customer_churn_prediction_model

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1 SyriaTel Customer Churn Prediction Project

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1.1 1.0) Project Overview

Customer churn is a major problem for businesses, especially in the telecommunication industry, where customers can easily switch from one service provider to another. Customer churn refers to the loss of customers who stop using a company's products or services. A high churn rate can have negative impacts on a company's revenue, profitability, and growth.

SyriaTel is a company that provides mobile phone and data services. The company was established in 2000 and has its headquarters in Damascus, Syrian Arab Republic.SyriaTel operates in the US and Syrian Arab Republic. The company wants to reduce its customer churn rate and retain its loyal customers. To do this, the company needs to identify the factors that influence customer churn and predict which customers are likely to leave in the near future.

1.2 1.1) Business Problem

The problem statement for predicting customer churn at SyriaTel is as follows:

Given a set of customer data, develop a Python classifier model that can accurately predict which customers are likely to churn.

This model can be used by SyriaTel to identify customers at risk of churning and to implement interventions to prevent them from leaving

1.3 1.2) Objectives

- **Develop a Churn Prediction Model**: The primary objective is to create an accurate machine learning model that can predict customer churn at Syriatel based on historical data. This model should provide a reliable indication of which customers are likely to churn in the near future.
- **Identify Key Churn Drivers**: Determine the key factors and customer behaviors that contribute to churn. Understanding why customers leave is crucial for developing effective retention strategies.
- **Implement Proactive Customer Retention**: Utilize the model's predictions to implement proactive customer retention strategies. These strategies should be tailored to the specific needs and risk factors of individual customers.

- **Reduce Churn Rate**: Ultimately, the goal is to reduce the churn rate at SyriaTel. By effectively using the churn prediction model and implementing retention strategies, the company should be able to retain a higher percentage of its customer base.

1.4 1.3) Metric of Success

The project will be considered successful if below are achieved:

- **Prediction Accuracy**: The accuracy of the churn prediction model is a fundamental metric of success. This should be measured by assessing the model's ability to correctly classify customers as churners or non-churners. Common evaluation metrics include accuracy, precision, recall, and F1-score.
- **Feature Importance**: Understanding which features or variables are the most influential in predicting churn is crucial. Analyzing feature importance can help SyriaTel focus on the key drivers of customer churn.
- **Reduction in Churn Rate**: The success of the project should be reflected in a measurable reduction in the churn rate compared to the period before the model's implementation. A lower churn rate indicates that the proactive retention strategies are effective.
- **Model Scalability**: If the model proves successful, consider how easily it can be scaled to handle a larger volume of customers and data. Scalability is essential for long-term success.
- **Timely Implementation**: Evaluate how quickly the churn prediction model and associated retention strategies can be implemented to address customer churn issues in a timely manner.

1.5 1.4) Understanding Data

The data for this project will be obtained from Kaggle. The dataset has the following variables:

- `state`: The state in which the customer lives.
- `account length`: The number of days the customer has had an account.
- `area code`: The area code of the customer's phone number.
- `phone number`: The customer's phone number.
- `international plan`: Whether or not the customer has an international calling plan.
- `voice mail plan`: Whether or not the customer has a voice mail plan.
- `number vmail messages`: The number of voicemail messages the customer has sent.
- `total day minutes`: The total number of minutes the customer has spent 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 the customer was charged by the telecom company for calls during the day.
- `total eve minutes`: The total number of minutes the customer has spent 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 the customer was charged by the telecom company for calls during the evening.

- `total night minutes`: The total number of minutes the customer has spent 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 the customer was charged by the telecom company for calls during the night.
- `total intl minutes`: The total number of minutes the customer has spent in international calls.
- `total intl calls`: The total number of international calls the customer has made.
- `total intl charge`: The total amount of money the customer was charged by the telecom company for international calls.
- `customer service calls`: The number of calls the customer has made to customer service.
- `churn`: Whether or not the customer terminated their contract.

1.6 1.5) Data Relevance and Validation

The data available is relevant for the intended modelling.

1.7 2.0) Reading and Understanding the Data

[ ]:
```
# importing necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
from scipy import stats
from sklearn.feature_selection import SelectFromModel
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪GridSearchCV
from sklearn.preprocessing import LabelEncoder, StandardScaler, MinMaxScaler,␣
↪OneHotEncoder
from sklearn.metrics import␣
↪accuracy_score,f1_score,recall_score,precision_score,confusion_matrix,␣
↪roc_curve,roc_auc_score,classification_report,confusion_matrix,␣
↪ConfusionMatrixDisplay, auc
from sklearn.ensemble import RandomForestClassifier,␣
↪GradientBoostingClassifier, BaggingClassifier, AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from imblearn.over_sampling import ADASYN, SMOTE
```

[ ]:
```
# reading the data
data = pd.read_csv('./data/bigml_59c28831336c6604c800002a.csv')
# setting the maximum number of columns that will be displayed
pd.set_option('display.max_columns',21)
data.head()
```

[ ]:
```
  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 minutes  total eve calls  total eve charge  \
0             45.07              197.4               99             16.78
1             27.47              195.5              103             16.62
2             41.38              121.2              110             10.30
3             50.90               61.9               88              5.26
4             28.34              148.3              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
```

[ ]:
```
data.tail()
```

[ ]:
```
     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 minutes  total eve calls  \
3328               77             26.55              215.5              126
3329               57             39.29              153.4               55
3330              109             30.74              288.8               58
3331              105             36.35              159.6               84
3332              113             39.85              265.9               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
```

1.8 2.1) Data Cleaning

[ ]:
```
data.shape
```

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

[ ]:
```
data.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')
```

[ ]:
```
# Renaming columns
data.rename(columns=lambda x: x.replace(' ', '_'), inplace=True)
data.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
```

[ ]:
```python
data.describe(include = 'all')
```

[ ]:
```
       state  account_length    area_code phone_number international_plan  \
count   3333     3333.000000  3333.000000         3333               3333
unique    51             NaN          NaN         3333                  2
top       WV             NaN          NaN     337-4101                 no
freq     106             NaN          NaN            1               3010
mean     NaN      101.064806   437.182418          NaN                NaN
std      NaN       39.822106    42.371290          NaN                NaN
min      NaN        1.000000   408.000000          NaN                NaN
25%      NaN       74.000000   408.000000          NaN                NaN
50%      NaN      101.000000   415.000000          NaN                NaN
75%      NaN      127.000000   510.000000          NaN                NaN
max      NaN      243.000000   510.000000          NaN                NaN

       voice_mail_plan  number_vmail_messages  total_day_minutes  \
count             3333            3333.000000        3333.000000
unique               2                    NaN                NaN
top                 no                    NaN                NaN
freq              2411                    NaN                NaN
mean               NaN               8.099010         179.775098
std                NaN              13.688365          54.467389
min                NaN               0.000000           0.000000
25%                NaN               0.000000         143.700000
50%                NaN               0.000000         179.400000
75%                NaN              20.000000         216.400000
max                NaN              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
unique              NaN               NaN                NaN              NaN
top                 NaN               NaN                NaN              NaN
freq                NaN               NaN                NaN              NaN
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
unique               NaN                  NaN                NaN
top                  NaN                  NaN                NaN
freq                 NaN                  NaN                NaN
```

```
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
unique                 NaN                 NaN               NaN
top                    NaN                 NaN               NaN
freq                   NaN                 NaN               NaN
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  churn
count         3333.000000             3333.000000   3333
unique                NaN                     NaN      2
top                   NaN                     NaN  False
freq                  NaN                     NaN   2850
mean             2.764581                1.562856    NaN
std              0.753773                1.315491    NaN
min              0.000000                0.000000    NaN
25%              2.300000                1.000000    NaN
50%              2.780000                1.000000    NaN
75%              3.270000                2.000000    NaN
max              5.400000                9.000000    NaN
```

[ ]:
```
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
```

Observation: there are no missing values

[ ]:
```
data.duplicated().sum()
```

[ ]:
```
0
```

[ ]:
```
# Feature engineering

# Adding total calls and total minutes
data['total_calls'] = data['total_day_calls'] + data['total_eve_calls'] +␣
 ↪data['total_night_calls'] \
    + data['total_intl_calls']
data['total_minutes'] = data['total_day_minutes'] + data['total_eve_minutes'] +␣
 ↪data['total_night_minutes'] \
    + data['total_intl_minutes']
```

Observation: there are no duplicated records

1.9 2.2) Analysis

[ ]:
```
# Checking numeric variables
# Selecting all numeric columns (int and float)
numeric_columns = data.select_dtypes(include=['int64', 'float64'])

# Getting the list of numeric column names
numeric_column_names = numeric_columns.columns.tolist()
numeric_column_names
```

[ ]:
```
['account_length',
 'area_code',
 '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',
```

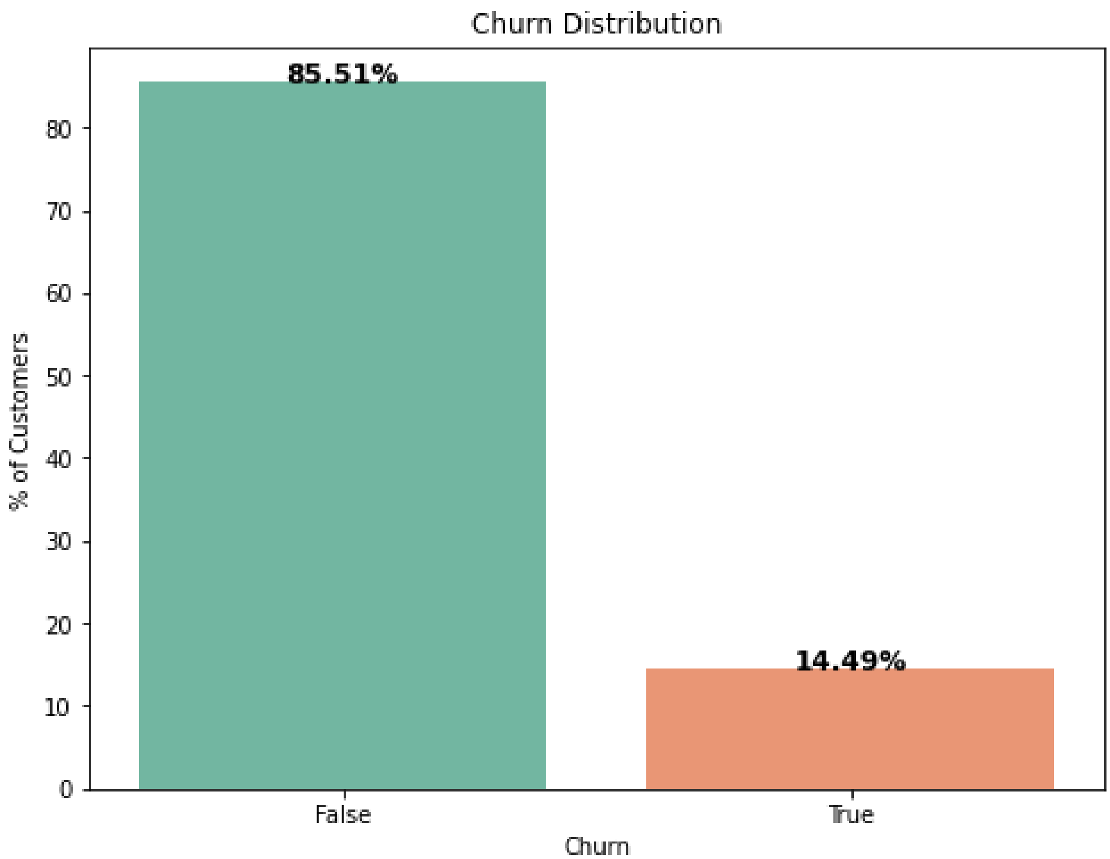
```
 'total_night_charge',
 'total_intl_minutes',
 'total_intl_calls',
 'total_intl_charge',
 'customer_service_calls',
 'total_calls',
 'total_minutes']
```

