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Phase-3-Project

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PHASE 3 PROJECT: SYRIA TELECOMMUNICATIONS CUSTOMER CHURN PROJECT

Done by: Edwin Mbuthia

1. BUSINESS UNDERSTANDING

SyriaTel is one of the leading telecommunications providers in Syria, established in 2000. It operates as a mobile network operator and is renowned for offering a wide range of telecommunication services, including mobile voice, data, and internet services across Syria. SyriaTel has played a pivotal role in the development of the country's telecommunications infrastructure, providing comprehensive coverage to both urban and rural areas. The company focuses on enhancing customer experience through innovative solutions, competitive pricing, and expanding its service offerings to meet the evolving needs of its customers. Despite the challenges posed by the ongoing conflict and economic difficulties in Syria, SyriaTel has managed to maintain its operations and continues to invest in network expansion and technological upgrades. Its mission is to connect people and improve lives by providing reliable and affordable telecommunication services, thereby contributing to the socio-economic development of Syria.

1.1 Business Problem

Syria Telcom seek to predict whether their customers will soon leave the company and shift to a different telco. High customer churn rates directly impact the revenue and profitability of telecommunications companies. Therefore, understanding the factors that contribute to churn would allow Syria telco to take proactive measures, such as targeted marketing, loyalty programs, or customer service improvements, to retain customers.

1.2 Objectives

- Develop a Predictive Model for Custmer Churn: The primary objective of this project is to build a Machine Learning classifier that predicts whether a customer will soon stop doing business with SyriaTel. The predictive capability of the model will minimize customer loss and stabilize the customer base hence reducing revenue loss.

- Drivers of Customer Churn: Second goal is to identify the factors that would result into high customer churn.
- Analyze Churn Trends across Different States: The last objective of this project if to examine churn trends across different states to better understand which states are likely to have high churn rates.

2. Data Understanding

I will first import all the necessary libraries that we will require to conduct the project.

In [1]:

```
# Import relevant Python modules
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline


from sklearn.model_selection import train_test_split, cross_validate,cross_val
from sklearn.pipeline import Pipeline

# Classification Models
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier

from sklearn.metrics import confusion_matrix, accuracy_score, f1_score, precis
from sklearn.metrics import ConfusionMatrixDisplay, classification_report, cla
from sklearn.dummy import DummyClassifier
from sklearn.metrics import roc_curve, auc, roc_auc_score

# Scalers
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder

# Class Imbalance
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from imblearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestClassifier
```

In [2]:

```
data = pd.read_csv('bigml_59c28831336c6604c800002a.csv')
data
```

Out[2]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls
0	KS	128	415	382-4657	no	yes	25	265.1	110
1	OH	107	415	371-	no	yes	26	161.6	123

				7191					
2	NJ	137	415	358-1921	no	no	0	243.4	114
3	OH	84	408	375-9999	yes	no	0	299.4	71
4	OK	75	415	330-6626	yes	no	0	166.7	113
...	...	...	...	...	...	...	...	...	...
3328	AZ	192	415	414-4276	no	yes	36	156.2	77
3329	WV	68	415	370-3271	no	no	0	231.1	57
3330	RI	28	510	328-8230	no	no	0	180.8	109
3331	CT	184	510	364-6381	yes	no	0	213.8	105
3332	TN	74	415	400-4344	no	yes	25	234.4	113

3333 rows × 21 columns

I will now explore the dataset to gain more insights.

In [3]:

```
data.shape
```

Out[3]:

```
(3333, 21)
```

In [4]:

```
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
```

```
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64
 20  churn                   3333 non-null   bool
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

In this dataset, there are no missing values

2.1 Data Description

In [5]:

```
data.columns
```

Out[5]:

```
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')
```

state: Categorical variable indicating the customer's state.

account length: Numeric variable indicating the length of the customer account.

area code: Numeric variable indicating the area code of the customer.

phone number: Categorical variable (likely to be excluded as it won't contribute to churn prediction).

international plan: Categorical variable indicating if the customer has an international plan.

voice mail plan: Categorical variable indicating if the customer has a voicemail plan.

number vmail messages: Numeric variable indicating the number of voicemail messages.

total day/eve/night/intl minutes: Numeric variables indicating usage minutes in various time segments.

total day/eve/night/intl calls: Numeric variables indicating the number of calls in various time segments.

total day/eve/night/intl charge: Numeric variables indicating charges in various time segments.

customer service calls: Numeric variable indicating the number of customer service calls made by the customer.

churn: Binary target variable indicating customer churn (True/False).

3.0 Data Exploration & Preparation

In this bit I looked for any missing values in my dataset, removed any irrelevant columnns & converted categorical variables into numerical variables.

In [6]:
```
# Check for missing values
data.isna().sum()
```

Out[6]:
```
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
```

There are no missing values within this dataset.

In [7]:
```
# Here i will drop the area code and phone number columns as they are not that

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

Out[7]:

	state	account length	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes
0	KS	128	no	yes	25	265.1	110	45.07	197.4
1	OH	107	no	yes	26	161.6	123	27.47	195.5
2	NJ	137	no	no	0	243.4	114	41.38	121.2
3	OH	84	yes	no	0	299.4	71	50.90	61.9

4	OK	75	yes	no	0	166.7	113	28.34	148.3
...	...	...	...	...	...	...	...	...	...
3328	AZ	192	no	yes	36	156.2	77	26.55	215.5
3329	WV	68	no	no	0	231.1	57	39.29	153.4
3330	RI	28	no	no	0	180.8	109	30.74	288.8
3331	CT	184	yes	no	0	213.8	105	36.35	159.6
3332	TN	74	no	yes	25	234.4	113	39.85	265.9

3333 rows × 19 columns

I will then combine the total day minutes, total evening minutes, total night minutes and the total international minutes columns to come up with a Total minutes column. I will also combine the total day charge, total evening charge, total night charge and the total international charge columns to come up with a Total charges column. Combine the total day calls, total evening calls, total night calls and the total international calls columns to come up with a Total calls column.

