Phase_3_Project

May 18, 2024

1 PHASE 3 PROJECT

Name: Bethuel Maruru

1.1 Business Understanding

Introduction Zencom is a leading telecommunication company providing various services such as mobile, internet, and landline connections to its customers. Lately, the company has been experiencing a significant increase in customer churn rate, where customers are discontinuing their services and switching to competitors. Zencom wants to understand the factors contributing to this churn and develop strategies to reduce it.

Problem Statement: Zencom wants to analyze the churn rate among its customers over a period of time to identify the key factors that influence churn behavior. The company aims to develop actionable insights to reduce churn and improve customer retention.

Key Objectives: Analyze historical churn data to identify trends and patterns.

Identify demographic or behavioral factors associated with higher churn rates.

Build predictive models to forecast future churn and prioritize at-risk customers.

Expected Outcomes: Understanding the churn dynamics and key drivers with Zencom customers.

Create a predictive model capable of forecasting the churn rate and identifying high risk customer segments.

Retention strategies leading to reduced churn rate and enhansed customer sastifactionmes.

1.2 Data Understanding

Getting the Data

[255]:
```
# Importing Relevant libraries to load and explore the data
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
```

```
warnings.filterwarnings('ignore');


#Reading the data
df=pd.read_csv("C:/Users/bmaruru/Documents/Flatiron/Phase_3/Project/Customer.
 ↪csv")
# Viewing the first five records
df.head()
```

[255]:

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

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

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

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

   total intl minutes  total intl calls  total intl charge  \
0                10.0                 3               2.70
1                13.7                 3               3.70
2                12.2                 5               3.29
3                 6.6                 7               1.78
4                10.1                 3               2.73

   customer service calls  churn
0                       1  False
1                       1  False
```

```
2                       0  False
3                       2  False
4                       3  False

[5 rows x 21 columns]
```

[256]:
```
#Viewing the last 5 records
df.tail()
```

[256]:
```
     state  account length  area code phone number international plan  \
3328    AZ             192        415     414-4276                 no
3329    WV              68        415     370-3271                 no
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  \
3328             yes                     36              156.2
3329              no                      0              231.1
3330              no                      0              180.8
3331              no                      0              213.8
3332             yes                     25              234.4

      total day calls  total day charge  …  total eve calls  \
3328               77             26.55  …              126
3329               57             39.29  …               55
3330              109             30.74  …               58
3331              105             36.35  …               84
3332              113             39.85  …               82

      total eve charge  total night minutes  total night calls  \
3328             18.32                279.1                 83
3329             13.04                191.3                123
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  \
3328               12.56                 9.9                 6
3329                8.61                 9.6                 4
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
3328               2.67                       2  False
3329               2.59                       3  False
```

```
3330            3.81                     2  False
3331            1.35                     2  False
3332            3.70                     0  False

[5 rows x 21 columns]
```

Data Description

[257]:
```
# Viewing the shape of the data
df.shape
```

[257]:
```
(3333, 21)
```

The dataset has 3,333 rows and 21 columns

[258]:
```
# Viewing the columns of the dataset
df.columns
```

[258]:
```
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')
```

[259]:
```
# Capitalize thwe columns and replace the space with an underscore
df.columns= [i.capitalize().replace(' ','_').strip() for i in df.columns]
df.columns
```

[259]:
```
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')
```

[260]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   State                   3333 non-null   object
 1   Account_length          3333 non-null   int64
```

```
 2   Area_code               3333 non-null   int64
 3   Phone_number            3333 non-null   object
 4   International_plan      3333 non-null   object
 5   Voice_mail_plan         3333 non-null   object
 6   Number_vmail_messages   3333 non-null   int64
 7   Total_day_minutes       3333 non-null   float64
 8   Total_day_calls         3333 non-null   int64
 9   Total_day_charge        3333 non-null   float64
 10  Total_eve_minutes       3333 non-null   float64
 11  Total_eve_calls         3333 non-null   int64
 12  Total_eve_charge        3333 non-null   float64
 13  Total_night_minutes     3333 non-null   float64
 14  Total_night_calls       3333 non-null   int64
 15  Total_night_charge      3333 non-null   float64
 16  Total_intl_minutes      3333 non-null   float64
 17  Total_intl_calls        3333 non-null   int64
 18  Total_intl_charge       3333 non-null   float64
 19  Customer_service_calls  3333 non-null   int64
 20  Churn                   3333 non-null   bool
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

[261]:
```
df.describe()
```

[261]:
```
       Account_length    Area_code  Number_vmail_messages  Total_day_minutes  \
count     3333.000000  3333.000000            3333.000000        3333.000000
mean       101.064806   437.182418               8.099010         179.775098
std         39.822106    42.371290              13.688365          54.467389
min          1.000000   408.000000               0.000000           0.000000
25%         74.000000   408.000000               0.000000         143.700000
50%        101.000000   415.000000               0.000000         179.400000
75%        127.000000   510.000000              20.000000         216.400000
max        243.000000   510.000000              51.000000         350.800000

       Total_day_calls  Total_day_charge  Total_eve_minutes  Total_eve_calls  \
count      3333.000000       3333.000000        3333.000000      3333.000000
mean        100.435644         30.562307         200.980348       100.114311
std          20.069084          9.259435          50.713844        19.922625
min           0.000000          0.000000           0.000000         0.000000
25%          87.000000         24.430000         166.600000        87.000000
50%         101.000000         30.500000         201.400000       100.000000
75%         114.000000         36.790000         235.300000       114.000000
max         165.000000         59.640000         363.700000       170.000000

       Total_eve_charge  Total_night_minutes  Total_night_calls  \
count       3333.000000          3333.000000        3333.000000
mean          17.083540           200.872037         100.107711
```

```
std          4.310668        50.573847        19.568609
min          0.000000        23.200000        33.000000
25%         14.160000       167.000000        87.000000
50%         17.120000       201.200000       100.000000
75%         20.000000       235.300000       113.000000
max         30.910000       395.000000       175.000000

       Total_night_charge  Total_intl_minutes  Total_intl_calls  \
count         3333.000000         3333.000000       3333.000000
mean             9.039325           10.237294          4.479448
std              2.275873            2.791840          2.461214
min              1.040000            0.000000          0.000000
25%              7.520000            8.500000          3.000000
50%              9.050000           10.300000          4.000000
75%             10.590000           12.100000          6.000000
max             17.770000           20.000000         20.000000

