PREDICTING CHURN IN TELECOM'S DATASET

- **Name** : Monica Wanjiru
- **TM** : Samuel Karu

- **DATE** : 23rd December 2024

- **COHORT** : Part_Time

Project Criteria

This project will follow the CRISP_DM Criteria

Business understanding
Data Understanding
Data preparation
Modeling
Evaluation
Deployment

Business Understanding

Project Overview

- Churn occurs when customers are leaving a company's services in pursuit of better services from other network providers.

- This is caused by dissatisfaction of the company's services or competitors offering better prices.

- Churn causes loss of the revenue to the company and it makes it hard to retain customers.

- Identifying potential churners will help to retain customers and improve customer satisfaction.

Business Problem

The business objective is to identify customers with a high likelihood of churning and develop effective strategies to retain them. This involves analyzing key factors contributing to customer dissatisfaction and churn, such as network quality, customer service issues, or pricing concerns. Additionally, the goal is to segment customers based on their behavior and churn likelihood, enabling tailored marketing and retention strategies that address each group's unique needs and preferences.

Objectives

1. Churn Prediction: Develop machine learning models to predict customers likely to churn by analyzing customer data and features.

2. Model Performance Assessment: Evaluate and compare machine learning models to identify the most accurate prediction model.
3. Increase Revenue: Retaining more customers will lead to higher revenue and an increase in market share.
4. Feature Insights: Analyze individual features to uncover key factors driving customer churn in the telecommunications company.

Data Source

My project utilizes data obtained from Kaggle, it is about customer churn in a telecommunication company.

Data Description

1. State: The U.S. state in which the customer resides, represented by a two-letter abbreviation.
2. Account Length: The duration (in days) that the customer has been with the service provider.
3. Area Code: The telephone area code associated with the customer's phone number.
4. International Plan: Indicates whether the customer has subscribed to an international calling plan ('yes' or 'no').
5. Voice Mail Plan: Indicates whether the customer has a voice mail feature ('yes' or 'no').
6. Number Vmail Messages: The count of voice mail messages the customer has.
7. Total Day Minutes: The total number of minutes the customer has used during the day.
8. Total Day Calls: The total number of calls made by the customer during the day.
9. Total Day Charge: The total charges incurred by the customer for daytime calls.
10. Total Eve Minutes: The total number of minutes the customer has used during the evening.
11. Total Eve Calls: The total number of calls made by the customer during the evening.
12. Total Eve Charge: The total charges incurred by the customer for evening calls.
13. Total Night Minutes: The total number of minutes the customer has used during the night.
14. Total Night Calls: The total number of calls made by the customer during the night.
15. Total Night Charge: The total charges incurred by the customer for nighttime calls.
16. Total Intl Minutes: The total number of minutes the customer has used for international calls.
17. Total Intl Calls: The total number of international calls made by the customer.
18. Total Intl Charge: The total charges incurred by the customer for international calls.
19. Customer Service Calls: The number of calls the customer has made to customer service.
20. Churn: Indicates whether the customer has discontinued the service ('yes' for churned, 'no' for active).

Data Preparation

```
# import relevant libraries
import csv
import pandas as pd
```

```
import seaborn as sns
import numpy as np


# Data visualization
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# Modeling
import sklearn
from sklearn.model_selection import
train_test_split,cross_val_score,GridSearchCV
from imblearn.over_sampling import SMOTE, SMOTENC
from sklearn.metrics import
accuracy_score,f1_score,recall_score,precision_score,confusion_matrix,
roc_curve,roc_auc_score,classification_report

# performance metrics
from scipy import stats
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import
variance_inflation_factor
from sklearn.preprocessing import StandardScaler

# Algorithms for supervised learning methods
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression

# Filtering future warnings
import warnings
warnings.filterwarnings('ignore')

# loading our dataset
data = pd.read_csv("bigml_Telecom_dataset.csv")

## preview the first and last 3 rows of our dataset
display(data.head(3))
display(data.tail(3))
```

```
  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

  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

   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

   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

   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

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

[3 rows x 21 columns]
     state  account length  area code phone number international plan
\
3330    RI              28        510     328-8230                 no

3331    CT             184        510     364-6381                yes

3332    TN              74        415     400-4344                 no


     voice mail plan  number vmail messages  total day minutes  \
3330              no                      0              180.8
3331              no                      0              213.8
3332             yes                     25              234.4

      total day calls  total day charge  ...  total eve calls  \
3330              109             30.74  ...               58
3331              105             36.35  ...               84
3332              113             39.85  ...               82

      total eve charge  total night minutes  total night calls  \
3330             24.55                191.9                 91
3331             13.57                139.2                137
3332             22.60                241.4                 77
```

```
      total night charge  total intl minutes  total intl calls  \
3330                8.64                14.1                 6
3331                6.26                 5.0                10
3332               10.86                13.7                 4

      total intl charge  customer service calls  churn
3330               3.81                       2  False
3331               1.35                       2  False
3332               3.70                       0  False

[3 rows x 21 columns]
```

Previewing the data to understand it features

```
print(f"The total number of rows to colums respectively is
{data.shape}")
```

```
The total number of rows to colums respectively is (3333, 21)
```

```
print(f"The dataset contains the following columns {data.columns}")
```

```
The dataset contains the following columns Index(['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 minutes', 'total eve calls', 'total eve charge',
       'total night minutes', 'total night calls', 'total night
charge',
       'total intl minutes', 'total intl calls', 'total intl charge',
       'customer service calls', 'churn'],
      dtype='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   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
```

```
# checking descriptive statistical of the dataset
data.describe().T
```

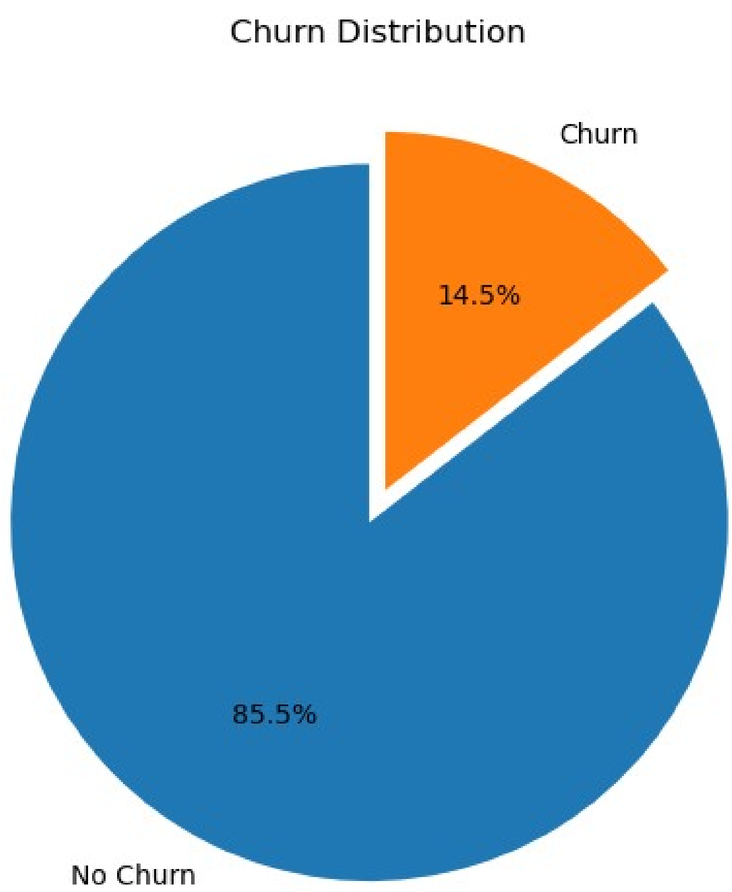
```
                         count        mean        std     min     25%
50%  \
account length          3333.0  101.064806  39.822106    1.00   74.00
101.00
area code               3333.0  437.182418  42.371290  408.00  408.00
415.00
number vmail messages   3333.0    8.099010  13.688365    0.00    0.00
0.00
total day minutes       3333.0  179.775098  54.467389    0.00  143.70
179.40
total day calls         3333.0  100.435644  20.069084    0.00   87.00
101.00
total day charge        3333.0   30.562307   9.259435    0.00   24.43
30.50
total eve minutes       3333.0  200.980348  50.713844    0.00  166.60
201.40
total eve calls         3333.0  100.114311  19.922625    0.00   87.00
100.00
total eve charge        3333.0   17.083540   4.310668    0.00   14.16
17.12
total night minutes     3333.0  200.872037  50.573847   23.20  167.00
201.20
total night calls       3333.0  100.107711  19.568609   33.00   87.00
100.00
total night charge      3333.0    9.039325   2.275873    1.04    7.52
9.05
total intl minutes      3333.0   10.237294   2.791840    0.00    8.50
10.30
total intl calls        3333.0    4.479448   2.461214    0.00    3.00
4.00
total intl charge       3333.0    2.764581   0.753773    0.00    2.30
2.78
customer service calls  3333.0    1.562856   1.315491    0.00    1.00
1.00
```

```
                              75%     max
account length             127.00  243.00
area code                  510.00  510.00
number vmail messages       20.00   51.00
total day minutes          216.40  350.80
total day calls            114.00  165.00
total day charge            36.79   59.64
total eve minutes          235.30  363.70
total eve calls            114.00  170.00
total eve charge            20.00   30.91
total night minutes        235.30  395.00
total night calls          113.00  175.00
total night charge          10.59   17.77
total intl minutes          12.10   20.00
total intl calls             6.00   20.00
total intl charge            3.27    5.40
customer service calls       2.00    9.00
```

```
"""
Perform value counts on the 'Churn' column to determine the
distribution of churned and non-churned customers.
This helps identify the proportion of customers who have discontinued
the services.
"""
churn_count = data.churn.value_counts()
print(f'There are {churn_count[False]} customers who did not churn and
{churn_count[True]} customers who churned')
```

```
There are 2850 customers who did not churn and 483 customers who
churned
```

```
"""
plotting a pie chart to view distribution of churn and no churn
"""
# Pie Chart the churn feature
data['churn'].value_counts().plot.pie(
    explode=[0.05, 0.05],
    autopct='%1.1f%%',
    startangle=90,
    shadow=False,
    figsize=(8, 6),
    labels=['No Churn', 'Churn'])
plt.ylabel('')
plt.title('Churn Distribution')
plt.show()
```



