, 2):
```

```
        knn = KNeighborsClassifier(n_neighbors=k)
        knn.fit(X_train, y_train)
        preds = knn.predict(X_test)
        f1 = f1_score(y_test, preds)
        if f1 > best_score:
            best_k = k
            best_score = f1

    print("Best Value for k: {}".format(best_k))
    print("F1-Score: {}".format(best_score))


find_best_k(X_train_scaled, y_train, X_test_scaled, y_test)
```

```
Best Value for k: 7
F1-Score: 0.40476190476190477
```

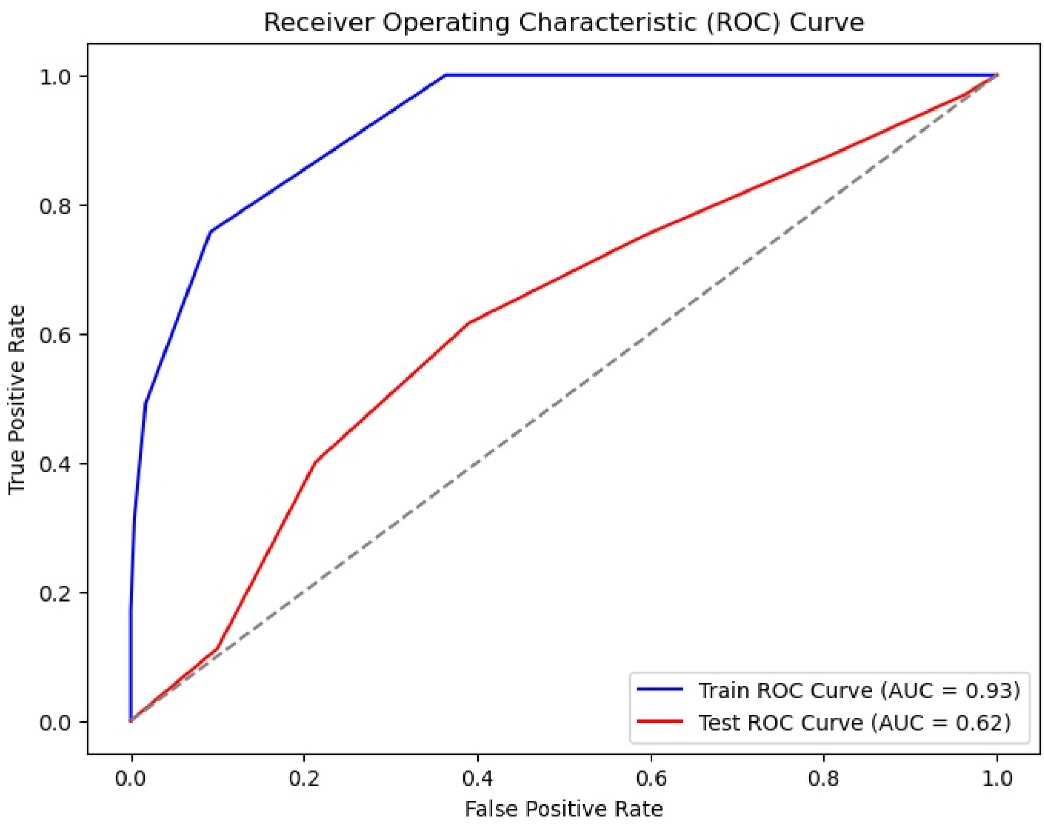
In [ ]:

```
# Create a new classifier with k=7
knn_classifier_7 = KNeighborsClassifier(n_neighbors=7)

# Fit the classifier on the training data
knn_classifier_7.fit(X_train_scaled, y_train)

# Predict on the test set
test_preds = knn_classifier_7.predict(X_test)

# Predict on the training set
train_preds = knn_classifier_7.predict(X_train_scaled)

# Define a function to print evaluation metrics
def print_metrics(labels, preds):
    print("Precision Score: {}".format(precision_score(labels, preds)))
    print("Recall Score: {}".format(recall_score(labels, preds)))
    print("Accuracy Score: {}".format(accuracy_score(labels, preds)))
    print("F1 Score: {}".format(f1_score(labels, preds)))

# Print evaluation metrics for the training set
print("Training Set Metrics:")
print_metrics(y_train, train_preds)

# Print evaluation metrics for the testing set
print("\nTesting Set Metrics:")
print_metrics(y_test, test_preds)
```

```
Training Set Metrics:
Precision Score: 0.9256198347107438
Recall Score: 0.3128491620111732
Accuracy Score: 0.8979591836734694
F1 Score: 0.46764091858037576

Testing Set Metrics:
Precision Score: 0.1825242718446602
Recall Score: 0.752
Accuracy Score: 0.4580335731414868
F1 Score: 0.29375
```

In [ ]:

```
# Calculate the probabilities for positive class (churned) for both training and testing sets
train_probs = knn_classifier_7.predict_proba(X_train_scaled)[:, 1]
test_probs = knn_classifier_7.predict_proba(X_test)[:, 1]

# Calculate the ROC curve for both training and testing sets
train_fpr, train_tpr, _ = roc_curve(y_train, train_probs)
test_fpr, test_tpr, _ = roc_curve(y_test, test_probs)

# Calculate the AUC score for both training and testing sets
train_auc = roc_auc_score(y_train, train_probs)
test_auc = roc_auc_score(y_test, test_probs)

# Plot the ROC curve
plt.figure(figsize=(8, 6))
plt.plot(train_fpr, train_tpr, label='Train ROC Curve (AUC = {:.2f})'.format(train_auc), color='blue')
plt.plot(test_fpr, test_tpr, label='Test ROC Curve (AUC = {:.2f})'.format(test_auc), color='red')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()

print("Training Set AUC Score:", train_auc)
print("Testing Set AUC Score:", test_auc)
```