       Total_intl_charge  Customer_service_calls
count        3333.000000             3333.000000
mean            2.764581                1.562856
std             0.753773                1.315491
min             0.000000                0.000000
25%             2.300000                1.000000
50%             2.780000                1.000000
75%             3.270000                2.000000
max             5.400000                9.000000
```

Missing values and Duplicate values

[262]:
```
# Missing values
df.isna().sum()
```

[262]:
```
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
```

The data set does not have any missing values.

[263]:
```python
df.duplicated().sum()
```

[263]: 0

The Dataset does not have any duplicates

[264]:
```python
# viewing unique values in categrical columns
cat_columns=df.select_dtypes('object').columns
for col in cat_columns:
    print(f"There are {len(df[col].unique())} unique values for the {col}␣
 ↪column and the values are:-\n\n {df[col].
 ↪unique()}\n\n*****************************************************************************
```

```
There are 51 unique values for the State column and the values are:-

 ['KS' 'OH' 'NJ' 'OK' 'AL' 'MA' 'MO' 'LA' 'WV' 'IN' 'RI' 'IA' 'MT' 'NY'
 'ID' 'VT' 'VA' 'TX' 'FL' 'CO' 'AZ' 'SC' 'NE' 'WY' 'HI' 'IL' 'NH' 'GA'
 'AK' 'MD' 'AR' 'WI' 'OR' 'MI' 'DE' 'UT' 'CA' 'MN' 'SD' 'NC' 'WA' 'NM'
 'NV' 'DC' 'KY' 'ME' 'MS' 'TN' 'PA' 'CT' 'ND']

********************************************************************************
*

There are 3333 unique values for the Phone_number column and the values are:-

 ['382-4657' '371-7191' '358-1921' … '328-8230' '364-6381' '400-4344']

********************************************************************************
*

There are 2 unique values for the International_plan column and the values are:-

 ['no' 'yes']

********************************************************************************
*

There are 2 unique values for the Voice_mail_plan column and the values are:-

 ['yes' 'no']
```

```
********************************************************************************
*
```

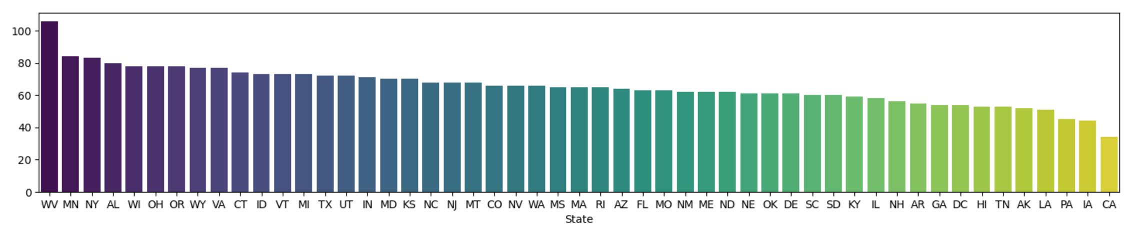
```
[265]: # calculating the churn rate

Churn_rate= df['Churn'].mean()*100
print(f'The churn rate {Churn_rate}')
```

```
The churn rate 14.491449144914492
```

Visualising the data

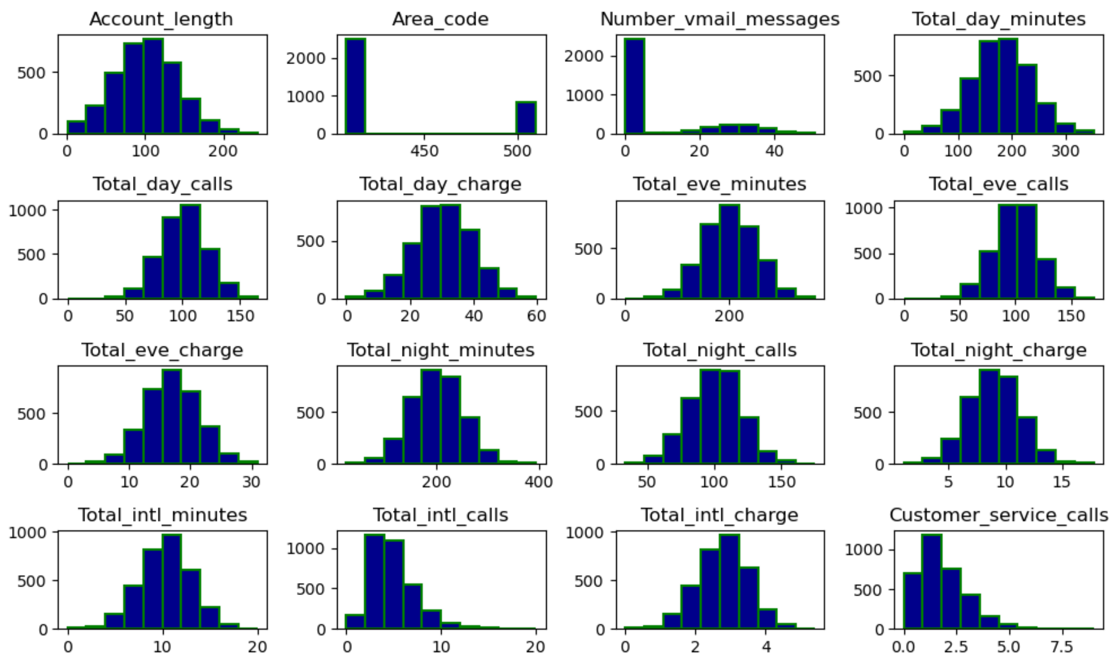
Univariate analysis