85.5% of customers did not churn but 14.5% of customers did churn

Explantory Data Analysis

```
# checking for missing values
data.isna().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
```

```
# checking for duplicates
data.duplicated().sum()
```

```
0
```

The dataset has no missing value or any duplicates

```
"""
Checking for unique values, if a column has no uniqiue values we will
drop that column
"""
data.nunique()
```

```
state                       51
account length             212
area code                    3
phone number              3333
international plan           2
voice mail plan              2
number vmail messages       46
total day minutes         1667
total day calls            119
total day charge          1667
total eve minutes         1611
total eve calls            123
total eve charge          1440
total night minutes       1591
total night calls          120
total night charge         933
total intl minutes         162
total intl calls            21
total intl charge          162
customer service calls      10
churn                        2
dtype: int64
```

```
# Dropping some columns
## some columns are irrelevant to our analysis so we will drop them

irr_cols = ['state', 'account length', 'area code', 'phone number']
data.drop(columns = irr_cols, inplace = True)
```

```
# preview columns length
print(f"Total number of remaing columns {len(data.columns)}")
```

```
Total number of remaing columns 17
```

Conducting univariante analysis

```
# spliting data according to the data type
## assign data types variable names
num_col = data.select_dtypes(include=['int64', 'float64'])
cat_col = data.select_dtypes(include=['object', 'bool'])
# display the columns
display(num_col.columns)
display(cat_col.columns)
```

```
Index(['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',
       'total night charge', 'total intl minutes', 'total intl calls',
       'total intl charge', 'customer service calls'],
      dtype='object')
```

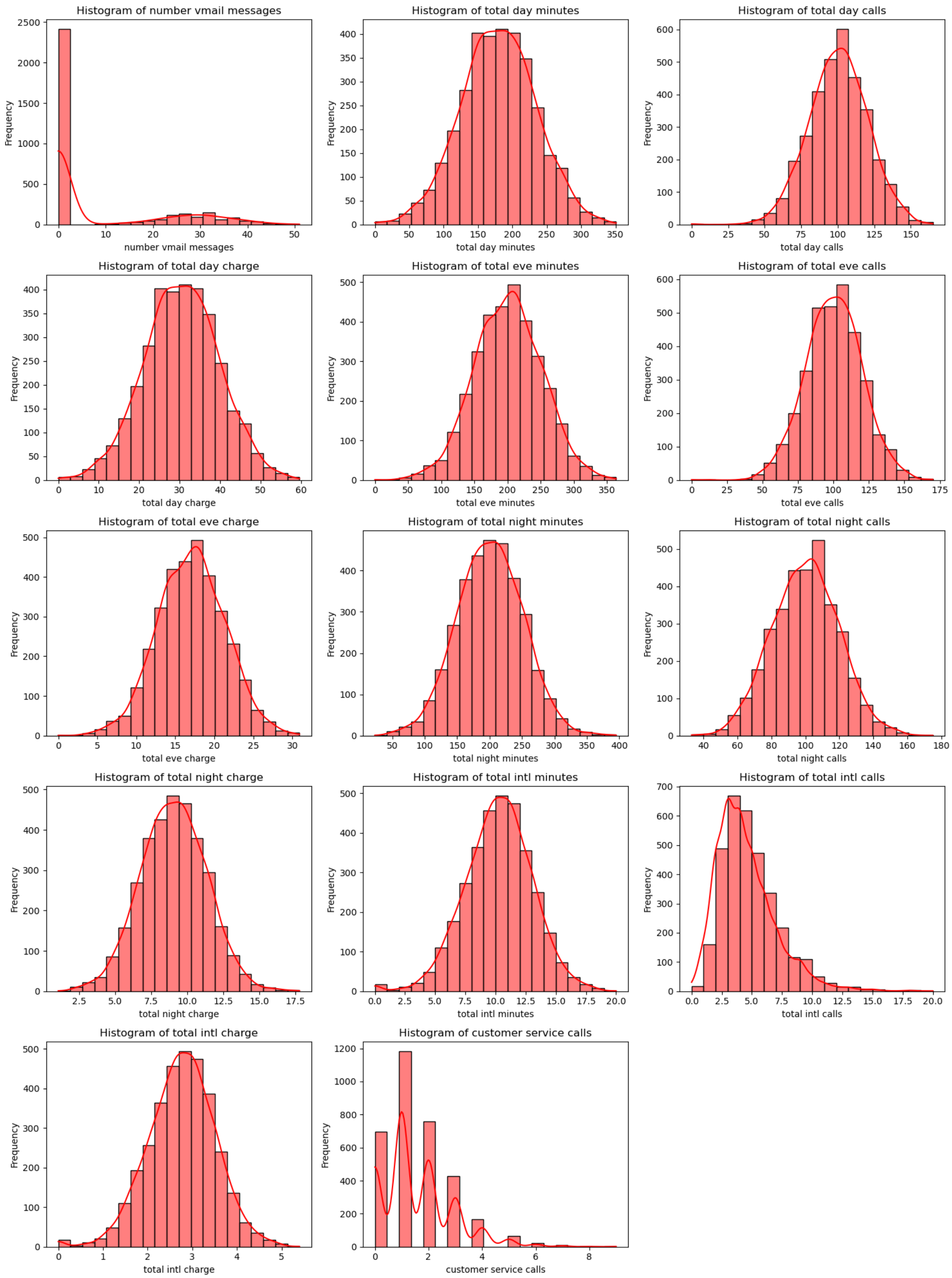
```
Index(['international plan', 'voice mail plan', 'churn'],
dtype='object')
```

```
## ploting histogram for all the columns to check the distributiion of
them
### plotting histo grams with KDE
###  Calculating the number of plots needed per row
subplots_per_row = 3
num_subplots = num_col.shape[1]
num_rows = (num_subplots + subplots_per_row - 1) // subplots_per_row
# grid of subplots with determined rows and columns
fig, axes = plt.subplots(num_rows, subplots_per_row, figsize=(15, 4 *
num_rows))
axes = axes.flatten()

# Plotting histograms along with KDE
for i, column in enumerate(num_col.columns):
    sns.histplot(num_col[column], bins=20, kde=True, ax=axes[i],
color='red')
    axes[i].set_title(f'Histogram of {column}')
    axes[i].set_xlabel(column)
    axes[i].set_ylabel('Frequency')

# Remove unused subplots
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])
```