```
Training Set AUC Score: 0.9278876888834383
Testing Set AUC Score: 0.6174837799717914
```

After using the best k-value; For the training set, the model exhibits a notable increase in precision, accurately identifying approximately 92.6% of predicted churn cases. However, its recall is relatively low, capturing only around 31.3% of all actual churn instances. Despite this, the model achieves an overall accuracy of approximately 89.8%, indicating its effectiveness in making correct predictions overall. The F1 score, reflecting the balance between precision and recall, shows improvement compared to previous iterations, suggesting a better equilibrium between these two metrics. Upon evaluation on the testing set, the model's performance sees slight enhancements, with a marginal increase in recall, while precision remains low. Consequently, the model's accuracy on the testing set shows only a minor improvement. The F1 score, while showing slight improvement, still indicates a challenge in achieving a balanced performance between precision and recall.while parameter tuning has led to modest improvements in certain metrics, the model's ability to generalize to unseen data remains limited. Also, the testing set AUC score of 0.617 indicates a notable drop in discriminative performance compared to the training set. While the model still demonstrates some ability to discriminate between churn and non-churn instances in the testing data, the lower AUC score suggests that its performance is less robust on unseen data.

MODEL 3: DECISION TREE

In [ ]:
```
dt_classifier = DecisionTreeClassifier(random_state=10)
dt_classifier.fit(X_train, y_train)
```

Out[ ]:
```
DecisionTreeClassifier
DecisionTreeClassifier(random_state=10)
```

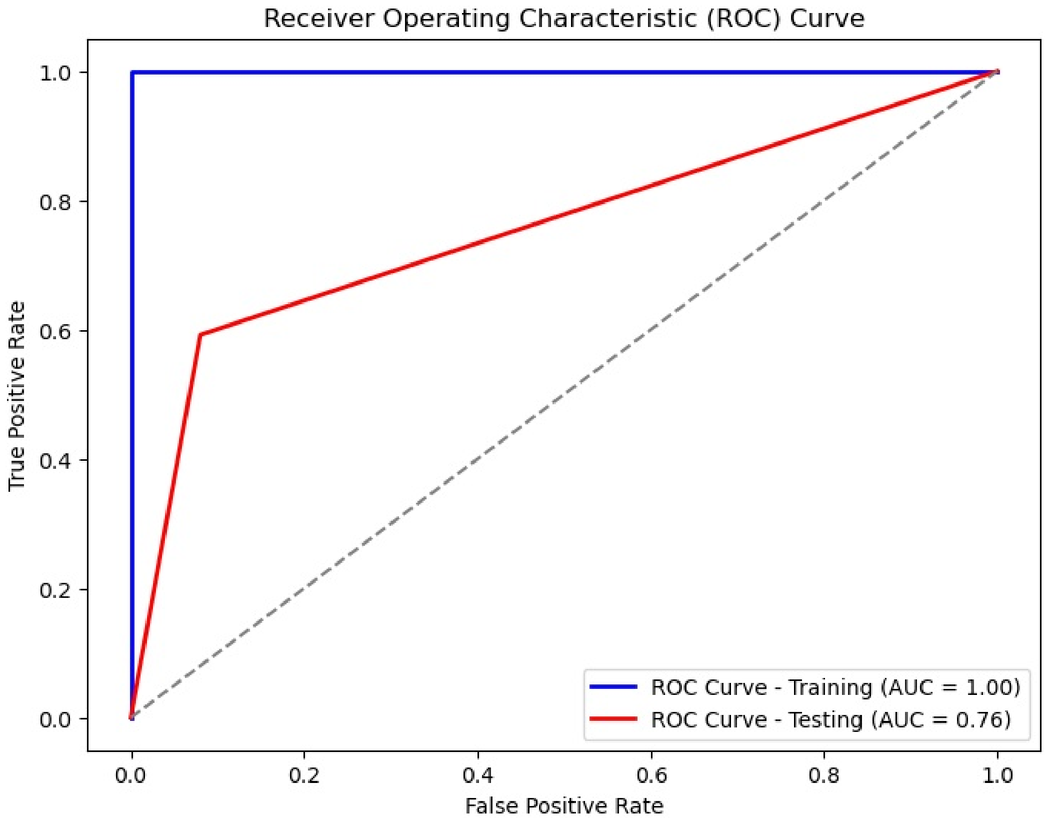
In [ ]:
```
# Predictions on training and testing sets
train_preds = dt_classifier.predict(X_train)
test_preds = dt_classifier.predict(X_test)
```

In [ ]:
```
def print_metrics(labels, preds):
    print("Precision Score: {:.3f}".format(precision_score(labels, preds)))
    print("Recall Score: {:.3f}".format(recall_score(labels, preds)))
    print("Accuracy Score: {:.3f}".format(accuracy_score(labels, preds)))
    print("F1 Score: {:.3f}".format(f1_score(labels, preds)))
    print("ROC AUC Score: {:.3f}".format(roc_auc_score(labels, preds)))

# Print evaluation metrics for the training set
print("Training Set Metrics:")
print_metrics(y_train, train_preds)

# Print evaluation metrics for the testing set
print("\nTesting Set Metrics:")
print_metrics(y_test, test_preds)

# Generate ROC curve and calculate AUC score for testing set
test_probs = dt_classifier.predict_proba(X_test)[:, 1]
fpr, tpr, _ = roc_curve(y_test, test_probs)
auc = roc_auc_score(y_test, test_probs)
```

```
Training Set Metrics:
Precision Score: 1.000
Recall Score: 1.000
Accuracy Score: 1.000
F1 Score: 1.000
ROC AUC Score: 1.000

Testing Set Metrics:
Precision Score: 0.565
Recall Score: 0.592
Accuracy Score: 0.871
F1 Score: 0.578
ROC AUC Score: 0.756
```

In [ ]:

```
# Calculate AUC score for training set
train_probs = dt_classifier.predict_proba(X_train)[:, 1]
fpr_train, tpr_train, _ = roc_curve(y_train, train_probs)
auc_train = roc_auc_score(y_train, train_probs)

plt.figure(figsize=(8, 6))

# Plot ROC curve for training set
plt.plot(fpr_train, tpr_train, color='blue', lw=2, label='ROC Curve - Training (AUC = {:.2f})'.format(auc_train

# Plot ROC curve for testing set
plt.plot(fpr, tpr, color='red', lw=2, label='ROC Curve - Testing (AUC = {:.2f})'.format(auc))

plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```



From the obtained outputs; For the training set, the model achieves perfect scores across all metrics, perfect precision, recall, accuracy, F1 score, and ROC AUC score, each at 100%. This performance underscores the model's ability to flawlessly predict churn within the confines of the training data. However, evaluation on the testing set, there's a discernible shift in performance. While the model maintains a respectable accuracy score of 87.1%, it exhibits a modest decline in precision (56.5%) and recall (59.2%) compared to the training set. Despite this decrease, the model's F1 score remains relatively high at 57.8%, indicative of a balanced trade-off between precision and recall. Furthermore, the ROC AUC score of 75.6% highlights the model's continued ability to effectively discriminate between churn and non-churn instances in unseen data.This discrepancy suggests that the model may have memorized the training data instead of generalizing well to unseen data, indicative of overfitting. To combat this the project tries to implement hyperparameter tuning.