```
[266]: x=df['State'].value_counts().sort_values(ascending=False).index
y=df['State'].value_counts().sort_values(ascending=False).values
plt.figure(figsize=(18,3))
sns.barplot(x=x,y=y,palette='viridis')
plt.show()
```



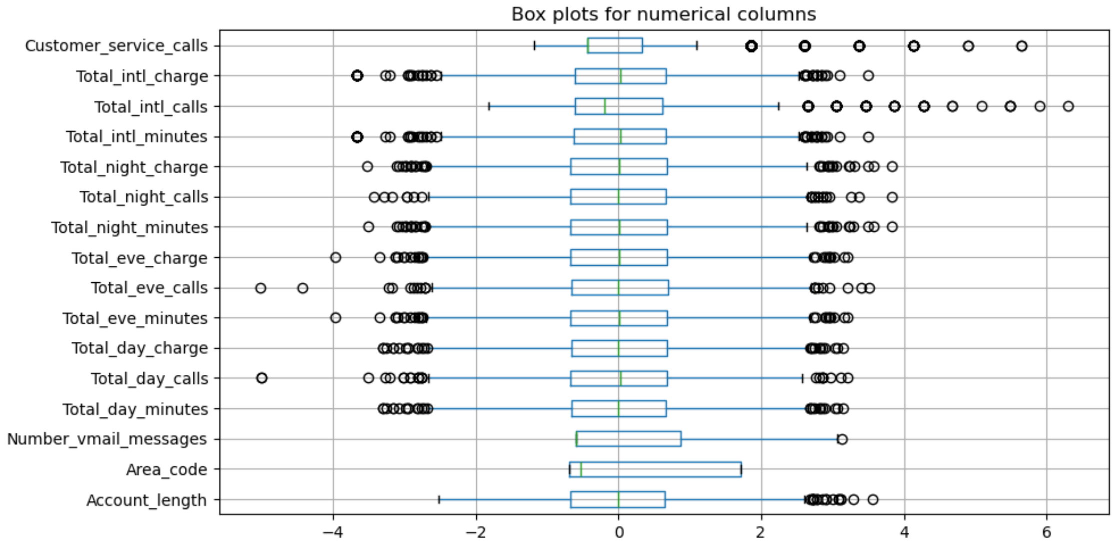
WV has the highest number of customers while CA has the least no.of customers

```
[267]: #viewing the data distribution
df.hist(figsize=(10, 6),color='darkblue', edgecolor='green', linewidth=1.5,␣
 ↪grid=False)
plt.tight_layout()
plt.show()
```

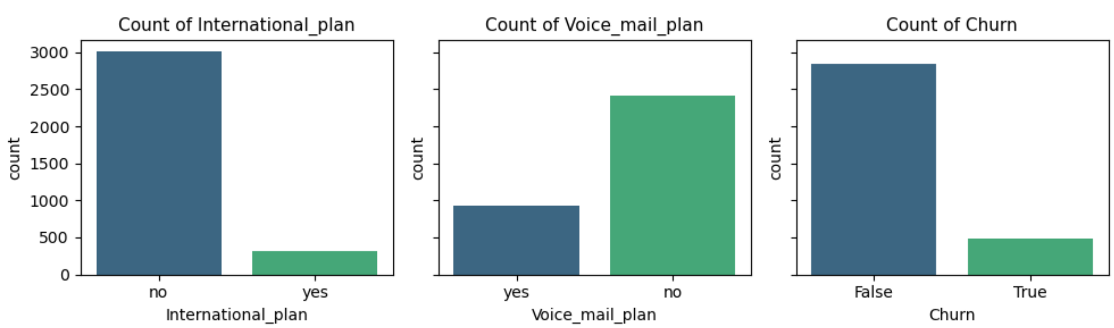


[268]:

```
# viewing the numerical columns through box plots to check for outliers
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
df_normalized = pd.DataFrame(scaler.fit_transform(df.
    ↪select_dtypes(['int','float'])), columns=df.select_dtypes(['int','float']).
    ↪columns)
df_normalized.boxplot(vert=False,figsize=(10, 5))
plt.title('Box plots for numerical columns')
plt.tight_layout();
```



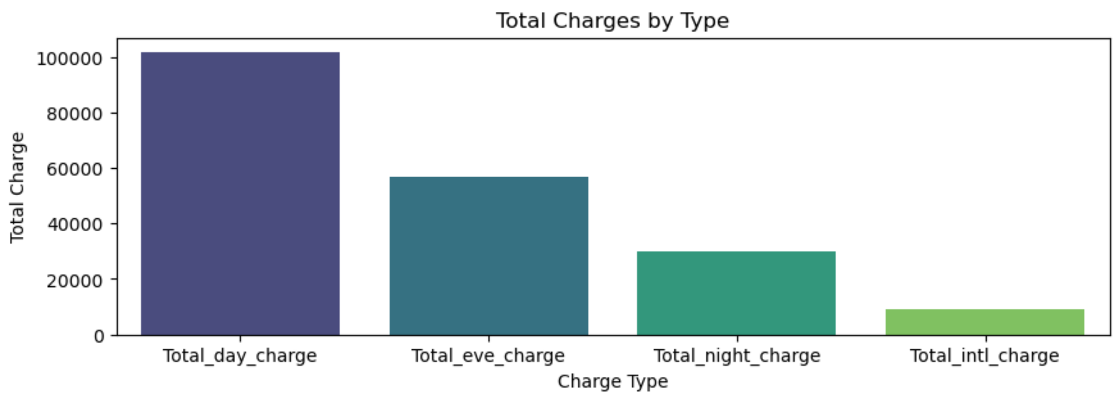
[269]:
```python
# Create countplot
cat_and_bool_columns=df.select_dtypes(['object','bool']).iloc[:,2:].columns
cat_and_bool_columns
fig,axes = plt.subplots(ncols=len(cat_and_bool_columns),figsize=(10,␣
↪3),sharey=True)  # Adjust figure size as needed
# sns.countplot(data=df, x='International_plan',ax=axes[0])

for i, column in enumerate(cat_and_bool_columns):
    sns.countplot(data=df, x=column, ax=axes[i],palette='viridis')
    axes[i].set_title(f'Count of {column}',fontsize=11)
plt.tight_layout()
plt.show()