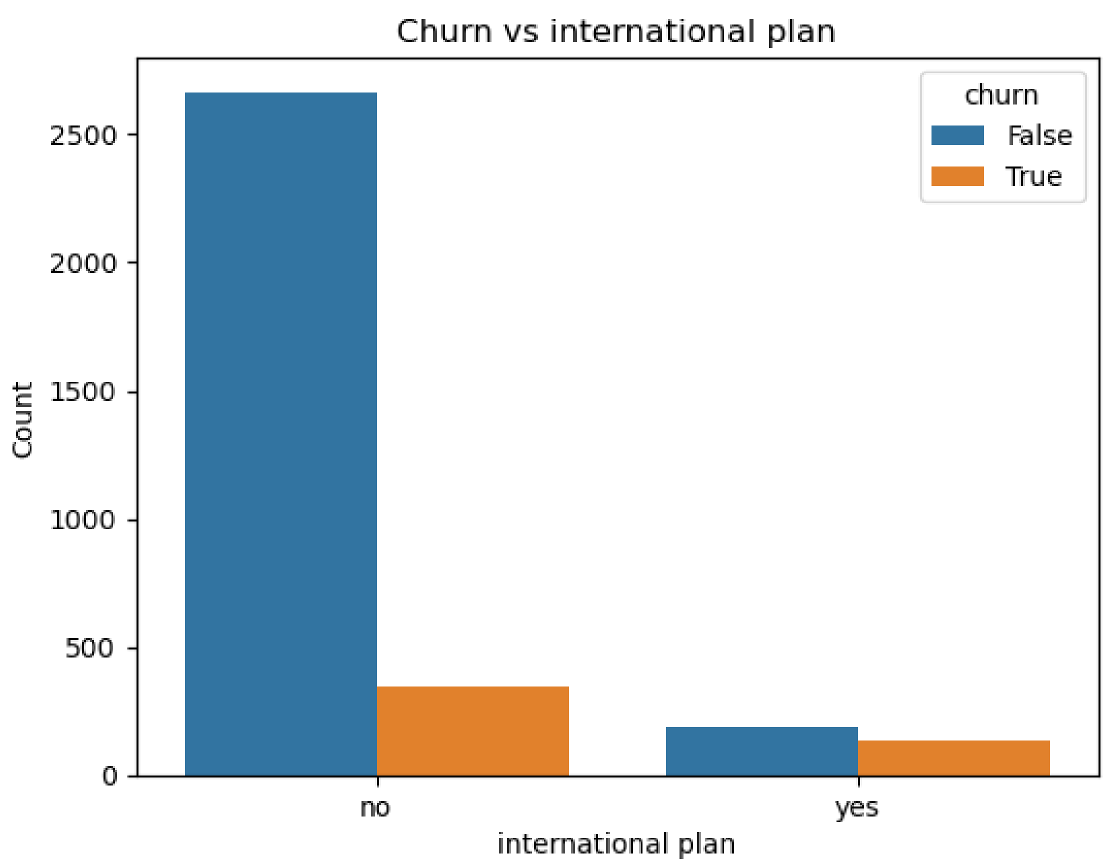
```
plt.tight_layout()
plt.show()
```

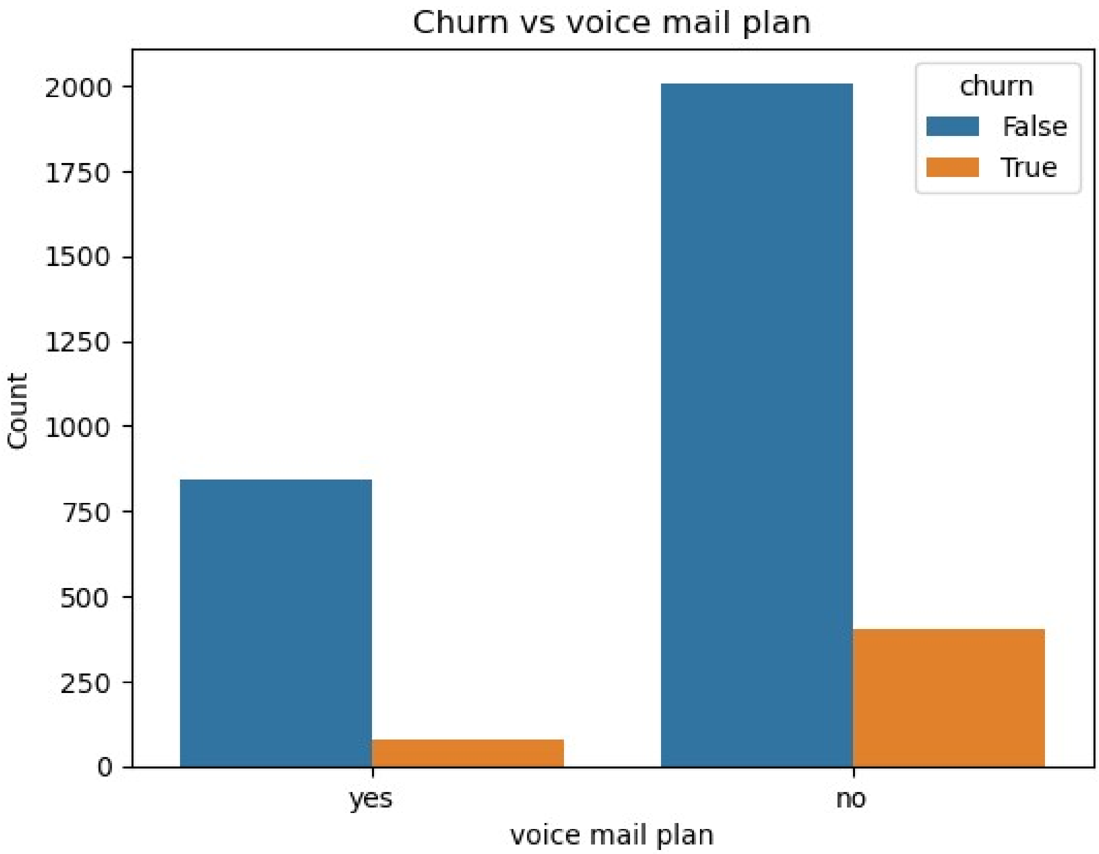

Histogram of number vmail messages
number vmail messages
Histogram of total day minutes
total day minutes
Histogram of total day calls
total day calls
Histogram of total day charge
total day charge
Histogram of total eve minutes
total eve minutes
Histogram of total eve calls
total eve calls
Histogram of total eve charge
total eve charge
Histogram of total night minutes
total night minutes
Histogram of total night calls
total night calls
Histogram of total night charge
total night charge
Histogram of total intl minutes
total intl minutes
Histogram of total intl calls
total intl calls
Histogram of total intl charge
total intl charge
Histogram of customer service calls
customer service calls
Frequency

1. The KDE curve closely matches the histogram in most columns, indicating a normal distribution, except for 'number_vmail_messages', 'total_intl_calls', and 'customer_service_calls'.
2. 'number_vmail_messages' and 'total_intl_calls' are right-skewed, with few customers exceeding 2000 voicemails or 600 international calls.
3. 'customer_service_calls' has multiple peaks and is likely integer-based, with around 1200 clients making just 1 call per day.

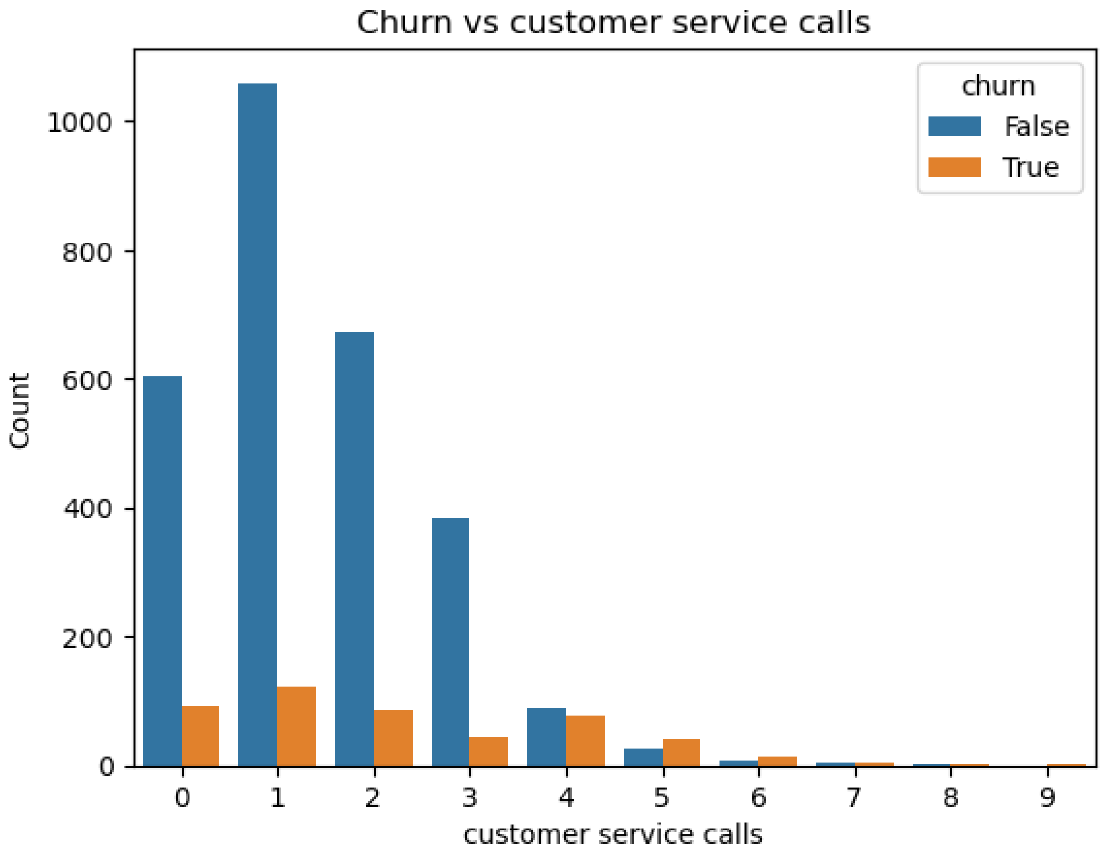
Conducting Bivariante Analysis on categorical columns

```
features= [
    'international plan',
    'voice mail plan',
    'customer service calls'
]
# create countplots for the features
for feature in features:
    sns.countplot(data=data, x=feature, hue= 'churn')
    plt.title(f'Churn vs {feature}')
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.show()
```