Hyperparameter Tuning

In [ ]:

```
# Define the parameter grid to search
param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [3, 5, 7, None],
    'min_samples_split': [2, 5, 10],
```

```
    'min_samples_leaf': [1, 2, 4]
}

# Initialize the GridSearchCV object
grid_search = GridSearchCV(estimator=DecisionTreeClassifier(random_state=10),
                           param_grid=param_grid,
                           cv=5,  # 5-fold cross-validatio
                           scoring='accuracy',
                           n_jobs=-1)  # Use all available CPU cores

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

# Print the best parameters found
print("Best Parameters:", grid_search.best_params_)

# Get the best model from the grid search
best_classifier_dt = grid_search.best_estimator_

# Evaluate the best model on the training set
train_preds = best_classifier_dt.predict(X_train)
print("\nTraining Set Evaluation Metrics:")
print_metrics(y_train, train_preds)

# Evaluate the best model on the testing set
test_preds = best_classifier_dt.predict(X_test)
print("\nTesting Set Evaluation Metrics:")
print_metrics(y_test, test_preds)
```

```
Best Parameters: {'criterion': 'gini', 'max_depth': 7, 'min_samples_leaf': 2, 'min_samples_split': 10}

Training Set Evaluation Metrics:
Precision Score: 0.917
Recall Score: 0.620
Accuracy Score: 0.938
F1 Score: 0.740
ROC AUC Score: 0.805

Testing Set Evaluation Metrics:
Precision Score: 0.753
Recall Score: 0.584
Accuracy Score: 0.909
F1 Score: 0.658
ROC AUC Score: 0.775
```

After tuning the model with the specified parameters {'criterion': 'gini', 'max_depth': 7, 'min_samples_leaf': 2, 'min_samples_split': 10}, there are noticeable improvements in the model's performance metrics compared to the untuned model. On the training set, the precision score remains high at 0.917, indicating that the model maintains a high proportion of true positive predictions among all positive predictions. However, there is a slight decrease in recall compared to the untuned model, suggesting that the model may miss some positive instances. Nevertheless, the overall accuracy score increases to 0.938, indicating that the model's predictions are mostly correct. The F1 score, which balances precision and recall, also improves to 0.740. On the testing set, similar trends are observed, with improvements in precision, accuracy, and F1 score compared to the untuned model. However, there is a slight decrease in recall. Overall, the model exhibits better generalization to unseen data after tuning, as indicated by the increased performance metrics on the testing set.

MODEL 4: RANDOM FOREST CLASSIFIER

In [ ]:

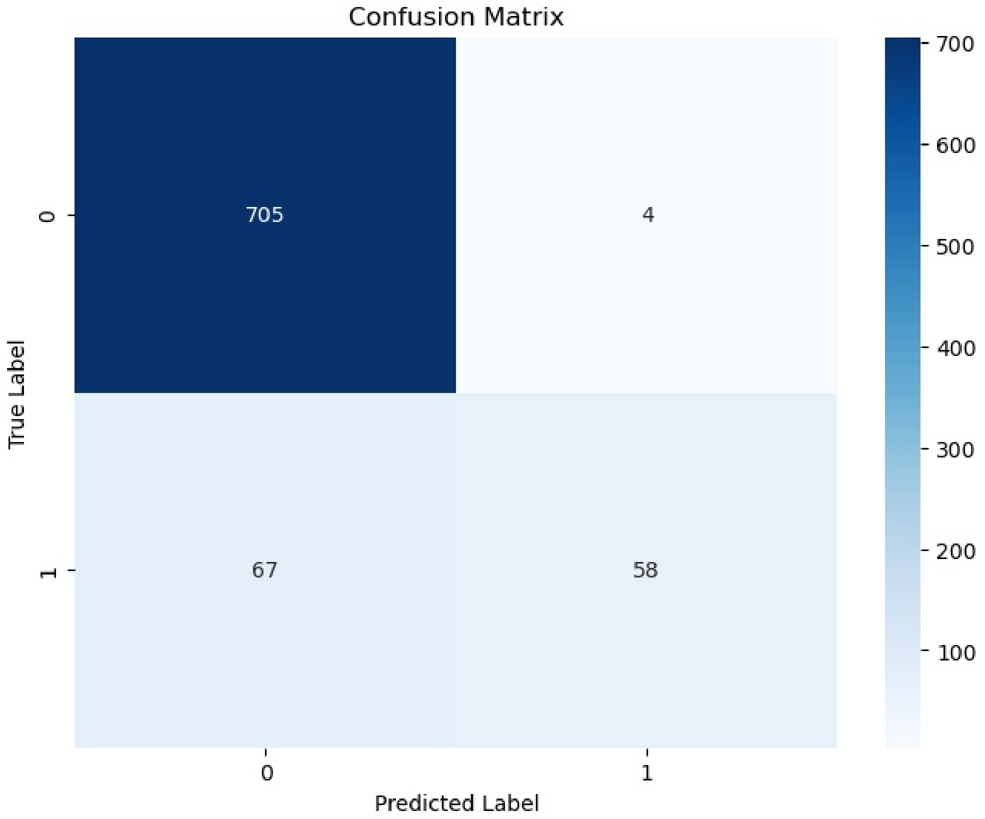
```
# Train a Random Forest classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=10)
rf_classifier.fit(X_train, y_train)

# Make predictions
y_pred = rf_classifier.predict(X_test)

# Evaluate model performance
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9148681055155875
              precision    recall  f1-score   support

       False       0.91      0.99      0.95       709
        True       0.94      0.46      0.62       125

    accuracy                           0.91       834
   macro avg       0.92      0.73      0.79       834
weighted avg       0.92      0.91      0.90       834
```

In [ ]:

```
# Compute confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Plot confusion matrix
plt.figure(figsize=(8, 6))
```

```
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```



The model seems to be performing well in predicting True Negative and True Positive but higher number of False Negative.

Tuning by feature importance

In [ ]:

```
# Get feature importances from the trained model
feature_importances = rf_classifier.feature_importances_

# Create a DataFrame to display feature importances
importance_df = pd.DataFrame({'Feature': X_train.columns, 'Importance': feature_importances})
importance_df = importance_df.sort_values(by='Importance', ascending=False)