# column
```



Outliers were noted in a number of columns amongst them customer_services_call,Total_intl_calls,Total_eve_calls and Total_day_calls

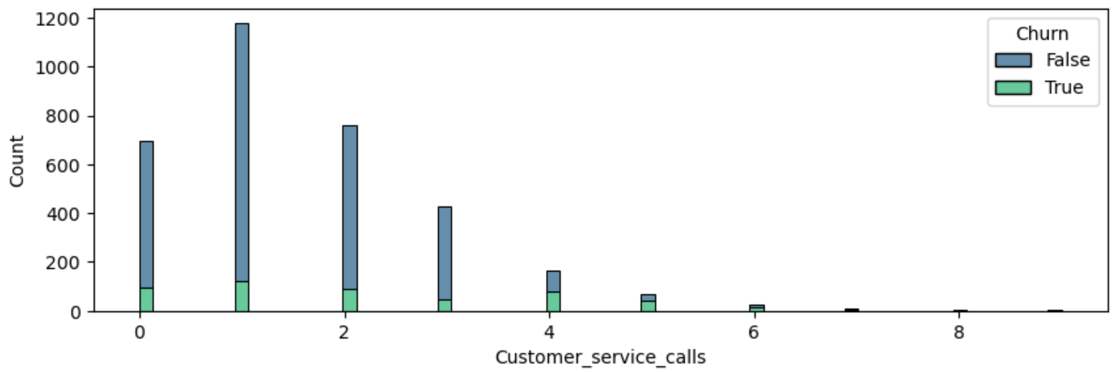
Bivarient analysis

[270]:
```
# viewing the Total charge by Total charge type
plt.figure(figsize=(10,3))
x=df[['Total_day_charge','Total_eve_charge','Total_night_charge','Total_intl_charge']].
  ↪sum().index
y=df[['Total_day_charge','Total_eve_charge','Total_night_charge','Total_intl_charge']].
  ↪sum().values

sum_df = pd.DataFrame({'Charge Type': x, 'Total Charge': y})

# Create bar plot
sns.barplot(x='Charge Type', y='Total Charge', data=sum_df,palette='viridis')

# Add labels and title
plt.xlabel('Charge Type')
plt.ylabel('Total Charge')
plt.title('Total Charges by Type')

# Show plot
plt.show()
```

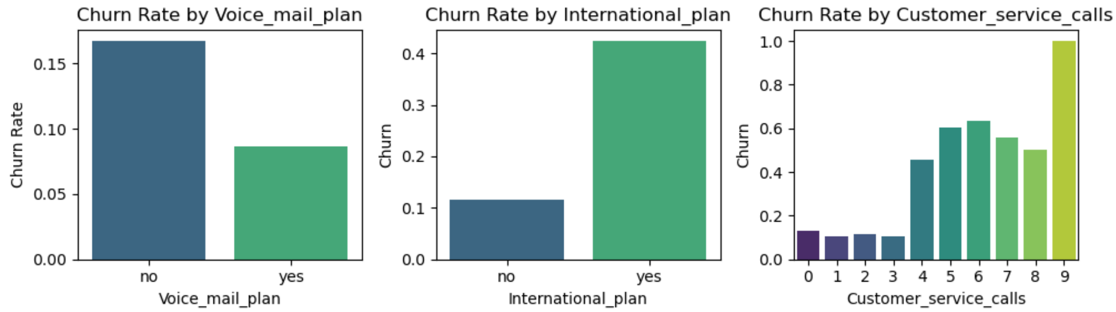


[271]:
```
# distribution of customer service calls and churning
plt.figure(figsize=(10,3))
sns.histplot(df, x='Customer_service_calls', hue='Churn',␣
  ↪multiple='stack',palette='viridis')
```

[271]: `<Axes: xlabel='Customer_service_calls', ylabel='Count'>`

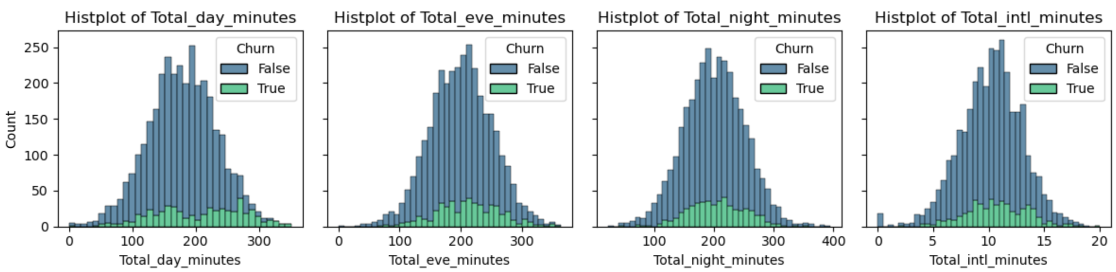



```
[272]: # Churn rate by Voice_mail_plan and International_plan
columns=['Voice_mail_plan','International_plan','Customer_service_calls']
churn_by_voice_mail_plan = df.groupby('Voice_mail_plan')['Churn'].mean().
 ↪reset_index()
fig,axes=plt.subplots(ncols=3,figsize=(10, 3),sharey=False)
sns.barplot(x='Voice_mail_plan', y='Churn', data=df.
 ↪groupby('Voice_mail_plan')['Churn'].mean().reset_index(),
 ↪palette='viridis',ax=axes[0])
sns.barplot(x='International_plan', y='Churn', data=df.
 ↪groupby('International_plan')['Churn'].mean().reset_index(),
 ↪palette='viridis',ax=axes[1])
sns.barplot(x='Customer_service_calls', y='Churn', data=df.
 ↪groupby('Customer_service_calls')['Churn'].mean().reset_index(),
 ↪palette='viridis',ax=axes[2])

axes[0].set_title('Churn Rate by Voice_mail_plan')
axes[1].set_title('Churn Rate by International_plan')
axes[2].set_title('Churn Rate by Customer_service_calls')
axes[0].set_ylabel('Churn Rate')
plt.tight_layout()
plt.show()
```



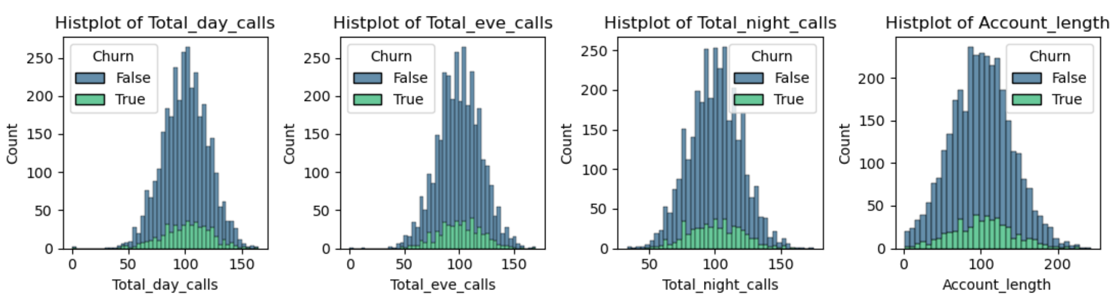
From the analysis of the customer care call, as the number of calls increases the churn rate also increases. Customers who had international plan had a high churn rate as compared to those who do not have.

[273]:
```
# Create histogram with hue
columns=['Total_day_minutes','Total_eve_minutes','Total_night_minutes','Total_intl_minutes']