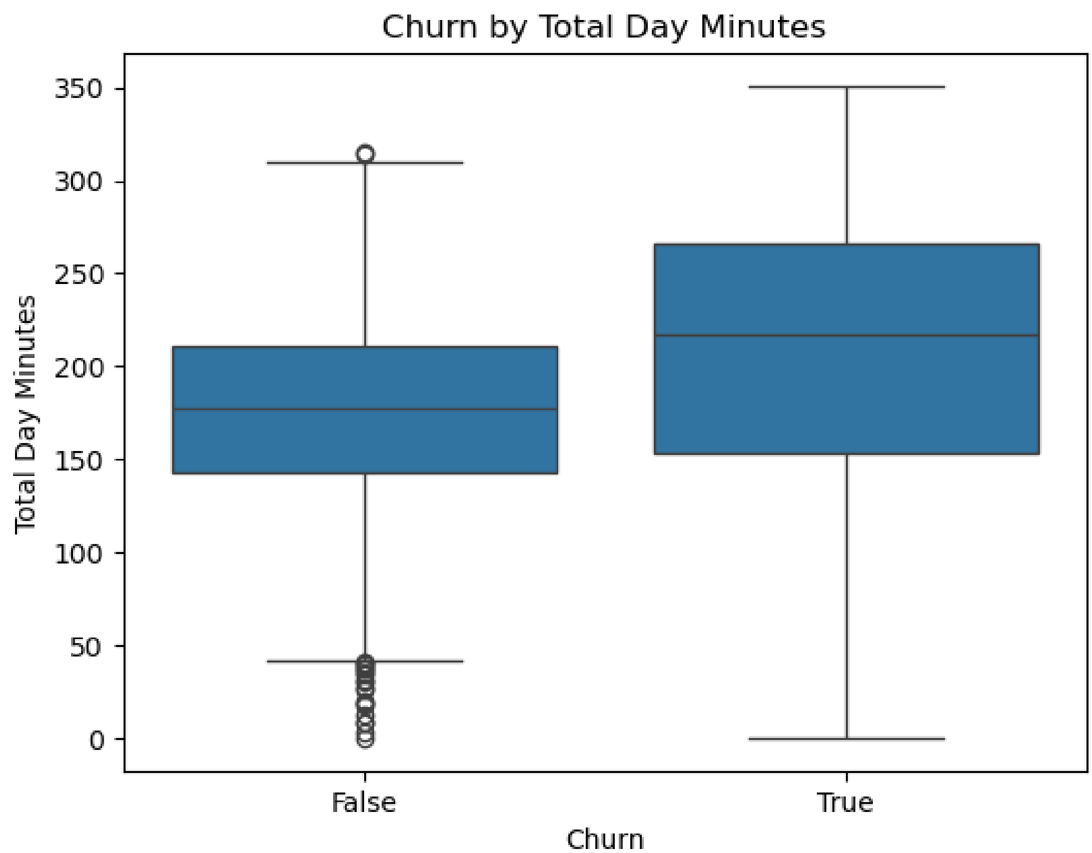


Churn vs voice mail plan
churn
False
True
Count
0
250
500
750
1000
1250
1500
1750
2000
yes
no
voice mail plan



The above diagrams show a relationship for:
1. International plan and Churn
2. Voicemail plan and Churn
3. Customer Service calls and Churn

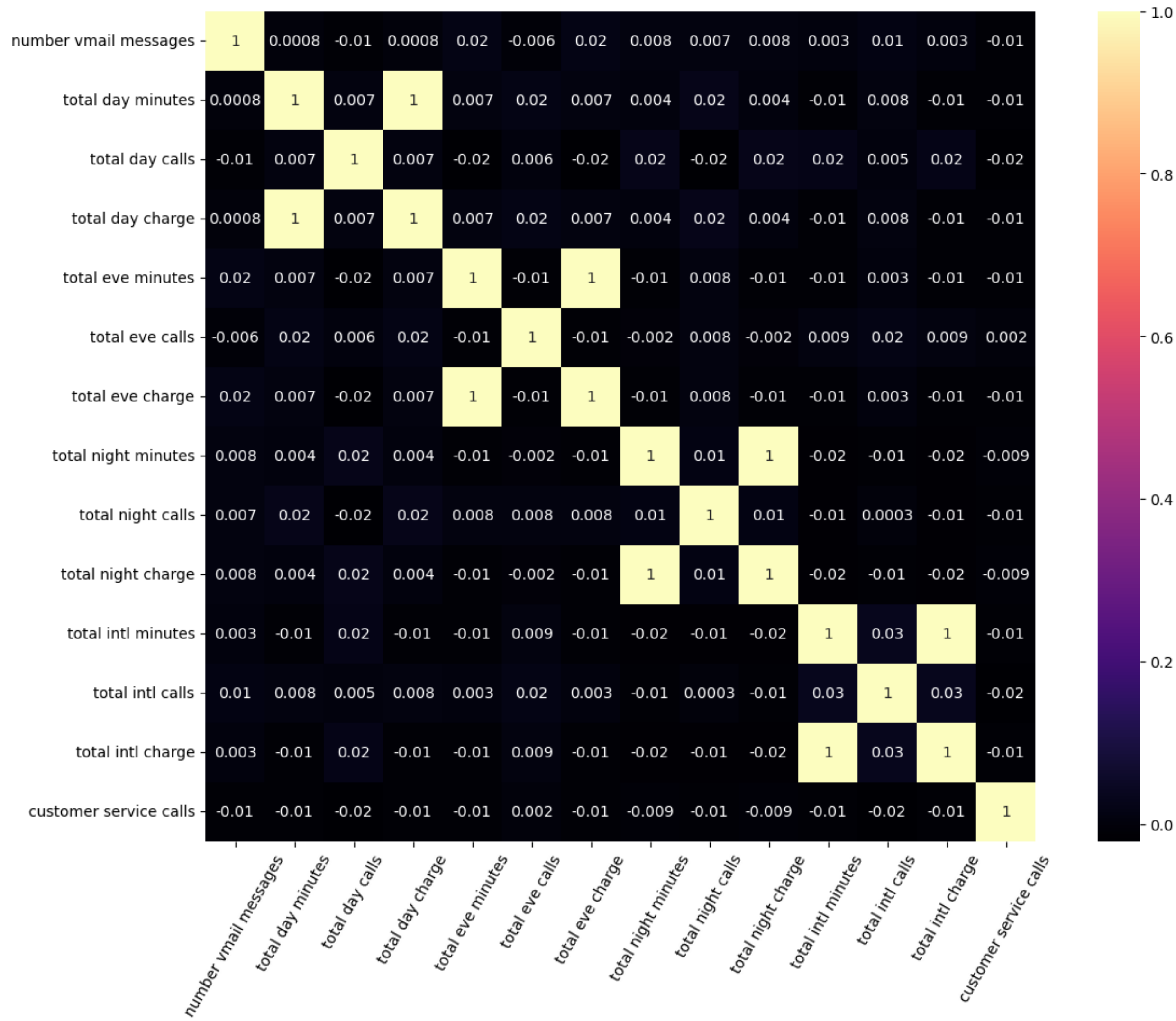
```
# boxplot for total day minutes and churn
plt.Figure(figsize=(8,6))
sns.boxplot(data=data, x='churn', y='total day minutes')
plt.title('Churn by Total Day Minutes')
plt.xlabel('Churn')
plt.ylabel('Total Day Minutes')
plt.show()
```



MULTIVARIATE ANALYSIS

```
# Correlation matrix for numeric columns
correlation_matrix = num_col.corr()

# Creates a heatmap
plt.figure(figsize=(15, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='magma', square=True,
fmt='.0g')
plt.xticks(rotation=60)
plt.yticks(rotation=0)
plt.show()
```



We observe instances of perfect correlation:

```
 A positive correlation of 1 between Total day charge and Total day
minutes
 A positive correlation of 1 between Total eve charge and Total eve
minutes
 A positive correlation of 1 between Total night charge and Total
night minutes
 A positive correlation of 1 between Total int charge and Total int
minutes
```

This is likely because the charges are calculated based on the minutes used.