[ ]:
```
# Checking categorical variables
# Selecting all non-numeric columns (object, bool)
non_numeric_columns = data.select_dtypes(include=['object','bool'])

# Getting the list of non-numeric columns names
non_numeric_column_names = non_numeric_columns.columns.tolist()
non_numeric_column_names
```

[ ]:
```
['state', 'phone_number', 'international_plan', 'voice_mail_plan', 'churn']
```

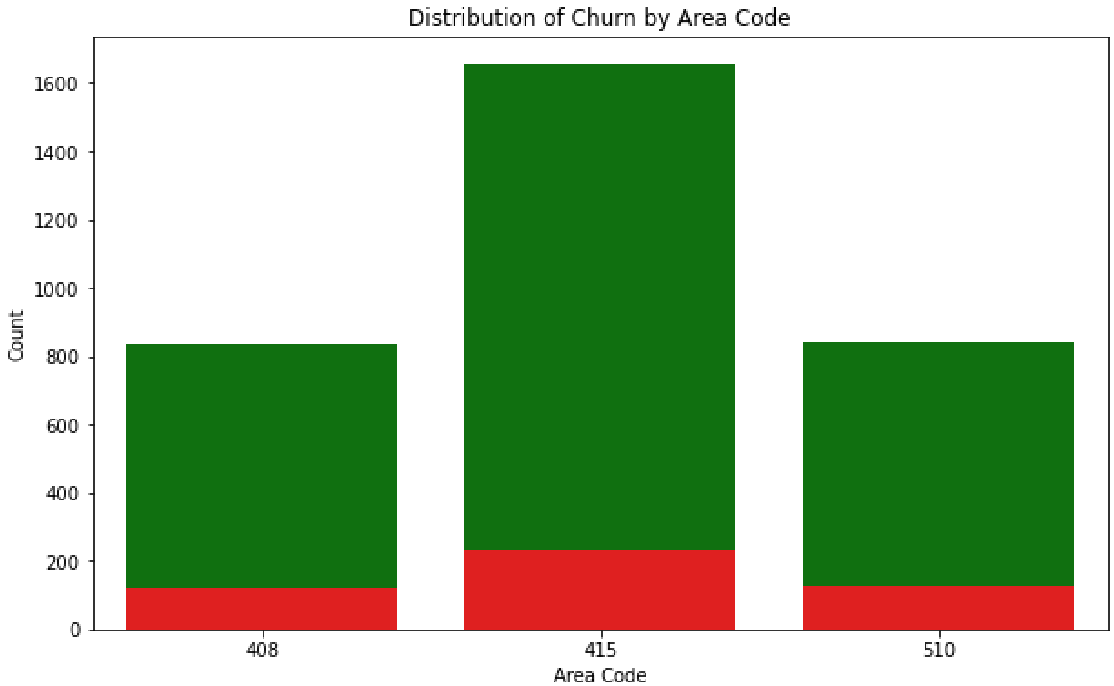
[ ]:
```
# Understanding churn feature

# Calculate and display churn value counts

churn_counts = data.churn.value_counts()
print(churn_counts)

# Calculate churn distribution as percentages
churn_perc = (churn_counts / len(data)) * 100

# Create a bar plot
plt.figure(figsize=(8, 6))
ax = sns.barplot(x=churn_perc.index, y=churn_perc, palette="Set2")
ax.set_xlabel('Churn')
ax.set_ylabel('% of Customers')
ax.set_title('Churn Distribution')

# Add percentage labels on top of the bars
for p in ax.patches:
    width, height = p.get_width(), p.get_height()
    x, y = p.get_x() + width / 2, p.get_y() + height
    ax.annotate(f'{height:.2f}%', (x, y), ha='center', color='black',␣
 ↪weight='bold', size=12)

plt.show()
```

```
False    2850
True      483
Name: churn, dtype: int64
```



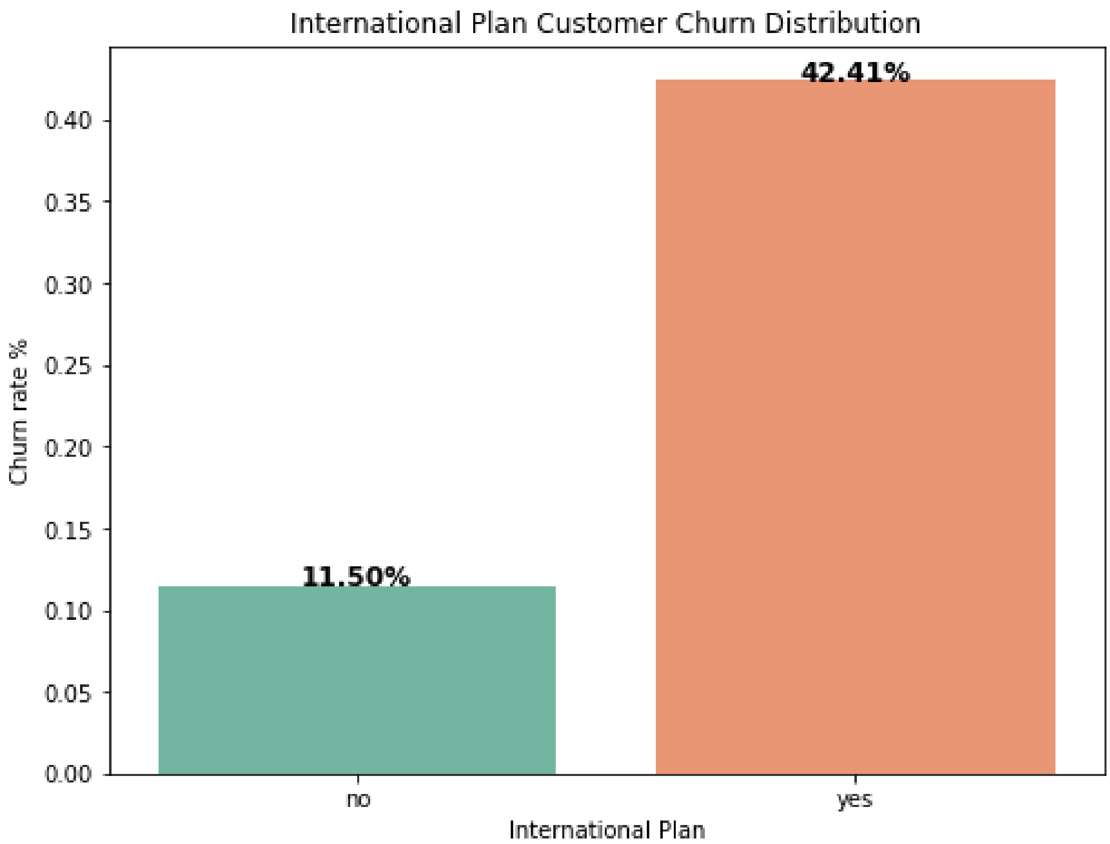
Observation: The variables have outliers but for our model we will use the data as is without correcting for outliers to maintain robustness of the model and maintain distribution characteristics.

[ ]:
```
# Calculating the distribution of the "area code" feature for churned and␣
↪non-churned customers

area_counts = data.groupby(['area_code', 'churn']).size().unstack()

# Create a bar plot
plt.figure(figsize=(10, 6))
sns.barplot(x=area_counts.index, y=area_counts[True], label='Churned',␣
↪color='red')
sns.barplot(x=area_counts.index, y=area_counts[False], label='Not Churned',␣
↪color='green', bottom=area_counts[True])
plt.title('Distribution of Churn by Area Code')
plt.xlabel('Area Code')
plt.ylabel('Count')
plt.show()
```



Observation: customer churn is a consistent across all three area codes. Area code 415 has the highest number of customers but still churns the same rate as the other two area codes.

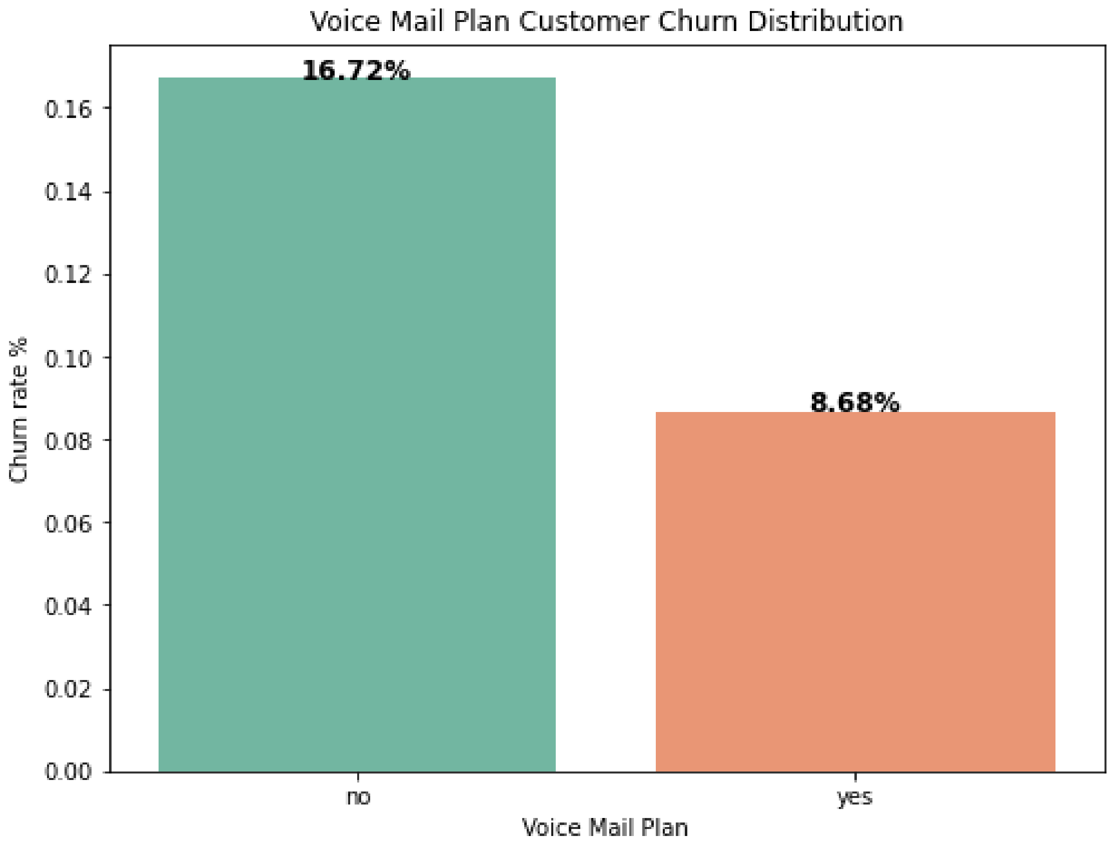
```
[ ]: # Calculating the distribution of the "international_plan" feature for churned␣
     ↪and non-churned customers

     intn_plan_churn = data.groupby(['international_plan'])['churn'].mean()

     # Create a bar plot
     plt.figure(figsize=(8, 6))
     ax = sns.barplot(x=intn_plan_churn.index, y=intn_plan_churn, palette="Set2")
     ax.set_xlabel('International Plan')
     ax.set_ylabel('Churn rate %')
     ax.set_title('International Plan Customer Churn Distribution')

     # Add percentage labels on top of the bars
     for p in ax.patches:
         width, height = p.get_width(), p.get_height()
         x, y = p.get_x() + width / 2, p.get_y() + height
         ax.annotate(f'{height * 100:.2f}%', (x, y), ha='center', color='black',␣
     ↪weight='bold', size=12)

     plt.show()
```