# Seting a threshold to select features
threshold = 0.05

# Select features above the threshold
selected_features = importance_df[importance_df['Importance'] > threshold]['Feature']

# Filter the training and testing data with selected features
X_train_selected = X_train[selected_features]
X_test_selected = X_test[selected_features]

# Train a new Random Forest classifier on the selected features
rf_classifier_tuned = RandomForestClassifier(n_estimators=100, random_state=10)
rf_classifier_tuned.fit(X_train_selected, y_train)

# Predictions on training and testing sets
train_preds_selected = rf_classifier_tuned.predict(X_train_selected)
test_preds_selected = rf_classifier_tuned.predict(X_test_selected)

# Evaluate the model on both training and testing sets
print("\nEvaluation Metrics - Training Set:")
print_metrics(y_train, train_preds_selected)

print("\nEvaluation Metrics with Selected Features - Testing Set:")
print_metrics(y_test, test_preds_selected)
```

```
Evaluation Metrics - Training Set:
Precision Score: 1.000
Recall Score: 1.000
Accuracy Score: 1.000
F1 Score: 1.000
ROC AUC Score: 1.000

Evaluation Metrics with Selected Features - Testing Set:
Precision Score: 0.810
Recall Score: 0.408
Accuracy Score: 0.897
F1 Score: 0.543
ROC AUC Score: 0.696
```

The evaluation metrics for the model with selected features indicate exemplary performance on the training set, with perfect scores across all metrics: precision, recall, accuracy, F1 score, and ROC AUC score. However, on the testing set, while the precision score remains relatively high at 0.810, there's a noticeable drop in recall to 0.408. This decrease in recall suggests that the model might be missing a significant portion of positive instances in the testing data. Consequently, the F1 score also decreases to 0.543, indicating a trade-off between precision and recall. The accuracy score remains high at 0.897, indicating overall correctness in the model's predictions. These disparities between training and testing set performance metrics might indicate overfitting, as the model seems to have memorized the training data rather than generalizing well to unseen data.

mitigating overfitting

In [ ]:

```python
# Define the parameter grid with ranges
param_grid = {
    'n_estimators': [50, 100, 150],
    'max_depth': [None, 5, 10, 15],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Initialize the Random Forest classifier
rf_classifier_GS = RandomForestClassifier(random_state=10)

# Initialize GridSearchCV
grid_search = GridSearchCV(estimator=rf_classifier_GS,
                           param_grid=param_grid,
                           cv=5,  # 5-fold cross-validation
                           scoring='accuracy',
                           n_jobs=-1)  # Use all available CPU cores

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

# Print the best parameters found
print("Best Parameters:", grid_search.best_params_)

# Get the best model from the grid search
best_classifier_rf = grid_search.best_estimator_

# Evaluate the best model
train_preds_rf = best_classifier_rf.predict(X_train)
test_preds_rf = best_classifier_rf.predict(X_test)

print("\nTraining Set Evaluation Metrics:")
print_metrics(y_train, train_preds_rf)

print("\nTesting Set Evaluation Metrics:")
print_metrics(y_test, test_preds_rf)
```

```
Best Parameters: {'max_depth': 15, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 50}

Training Set Evaluation Metrics:
Precision Score: 1.000
Recall Score: 0.925
Accuracy Score: 0.989
F1 Score: 0.961
ROC AUC Score: 0.962

Testing Set Evaluation Metrics:
Precision Score: 0.877
Recall Score: 0.456
Accuracy Score: 0.909
F1 Score: 0.600
ROC AUC Score: 0.722
```

After tuning the model with the specified parameters {'max_depth': 15, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 50}, there are notable improvements in both training and testing set performance metrics. On the training set, the model achieves perfect precision, indicating that all positive predictions are indeed correct. The recall score increases to 0.925, suggesting better capture of positive instances compared to the untuned model. The accuracy score rises significantly to 0.989, indicating a high proportion of correct predictions overall. Moreover, the F1 score also improves to 0.961, indicating a better balance between precision and recall. The ROC AUC score increases to 0.962, suggesting improved discrimination between positive and negative instances. On the testing set, the precision score increases to 0.877, indicating an improvement in the proportion of true positive predictions among all positive predictions. However, there's still a gap between precision and recall, as the recall score remains at 0.456. This suggests that the model may still be missing some positive instances. Nonetheless, the accuracy score remains high at 0.909, indicating overall correctness in the model's predictions on the testing set. The F1 score improves to 0.600, indicating a better balance between precision and recall compared to the untuned model. The ROC AUC score also increases to 0.722, indicating improved discrimination ability, though it's still not exceptional. Overall, the model's performance improves after tuning, with notable enhancements in various metrics on both training and testing sets, suggesting better generalization to unseen data.

MODEL 5: EXTREME GRADIENT BOOSTING (XGBOOST)

In [ ]:
```
# Initialize XGBoost classifier
xgb_classifier = xgb.XGBClassifier(objective='binary:logistic', random_state=10)

# Train the classifier
xgb_classifier.fit(X_train, y_train)

# Predictions on training and testing sets
train_preds = xgb_classifier.predict(X_train)
test_preds = xgb_classifier.predict(X_test)

# Evaluate the model
print("\nTraining Set Evaluation Metrics:")
print("Precision Score: {:.4f}".format(precision_score(y_train, train_preds)))
print("Recall Score: {:.4f}".format(recall_score(y_train, train_preds)))
print("Accuracy Score: {:.4f}".format(accuracy_score(y_train, train_preds)))
print("F1 Score: {:.4f}".format(f1_score(y_train, train_preds)))

print("\nTesting Set Evaluation Metrics:")
print("Precision Score: {:.4f}".format(precision_score(y_test, test_preds)))
print("Recall Score: {:.4f}".format(recall_score(y_test, test_preds)))
print("Accuracy Score: {:.4f}".format(accuracy_score(y_test, test_preds)))
print("F1 Score: {:.4f}".format(f1_score(y_test, test_preds)))
```

```
Training Set Evaluation Metrics:
Precision Score: 1.0000
Recall Score: 1.0000
Accuracy Score: 1.0000
F1 Score: 1.0000