fig,axes=plt.subplots(ncols=4,figsize=(12,3),sharey=True)
for i,col in enumerate(columns):
    sns.histplot(df, x=col, hue='Churn',␣
 ↪multiple='stack',ax=axes[i],palette='viridis')
    axes[i].set_title('Histplot of '+col)
plt.tight_layout()
```



All category for call minutes are all normally distrubuted.

[274]:
```
# Viewing the distribution of number of calls and churning
columns=['Total_day_calls','Total_eve_calls','Total_night_calls','Account_length']

fig,axes=plt.subplots(ncols=4,figsize=(11,3),sharey=False)
for i,col in enumerate(columns):
    sns.histplot(df, x=col, hue='Churn',␣
 ↪multiple='stack',ax=axes[i],palette='viridis')
    axes[i].set_title('Histplot of '+col)
plt.tight_layout()
plt.show()
```

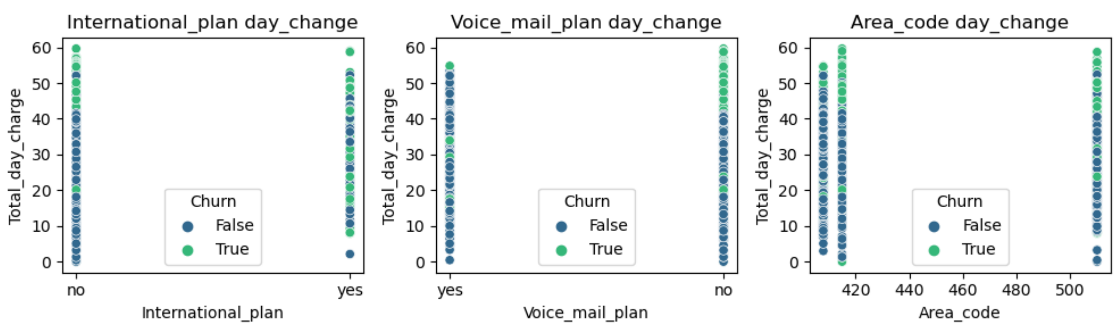


Total day calls, total evening calls and total night calls are normally distributed since they have a bell shaped curve

Highest income is generated during the day and inernational calls have the lowest income

Multivariate Analysis

[275]:
```
# visualising more than two variables
df1=df.copy()

columnsdf1=['International_plan','Voice_mail_plan','Area_code']



# Create scatter plots
fig,axes=plt.subplots(ncols=3,figsize=(10,3))
for i,col in enumerate(columnsdf1):
    sns.scatterplot(x=col, y='Total_day_charge', data=df1, palette='viridis',␣
    ↪hue='Churn',ax=axes[i])
    axes[i].set_title(col+" day_change")

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



1.3 Data Preperation

[276]:
```
# changing ['Voice_mail_plan','International_plan'] columns from object to bool
df=df.applymap(lambda x: True if x == 'yes' else (False if x == 'no' else x) )
df[['International_plan','Voice_mail_plan']].info()
```

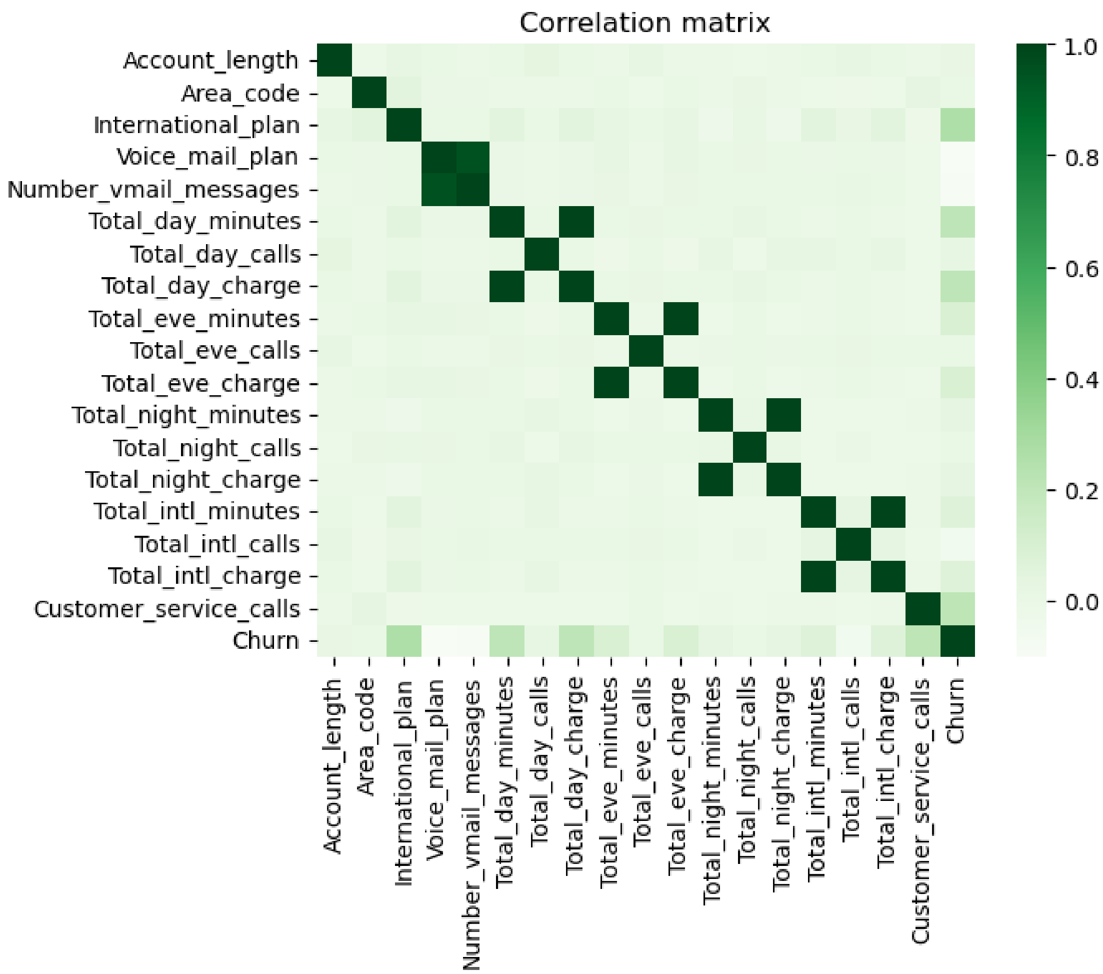
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 2 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   International_plan  3333 non-null   bool
```