Observation: international plan customers have high churn rates of 42%

[ ]:
```
# Calculating the distribution of the "international_plan" feature for churned␣
↪and non-churned customers

voice_m_plan_churn = data.groupby(['voice_mail_plan'])['churn'].mean()

# Creating a bar plot
plt.figure(figsize=(8, 6))
ax = sns.barplot(x=voice_m_plan_churn.index, y=voice_m_plan_churn,␣
↪palette="Set2")
ax.set_xlabel('Voice Mail Plan')
ax.set_ylabel('Churn rate %')
ax.set_title('Voice Mail Plan Customer Churn Distribution')

# Adding percentage labels on top of the bars
for p in ax.patches:
    width, height = p.get_width(), p.get_height()
    x, y = p.get_x() + width / 2, p.get_y() + height
    ax.annotate(f'{height * 100:.2f}%', (x, y), ha='center', color='black',␣
↪weight='bold', size=12)
```

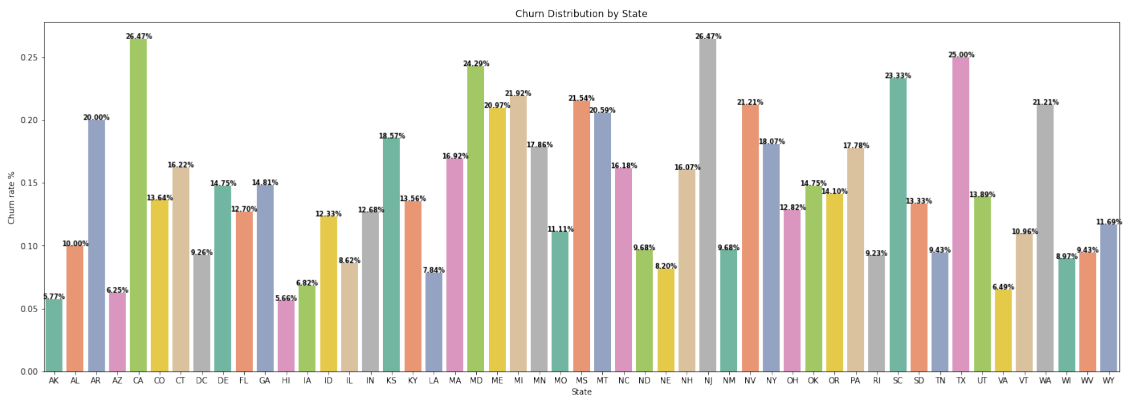
```
plt.show()
```



Observation: voice mail plan churn low

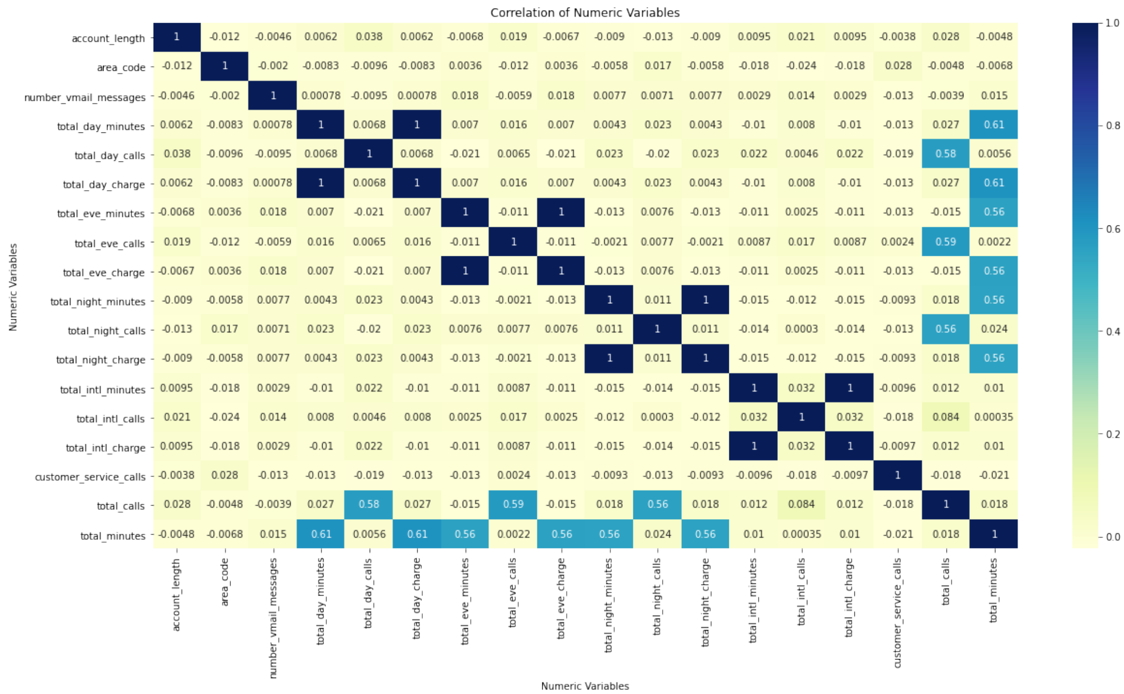
[ ]:
```
# Calculating the distribution of the "state" feature for churned and␣
↪non-churned customers

state_churn = data.groupby(['state'])['churn'].mean()

# Creating a bar plot
plt.figure(figsize=(24, 8))
ax = sns.barplot(x=state_churn.index, y=state_churn, palette="Set2")
ax.set_xlabel('State')
ax.set_ylabel('Churn rate %')
ax.set_title('Churn Distribution by State')

# Adding percentage labels on top of the bars
for p in ax.patches:
    width, height = p.get_width(), p.get_height()
    x, y = p.get_x() + width / 2, p.get_y() + height
```

```
    ax.annotate(f'{height * 100:.2f}%', (x, y), ha='center', color='black',␣
↪weight='bold', size=8)

plt.show()
```



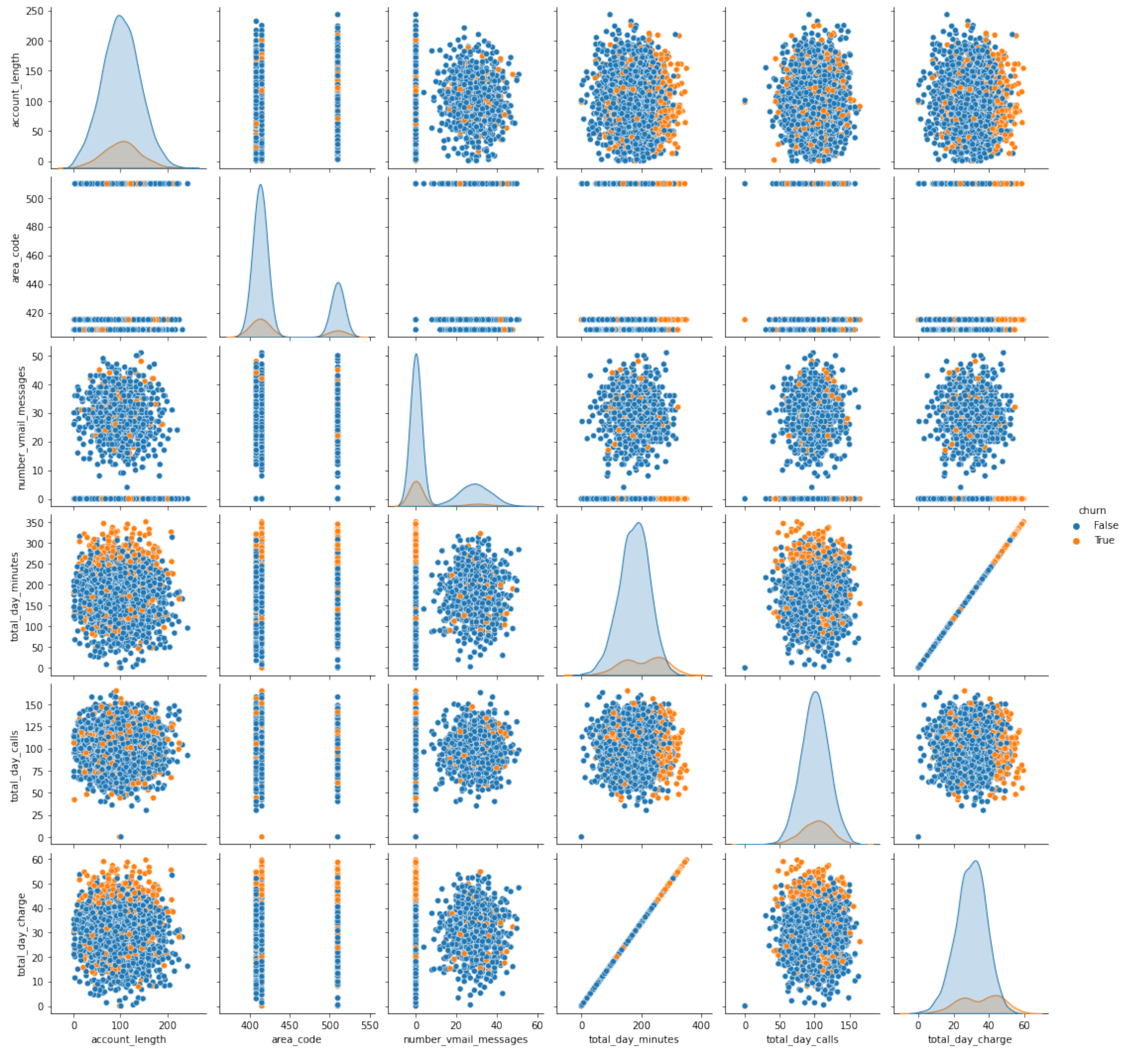
Observation: churn is almost the same in all states so has low to no impact