Testing Set Evaluation Metrics:
Precision Score: 0.8293
Recall Score: 0.5440
Accuracy Score: 0.9149
F1 Score: 0.6570
```

The evaluation metrics demonstrate a model that performs flawlessly on the training set, achieving perfect scores across all metrics: precision, recall, accuracy, and F1 score. This suggests the model has learned the training data very well, with no false positives or negatives.

On the testing set, the model maintains strong performance but shows some degradation compared to the training set. The precision score remains high at 0.8293, indicating a good proportion of true positive predictions among all positive predictions. However, there's a decrease in recall to 0.5440, suggesting the model may miss some positive instances. The accuracy score remains high at 0.9149, indicating overall correctness in the model's predictions on the testing set. The F1 score also decreases to 0.6570, indicating a balance between precision and recall but slightly lower than the training set. Overall, while the model's performance on the testing set is strong, the slight drop in recall suggests it may struggle to capture all positive instances, which could be indicative of overfitting. Regularization techniques or further tuning may be needed to address this and improve generalization to unseen data.

Hyperparameter tuning

In [ ]:
```
# Initialize XGBoost classifier
xgb_classifier_tuned = xgb.XGBClassifier(objective='binary:logistic', random_state=10)

# Define the parameter grid for tuning
param_grid = {
    'learning_rate': [0.01, 0.1, 0.3],
    'max_depth': [3, 5, 7],
    'n_estimators': [100, 200, 300],
    'min_child_weight': [1, 3, 5],
    'subsample': [0.5, 0.7, 0.9],
    'colsample_bytree': [0.5, 0.7, 0.9]
}

# Define F1 score as the evaluation metric for grid search
scorer = make_scorer(f1_score)

# Initialize GridSearchCV
grid_search1 = GridSearchCV(estimator=xgb_classifier_tuned,
                           param_grid=param_grid,
                           scoring=scorer,
                           cv=5,
                           n_jobs=-1)
```

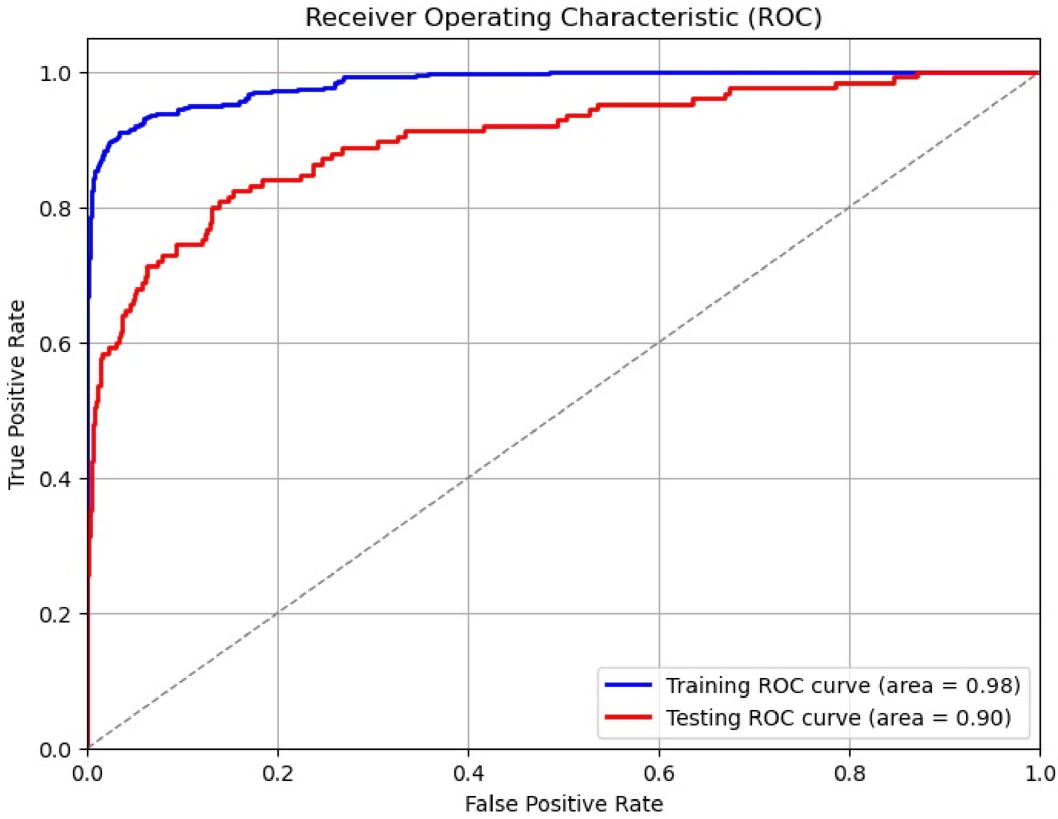
```python
# Perform grid search to find the best hyperparameters
grid_search1.fit(X_train, y_train)

# Print the best parameters found
print("Best Parameters:", grid_search1.best_params_)

# Get the best model from the grid search
best_classifier_xgb = grid_search1.best_estimator_

# Evaluate the best model
train_preds = best_classifier_xgb.predict(X_train)
test_preds = best_classifier_xgb.predict(X_test)

# Print evaluation metrics
print("\nTraining Set Evaluation Metrics:")
print("F1 Score: {:.4f}".format(f1_score(y_train, train_preds)))
print("\nTesting Set Evaluation Metrics:")
print("F1 Score: {:.4f}".format(f1_score(y_test, test_preds)))
```

```
Best Parameters: {'colsample_bytree': 0.9, 'learning_rate': 0.1, 'max_depth': 5, 'min_child_weight': 3, 'n_esti
mators': 100, 'subsample': 0.9}

Training Set Evaluation Metrics:
F1 Score: 0.8210

Testing Set Evaluation Metrics:
F1 Score: 0.6564
```

In [ ]:
```python
# Evaluate the model
print("\nTraining Set Evaluation Metrics:")
print("Precision Score: {:.4f}".format(precision_score(y_train, train_preds)))
print("Recall Score: {:.4f}".format(recall_score(y_train, train_preds)))
print("Accuracy Score: {:.4f}".format(accuracy_score(y_train, train_preds)))
print("F1 Score: {:.4f}".format(f1_score(y_train, train_preds)))

print("\nTesting Set Evaluation Metrics:")
print("Precision Score: {:.4f}".format(precision_score(y_test, test_preds)))
print("Recall Score: {:.4f}".format(recall_score(y_test, test_preds)))
print("Accuracy Score: {:.4f}".format(accuracy_score(y_test, test_preds)))
print("F1 Score: {:.4f}".format(f1_score(y_test, test_preds)))
```

```
Training Set Evaluation Metrics:
Precision Score: 0.9960
Recall Score: 0.6983
Accuracy Score: 0.9564
F1 Score: 0.8210