In [8]:

```
data['Total minutes'] = data['total day minutes'] + data['total eve minutes']
data['Total charges'] = data['total day charge'] + data['total eve charge'] +
data['Total calls'] = data['total day calls'] + data['total eve calls'] + data
data
```

Out[8]:

	state	account length	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes
0	KS	128	no	yes	25	265.1	110	45.07	197.4
1	OH	107	no	yes	26	161.6	123	27.47	195.5
2	NJ	137	no	no	0	243.4	114	41.38	121.2
3	OH	84	yes	no	0	299.4	71	50.90	61.9
4	OK	75	yes	no	0	166.7	113	28.34	148.3
...	...	...	...	...	...	...	...	...	...
3328	AZ	192	no	yes	36	156.2	77	26.55	215.5
3329	WV	68	no	no	0	231.1	57	39.29	153.4
3330	RI	28	no	no	0	180.8	109	30.74	288.8
3331	CT	184	yes	no	0	213.8	105	36.35	159.6
3332	TN	74	no	yes	25	234.4	113	39.85	265.9

3333 rows × 22 columns

In [9]:

```
columns_to_drop = [ 'total day minutes', 'total eve minutes', 'total night min
    'total day charge', 'total eve charge', 'total night charge', 'total intl 
    'total day calls', 'total eve calls', 'total night calls', 'total intl cal
data.drop(columns=columns_to_drop, inplace=True)
```

In [10]:

```
data
```

Out[10]:

	state	account length	international plan	voice mail plan	number vmail messages	customer service calls	churn	Total minutes	To char
0	KS	128	no	yes	25	1	False	717.2	75
1	OH	107	no	yes	26	1	False	625.2	59
2	NJ	137	no	no	0	0	False	539.4	62
3	OH	84	yes	no	0	2	False	564.8	66
4	OK	75	yes	no	0	3	False	512.0	52
...	...	...	...	...	...	...	...	...	
3328	AZ	192	no	yes	36	2	False	660.7	60
3329	WV	68	no	no	0	3	False	585.4	63
3330	RI	28	no	no	0	2	False	675.6	67
3331	CT	184	yes	no	0	2	False	517.6	57
3332	TN	74	no	yes	25	0	False	755.4	77

3333 rows × 10 columns

In [11]:

```
#Move the target variable column 'Churn' and have it as the last column in our
column_to_move = 'churn'
column_data = data.pop(column_to_move)
data[column_to_move] = column_data

data
```

Out[11]:

	state	account length	international plan	voice mail plan	number vmail messages	customer service calls	Total minutes	Total charges	To ca
0	KS	128	no	yes	25	1	717.2	75.56	3
1	OH	107	no	yes	26	1	625.2	59.24	3
2	NJ	137	no	no	0	0	539.4	62.29	3

3	OH	84	yes	no	0	2	564.8	66.80	2
4	OK	75	yes	no	0	3	512.0	52.09	3
...	...	...	...	...	...	...	...	...	
3328	AZ	192	no	yes	36	2	660.7	60.10	2
3329	WV	68	no	no	0	3	585.4	63.53	2
3330	RI	28	no	no	0	2	675.6	67.74	2
3331	CT	184	yes	no	0	2	517.6	57.53	3
3332	TN	74	no	yes	25	0	755.4	77.01	2

3333 rows × 10 columns

Explore Categorical Variables

Here i will explore the categorical data within my dataset.

In [12]:

```
categorical = [var for var in data.columns if data[var].dtype=='O']
print('There are {} categorical variables\n'.format(len(categorical)))

print('The categorical variables are :', categorical)
```

```
There are 3 categorical variables

The categorical variables are : ['state', 'international plan', 'voice mail pla
n']
```

There are 3 categorical variables in this dataset. First, I will check missing values in categorical variables.

In [13]:

```
data[categorical].isna().sum()
```

Out[13]:

```
state                 0
international plan    0
voice mail plan       0
dtype: int64
```

There are no missing values in the categorical columns. I will then proceed to check on the labels in each of the categorical variables.