```
 1   Voice_mail_plan     3333 non-null   bool
dtypes: bool(2)
memory usage: 6.6 KB
```

[277]:
```
# view the correlation between various fields and churning
con_columns=df.select_dtypes(['int','float','bool']).columns
corr=df[con_columns].corr()['Churn']
corr
```

[277]:
```
Account_length            0.016541
Area_code                 0.006174
International_plan        0.259852
Voice_mail_plan          -0.102148
Number_vmail_messages    -0.089728
Total_day_minutes         0.205151
Total_day_calls           0.018459
Total_day_charge          0.205151
Total_eve_minutes         0.092796
Total_eve_calls           0.009233
Total_eve_charge          0.092786
Total_night_minutes       0.035493
Total_night_calls         0.006141
Total_night_charge        0.035496
Total_intl_minutes        0.068239
Total_intl_calls         -0.052844
Total_intl_charge         0.068259
Customer_service_calls    0.208750
Churn                     1.000000
Name: Churn, dtype: float64
```

[278]:
```
# Viewing correlation between numeric columns and churn column
sns.heatmap(df[con_columns].corr(), cmap='Greens')
plt.title('Correlation matrix');
```



[279]:
```python
# selecting columns that have a high correlation to churning
columns=['International_plan','Total_day_minutes','Total_eve_minutes','Total_night_minutes','T
df=df[columns]
df.head()
```

[279]:
```
   International_plan  Total_day_minutes  Total_eve_minutes  \
0               False              265.1              197.4
1               False              161.6              195.5
2               False              243.4              121.2
3                True              299.4               61.9
4                True              166.7              148.3

   Total_night_minutes  Total_intl_minutes  Customer_service_calls  Churn
0                244.7                10.0                       1  False
1                254.4                13.7                       1  False
2                162.6                12.2                       0  False
```

```
3              196.9            6.6                      2  False
4              186.9           10.1                      3  False
```

1.4 Modeling

[280]:
```python
from sklearn.model_selection import train_test_split,cross_val_score, KFold,␣
 ↪GridSearchCV, cross_validate
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score,recall_score,precision_score␣
 ↪,f1_score,confusion_matrix, classification_report, ConfusionMatrixDisplay,␣
 ↪make_scorer
from sklearn.metrics import classification_report
from imblearn.over_sampling import SMOTE
```

[281]:
```python
# selecting X and y
y=df['Churn']
X=df.drop(columns='Churn',axis=1)
```

[282]:
```python
# spliting the data into Train and test
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.
 ↪25,random_state=42,stratify=y)

print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(2499, 6) (834, 6) (2499,) (834,)
```

[283]:
```python
# Standardiszing the training and test data
X_train_scaled=pd.DataFrame(scaler.fit_transform(X_train.
 ↪select_dtypes(['int','float'])),columns=X_train.
 ↪select_dtypes(['int','float']).columns,index=X_train.index)
X_test_scaled=pd.DataFrame(scaler.fit_transform(X_test.
 ↪select_dtypes(['int','float'])),columns=X_test.
 ↪select_dtypes(['int','float']).columns,index=X_test.index)
```

[284]:
```python
# selecting the bool column from the training and test data
X_train_bool=X_train.select_dtypes('bool')
X_test_bool=X_test.select_dtypes('bool')
```

[285]:
```python
# concatinating the two data frames
X_train_scaled = pd.concat([X_train_scaled, X_train_bool], axis=1)
X_test_scaled = pd.concat([X_test_scaled, X_test_bool], axis=1)
X_train_scaled.head()
```

[285]:
```
      Total_day_minutes  Total_eve_minutes  Total_night_minutes  \
556           -0.372962           2.020613             0.528564
2596          -1.064668          -1.237400             0.474135
944           -0.218020          -0.205860            -0.154825
1152           0.549313          -0.558237            -2.148546
3060           0.597271          -0.231451             3.054482