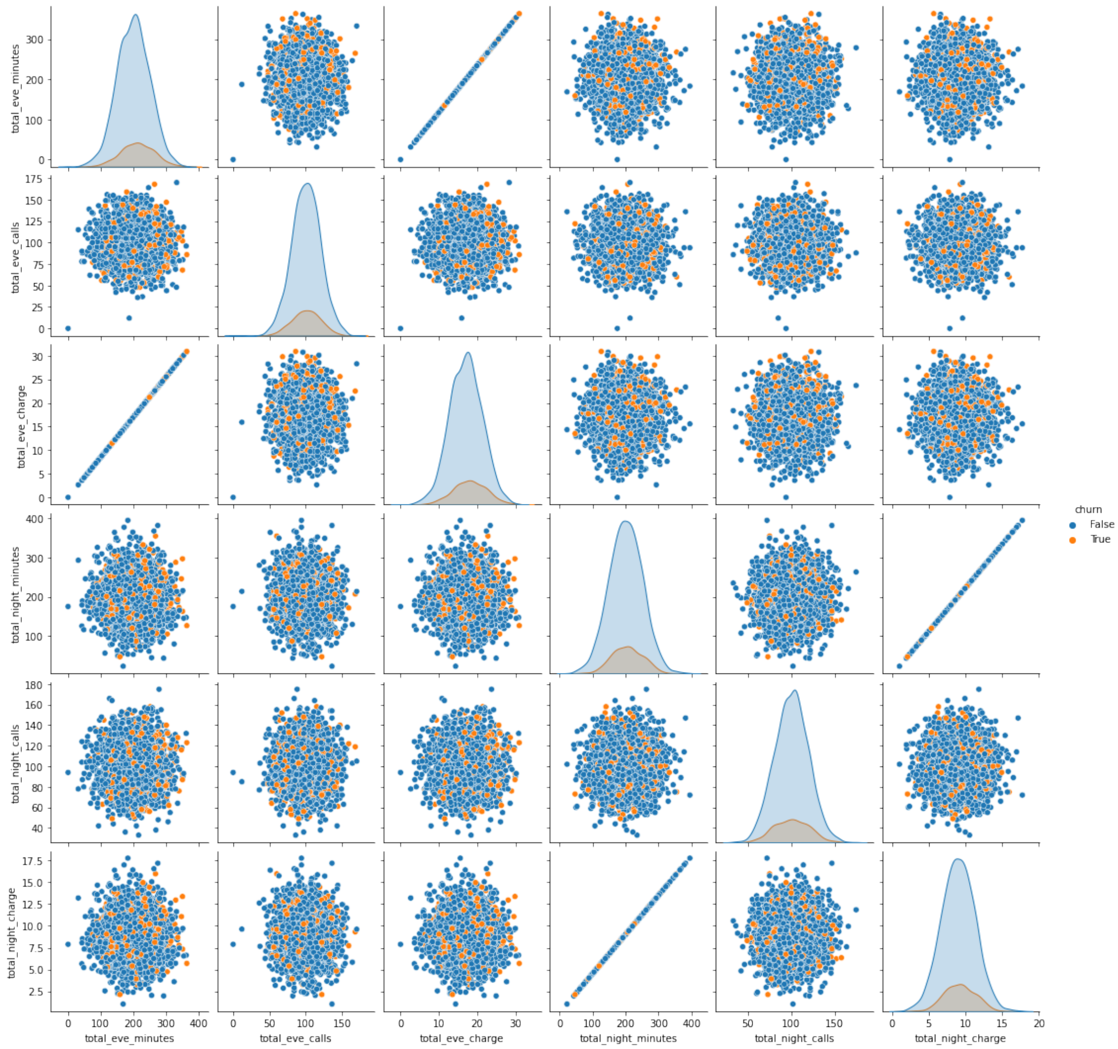
[ ]:
```
# Calculating the correlation matrix of Numeric features
correlation_matrix = data[numeric_column_names].corr()

# Creating a heatmap
plt.figure(figsize=(20, 10))
sns.heatmap(correlation_matrix, annot=True, cmap="YlGnBu")

# Set labels and title
plt.xlabel("Numeric Variables")
plt.ylabel("Numeric Variables")
plt.title("Correlation of Numeric Variables")

# Showing the heatmap
plt.show()
```

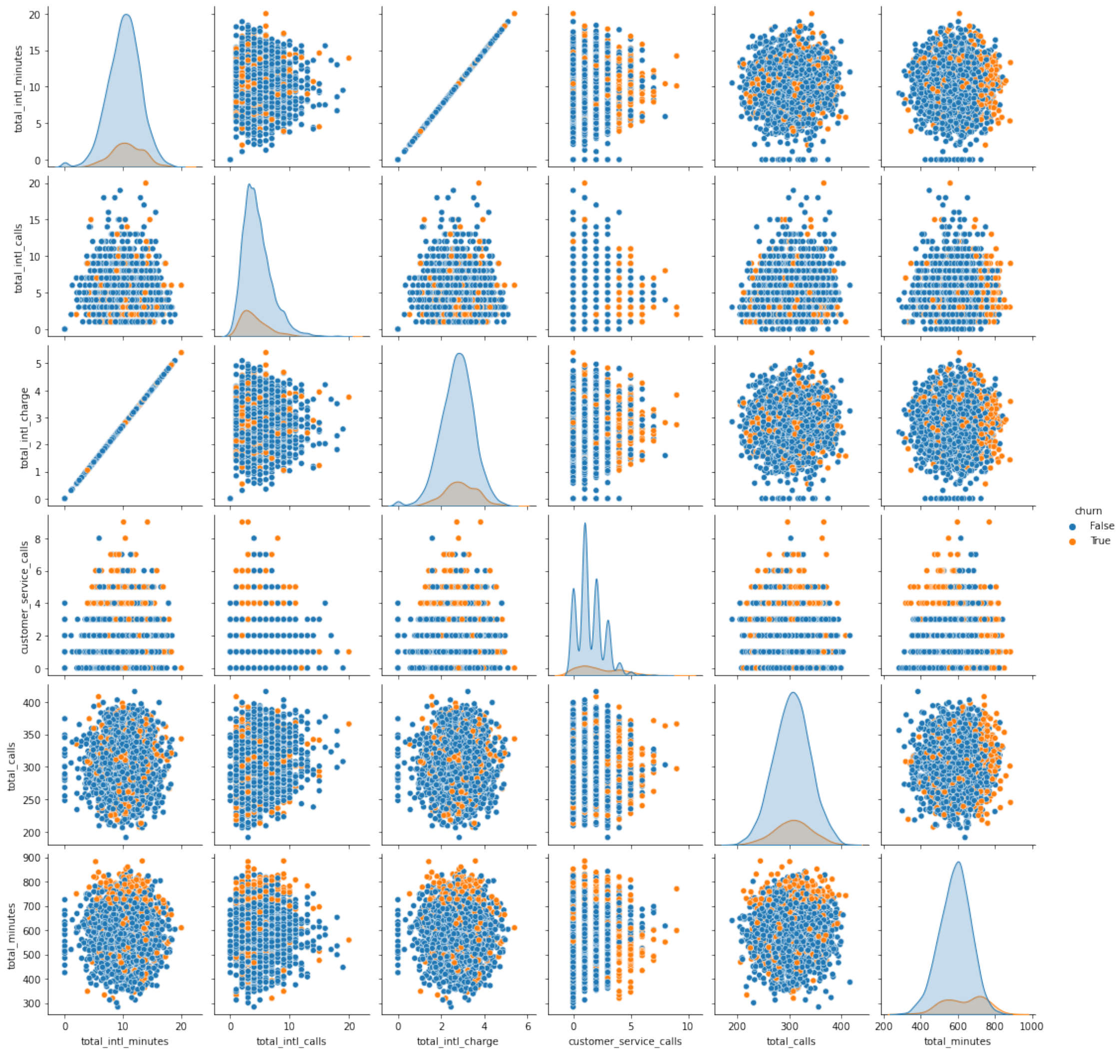


observation: some features are highly correlated with correlation of 1 such as total_night_minutes and total_night_charge. This makes sense as charges are based on talk time. This implies multicollinearity. This has a little of impact on non-linear models.

[ ]:
```python
# Creating pair plots of numeric features

# variables to show in each pair plot
variables_per_plot = 6

# Spliting numeric_column_names into subsets for pair plots
subsets = [numeric_column_names[i:i + variables_per_plot] for i in range(0,␣
↪len(numeric_column_names), variables_per_plot)]

# Create a pair plot for each subset
for subset in subsets:
    pair_plot = sns.pairplot(data, vars=subset, hue="churn", height=2.5)
    plt.show()
```