Explore the state variable

In [14]:

```
data['state'].unique()
```

Out[14]:

```
array(['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'], dtype=object)
```

In [15]:

```
# check frequency distribution of values in state variable
data["state"].value_counts()
```

Out[15]:

```
WV    106
MN     84
NY     83
AL     80
WI     78
OH     78
OR     78
VA     77
WY     77
CT     74
MI     73
ID     73
VT     73
TX     72
UT     72
IN     71
KS     70
MD     70
NJ     68
NC     68
MT     68
WA     66
CO     66
NV     66
MS     65
RI     65
MA     65
AZ     64
FL     63
MO     63
ND     62
NM     62
ME     62
OK     61
DE     61
NE     61
SD     60
SC     60
KY     59
IL     58
NH     56
AR     55
DC     54
GA     54
TN     53
HI     53
AK     52
LA     51
PA     45
IA     44
CA     34
Name: state, dtype: int64
```

In [16]:
```
# let's do One Hot Encoding of Location variable
# get k-1 dummy variables after One Hot Encoding
# preview the dataset with head() method

pd.get_dummies(data["state"], drop_first=True).head()
```

Out[16]:

	AL	AR	AZ	CA	CO	CT	DC	DE	FL	GA	...	SD	TN	TX	UT	VA	VT	WA	V
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	

5 rows × 50 columns

Explore the International Plan Variable

In [17]:
```
data["international plan"].value_counts()
```

Out[17]:
```
no     3010
yes     323
Name: international plan, dtype: int64
```

Explore the Voice mail plan variable

In [18]:
```
data["voice mail plan"].value_counts()
```

Out[18]:
```
no     2411
yes     922
Name: voice mail plan, dtype: int64
```

Explore the Numerical variables

In [19]:
```
numerical = [var for var in data.columns if data[var].dtype !='O' if data[var]
print('There are {} numerical variables\n'.format(len(numerical)))

print('The numerical variables are :', numerical)
```

```
There are 6 numerical variables

The numerical variables are : ['account length', 'number vmail messages', 'custo
mer service calls', 'Total minutes', 'Total charges', 'Total calls']
```

Summary of numerical variables

Summary of numerical variables

.There are 6 numerical variables.

.These are given by account length, number of voice mail messages, customer service calls, total minutes, total charges and total calls.

.All of the numerical variables are of continuous type.

In [20]:

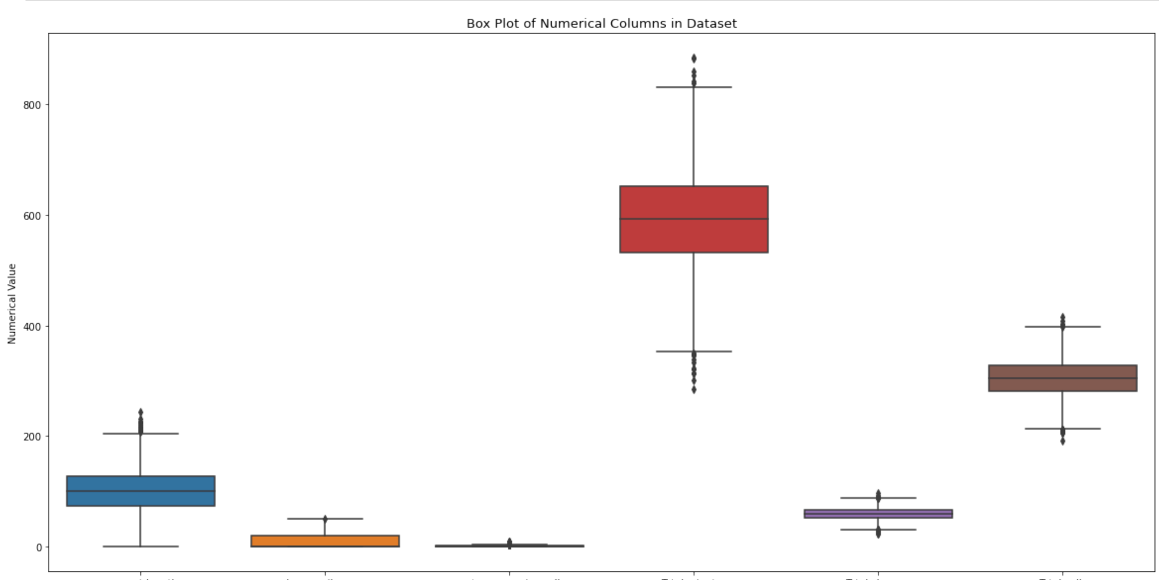
```
data[numerical].describe()
```

Out[20]:

	account length	number vmail messages	customer service calls	Total minutes	Total charges	Total calls
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000
mean	101.064806	8.099010	1.562856	591.864776	59.449754	305.137114
std	39.822106	13.688365	1.315491	89.954251	10.502261	34.448164
min	1.000000	0.000000	0.000000	284.300000	22.930000	191.000000
25%	74.000000	0.000000	1.000000	531.500000	52.380000	282.000000
50%	101.000000	0.000000	1.000000	593.600000	59.470000	305.000000
75%	127.000000	20.000000	2.000000	652.400000	66.480000	328.000000
max	243.000000	51.000000	9.000000	885.000000	96.150000	416.000000

In [21]:

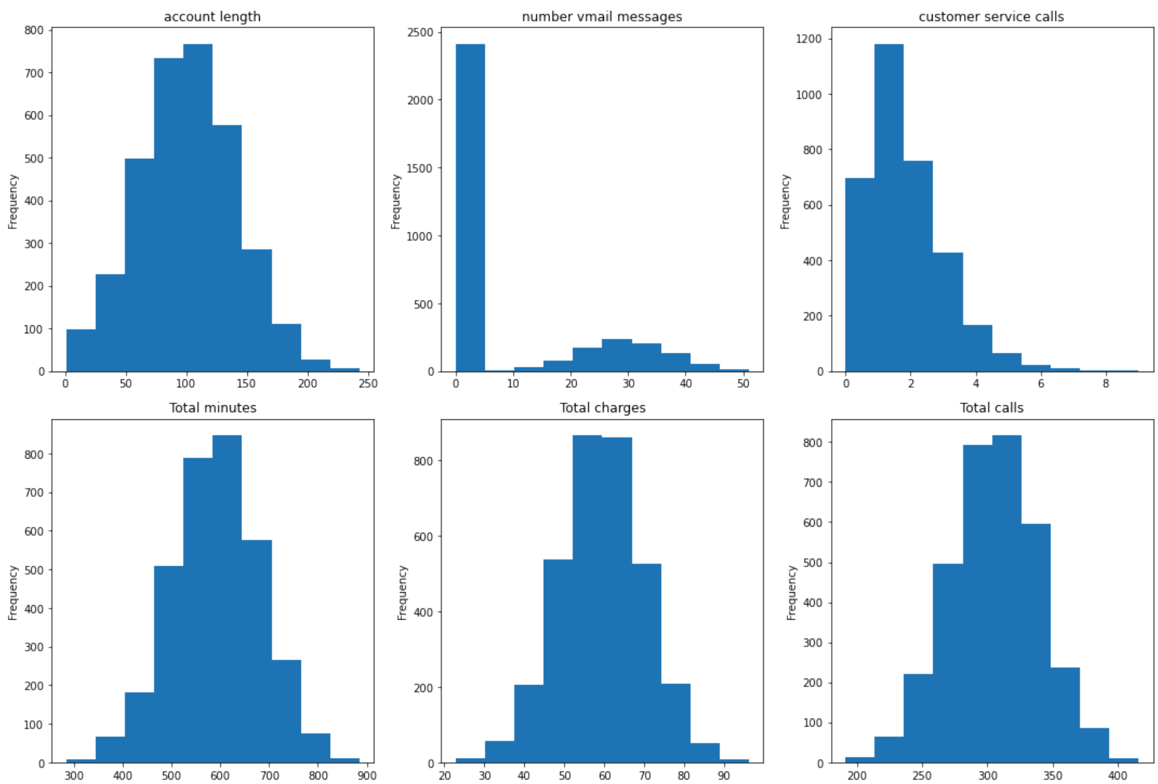
```
numerical_col = ['account length','number vmail messages','customer service ca
plt.figure(figsize=(20, 10))
sns.boxplot(data=[data[col] for col in numerical_col])
plt.title("Box Plot of Numerical Columns in Dataset", fontsize=13)
plt.ylabel("Numerical Value")
plt.xticks(range(0,6), numerical_col)
plt.show()
```



From the boxplot above, we can see that all the numerical columns contain outliers.

Check for Distribution of the Numerical variables

In [22]:
```
numerical_col = ['account length','number vmail messages','customer service ca
fig = plt.figure(figsize=(15, 15))
for i, col in enumerate(numerical_col):
    ax = plt.subplot(3, 3, i+1)
    data[col].plot(kind='hist', ax=ax, title=col)
plt.tight_layout()
plt.show()
```



In [23]:
```
# find outliers for account length variable
IQR = data["account length"].quantile(0.75) - data["account length"].quantile(
Lower_fence = data["account length"].quantile(0.25) - (IQR * 3)
Upper_fence = data["account length"].quantile(0.75) + (IQR * 3)
print('Account length outliers are values < {lowerboundary} or > {upperboundar
```

```
Account length outliers are values < -85.0 or > 286.0
```

In [24]:
```
# find outliers for Number of voice mail messages variable
IQR = data["number vmail messages"].quantile(0.75) - data["number vmail messag
Lower_fence = data["number vmail messages"].quantile(0.25) - (IQR * 3)
Upper_fence = data["number vmail messages"].quantile(0.75) + (IQR * 3)
print('Number voice mail messages outliers are values < {lowerboundary} or > {
```

```
Number voice mail messages outliers are values < -60.0 or > 80.0
```

In [25]:

```
# find outliers for Customer service calls messages variable
IQR = data["customer service calls"].quantile(0.75) - data["customer service c
Lower_fence = data["customer service calls"].quantile(0.25) - (IQR * 3)
Upper_fence = data["customer service calls"].quantile(0.75) + (IQR * 3)
print('Customer service calls outliers are values < {lowerboundary} or > {uppe
```

```
Customer service calls outliers are values < -2.0 or > 5.0
```

In [26]:

```
# find outliers for Total minutes variable
IQR = data["Total minutes"].quantile(0.75) - data["Total minutes"].quantile(0.
Lower_fence = data["Total minutes"].quantile(0.25) - (IQR * 3)
Upper_fence = data["Total minutes"].quantile(0.75) + (IQR * 3)
print('Total minutes outliers are values < {lowerboundary} or > {upperboundary
```

```
Total minutes outliers are values < 168.79999999999973 or > 1015.1000000000004
```

In [27]:

```
# find outliers for Total charges variable
IQR = data["Total charges"].quantile(0.75) - data["Total charges"].quantile(0.
Lower_fence = data["Total charges"].quantile(0.25) - (IQR * 3)
Upper_fence = data["Total charges"].quantile(0.75) + (IQR * 3)
print('Total charges outliers are values < {lowerboundary} or > {upperboundary
```

```
Total charges outliers are values < 10.079999999999998 or > 108.78
```

In [28]:

```
# find outliers for Total calls variable
IQR = data["Total calls"].quantile(0.75) - data["Total calls"].quantile(0.25)
Lower_fence = data["Total calls"].quantile(0.25) - (IQR * 3)
Upper_fence = data["Total calls"].quantile(0.75) + (IQR * 3)
print('Total calls outliers are values < {lowerboundary} or > {upperboundary}'
```

```
Total calls outliers are values < 144.0 or > 466.0
```

3.1 Data Preprocessing

In this section, using OneHot Encoder, I will create a new binary column for each unique category, with 1 indicating the presence of the category and 0 otherwise. I will first check my target variable column.