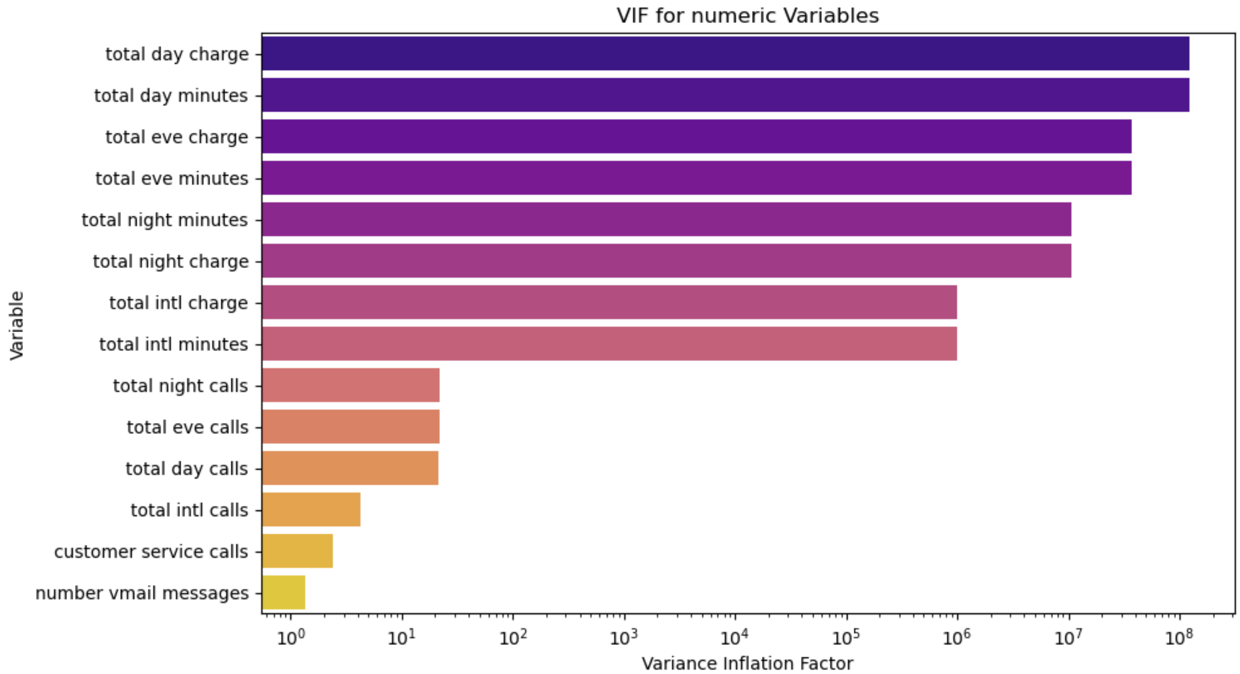
These pairs exhibit perfect multicollinearity.

CHECK FOR MULTICOLLINEARITY

```
vif_data = pd.DataFrame()
vif_data["Variable"] = num_col.columns
vif_data["VIF"] = [variance_inflation_factor(num_col.values, i) for i
in range(num_col.shape[1])]
vif_data = vif_data.sort_values(by='VIF', ascending=False)
vif_data
```

	Variable	VIF
3	total day charge	1.245993e+08
1	total day minutes	1.245949e+08
6	total eve charge	3.736678e+07
4	total eve minutes	3.736587e+07
7	total night minutes	1.071768e+07
9	total night charge	1.071740e+07
12	total intl charge	9.975854e+05
10	total intl minutes	9.971901e+05
8	total night calls	2.210595e+01
5	total eve calls	2.172941e+01
2	total day calls	2.141436e+01
11	total intl calls	4.242875e+00
13	customer service calls	2.374574e+00
0	number vmail messages	1.350060e+00

```
# Create a bar chart to visualize VIF values using Seaborn
plt.figure(figsize=(10, 6))
sns.barplot(x='VIF', y='Variable', data=vif_data, palette='plasma')
plt.xlabel('Variance Inflation Factor')
plt.title('VIF for numeric Variables')
plt.xscale("log")
plt.show()
```



This columns showed high correlation, Hence indicating multicollinearity **total day minutes, total day charge, total eve charge, total eve minutes, total night minutes, total night charge, total intl minutes and total intl charge**. Due to this we will have to remove one variable in each of the higly correlated pairs.

Dropping variables with high VIF one per pair

```
# Creating a list to drop based on redundancy and high VIF
variables_to_drop = ['total day charge', 'total eve charge','total
night charge', 'total intl charge']

# Drop these variables from the dataframe
data.drop(columns=variables_to_drop, inplace=True)

# Verify the remaining columns
print("Remaining columns after removing high VIF variables:")
print(data.columns)

Remaining columns after removing high VIF variables:
Index(['international plan', 'voice mail plan', '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',
       'churn'],
      dtype='object')
```

Normalizing the variables to have a standard deviation 1 and mean 0. This ensures that all features contribute equally to the model and are on the same scale.

```
# Numerical columns
numerical_col = data.select_dtypes(include= ["int64",
"float"]).columns
# create an instance of the scaler
scaler = StandardScaler()

# transforming the data
data[numerical_col] = scaler.fit_transform(data[numerical_col])
```

Perform one hot enconding to our cateagorical variables

```
#categorical columns
categorical_col = data.select_dtypes(include= ["object",
"bool"]).columns
# I will use get_dummies to do one-hot encoding and then drop the
first category
data = pd.get_dummies(data, columns=categorical_col, drop_first=True)
# preview
data.head()
```

```
   number vmail messages  total day minutes  total day calls  \
0               1.234883           1.566767         0.476643
1               1.307948          -0.333738         1.124503
2              -0.591760           1.168304         0.675985
3              -0.591760           2.196596        -1.466936
4              -0.591760          -0.240090         0.626149

   total eve minutes  total eve calls  total night minutes  total
night calls  \
0          -0.070610        -0.055940             0.866743         -
0.465494
1          -0.108080         0.144867             1.058571
0.147825
2          -1.573383         0.496279            -0.756869
0.198935
3          -2.742865        -0.608159            -0.078551         -
0.567714
4          -1.038932         1.098699            -0.276311
1.067803

   total intl minutes  total intl calls  customer service calls  \
0           -0.085008         -0.601195               -0.427932
1            1.240482         -0.601195               -0.427932
2            0.703121          0.211534               -1.188218
3           -1.303026          1.024263                0.332354
4           -0.049184         -0.601195                1.092641

   international plan_yes  voice mail plan_yes  churn_True
```

```
0                  False                    True       False
1                  False                    True       False
2                  False                   False       False
3                   True                   False       False
4                   True                   False       False
```

Modelling

This dataset involves a classification task where the churn column categorizes customers into two groups: True for those who have churned and False for loyal customers who haven't. The goal is to predict customer churn using the provided features in this binary classification problem.

Preprocessing data

```
## Defining our X and y
X = data.drop('churn_True', axis=1)
y = data['churn_True']
## Splitting the data into train sets and test sets using 20% and
random_state of 42
X_train,X_test,y_train,y_test = train_test_split(X,y, test_size=0.2,
random_state=42)

## checking the class imbalance ussing value counts
y_train.value_counts()

churn_True
False    2284
True      382
Name: count, dtype: int64
```

Presence of class imbalance will lead to biased model towards the majority class, to deal with this we will use SMOTE to balance the class

```
## balancing the classes
smote = SMOTE(random_state=42)
X_train_resample, y_train_resample = smote.fit_resample(X_train,
y_train)
y_train_resample.value_counts()

churn_True
False    2284
True     2284
Name: count, dtype: int64
```