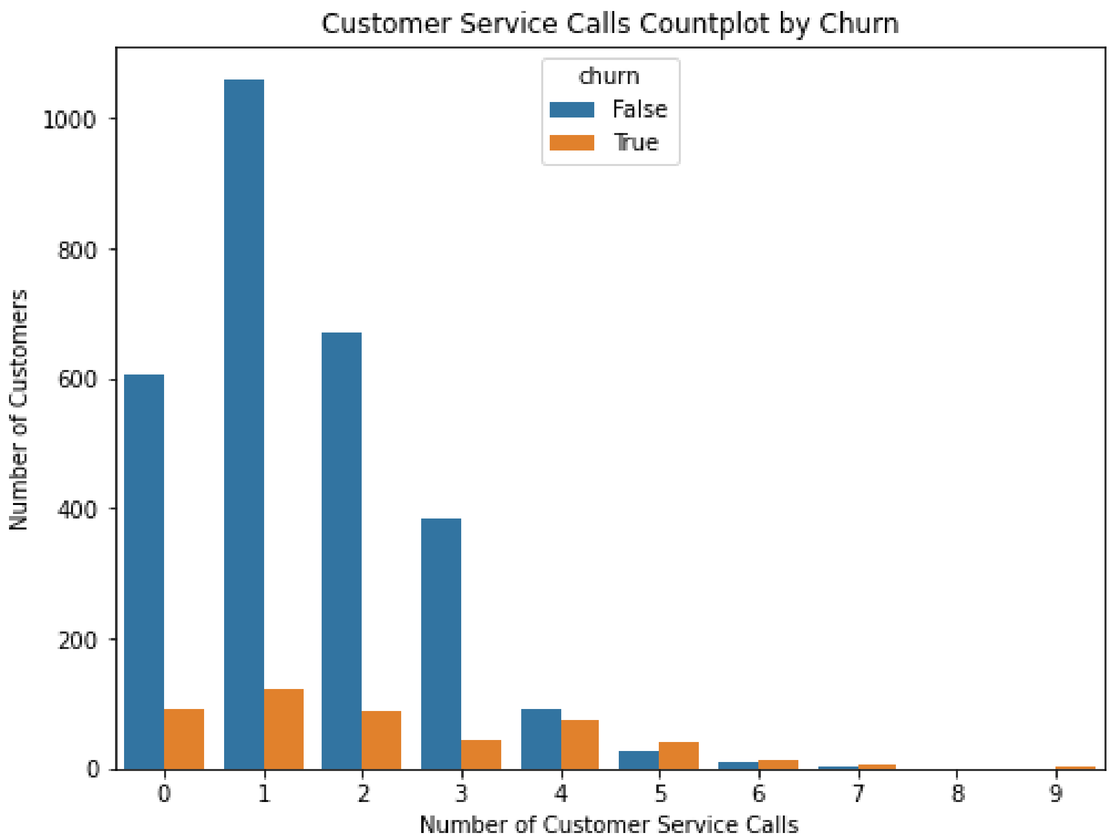

account_length
area_code
number_vmail_messages
total_day_minutes
total_day_calls
total_day_charge
churn
False
True


total_eve_minutes
total_eve_calls
total_eve_charge
total_night_minutes
total_night_calls
total_night_charge
churn
False
True



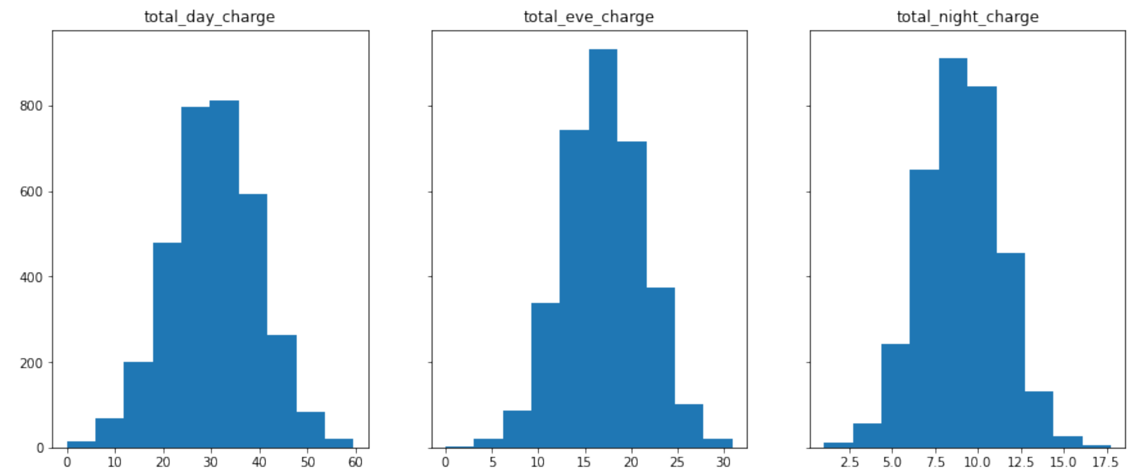
Observation: more customer service calls seem to lead to more customers leaving

[ ]:
```
# Understanding customer service calls and churn

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

sns.countplot(data=data, x='customer_service_calls', hue='churn')

# Set labels and title
plt.xlabel("Number of Customer Service Calls")
plt.ylabel("Number of Customers")
plt.title("Customer Service Calls Countplot by Churn")

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



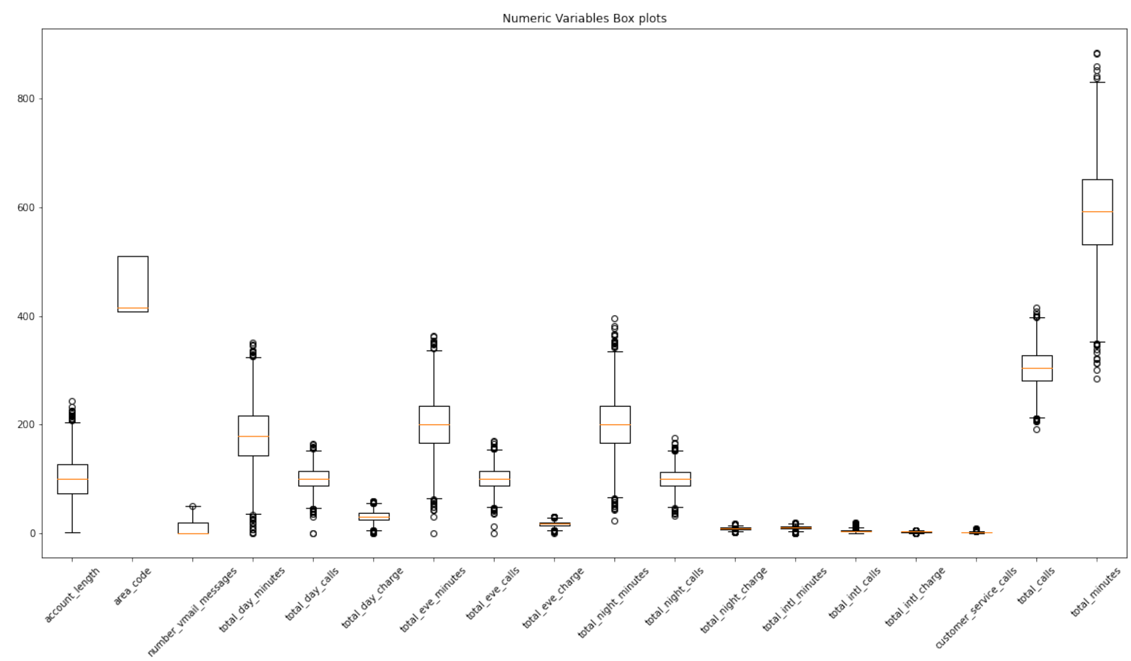
Observation: customer service calls above 4 are leading to a higher churn rate

[ ]:
```
#Understanding service charges
columns_of_interest = ['total_day_charge', 'total_eve_charge',␣
↪'total_night_charge']

# Creating subplots with shared y-axis
fig, axs = plt.subplots(1, len(columns_of_interest), figsize=(15, 6),␣
↪sharey=True)

# Creating histograms for each column
for i, column in enumerate(columns_of_interest):
    axs[i].hist(data[column])
    axs[i].set_title(column)

# Showing the histograms
plt.show()
```



Observation: the variables are normally distributed

[ ]:
```
# Creating a box plot
plt.figure(figsize=(20, 10))
plt.boxplot(data[numeric_column_names].values, labels=numeric_column_names)
plt.title("Numeric Variables Box plots")

# Rotating x-axis labels for readability
plt.xticks(rotation=45)

# Showing the box plots
plt.show()
```



1.10 2.3) Building Models

1.10.1 2.3.1) Data preparation

[ ]:
```python
# Dividing the data into features and target variable
X = data.drop(['churn', 'phone_number'], axis=1)
y = data['churn']
```

Phone number is dropped since it has many categories and is not relevant in the model. A phone number would most likely not determine whether a customer leaves or not.

[ ]:
```python
predictors = list(X.columns)
predictors
```

[ ]:
```
['state',
 'account_length',
 'area_code',
 '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',
 'total_calls',
 'total_minutes']
```

[ ]:
```python
# Spliting the data into training and test sets

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

[ ]:
```python
X_test.head()
```

[ ]:
```
     state  account_length  area_code international_plan voice_mail_plan  \
438     WY             113        510                 no              no
2674    IL              67        415                 no              no
1345    SD              98        415                 no              no
1957    KY             147        408                 no              no
```

```
2148    WY              96        408                 no               no

      number_vmail_messages  total_day_minutes  total_day_calls  \
438                       0              155.0               93
2674                      0              109.1              117
1345                      0                0.0                0
1957                      0              212.8               79
2148                      0              144.0              102

      total_day_charge  total_eve_minutes  total_eve_calls  total_eve_charge  \
438              26.35              330.6              106             28.10
2674             18.55              217.4              124             18.48
1345              0.00              159.6              130             13.57
1957             36.18              204.1               91             17.35
2148             24.48              224.7               73             19.10

      total_night_minutes  total_night_calls  total_night_charge  \
438                 189.4                123                8.52
2674                188.4                141                8.48
1345                167.1                 88                7.52
1957                156.2                113                7.03
2148                227.7                 91               10.25

      total_intl_minutes  total_intl_calls  total_intl_charge  \
438                 13.5                 3               3.65
2674                12.8                 6               3.46
1345                 6.8                 1               1.84
1957                10.2                 2               2.75
2148                10.0                 7               2.70

      customer_service_calls  total_calls  total_minutes
438                        1          325          688.5
2674                       0          388          527.7
1345                       4          219          333.5
1957                       1          285          583.3
2148                       1          273          606.4
```

[ ]:
```
# Preprocessing the data

# Checking and selecting categorical variables
obj_train_columns = X_train.select_dtypes(include=['object', 'bool']).
 ↪drop('state', axis=1)
obj_train_list = obj_train_columns.columns.tolist()

# One-hot encoding 'state'
ohe = OneHotEncoder(sparse=False, handle_unknown="ignore")
```

```
# Fitting and transforming on ohe on train data
train_state_encoded = ohe.fit_transform(X_train[["state"]])
# Creating custom column names for one-hot encoded feature
col_names = [f"state_{state}" for state in ohe.categories_[0]]
train_state_encoded = pd.DataFrame(train_state_encoded, index=X_train.index,␣
↪columns=col_names)
X_train = pd.concat([X_train.drop("state", axis=1), train_state_encoded],␣
↪axis=1)

# Transforming on test data
test_state_encoded = ohe.transform(X_test[["state"]])
test_state_encoded = pd.DataFrame(test_state_encoded, index=X_test.index,␣
↪columns=col_names)
X_test = pd.concat([X_test.drop("state", axis=1), test_state_encoded], axis=1)

# One-hot encoding 'area_code'

# Fitting and transforming on ohe on train data
train_area_code_encoded = ohe.fit_transform(X_train[["area_code"]])
# Creating custom column names for one-hot encoded feature
col_names = [f"area_code_{code}" for code in ohe.categories_[0]]
train_area_code_encoded = pd.DataFrame(train_area_code_encoded, index=X_train.
↪index, columns=col_names)
X_train = pd.concat([X_train.drop("area_code", axis=1),␣
↪train_area_code_encoded], axis=1)

# Transforming on test data
test_area_code_encoded = ohe.transform(X_test[["area_code"]])
test_area_code_encoded = pd.DataFrame(test_area_code_encoded, index=X_test.
↪index, columns=col_names)
X_test = pd.concat([X_test.drop("area_code", axis=1), test_area_code_encoded],␣
↪axis=1)

# Label encoding for other categorical variables
label_encoders = {}
for feat in obj_train_list:
    le = LabelEncoder()
    X_train[feat] = le.fit_transform(X_train[feat])
    X_test[feat] = le.transform(X_test[feat])
    label_encoders[feat] = le

# Label encoding for target variable
y_encoder = LabelEncoder()
y_train = y_encoder.fit_transform(y_train)
y_test = y_encoder.transform(y_test)
```

```
# Scaling the data
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
# Creating a MinMaxScaler instance
scaler = MinMaxScaler()

# Geting the numeric columns of train data
numeric_columns = X_train.select_dtypes(include=['int64', 'float64']).columns

# Scaling the numeric columns of train data
X_train[numeric_columns] = scaler.fit_transform(X_train[numeric_columns])

# Geting the numeric columns of test data
numeric_columns_test = X_test.select_dtypes(include=['int64', 'float64']).
 ↪columns

# Scaling the numeric columns of test data
X_test[numeric_columns_test] = scaler.
 ↪fit_transform(X_test[numeric_columns_test])
```