In [29]:

```
data['churn'].unique()
```

Out[29]:

```
array([False,  True])
```

Our target variable is binary so there is no need of OneHot Encoding it.

3.1.1 SPLITTING THE DATA INTO FEATURE (X) AND TARGET (y) DATASETS

In [30]:

```
X = data.drop(columns=['churn'], axis=1)
y = data['churn']
X.head()
```

Out[30]:

	state	account length	international plan	voice mail plan	number vmail messages	customer service calls	Total minutes	Total charges	Total calls
0	KS	128	no	yes	25	1	717.2	75.56	303
1	OH	107	no	yes	26	1	625.2	59.24	332
2	NJ	137	no	no	0	0	539.4	62.29	333
3	OH	84	yes	no	0	2	564.8	66.80	255
4	OK	75	yes	no	0	3	512.0	52.09	359

One Hot Encoding Categorical Columns

In [31]:

```
X = pd.get_dummies(X, columns=categorical,drop_first=True)
X
```

Out[31]:

	account length	number vmail messages	customer service calls	Total minutes	Total charges	Total calls	state_AL	state_AR	stat
0	128	25	1	717.2	75.56	303	0	0	
1	107	26	1	625.2	59.24	332	0	0	
2	137	0	0	539.4	62.29	333	0	0	
3	84	0	2	564.8	66.80	255	0	0	
4	75	0	3	512.0	52.09	359	0	0	
...	...	...	...	...	...	...	...	...	
3328	192	36	2	660.7	60.10	292	0	0	
3329	68	0	3	585.4	63.53	239	0	0	
3330	28	0	2	675.6	67.74	264	0	0	
3331	184	0	2	517.6	57.53	336	0	0	
3332	74	25	0	755.4	77.01	276	0	0	

3333 rows × 58 columns

4. Modelling

4.1 What is the goal of Machine Learning?

The goal is to help SyriaTel proactively identify customers who are at risk of leaving, allowing the company to intervene and reduce churn, which is critical for maintaining revenue and market share.

Accurately predicting whether or not a customer is going to leave SyriaTel would help the company take steps to try and retain the customers.The model would also help allocate resources to the right customers. Those who aren't likely to leave the company.

It would also help the company address the various painpoints that are most likely going to lead to customer churn.

For this project, I will build several models using different classifiers and then compare the performance metrics to choose the best classifier. These will be:

- Logistic Regression
- Decision Tree Classifier
- Cross-validation modelling

4.2 Test-Train-Split

I will first perform a test train test split of my data. The training set will be 80% and the testing set 20%. Then set the random state to 42 to ensure reproducibility.