      Total_intl_minutes  Customer_service_calls  International_plan
556             0.619251               -1.202844               False
2596           -1.575545               -0.432691               False
944            -0.371947                1.877769               False
1152           -0.513547               -0.432691               False
3060           -0.655147                1.107615               False
```

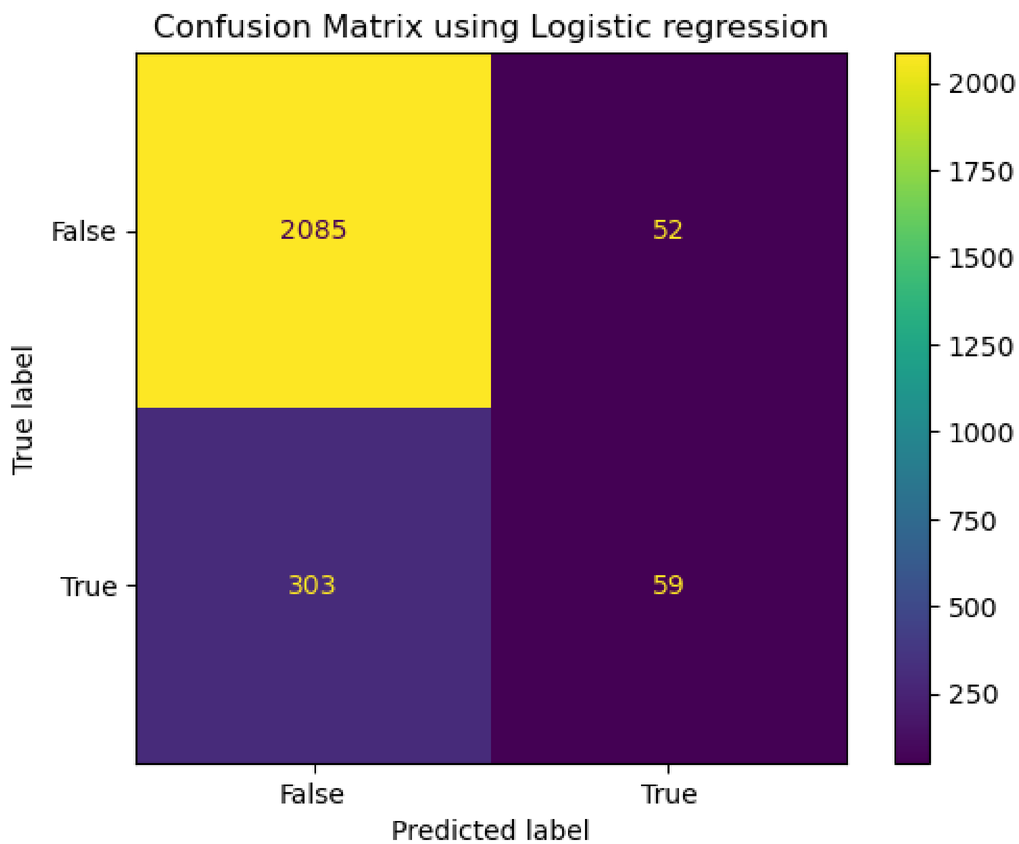
[286]:
```
model=LogisticRegression(random_state=42)
model.fit(X_train_scaled,y_train)
```

[286]:
```
LogisticRegression(random_state=42)
```

[287]:
```
y_pred=model.predict(X_test_scaled)

conf_matrix = confusion_matrix(y_test, y_pred)
conf_matrix
```

[287]:
```
array([[691,  22],
       [ 99,  22]], dtype=int64)
```

[288]:
```
# Plot confusion matrix for the training data
ConfusionMatrixDisplay.
 ↪from_estimator(estimator=model,X=X_train_scaled,y=y_train,cmap='viridis')
plt.title('Confusion Matrix using Logistic regression');
```



Model Evaluation

[289]:
```
# Performing model evaluation through Kfold cross validation
kf = KFold(n_splits=5, shuffle=True, random_state=42)

# Perform cross-validation
cv_results = cross_val_score(model, X_train_scaled, y_train, cv=kf,␣
↪scoring='accuracy')

print(f"Cross-validation accuracies: {cv_results}")
print(f"Mean cross-validation accuracy: {cv_results.mean()}")
```

```
Cross-validation accuracies: [0.848      0.886      0.826      0.862
0.85571142]
Mean cross-validation accuracy: 0.8555422845691384
```

[290]:
```
model_accuracy = cross_val_score (model,X_test_scaled, y_test, cv=3,␣
↪scoring='accuracy').mean()
model_recall = cross_val_score (model,X_test_scaled,␣
↪y_test,cv=3,scoring=make_scorer (recall_score)).mean()
```

```
model_precision = cross_val_score (model,X_test_scaled,␣
 ↪y_test,cv=3,scoring=make_scorer (precision_score)).mean()
model_f1 = cross_val_score (model,X_test_scaled,␣
 ↪y_test,cv=3,scoring=make_scorer (f1_score)).mean ()

print(f"""Logistic_Regression Scores
***************************
Accuracy: {model_accuracy:1.3f}
Recall: {model_recall:1.3f}
Precision: {model_precision:1.3f}
F1 Score: {model_f1:1.3f}
""")
```

```
Logistic_Regression Scores
***************************
Accuracy: 0.853
Recall: 0.140
Precision: 0.476
F1 Score: 0.214
```

Interpretation 85.3% of the instances were classified correctly.

14% of the actual positive instances were correctly classified as positive

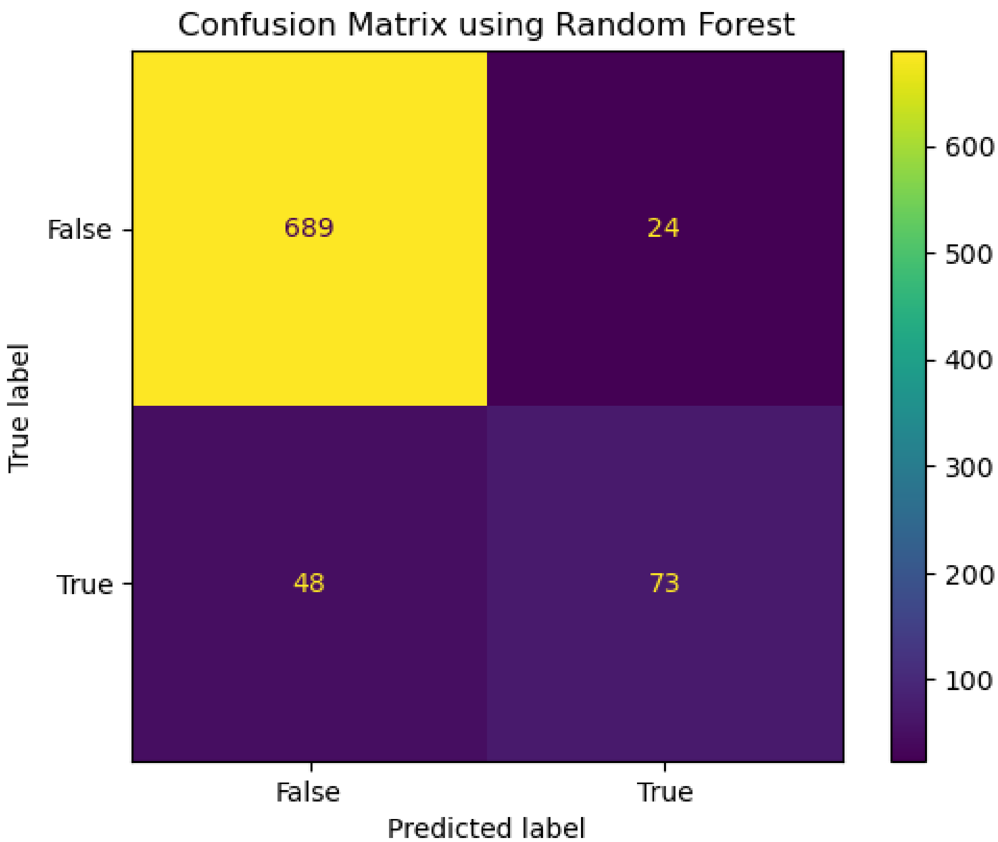
47.6% of the instances classified as positive by the model were actually positive.

[291]:
```
## building different models
def model_building(model_name):