[ ]:
```
# Calculating the class distribution in the training set
unique, counts = np.unique(y_train, return_counts=True)
class_distribution_train = dict(zip(unique, counts))

print("Class Distribution in Training Set:")
for class_label, count in class_distribution_train.items():
    print(f"Class {class_label}: {count} samples")

# Calculating the class distribution in the testing set
unique, counts = np.unique(y_test, return_counts=True)
class_distribution_test = dict(zip(unique, counts))

print("\nClass Distribution in Testing Set:")
for class_label, count in class_distribution_test.items():
    print(f"Class {class_label}: {count} samples")
```

```
Class Distribution in Training Set:
Class 0: 2284 samples
Class 1: 382 samples

Class Distribution in Testing Set:
Class 0: 566 samples
Class 1: 101 samples
```

Observation: the data still has class imbalance. SMOTE technique should be applied to resolve the unbalanced response variable.

[ ]:
```
# Performing SMOTE

# Previous original class distribution
unique, counts = np.unique(y_train, return_counts=True)
class_distribution_train = dict(zip(unique, counts))

print("Class Distribution in Training Set:")
for class_label, count in class_distribution_train.items():
    print(f"Class {class_label}: {count} samples")

# Fit SMOTE to training data
X_train_resampled, y_train_resampled = SMOTE().fit_resample(X_train, y_train)

# Preview synthetic sample class distribution
print('\n')
unique, counts = np.unique(y_train_resampled, return_counts=True)
class_distribution_train_resampled = dict(zip(unique, counts))

print("Class Distribution in Resampled Training Set:")
for class_label, count in class_distribution_train_resampled.items():
    print(f"Class {class_label}: {count} samples")
```

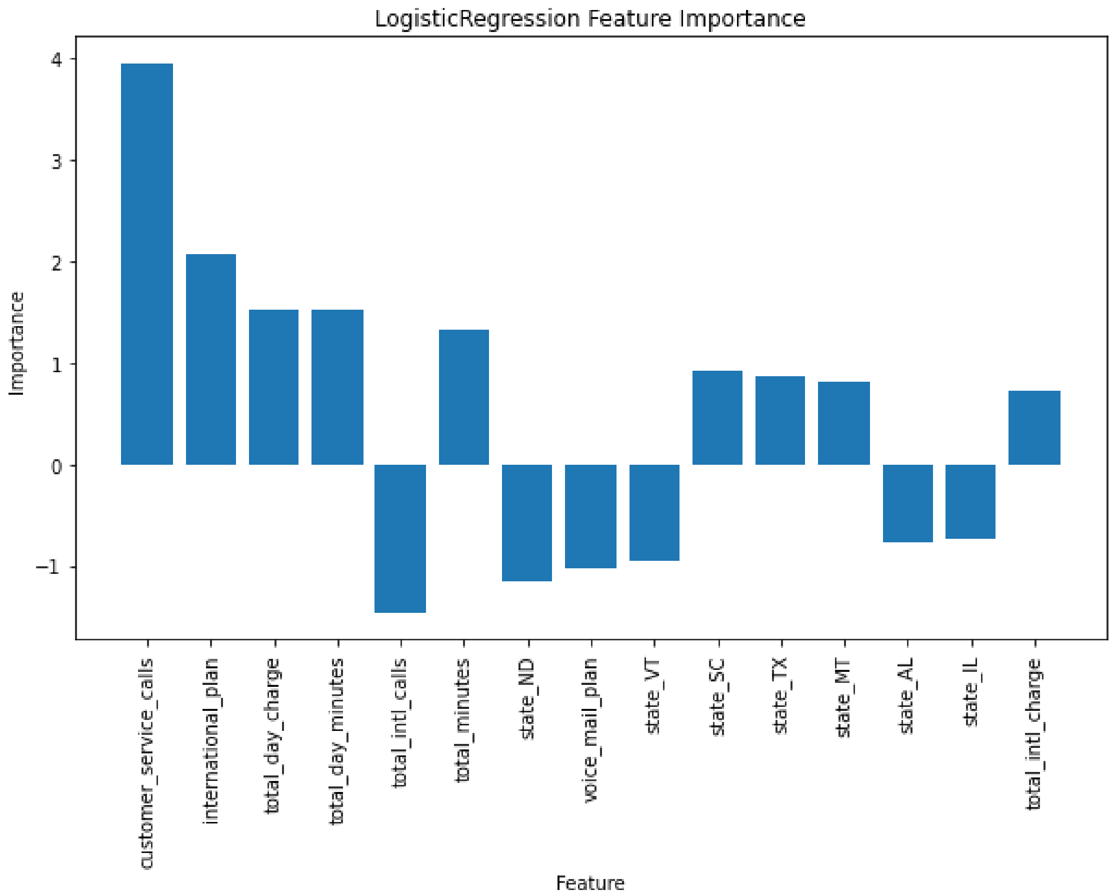
```
Class Distribution in Training Set:
Class 0: 2284 samples
Class 1: 382 samples


Class Distribution in Resampled Training Set:
Class 0: 2284 samples
Class 1: 2284 samples
```

Observation: SMOTE solves the class imbalance problem

1.10.2 2.3.2) Logistic Regression

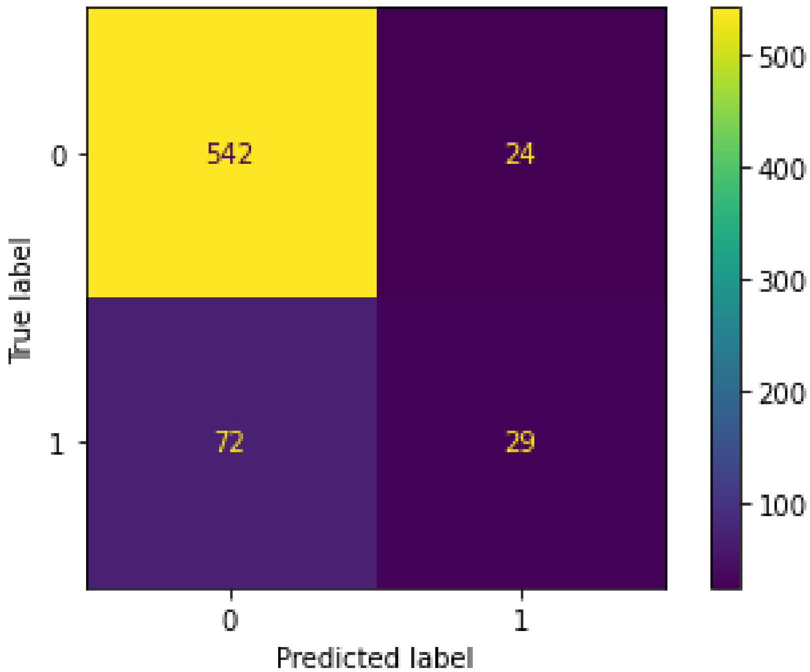
[ ]:
```
# Base Model with class imbalance

# Instantiating and fitting a LogisticRegression
logr = LogisticRegression()
logr.fit(X_train, y_train)

# Getting the coefficients of the features
feature_importance = logr.coef_[0]

# Creating a list of feature names
feature_names = X_train.columns

# Sorting the features by their importance
```

```
sorted_indices = np.argsort(np.abs(feature_importance))[::-1]
sorted_feature_importance = feature_importance[sorted_indices][0:15]
sorted_feature_names = feature_names[sorted_indices][0:15]

# Ploting the feature importance
plt.figure(figsize=(10, 6))
plt.bar(range(len(sorted_feature_importance)), sorted_feature_importance)
plt.xticks(range(len(sorted_feature_importance)), sorted_feature_names,␣
 ↪rotation=90)
plt.xlabel("Feature")
plt.ylabel("Importance")
plt.title("LogisticRegression Feature Importance")
plt.show()


# Calculating cross-validation scores
logr_scores = cross_val_score(logr, X_train, y_train, cv=3)
mean_logr_score = np.mean(logr_scores)

print(f"Mean Cross Validation Score: {mean_logr_score:.2%}")
print("\n")

# Making predictions on the test data
y_pred = logr.predict(X_test)

# Calculating a classification report
classification_metrics = classification_report(y_test, y_pred)

# Printing the classification report
print(classification_metrics)

# ConfusionMatrixDisplay

confusion = confusion_matrix(y_test, y_pred)

disp = ConfusionMatrixDisplay(confusion_matrix=confusion)

disp.plot()
```




```
Mean Cross Validation Score: 86.23%

              precision    recall  f1-score   support

           0       0.88      0.96      0.92       566
           1       0.55      0.29      0.38       101

    accuracy                           0.86       667
   macro avg       0.71      0.62      0.65       667
weighted avg       0.83      0.86      0.84       667
```