In [32]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y, test_size=0.2,random_sta
```

In [33]:
```
X_train.shape
```

Out[33]: (2666, 58)

In [34]:
```
y_train.shape
```

Out[34]: (2666,)

In [35]:
```
X_train.describe()
```

Out[35]:

	account length	number vmail messages	customer service calls	Total minutes	Total charges	Total calls
count	2666.000000	2666.000000	2666.000000	2666.000000	2666.000000	2666.000000
mean	100.691673	7.981245	1.573143	591.066579	59.380780	304.867967
std	39.522338	13.647218	1.338454	89.597407	10.437991	34.219452
min	1.000000	0.000000	0.000000	284.300000	23.250000	191.000000

25%	73.000000	0.000000	1.000000	532.100000	52.320000	281.000000
50%	100.000000	0.000000	1.000000	592.400000	59.415000	305.000000
75%	127.000000	19.000000	2.000000	651.275000	66.287500	328.000000
max	243.000000	51.000000	9.000000	885.000000	96.150000	408.000000

8 rows × 58 columns

From the above code block,we can see that the mean values have a high range difference with the highest value being 591 and the lowest being 0.01. I will therefore scale the features to standardize the contribution of each feature to the model, ensuring faster and more stable convergence.

In [36]:
```
scaler = StandardScaler()
scaler.fit(X_train)
```

Out[36]:
```
StandardScaler()
```

In [37]:
```
X_train = pd.DataFrame(
    scaler.transform(X_train),
    columns=X_train.columns
    )
```

In [38]:
```
X_test = pd.DataFrame(scaler.transform(X_test),columns=X_test.columns)
```

In [39]:
```
X_train.describe()
```

Out[39]:

	account length	number vmail messages	customer service calls	Total minutes	Total charges	
count	2.666000e+03	2.666000e+03	2.666000e+03	2.666000e+03	2.666000e+03	2.6
mean	1.332601e-17	1.066081e-17	-2.998352e-18	5.303751e-16	-2.318725e-16	-3.
std	1.000188e+00	1.000188e+00	1.000188e+00	1.000188e+00	1.000188e+00	1.0
min	-2.522887e+00	-5.849355e-01	-1.175564e+00	-3.424476e+00	-3.462118e+00	-3.3
25%	-7.007902e-01	-5.849355e-01	-4.282933e-01	-6.582517e-01	-6.765770e-01	-6.
50%	-1.750409e-02	-5.849355e-01	-4.282933e-01	1.488515e-02	3.279005e-03	3.
75%	6.657820e-01	8.075508e-01	3.189776e-01	6.721145e-01	6.618147e-01	6.
max	3.601382e+00	3.152791e+00	5.549874e+00	3.281217e+00	3.523295e+00	3.0

max	3.001302e+00	3.132791e+00	3.349874e+00	3.281217e+00	3.323293e+00	3.(

8 rows × 58 columns

4.3 Baseline Metrics

Before modelling, i will first determine what to expect to get with a 'dummy' model that always predicts a customer will leave the company(True). 0(False) will represent the likelihood of retaining a customer while 1(True) represents the likelihood of a customer leaving.

Since I am going to use the test data to model, i will use the test data here.

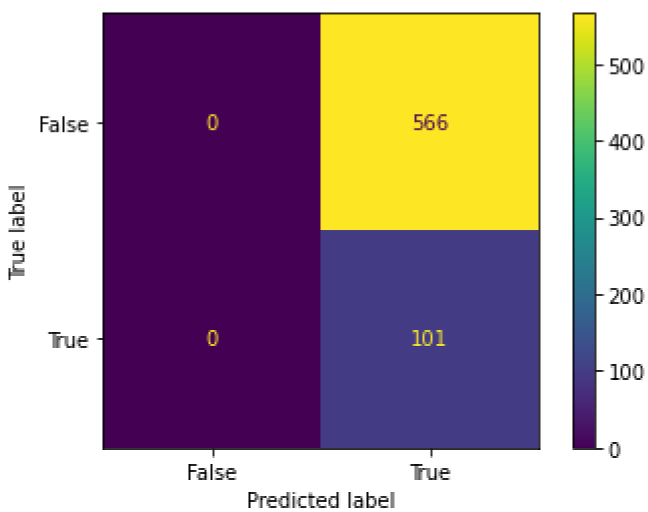
In [40]:
```
np.bincount(y_test)
```

Out[40]:
```
array([566, 101], dtype=int64)
```

From the above code block, it is evident that the target is imbalanced. I will then calculate different classification metrics to evaluate the model's performance for the True and False labels.

Below is the confusion matrix:

In [41]:
```
ConfusionMatrixDisplay.from_estimator(estimator=DummyClassifier(strategy='cons
```



For the baseline metrics, I will assume that the model always chooses 1.

In [42]:
```
baseline_accuracy = 101/(101+566)
baseline_precision =  101/(101+566)
baseline_recall = 101/101
baseline_f1score = 2*((baseline_precision*baseline_recall)/(baseline_precision

print('baseline accuracy:',baseline_accuracy)
```

```
print('baseline_precision:',baseline_precision)
print('baseline_recall:',baseline_recall)
print('baseline_f1score:',baseline_f1score)
```

```
baseline_accuracy: 0.15142428785607195
baseline_precision: 0.15142428785607195
baseline_recall: 1.0
baseline_f1score: 0.2630208333333333
```

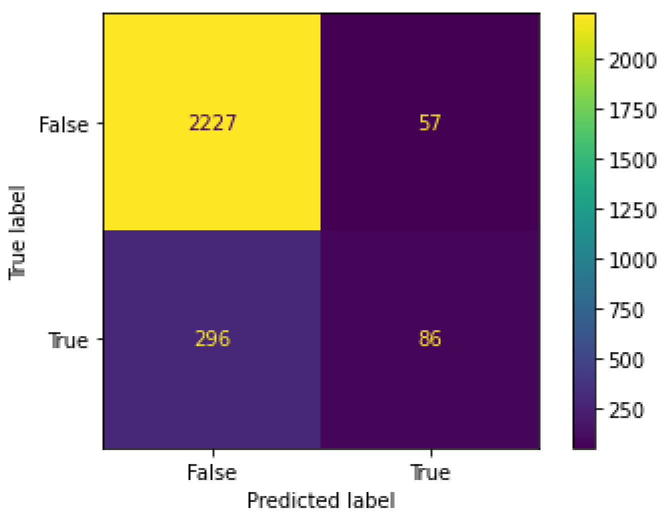
4.4 Instantiate & Fit a Logistic Regression Model

I will then use the LogisticRegression model from scikit-learn, specify a random state of 42 as well as and use default hyperparameters.

I will then use the scaled data to fit the model and i will also display the confusion matrix.

In [43]:
```
model=LogisticRegression(random_state=42,solver='liblinear')
model.fit(X_train,y_train)