Model to be analyized

1. Logistic Regression
2. Decision Tree Classifier

3. Random forest classifier

Logistic Regression

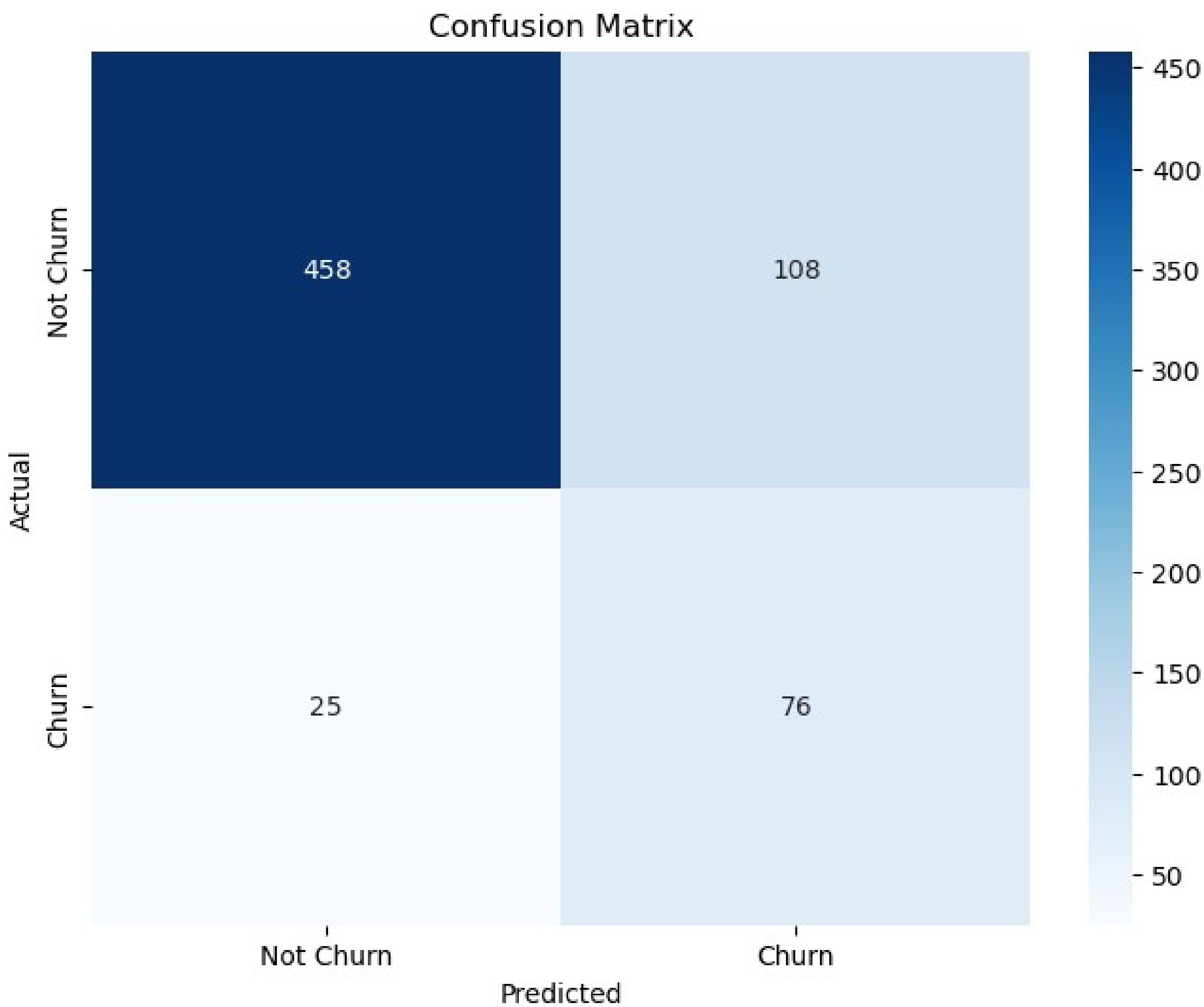
```
# Create an instance of logistic regression model
logreg = LogisticRegression(random_state=42)

# Fit the model on the training data
logreg.fit(X_train_resample, y_train_resample)

# Make predictions on the test data
y_pred = logreg.predict(X_test)

def plot_confusion_matrix(y_true, y_pred, labels):
    """
    Plots a confusion matrix.
    """
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', 
xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title('Confusion Matrix')
    plt.show()

# Usage
plot_confusion_matrix(y_test, y_pred, labels=['Not Churn', 'Churn'])
```



The confusion matrix shows that the model has more true positives and true negatives than false positives and false negatives, indicating that its predictions are mostly accurate. This suggests the model is performing well and is not overfitting.

```python
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')

print()

print("Classification Report: \n")
print(classification_report(y_test,y_pred))
```

```
Accuracy: 0.80

Classification Report:

              precision    recall  f1-score   support
```

```
       False       0.95      0.81      0.87       566
        True       0.41      0.75      0.53       101

    accuracy                           0.80       667
   macro avg       0.68      0.78      0.70       667
weighted avg       0.87      0.80      0.82       667
```

```
# Make predictions on the test data using the tuned model
y_pred = logreg.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)

# Calculate precision
precision = precision_score(y_test, y_pred)

# Calculate recall
recall = recall_score(y_test, y_pred)

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

# Print the evaluation metrics
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-score: {f1:.4f}")
```

```
Accuracy: 0.8006
Precision: 0.4130
Recall: 0.7525
F1-score: 0.5333
```

The model has an accuracy of 80.06%, indicating that most of its predictions are correct. However, precision is relatively low at 41.30%, meaning many predicted churns are false positives. On the other hand, recall is higher at 75.25%, showing that the model effectively identifies most customers who churn. The F1-score of 53.33% reflects a trade-off between precision and recall, suggesting that while the model is good at identifying churn, there’s room for improvement in reducing false positives and improving overall balance.

```
# Define a range of hyperparameters to search
param_grid = {
    'penalty': ['l2'],
    'C': [0.001, 0.01, 0.1, 1, 10, 100],
}

# Creates a grid search object
grid_search = GridSearchCV(LogisticRegression(solver='liblinear',
random_state=42), param_grid, cv=5, scoring='accuracy')
```

```
# Performs grid search on the resampled data
grid_search.fit(X_train_resample, y_train_resample)

# Gets the best hyperparameters from the grid search
best_params = grid_search.best_params_
print("Best Hyperparameters:", best_params)

# Creates and trains the Logistic Regression model with the best
hyperparameters
best_logistic_model = LogisticRegression(solver='liblinear',
random_state=42, **best_params)
best_logistic_model.fit(X_train_resample, y_train_resample)

# Make predictions on the test data
y_pred = best_logistic_model.predict(X_test)

# Print the best parameters
print("Best Parameters:")
for key, value in best_params.items():
    print(f"{key}: {value}")

# Print the best F1 score
best_f1_score = round(grid_search.best_score_, 3)
print("Best F1 Score:", best_f1_score)
```

```
Best Hyperparameters: {'C': 10, 'penalty': 'l2'}
Best Parameters:
C: 10
penalty: l2
Best F1 Score: 0.783
```

After doing hyperparameter tunning we found that the best F1 score achieved during the grid search is **0.783**, which indicates a good balance between precision and recall