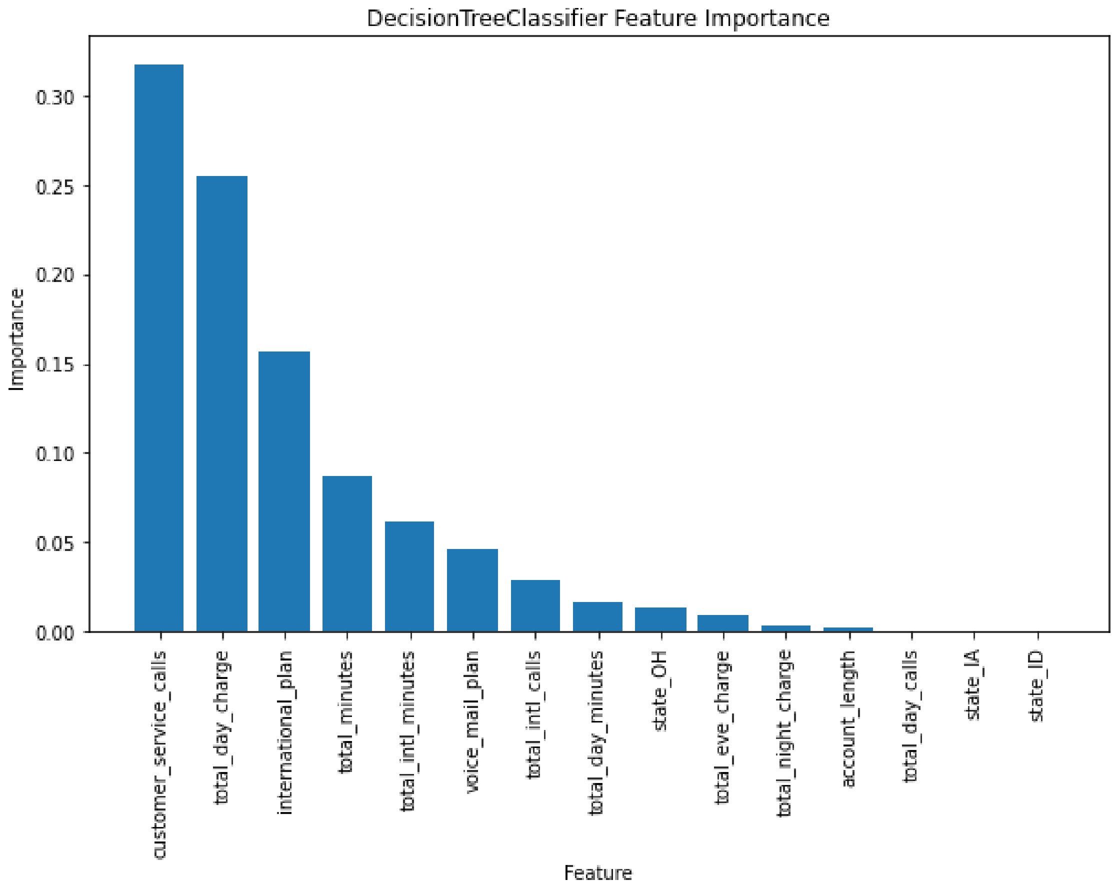
[ ]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x211cd453fa0>



1.10.3 2.3.3) Decision Tree Classifier

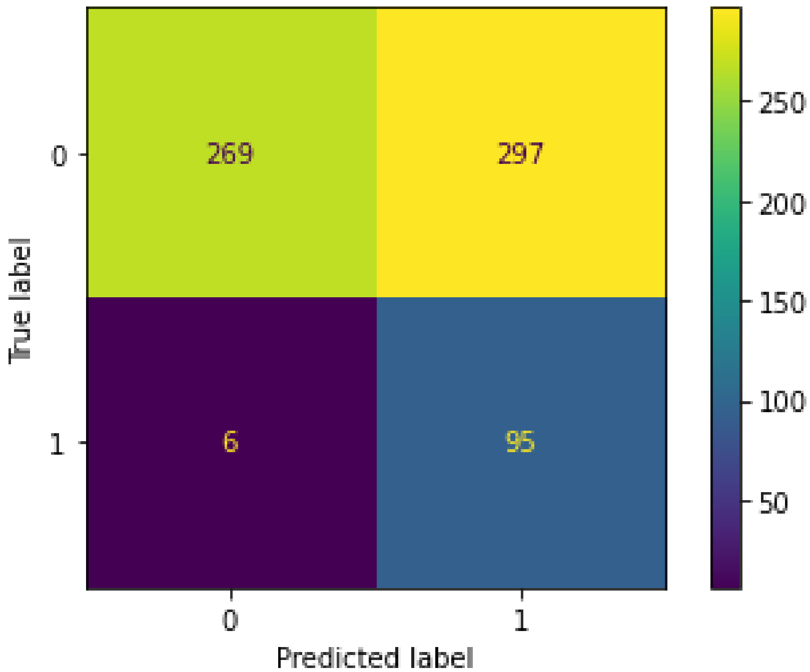
[ ]:
```
# Instantiating and fitting a DecisionTreeClassifier
dtc = DecisionTreeClassifier(max_depth=5, random_state=42)
dtc.fit(X_train_resampled, y_train_resampled)

# Getting the feature importances
feature_importance = dtc.feature_importances_

# Creating a list of feature names
feature_names = X_train_resampled.columns

# Sorting the features by their importance
sorted_indices = feature_importance.argsort()[::-1]
sorted_feature_importance = feature_importance[sorted_indices][:15]
sorted_feature_names = feature_names[sorted_indices][:15]

# Plot the feature importance
plt.figure(figsize=(10, 6))
plt.bar(range(len(sorted_feature_importance)), sorted_feature_importance)
plt.xticks(range(len(sorted_feature_importance)), sorted_feature_names,␣
 ↪rotation=90)
plt.xlabel("Feature")
plt.ylabel("Importance")
```

```python
plt.title("DecisionTreeClassifier Feature Importance")
plt.show()

# Calculating cross-validation scores
dtc_scores = cross_val_score(dtc, X_train_resampled, y_train_resampled, cv=3)
mean_dtc_score = np.mean(dtc_scores)

print(f"Mean Cross Validation Score: {mean_dtc_score:.2%}")
print("\n")

# Making predictions on the test data
y_pred = dtc.predict(X_test)

# Calculating a classification report
classification_metrics = classification_report(y_test, y_pred)

# Printing the classification report
print(classification_metrics)

# ConfusionMatrixDisplay

confusion = confusion_matrix(y_test, y_pred)

disp = ConfusionMatrixDisplay(confusion_matrix=confusion)

disp.plot()
```




```
Mean Cross Validation Score: 85.88%

              precision    recall  f1-score   support

           0       0.98      0.48      0.64       566
           1       0.24      0.94      0.39       101

    accuracy                           0.55       667
   macro avg       0.61      0.71      0.51       667
weighted avg       0.87      0.55      0.60       667
```

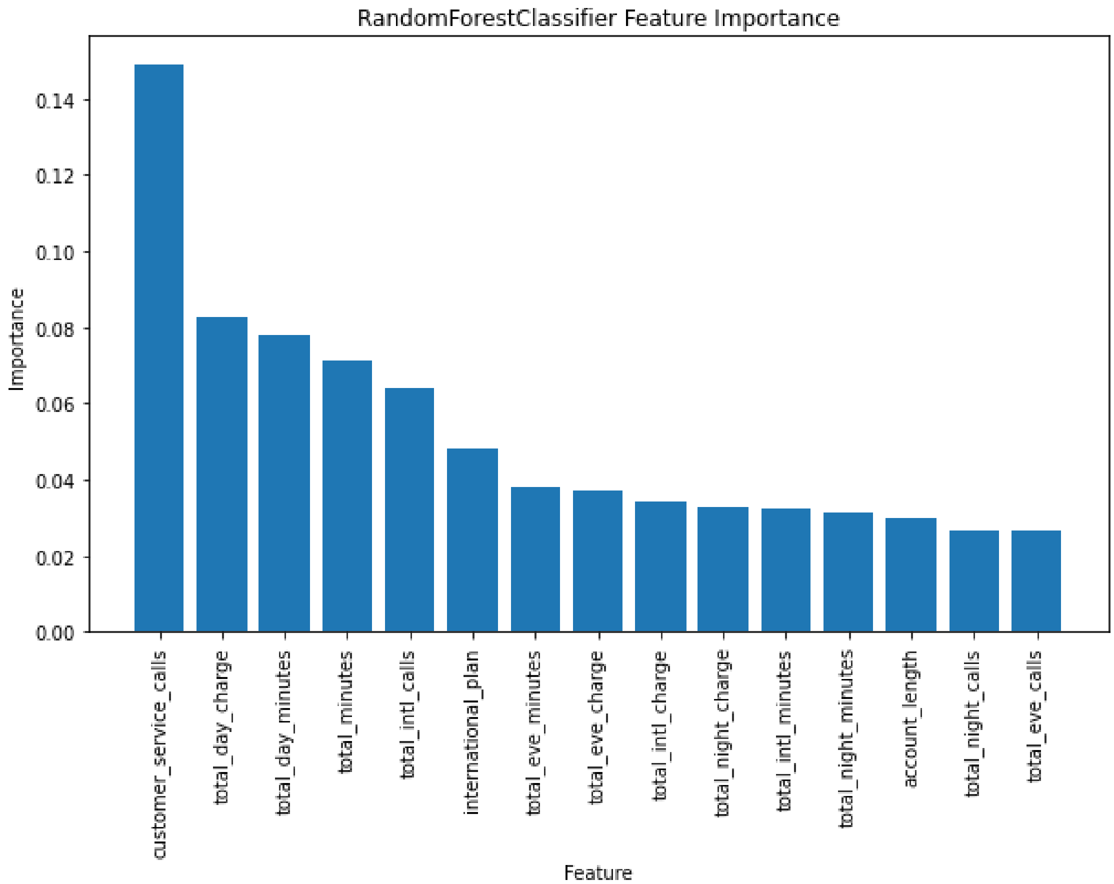
[ ]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x211cb4f3610>



1.10.4 2.3.4) Random Forest Classifier

[ ]:
```
# Instantiating and fitting a RandomForestClassifier
rdmf = RandomForestClassifier(random_state=42)
rdmf.fit(X_train_resampled, y_train_resampled)

# Getting the feature importances
feature_importance = rdmf.feature_importances_

# Creating a list of feature names
feature_names = X_train_resampled.columns

# Sorting the features by their importance
sorted_indices = feature_importance.argsort()[::-1]
sorted_feature_importance = feature_importance[sorted_indices][:15]
sorted_feature_names = feature_names[sorted_indices][:15]

# Plot the feature importance
plt.figure(figsize=(10, 6))
plt.bar(range(len(sorted_feature_importance)), sorted_feature_importance)
plt.xticks(range(len(sorted_feature_importance)), sorted_feature_names,␣
 ↪rotation=90)
plt.xlabel("Feature")
plt.ylabel("Importance")
```