    np.random.seed(42)

    model = model_name
    model.fit(X_train_scaled, y_train)
    print(f"{model_name}\n***************************************")

    model_accuracy = cross_val_score (model,X_test_scaled, y_test, cv=3,␣
 ↪scoring='accuracy').mean()
    model_recall = cross_val_score (model,X_test_scaled,␣
 ↪y_test,cv=3,scoring=make_scorer (recall_score)).mean()
    model_precision = cross_val_score (model,X_test_scaled,␣
 ↪y_test,cv=3,scoring=make_scorer (precision_score)).mean()
    model_f1 = cross_val_score (model,X_test_scaled,␣
 ↪y_test,cv=3,scoring=make_scorer (f1_score)).mean ()
    print(f"""
    Accuracy: {model_accuracy:1.3f}
    Recall: {model_recall:1.3f}
    Precision: {model_precision:1.3f}
```

```
    F1 Score: {model_f1:1.3f}
    """)
## dictionary with different models
model_dict = {'lr':LogisticRegression(random_state=42),
              'dt':DecisionTreeClassifier(random_state=42),
              'knn':KNeighborsClassifier(),
              'rf': RandomForestClassifier(random_state=42)}

## calling to build and evaluate models
for key in model_dict.keys():
    model_building(model_dict[key])
```

```
LogisticRegression(random_state=42)
***************************************

    Accuracy: 0.853
    Recall: 0.140
    Precision: 0.476
    F1 Score: 0.214

DecisionTreeClassifier(random_state=42)
***************************************

    Accuracy: 0.857
    Recall: 0.496
    Precision: 0.509
    F1 Score: 0.502

KNeighborsClassifier()
***************************************

    Accuracy: 0.891
    Recall: 0.331
    Precision: 0.824
    F1 Score: 0.467

RandomForestClassifier(random_state=42)
***************************************

    Accuracy: 0.900
    Recall: 0.479
    Precision: 0.764
    F1 Score: 0.581
```

[292]:
```python
# Plot confusion matrix for best model

ConfusionMatrixDisplay.
 ↪from_estimator(estimator=RandomForestClassifier(random_state=42).
 ↪fit(X_train_scaled,y_train),X=X_test_scaled,y=y_test,cmap='viridis')
plt.title('Confusion Matrix using Random Forest');
```



Hyperparameter Tuning:

[293]:
```python
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier

# Define the parameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_features': ['auto', 'sqrt', 'log2'],
    'max_depth': [10, 20, 30, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False]
```

```
}

# Create a base model
rf = RandomForestClassifier(random_state=42)

# Instantiate the grid search model
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid,
                           cv=3, n_jobs=-1, verbose=2)

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

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

# Get the best model
best_rf = grid_search.best_estimator_
```

```
Fitting 3 folds for each of 648 candidates, totalling 1944 fits
Best parameters found:  {'bootstrap': True, 'max_depth': 10, 'max_features':
'sqrt', 'min_samples_leaf': 2, 'min_samples_split': 5, 'n_estimators': 200}
```

[294]:

```
# Perform 5-fold cross-validation
cv_scores = cross_val_score(best_rf, X_train_scaled, y_train, cv=5,␣
 ↪scoring='accuracy')

# Generating the scres for the tuned model.
scoring = {
    'precision': make_scorer(precision_score),
    'recall': make_scorer(recall_score),
    'f1': make_scorer(f1_score)
}
cv_results = cross_validate(model, X_train_scaled, y_train, cv=5,␣
 ↪scoring=scoring)
precision_mean = cv_results['test_precision'].mean()
precision_std = cv_results['test_precision'].std()
recall_mean = cv_results['test_recall'].mean()
recall_std = cv_results['test_recall'].std()
f1_mean = cv_results['test_f1'].mean()
f1_std = cv_results['test_f1'].std()

print("Accuracy: ", cv_scores.mean())
print(f"Precision: {precision_mean:.3f}")
print(f"Recall: {recall_mean:.3f}")
print(f"F1 Score: {f1_mean:.3f}")
```

```
Accuracy:  0.9239703406813626
Precision: 0.501
```

```
Recall: 0.157
F1 Score: 0.238
```

After hyperparameter tuning the accuracy of the model has increased t 92.40% but all the other metrics have decreased. The original random forest model is better.

1.5 Evaluation:

Model Selection The Random Forest classifier achieved the highest accuracy among the four models. It also has the high precision, indicating a low false positive rate, and a relatively higher recall compared to the other models, suggesting better performance in identifying positive cases. The F1 score is also the highest, indicating a good balance between precision and recall.

90.0% of the instances were classified correctly.

47.9% of the actual positive instances were correctly classified as positive

76.4% of the instances classified as positive by the model were actually positive.

An F1 score of 58.1% indicates the model has moderate performance in balancing precision and recall.

Analysis Based on the available data, the key predictors of customer churn rate are:

A higher number of customer service calls may indicate dissatisfaction or issues with the service, which could lead to churn..

Customers with international plans may have different usage patterns or needs compared to those without such plans, affecting their likelihood of chuls.

High usage of daytime minutes may indicate active engagement with the service, potentially reducing the likelihoodalls.

Similar to daytime minutes, high usage of evening minutes might signify engagement with the service, potentcingy calls.

Nighttime usage patterns can also provide insights into customer behavior anal calls.

International calling behavior can be a significant factor in predicting churn, especially for customersnational call planead to churn.

Conclusion and recommedation These predictors provide valuable insights into customer behavior, usage patterns, and potential pain points that may contribute to churn. Zencom should take proactive measures to retain customers, such as targeted marketing campaigns, personalized offers, or improving customer service experiences.