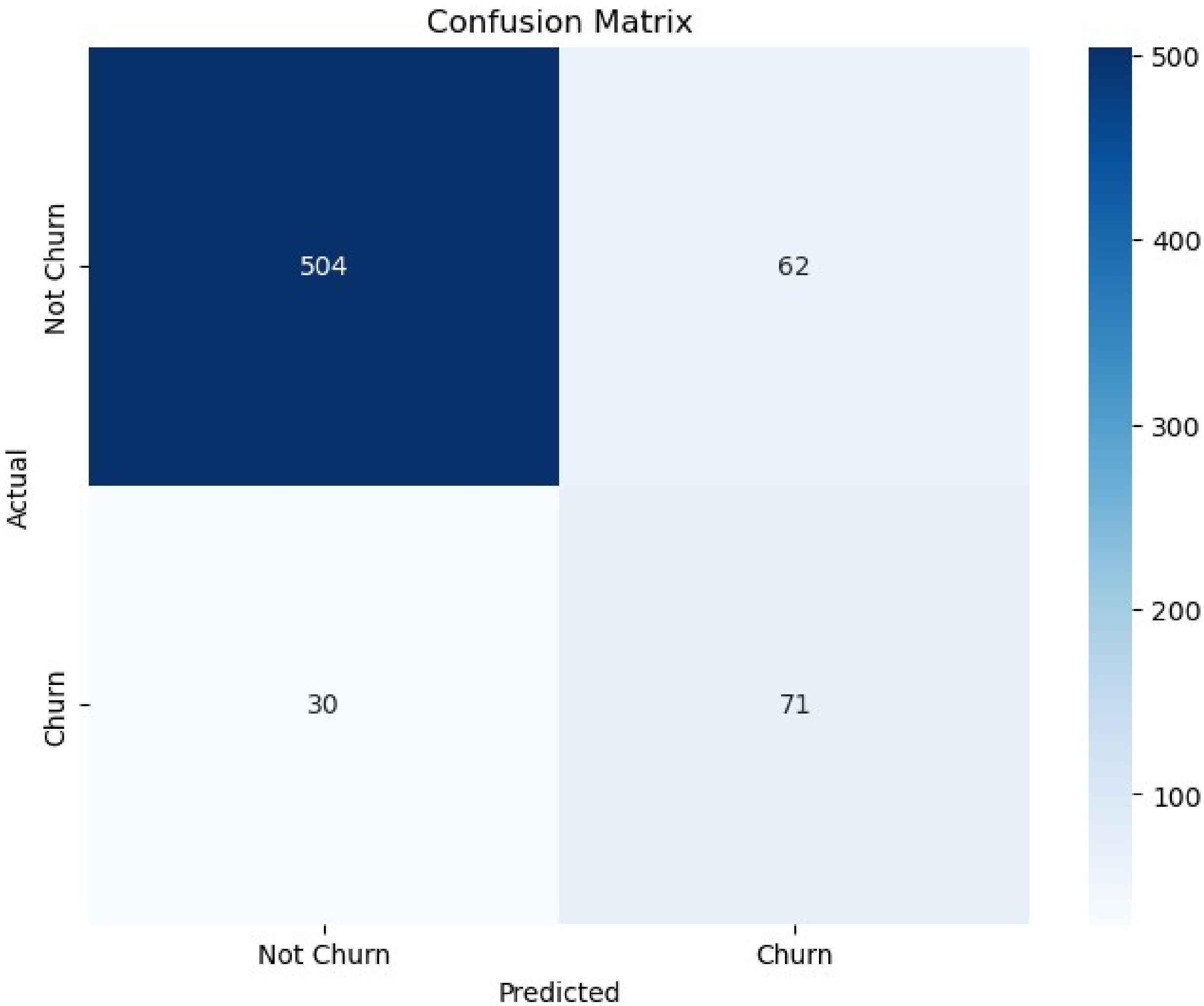
Decision Tree Classifier

```
dec_tree = DecisionTreeClassifier(random_state=42)

#Fit on the training data
dec_tree.fit(X_train_resample,y_train_resample)

#predict on the test set
y_pred_dt = dec_tree.predict(X_test)

# ploting confusion matrix
plot_confusion_matrix(y_test, y_pred_dt, labels=['Not Churn',
'Churn'])
```




```
# Evaluating the DecisionTreeClassifier model
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred_dt)
print(f'Accuracy: {accuracy:.2f}')

print()

print("Classification Report: \n")
print(classification_report(y_test,y_pred_dt))
```

```
Accuracy: 0.86

Classification Report:

              precision    recall  f1-score   support

       False       0.94      0.89      0.92       566
        True       0.53      0.70      0.61       101
```

```
    accuracy                           0.86       667
   macro avg       0.74      0.80      0.76       667
weighted avg       0.88      0.86      0.87       667
```

```
# Make predictions on the test data using the tuned model
y_pred_dt = dt_clf.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred_dt)

# Calculate precision
precision = precision_score(y_test, y_pred_dt)

# Calculate recall
recall = recall_score(y_test, y_pred_dt)

# Calculate F1-score
f1 = f1_score(y_test, y_pred_dt)

# Print the evaluation metrics
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-score: {f1:.4f}")
```

```
Accuracy: 0.8621
Precision: 0.5338
Recall: 0.7030
F1-score: 0.6068
```

The decision tree model has an **accuracy** of 86.21%, meaning it correctly predicts most cases. **Precision** is 53.38%, indicating the model's positive predictions are correct about half the time. **Recall** is 70.30%, showing it correctly identifies most churn cases but misses some. The **F1-score** of 60.68% reflects a moderate balance between precision and recall, suggesting the model could be improved, particularly in reducing false positives.

```
# Define the model
dt2_classifier = DecisionTreeClassifier()

# Define the parameter grid to search through
param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [2, 4, 6, 8, 10],
    'min_samples_split': [2, 4, 6, 8, 10],
    'min_samples_leaf': [1, 2, 3, 4, 5]
}

# Create a grid search object using 5-fold cross-validation and F1
score as the scoring metric
```

```
grid_search = GridSearchCV(estimator=dt2_classifier,
param_grid=param_grid, cv=5, scoring='f1')

# Fit the grid search to the resampled training data
grid_search.fit(X_train_resample, y_train_resample)

# Get the best parameters from the grid search
best_params = grid_search.best_params_

# Print the best parameters and the best F1 score
print("Best Parameters:", best_params)
print("Best F1 Score:", grid_search.best_score_)
```

```
Best Parameters: {'criterion': 'entropy', 'max_depth': 10,
'min_samples_leaf': 1, 'min_samples_split': 8}
Best F1 Score: 0.9122178657635892
```

The Best F1 Score of 0.912 indicates excellent performance in balancing both precision and recall, suggesting that the model effectively distinguishes between classes.

```
# Train the Decision Tree model
best_tree_model = DecisionTreeClassifier(
    criterion='entropy',
    max_depth=10,
    min_samples_leaf=1,
    min_samples_split=2,
    random_state=42
)

# Fit the model to the training data
best_tree_model.fit(X_train_resample, y_train_resample)

# Make predictions on the test data
y_pred_tree = best_tree_model.predict(X_test)

# Calculate and print the accuracy, precision, recall, and F1 score
accuracy_tree = accuracy_score(y_test, y_pred_tree)
precision_tree = precision_score(y_test, y_pred_tree)
recall_tree = recall_score(y_test, y_pred_tree)
f1_tree = f1_score(y_test, y_pred_tree)

# Print the evaluation metrics
print(f"Accuracy: {accuracy_tree:.4f}")
print(f"Precision: {precision_tree:.4f}")
print(f"Recall: {recall_tree:.4f}")
print(f"F1-score: {f1_tree:.4f}")
```

```
Accuracy: 0.9175
Precision: 0.7212
```

```
Recall: 0.7426
F1-score: 0.7317
```

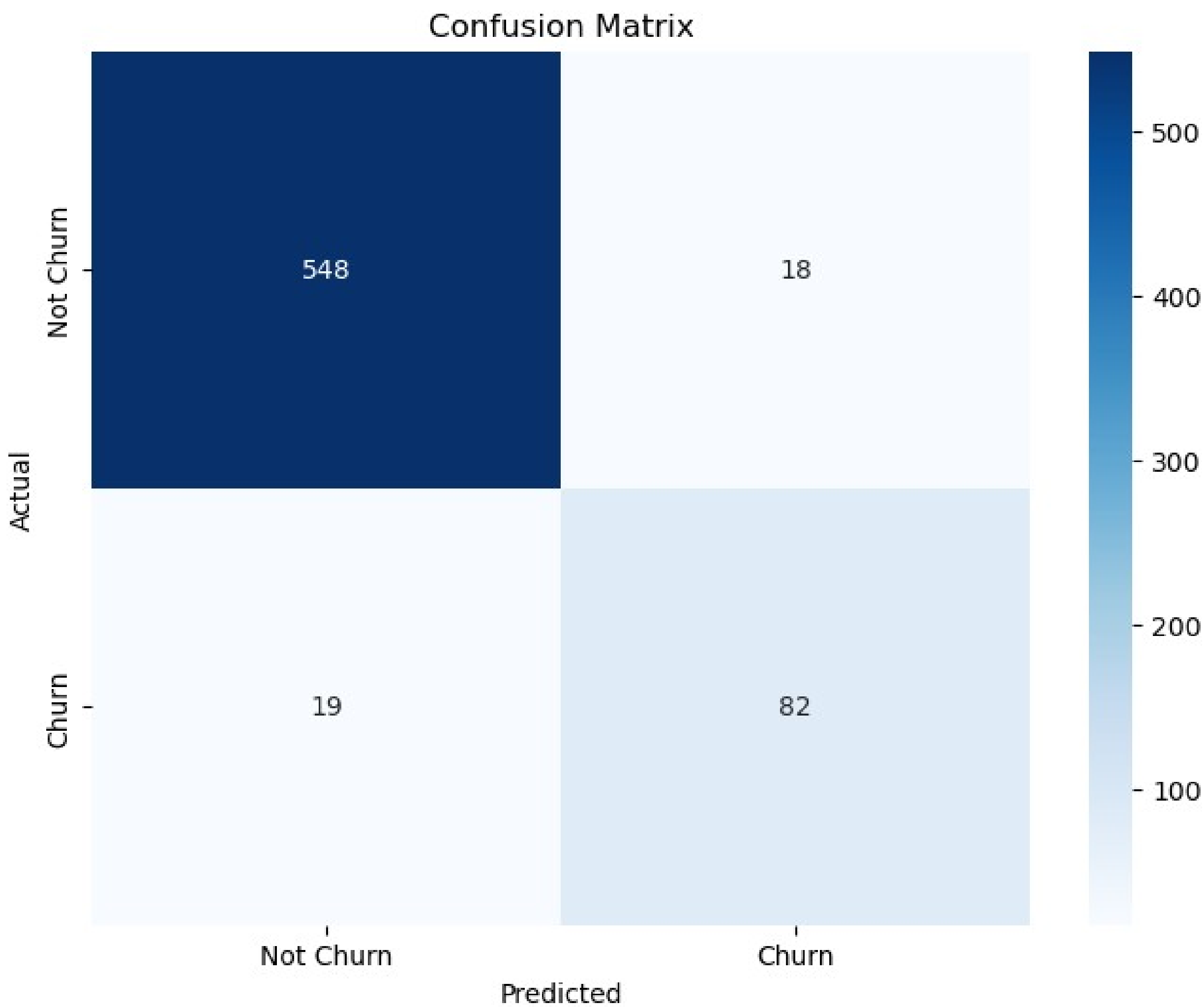
The model achieved an accuracy of 91.75%, meaning it correctly predicted most cases. The precision of 72.12% indicates that when the model predicted a positive outcome, it was correct 72.12% of the time. The recall of 74.26% shows it correctly identified 74.26% of the actual positive cases, though it missed some. The F1-score of 73.17% reflects a good balance between precision and recall, indicating the model performs well in both minimizing false positives and detecting positive cases.