Testing Set Evaluation Metrics:
Precision Score: 0.9143
Recall Score: 0.5120
Accuracy Score: 0.9197
F1 Score: 0.6564
```

In [ ]:
```python
from sklearn.metrics import auc, roc_curve
# Predict probabilities for the positive class
train_probs = best_classifier_xgb.predict_proba(X_train)[:, 1]
test_probs = best_classifier_xgb.predict_proba(X_test)[:, 1]

# Compute ROC curve and ROC area for training set
from sklearn.metrics import auc, roc_curve
fpr_train, tpr_train, _ = roc_curve(y_train, train_probs)
roc_auc_train = auc(fpr_train, tpr_train)

# Compute ROC curve and ROC area for testing set
fpr_test, tpr_test, _ = roc_curve(y_test, test_probs)
roc_auc_test = auc(fpr_test, tpr_test)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr_train, tpr_train, color='blue', lw=2, label='Training ROC curve (area = {:.2f})'.format(roc_auc_tr
plt.plot(fpr_test, tpr_test, color='red', lw=2, label='Testing ROC curve (area = {:.2f})'.format(roc_auc_test))
plt.plot([0, 1], [0, 1], color='gray', lw=1, 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)')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```



After tuning, the model's performance shows improvements in both the training and testing sets. On the training set, the precision score remains high at 0.9960, indicating a high proportion of true positive predictions among all positive predictions. However, there's a decrease in recall to 0.6983, suggesting that the model may be missing some positive instances. Despite this, the accuracy score increases to 0.9564, indicating a high proportion of correct predictions overall. The F1 score also improves to 0.8210, suggesting a better balance between precision and recall compared to the previous tuning.On the testing set, the precision score further improves to 0.9143, indicating better performance in correctly identifying positive instances. However, there's still a gap between precision and recall, as the recall score remains at 0.5120. This suggests that the model may still struggle to capture all positive instances. Nonetheless, the accuracy score maintains its high level at 0.9197, indicating overall correctness in the model's predictions on the testing set. The F1 score also improves to 0.6564, indicating a better balance between precision and recall compared to the previous tuning. Overall, the model's performance improves after further tuning, with enhancements in various metrics on both the training and testing sets.

Model pickling

In [ ]:
```
with open ("customer_churn_model.pkl","wb") as f:
    joblib.dump(xgb_classifier_tuned,f)
```

In [ ]:

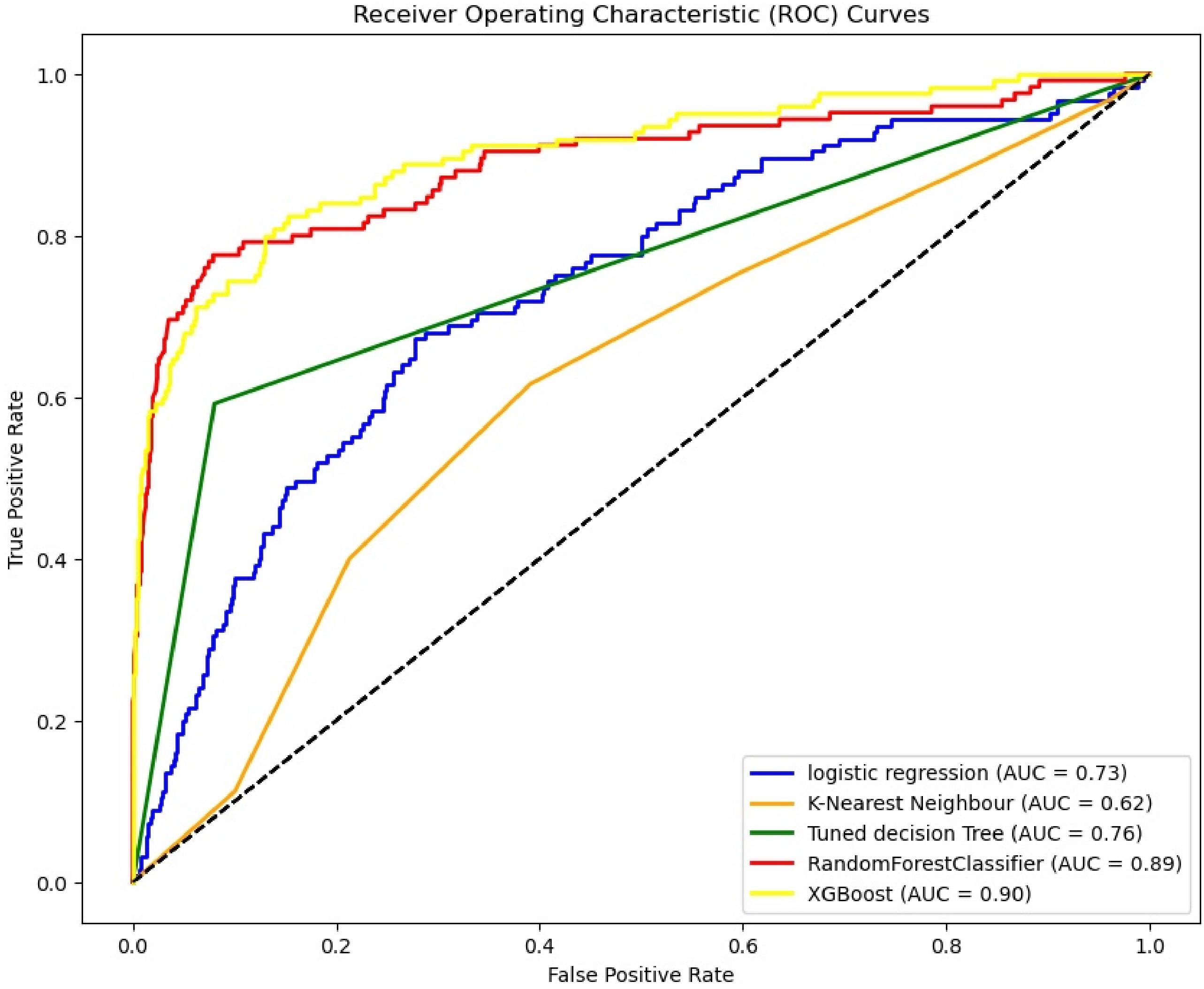
7. EVALUATION

Best Overal Model

In [ ]:
```
# Define models and their labels
models = [logreg, knn_classifier_7, dt_classifier,best_classifier_rf, best_classifier_xgb]
model_labels = ['logistic regression', 'K-Nearest Neighbour', 'Tuned decision Tree','RandomForestClassifier' ,

# 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: 0.7306
K-Nearest Neighbour ROC AUC Score: 0.6175
Tuned decision Tree ROC AUC Score: 0.7558
RandomForestClassifier ROC AUC Score: 0.8882
XGBoost ROC AUC Score: 0.9012
```



From the above comparison the XGBoost performs exemplary well.