ConfusionMatrixDisplay.from_estimator(estimator=model, X=X_train, y=y_train);
```



Cross-Validation to Evaluate the Fitted Model

Using Cross-Validation, i will evaluate the expected accuracy of the fitted model prior to the test data.

In [44]:
```
cv_scores = cross_val_score(model,X_train,y_train)
cv = cv_scores.mean()
cv
```

Out[44]: `0.860836477854839`

Compare the Baseline & Fitted Model Scores

I will now use the test data to calculate the accuracy, recall, precision and f1scores of the fitted model.

In [45]:
```
y_pred = model.predict(X_test)
model_accuracy = accuracy_score(y_test,y_pred)
model_recall = recall_score(y_test,y_pred)
model_precision = precision_score(y_test,y_pred)
model_f1score = f1_score(y_test,y_pred)

print(f"""
Accuracy
Baseline: {baseline_accuracy:1.3f} Fitted Model: {model_accuracy:1.3f}
Recall
Baseline: {baseline_recall:1.3f} Fitted Model: {model_recall:1.3f}
Precision
Baseline: {baseline_precision:1.3f} Fitted Model: {model_precision:1.3f}
F1 Score
Baseline: {baseline_f1score:1.3f} Fitted Model: {model_f1score:1.3f}
""")
print('cv:', cv)
```

```
Accuracy
Baseline: 0.151 Fitted Model: 0.850
Recall
Baseline: 1.000 Fitted Model: 0.178
Precision
Baseline: 0.151 Fitted Model: 0.514
F1 Score
Baseline: 0.263 Fitted Model: 0.265

cv: 0.860836477854839
```

Outcome Analysis

1. **Accuracy**

   - **Baseline: 0.151 (15.1%)**
     The baseline model has an accuracy of 15.1%, which suggests it is only slightly better than random guessing. This low accuracy indicates that the baseline model is not effective at predicting the correct outcomes.
   - **Fitted Model: 0.850 (85%)**
     The fitted model, with an accuracy of 85%, is significantly better, correctly predicting 85% of the instances. This substantial improvement indicates that the fitted model is far more effective at making accurate predictions compared to the baseline.

2. **Recall**

   - **Baseline: 1.000 (100%)**
     The recall for the baseline model is 100%, meaning it correctly identifies all positive instances in the dataset. However, this might also indicate that the baseline model predicts "positive" for almost every instance, which could lead to other metrics being low.

- **Fitted Model: 0.178 (17.8%)**
  The fitted model's recall is much lower at 17.8%, suggesting it is missing many true positive instances. This indicates that while the fitted model is accurate overall, it may not be good at capturing all actual positive cases. This could be due to a conservative approach where the model favors precision or is tuned to minimize false positives.

3. **Precision**

   - **Baseline: 0.151 (15.1%)**
     The baseline model's precision is 15.1%, indicating that only a small fraction of the predicted positives are actually true positives. This is consistent with a model that classifies most instances as positive to achieve high recall.
   - **Fitted Model: 0.514 (51.4%)**
     The fitted model has a much higher precision of 51.4%, meaning that more than half of the positive predictions made by the model are correct. This shows that while the fitted model is more selective in predicting positives, it does so more accurately than the baseline model.

4. **F1 Score**

   - **Baseline: 0.263 (26.3%)**
     The baseline model has an F1 score of 26.3%, which is low and reflects the imbalance between its high recall and low precision.
   - **Fitted Model: 0.265 (26.5%)**
     The F1 score for the fitted model is only slightly higher at 26.5%. This suggests that while the fitted model balances precision and recall better than the baseline, it still struggles with maintaining high performance across both metrics. This could indicate class imbalance or that the model's decision threshold might need adjustment.

5. **Cross-Validation (CV) Score: 0.86 (86%)**

   - The CV score of 0.86 shows that the model's expected accuracy on unseen data is 86%, which aligns well with the fitted model's accuracy score (0.85). This indicates the model generalizes well and suggests that overfitting is not a major concern.

Key Insights

- **Accuracy Improvement**: The fitted model has a significantly higher accuracy than the baseline, indicating it is much better at predicting the correct outcomes overall.
- **Trade-off Between Recall and Precision**: The baseline model has a perfect recall but poor precision, meaning it identifies all actual positives but at the cost of many false positives. The fitted model, however, has much better precision but lower recall, suggesting it is more conservative and focuses on reducing false positives.
- **F1 Score Analysis**: The F1 score for both models is relatively low, which suggests there is still room for improvement in balancing precision and recall. The slight

improvement over the baseline indicates the fitted model's predictions are slightly more balanced but still not optimal.
- **Generalization Performance**: The high CV score (0.86) suggests that, despite some weaknesses in recall, the model is likely to perform well on new data.

Suggestions for Improvement of the model

- **Handle Class Imbalance**: If there is an imbalance in the dataset (e.g., more negatives than positives), consider using techniques like oversampling, undersampling, or using algorithms that handle class imbalance better.

4.5 **Dealing with the imbalanced data**

I will first find the class imbalance in the train and test data.

In [46]:
```
# Training set
print(y_train.value_counts())
print('\n')
# Test set
print(y_test.value_counts())
```