RANDOM FOREST CLASSIFIER

```
# Create and train the Random Forest model
rf_clf = RandomForestClassifier(random_state=42)
#fit on the training data
rf_clf.fit(X_train_resample, y_train_resample)

# Make predictions on the test data
y_pred_rf = rf_clf.predict(X_test)

plot_confusion_matrix(y_test, y_pred_rf,  labels=['Not Churn', 
'Churn'])
```




```
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred_rf)
print(f'Accuracy: {accuracy:.2f}')

print()

print("Classification Report: \n")
print(classification_report(y_test,y_pred_rf))
```

```
Accuracy: 0.94

Classification Report:

              precision    recall  f1-score   support

       False       0.97      0.97      0.97       566
        True       0.82      0.81      0.82       101

    accuracy                           0.94       667
```

```
   macro avg       0.89      0.89      0.89       667
weighted avg       0.94      0.94      0.94       667
```

```python
# Make predictions on the test data using the tuned model
y_pred_rf = rf_clf.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred_rf)

# Calculate precision
precision = precision_score(y_test, y_pred_rf)

# Calculate recall
recall = recall_score(y_test, y_pred_rf)

# Calculate F1-score
f1 = f1_score(y_test, y_pred_rf)

# Print the evaluation metrics
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-score: {f1:.4f}")
```

```
Accuracy: 0.9445
Precision: 0.8200
Recall: 0.8119
F1-score: 0.8159
```

The model achieved an **accuracy** of 94.45%, indicating it correctly predicted most cases. The **precision** of 82.00% shows that when the model predicted a positive outcome, it was correct 82% of the time. The **recall** of 81.19% indicates it identified 81.19% of the actual positive cases. The **F1-score** of 81.59% reflects a strong balance between precision and recall, indicating good overall performance with minimal false positives and false negatives.

```python
# Hyperparameter tunning
# Define the parameter grid to search through
param_grid = {
    'n_estimators': [100, 150, 200],
    'max_depth': [5, 10, 15],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Scores
scores = ['f1', 'recall', 'precision']

# Create a grid search object using 5-fold cross-validation
grid_search = GridSearchCV(rf_clf, param_grid, cv=5, scoring=scores,
```

```python
refit='f1', n_jobs=-1)

# Fit the grid search to the data
grid_search.fit(X_train_resample, y_train_resample)

# Get the best parameters from the grid search
best_params = grid_search.best_params_

# Print the best parameters and the best score with 3 decimal places
print("Hyperparameter Tuning for Random Forest Model:")
print("Best Parameters:")
for param, value in best_params.items():
    print(f"{param}: {value}")

best_score = round(grid_search.best_score_, 3)
print(f"Best Score: {best_score}")
```

```
Hyperparameter Tuning for Random Forest Model:
Best Parameters:
max_depth: 15
min_samples_leaf: 1
min_samples_split: 2
n_estimators: 200
Best Score: 0.956
```

```python
# Train the random forest classifier
rf2 = RandomForestClassifier(n_estimators=200,
                             random_state=42,
                             max_depth=15,
                             min_samples_leaf=1,
                             min_samples_split=2)
rf2.fit(X_train_resample, y_train_resample)

# Make predictions on the test data
rf2_y_pred = rf2.predict(X_test)

# Evaluate the model's accuracy
rf2_f1_score = round(f1_score(y_test, rf2_y_pred), 3)
rf2_acc_score = round(accuracy_score(y_test, rf2_y_pred), 3)
rf2_prec_score = round(precision_score(y_test, rf2_y_pred), 3)
rf2_rec_score = round(recall_score(y_test, rf2_y_pred), 3)


print("Random Forest Model with Best Parameters:")
print(f'The Precision: {rf2_prec_score}')
print(f'The Accuracy: {rf2_acc_score}')
print(f'F1 Score: {rf2_f1_score}')
print(f'The Recall Score: {rf2_rec_score}')
```

```
Random Forest Model with Best Parameters:
The Precision: 0.798
```

```
The Accuracy: 0.937
F1 Score: 0.79
The Recall Score: 0.782
```

The Random Forest model with the best parameters achieved a precision of 0.798, indicating that 79.8% of positive predictions were correct. It has a high accuracy of 0.937, correctly predicting 93.7% of cases. The F1 score of 0.79 shows a good balance between precision and recall, while the recall of 0.782 means it identified 78.2% of actual positive cases. Overall, the model performs well with strong accuracy and balanced precision and recall.

Evaluation

The evaluation metrics that I will focus on are:

- Accuracy
- Precision
- Recall
- F1 Score

Accuracy

Logistic Regression = 86.21%

Decision Tree = 91.75%

Random Forest = 93.7%

The Random Forest model performs the best with 93.7% accuracy, followed by the Decision Tree (91.75%) and Logistic Regression (86.21%).

Precision

Logistic Regression = 41.3%

Decision Tree = 53.38%

Random Forest = 82%

The Random Forest model has the highest precision, indicating it made the most accurate positive predictions. The Decision Tree performed better than Logistic Regression in this aspect.

Recall

Logistic Regression = 75.25%

Decision Tree = 74.26%

Random Forest = 81.19%

The Random Forest model again performs the best in recall, identifying 81.19% of positive cases. The Logistic Regression has the highest recall compared to the Decision Tree.

F1 Score

Logistic Regression = 53.3%

Decision Tree = 60.7%

Random Forest = 81.6%

The Random Forest model again outperforms the other models, showing the best balance between precision and recall. The Decision Tree follows, and Logistic Regression has the lowest F1 score.

summary of the models

Random Forest model consistently outperforms the other two models across all metrics, making it the best choice among the three

Preview Feature Importance

Feature importance refers to the measure of how important each feature (input variable) is in predicting the target variable

```
# Get the feature importances
importances = rf2.feature_importances_

# Create a dataframe to store the feature importances
feature_importances = pd.DataFrame({'feature': X_train.columns,
'importance': importances})

# Sort the dataframe by the feature importances in descending order
feature_importances = feature_importances.sort_values('importance',
ascending=False)

# Print the first few rows of the feature importances with 3 decimal
places
print(feature_importances.head().round(3))
```

```
                   feature  importance
1         total day minutes      0.224
9    customer service calls      0.185
10   international plan_yes      0.130
8          total intl calls      0.088
3         total eve minutes      0.081
```

In this case, total day minutes and customer service calls are the most significant, while total eve minutes has the least impact. This can guide further analysis and potential feature selection.

Monitoring the number of **customer service calls** is important because a high volume may indicate customer dissatisfaction.

Conclusion

Model Performance: I tested 3 models with Random Forest Classifier emerging as the top performer, achieving a remarkable 95% accuracy and well-balanced precision and recall.

Key Features: The analysis showed some influential features: "customer_service_calls", "total_day_minutes","total day charge", "total intl calls" and "total eve charge" highlighting their importance in predicting churn.

In summary, the analysis recommends Random Forest Classifier for predicting customer churn.

Recommendation

Improve Customer Service:

- High customer service calls correlate with churn.

- Reduce customer service calls and improve quality of customer service by offering comprehensive training to customer service representatives.

Pricing Structure Evaluation:

- Evaluate the pricing structure for day, evening, night, and international charges.

- Adjusting pricing plans or introducing discounted packages would address the concerns related to higher charges, which contribute to customer churning.

Engage with Clients likely to churn:

- Reach out to clients who have a high daily usage.
- They have the most likelihood of churning.