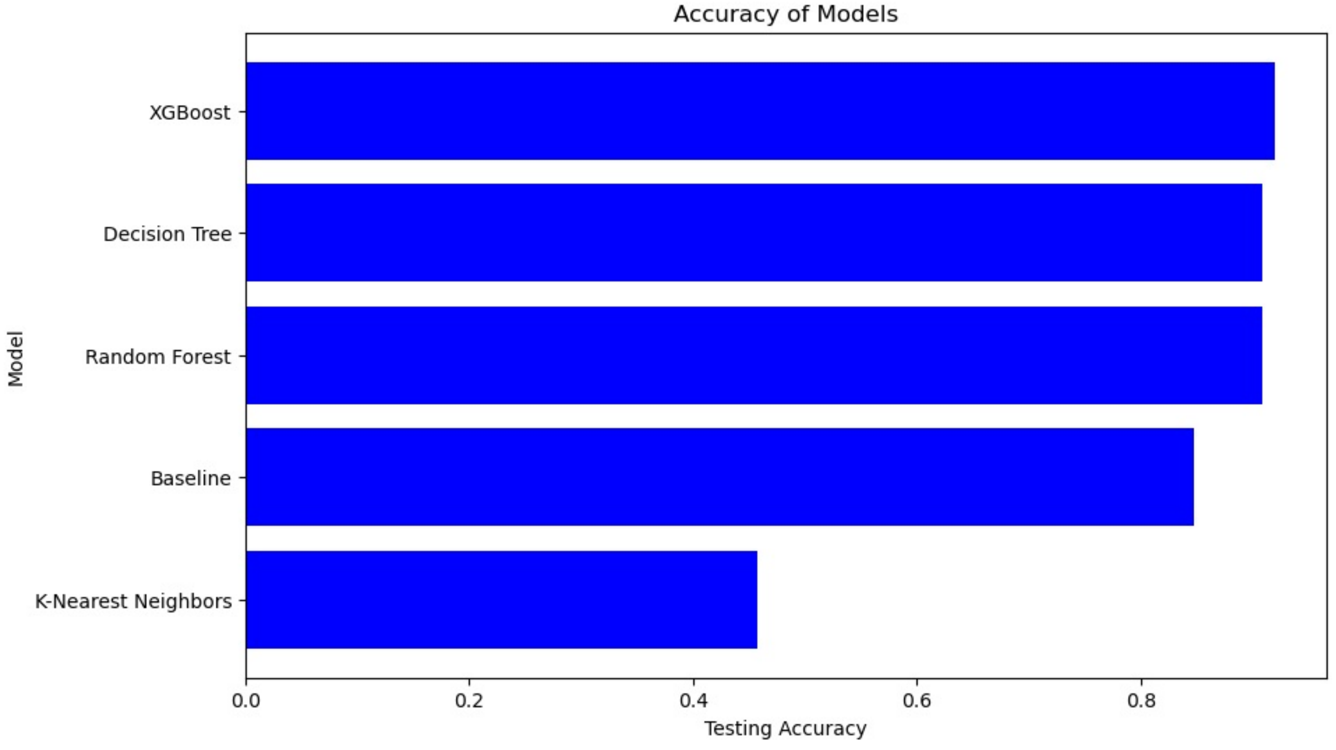
In [ ]:
```
Modeldata = {
    'Model': ['Baseline', 'K-Nearest Neighbors', 'Decision Tree', 'Random Forest', 'XGBoost'],
    'Training Accuracy': [0.8539, 0.8980, 0.9380, 0.9890, 0.9564],
    'Training Precision': [0.4054, 0.9256, 0.9170, 1.0000, 0.9960],
    'Training Recall': [0.0419, 0.3128, 0.6200, 0.9250, 0.6983],
    'Training F1-Score': [0.0759, 0.4676, 0.7400, 0.9610, 0.8210],
    'Training ROC AUC': [0.7090, 0.9279, 0.8050, 0.9620, 0.9800],
    'Testing Accuracy': [0.8477, 0.4580, 0.9090, 0.9090, 0.9197],
    'Testing Precision': [0.4000, 0.1825, 0.7530, 0.8770, 0.9143],
    'Testing Recall': [0.0320, 0.7520, 0.5840, 0.4560, 0.5120],
    'Testing F1-Score': [0.0593, 0.2938, 0.6580, 0.6000, 0.6564],
    'Testing ROC AUC': [0.7306, 0.6175, 0.7750, 0.8900, 0.9000]
}

Models_df = pd.DataFrame(Modeldata)
Models_df
```

Out[ ]:

	Model	Training Accuracy	Training Precision	Training Recall	Training F1-Score	Training ROC AUC	Testing Accuracy	Testing Precision	Testing Recall	Testing F1-Score	Testing ROC AUC
0	Baseline	0.8539	0.4054	0.0419	0.0759	0.7090	0.8477	0.4000	0.032	0.0593	0.7306
1	K-Nearest Neighbors	0.8980	0.9256	0.3128	0.4676	0.9279	0.4580	0.1825	0.752	0.2938	0.6175
2	Decision Tree	0.9380	0.9170	0.6200	0.7400	0.8050	0.9090	0.7530	0.584	0.6580	0.7750
3	Random Forest	0.9890	1.0000	0.9250	0.9610	0.9620	0.9090	0.8770	0.456	0.6000	0.8900
4	XGBoost	0.9564	0.9960	0.6983	0.8210	0.9800	0.9197	0.9143	0.512	0.6564	0.9000

In [ ]:

```python
# Sort DataFrame based on Training Accuracy
df_sorted = Models_df.sort_values(by='Testing Accuracy', ascending=False)

# Plot the bar graph
plt.figure(figsize=(10, 6))
plt.barh(df_sorted['Model'], df_sorted['Testing Accuracy'], color='blue')
plt.xlabel('Testing Accuracy')
plt.ylabel('Model')
plt.title('Accuracy of Models')
plt.gca().invert_yaxis()
plt.show()
```



From the different models used, which were:

1. Base Model - Logistic regression
2. K-Nearest Neighbours (KNN)
3. Decision trees
4. Random Forest classiffier
5. XGBoost

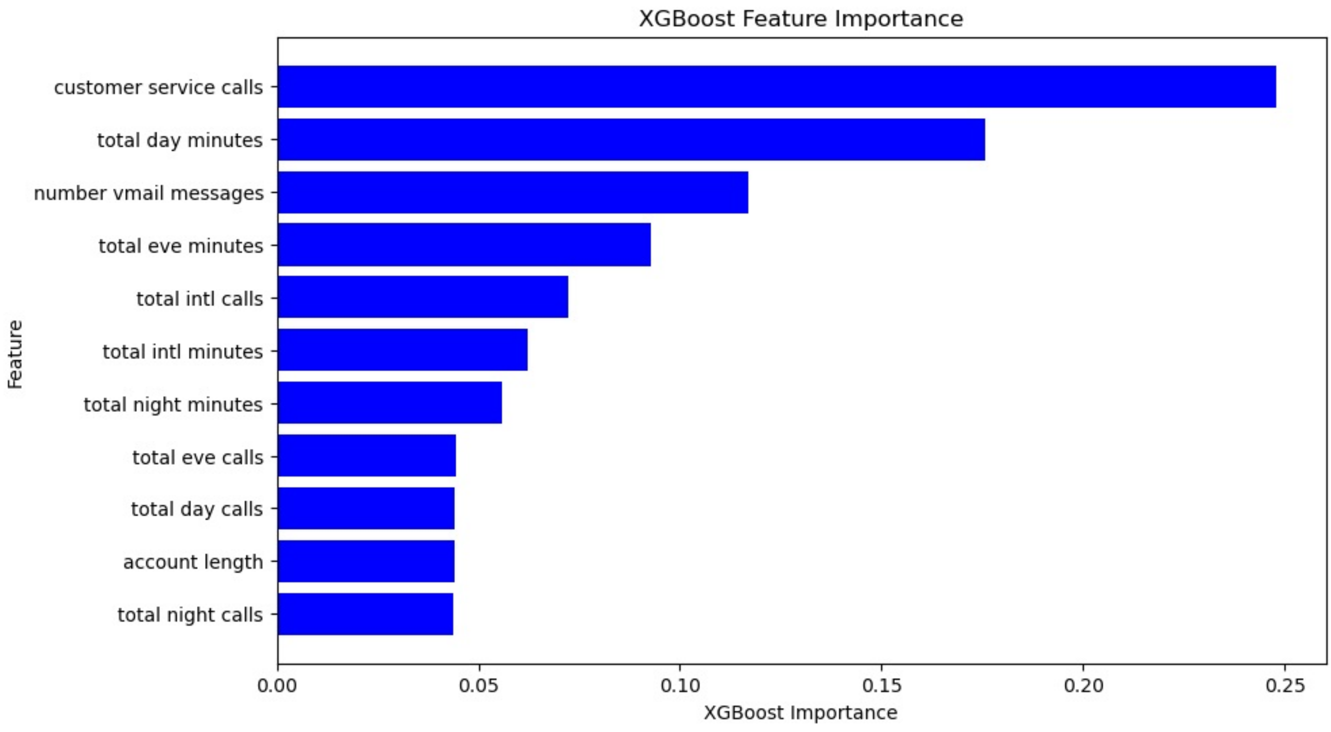
The Best overal model proved to be the XGBoost model given that: Based on accuracy, The best model was one from XGBoost with an test accuracy of 91.97% and training accuracy of 95.64%. Based also on the Test ROC and AUC score, which is measure of the ability of model to distinguish positive and negative outcomes, XGBoost was the best with a score of 90%.

Feature importance based on the best model

In [ ]:

```python
# Get feature importances
feature_importance_xgboost = best_classifier_xgb.feature_importances_

# Create a DataFrame to hold feature names and their importances
feature_importance_xgboost_df = pd.DataFrame({'Feature': X_train.columns, 'XGBoost Importance': feature_importa

# Sort the DataFrame by importance in descending order
feature_importance_xgboost_df = feature_importance_xgboost_df.sort_values(by='XGBoost Importance', ascending=Fa

# Plot feature importances
plt.figure(figsize=(10, 6))
plt.barh(feature_importance_xgboost_df['Feature'], feature_importance_xgboost_df['XGBoost Importance'], color='
```

```
plt.xlabel('XGBoost Importance')
plt.ylabel('Feature')
plt.title('XGBoost Feature Importance')
plt.gca().invert_yaxis()  # Invert the y-axis to display the most important features at the top
plt.show()
```



Top five features

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

- **Customer Service calls:** The number of customer services calls made by a customer
- **Total day minutes:** The total amount of time the customer has spent on daytime calls in minutes
- **Number vmail messages:** Represent the number of voicemail messages left by a customer.
- **Total eve minutes:** The total number of minutes the customer has been in calls during the evening.
- **Total intl calls:** The total number of international calls the customer has made.

Were the Objectives met

Main Objective

Several predictive models were built, from which the top-performing one was selected as the best overall, The **XGBoost** was chosen as was considered fit in predicting the patterns of customers churning

Specific Objectives

1. Key factors influencing cusomer churning was identified as: Customer service calls, Total day minutes, Number of voice mail messages, total evening minutes and total international calls.
2. The classifiers were identified using metrics such as accuracy, precision, recall, F1 score, and confusion matrix after which XGBoost was selected as being the most effective.
3. Actionable recommendations given based on the analysis.

The Objectives were all met.

8. CONCLUSION

RECOMMENDATIONS

1. Improve on customer services: This may include services such as wait time and customer satisfaction.

2. Introduce customised and affordable call plans for both day and night calls

3. Service Quality Improvement: Continuously monitor service quality metrics such as network reliability, call quality, and data speed, and invest in infrastructure upgrades to ensure optimal service delivery.

4. Transparent Pricing: Provide transparent pricing structures and billing processes to avoid billing disputes and customer dissatisfaction.

5. Proactive Customer Outreach: Regularly reach out to customers to gather feedback, address concerns, and offer assistance before they consider switching providers.

6. Security Measures: Implement stringent security measures to protect voicemail messages from unauthorized access and ensure customer privacy and data protection.

7. Provide a wide range of countries covered by international plan.

8. Constantly and consistently conduct customer churn analysis.

NEXT STEPS

1. 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.

2. 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.

3. 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.

4. 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.