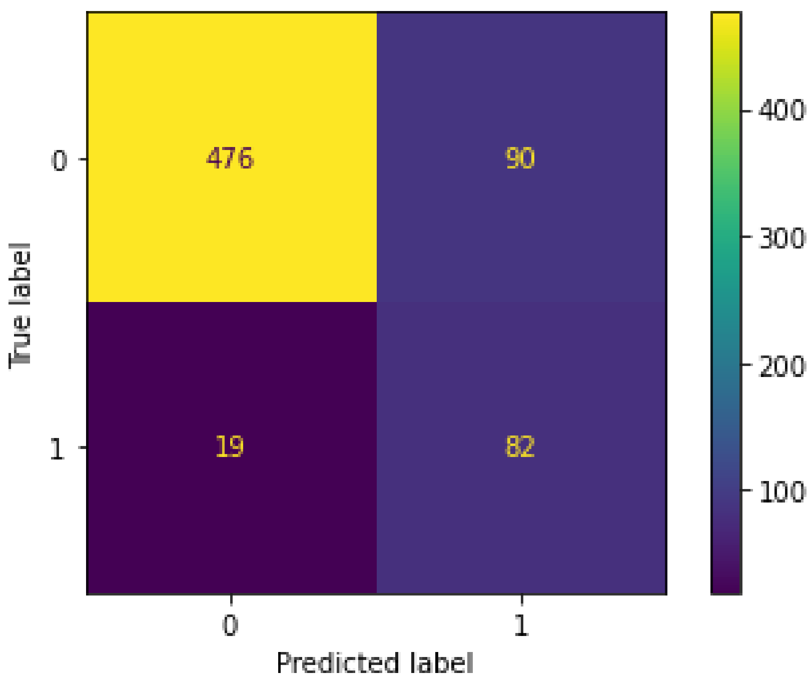
```python
plt.title("RandomForestClassifier Feature Importance")
plt.show()

# Calculating cross-validation scores
rdmf_scores = cross_val_score(rdmf, X_train_resampled, y_train_resampled, cv=3)
mean_rdmf_score = np.mean(rdmf_scores)

print(f"Mean Cross Validation Score: {mean_rdmf_score:.2%}")
print("\n")

# Making predictions on the test data
y_pred = rdmf.predict(X_test)

# Calculating a classification report
classification_metrics = classification_report(y_test, y_pred)

# Printing the classification report
print(classification_metrics)

# ConfusionMatrixDisplay

confusion = confusion_matrix(y_test, y_pred)

disp = ConfusionMatrixDisplay(confusion_matrix=confusion)

disp.plot()
```




```
Mean Cross Validation Score: 93.85%
```

```
              precision    recall  f1-score   support

           0       0.96      0.84      0.90       566
           1       0.48      0.81      0.60       101

    accuracy                           0.84       667
   macro avg       0.72      0.83      0.75       667
weighted avg       0.89      0.84      0.85       667
```

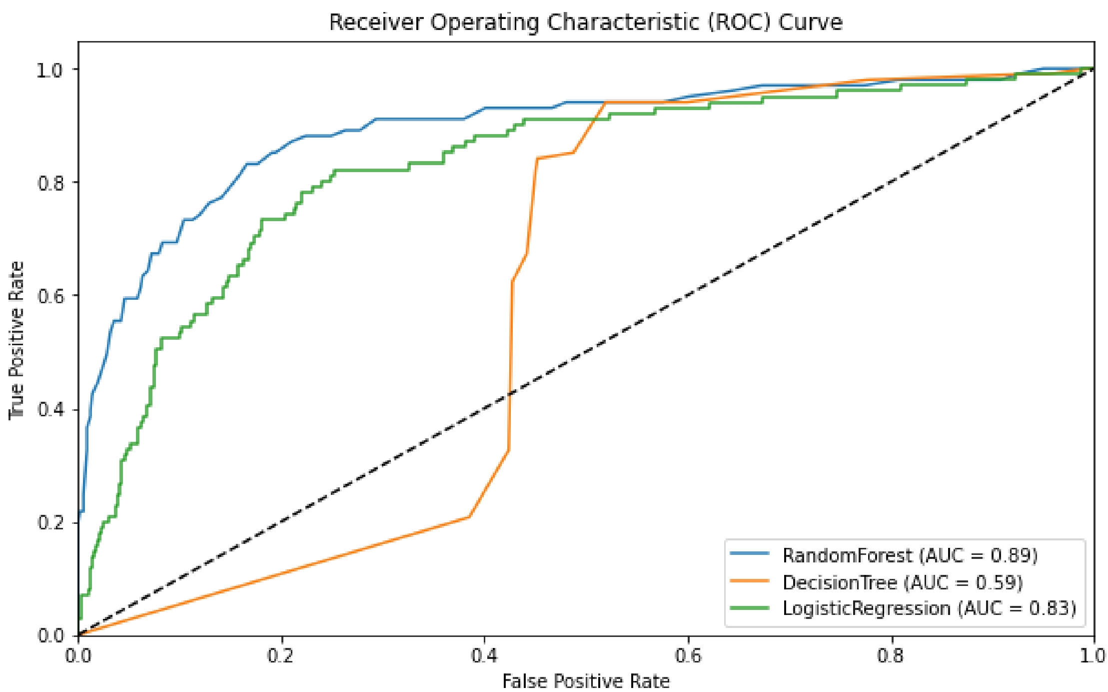
[ ]: `<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x211caf68970>`



1.10.5 2.3.5) ROC model Comparison

[ ]:
```
# ROC

# Making predictions
rf_probabilities = rdmf.predict_proba(X_test)[:, 1]
dt_probabilities = dtc.predict_proba(X_test)[:, 1]
lr_probabilities = logr.predict_proba(X_test)[:, 1]

# Computing ROC curves
rf_fpr, rf_tpr, _ = roc_curve(y_test, rf_probabilities)
dt_fpr, dt_tpr, _ = roc_curve(y_test, dt_probabilities)
lr_fpr, lr_tpr, _ = roc_curve(y_test, lr_probabilities)

# Computing AUC
rf_auc = auc(rf_fpr, rf_tpr)
dt_auc = auc(dt_fpr, dt_tpr)
lr_auc = auc(lr_fpr, lr_tpr)

# Plotting ROC curves
plt.figure(figsize=(10, 6))
plt.plot(rf_fpr, rf_tpr, label=f'RandomForest (AUC = {rf_auc:.2f})')
plt.plot(dt_fpr, dt_tpr, label=f'DecisionTree (AUC = {dt_auc:.2f})')
plt.plot(lr_fpr, lr_tpr, label=f'LogisticRegression (AUC = {lr_auc:.2f})')
```

```
plt.plot([0, 1], [0, 1], 'k--')

plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```



Based on the AUC values, RandomForest is the best classifier, followed by LogisticRegression and DecisionTree. The RandomForest classifier has a very good AUC value of 0.90. This means that it is very good at distinguishing between positive and negative cases.

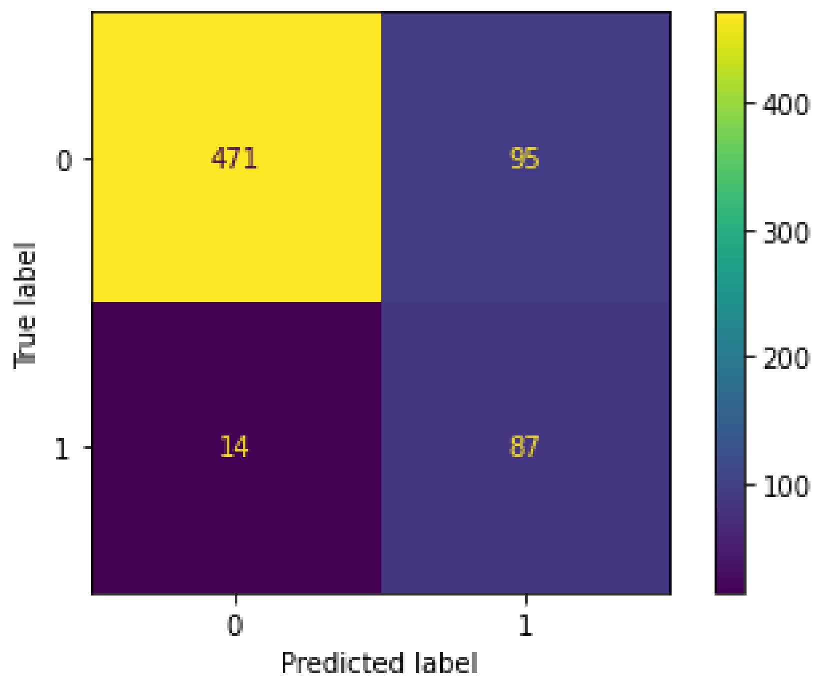
1.10.6 2.3.6) Grid Search CV Hyperparameter tuning for Random Forest

[ ]:
```
# Defining hyperparameters for the Random Forest Classifier
rdmf_param_grid = {
    "criterion": ["gini", "entropy"],
    "max_depth": [5,10],
    "min_samples_split": [5, 15],
    "n_estimators": [100, 500],
}
```

```python
# Instantiating and fitting a GridSearchCV for Decision Tree
rdmf_grid_search = GridSearchCV(rdmf, rdmf_param_grid, cv=3,␣
↪return_train_score=True)
rdmf_grid_search.fit(X_train_resampled, y_train_resampled)

# You can access the best parameters:
best_params = rdmf_grid_search.best_params_
print(f"Best Paramenters: {best_params}")

# The best estimator
best_rdmf = rdmf_grid_search.best_estimator_

# Making predictions on the test data
y_pred = best_rdmf.predict(X_test)

# Calculating a classification report
classification_metrics = classification_report(y_test, y_pred)

# Printing the classification repor
print(classification_metrics)

# ConfusionMatrixDisplay
confusion = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=confusion)
disp.plot()
```

```
Best Paramenters: {'criterion': 'entropy', 'max_depth': 10, 'min_samples_split':
5, 'n_estimators': 500}
              precision    recall  f1-score   support

           0       0.97      0.83      0.90       566
           1       0.48      0.86      0.61       101

    accuracy                           0.84       667
   macro avg       0.72      0.85      0.76       667
weighted avg       0.90      0.84      0.85       667
```

[ ]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x211cad5d310>



Observation: Grid Search improved the Random Forest marginally.

1.11 2.4) Conclusion

- TThe hyperparameter tuned random forest model is the best model for predicting customer churn, with a high recall of 0.84 for the negative class. However, the model has a lower recall of 0.83 for the positive class, meaning that 17% of actual churners are incorrectly predicted as non-churners.
- It is evident that high customer service calls are the largest contributor to high customer churn.
- Also, it can be observed that the factors including day munites and day charge leading to a higher bill are deterring the customer from continuing their phone plan.
- International plan customers were also seen to switch providers at a higher rate.

1.12 2.5) Recommendation

- Focus on reducing the number of customer service calls. This could be done by improving the customer experience, making it easier for customers to find the information they need, and resolving customer issues quickly and efficiently.
- Offer competitive pricing plans and data packages. This could help to reduce churn among customers who are leaving because they are unhappy with their bill.
- Target international plan customers with tailored retention programs. This could include offering discounts, promotions, or other benefits to encourage these customers to stay with the company.

In addition to these general recommendations, the company can also use the insights from the data to develop more targeted retention strategies for specific customer segments. For example, the company could offer customers who have made multiple customer service calls a free month of service or a discount on their next bill. The company could also offer customers who have high day minutes and day charge a data upgrade or a discount on a new phone.