```
False    2284
True      382
Name: churn, dtype: int64


False    566
True     101
Name: churn, dtype: int64
```

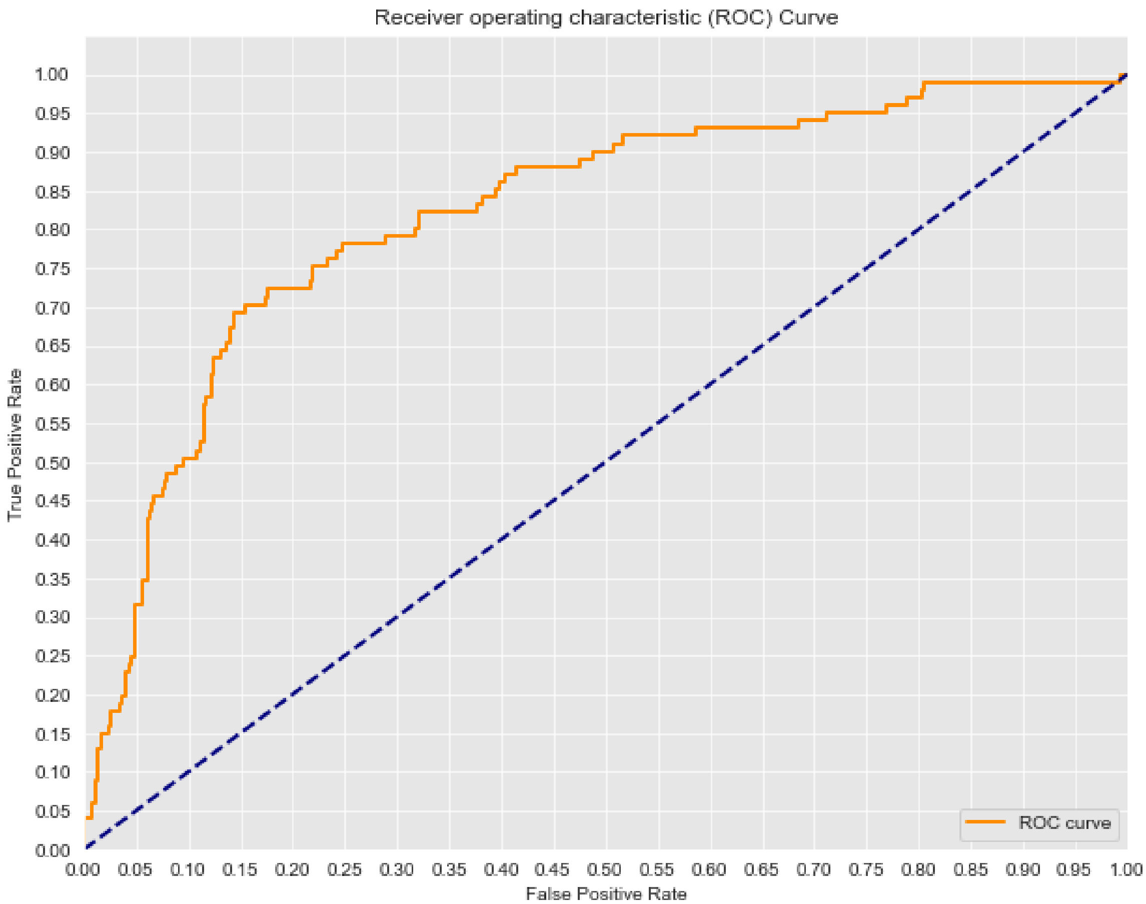
In [47]:
```
y_score =model.decision_function(X_test)
# False positive rate and true positive rate
fpr, tpr, thresholds = roc_curve(y_test, y_score)

# Seaborn's beautiful styling
sns.set_style('darkgrid', {'axes.facecolor': '0.9'})

# Print AUC
print('AUC: {}'.format(auc(fpr, tpr)))

# Plot the ROC curve
plt.figure(figsize=(10, 8))
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

```
AUC: 0.8209250253647272
```



This graph is a **Receiver Operating Characteristic (ROC) Curve**, a tool used to evaluate the performance of a binary classification model.

Key Elements of the ROC Curve:

1. **True Positive Rate (TPR)** (y-axis): Also known as sensitivity or recall, this measures the proportion of actual positives correctly identified by the model.
2. **False Positive Rate (FPR)** (x-axis): This measures the proportion of actual negatives that were incorrectly identified as positive by the model.

Explanation of the Graph:

- **Orange Line**: Represents the ROC curve, which plots the TPR against the FPR at various threshold settings. The curve shows the trade-off between sensitivity and specificity (True Negative Rate) across different thresholds.
- **Diagonal Blue Line**: Represents a random classifier with no predictive power, which would give a line at a 45-degree angle (i.e., TPR = FPR). A model whose ROC curve is close to this line is no better than random guessing.
- **Area Under the Curve (AUC = 0.82)**: The AUC value is 0.82, indicating that the model has a good ability to distinguish between the two classes. An AUC value of 1.0 represents a perfect model, while an AUC value of 0.5 suggests a model with no discriminative power.

Oversampling and Undersampling to handle Imbalance

In [48]:

```
# Define SMOTE for oversampling
smote = SMOTE(sampling_strategy=0.5, random_state=42)  # You can adjust the sa

# Define RandomUnderSampler for undersampling
undersample = RandomUnderSampler(sampling_strategy=0.75, random_state=42)  # A

# Create a pipeline that combines both
pipeline = Pipeline(steps=[('smote', smote), ('undersample', undersample)])
X_train_resampled, y_train_resampled = pipeline.fit_resample(X_train, y_train)
model = LogisticRegression(random_state=42)
model.fit(X_train_resampled, y_train_resampled)
y_pred = model.predict(X_test)
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
[[474  92]
 [ 33  68]]
              precision    recall  f1-score   support

       False       0.93      0.84      0.88       566
        True       0.42      0.67      0.52       101

    accuracy                           0.81       667
   macro avg       0.68      0.76      0.70       667
weighted avg       0.86      0.81      0.83       667
```

Balanced Improvement: The application of oversampling and undersampling techniques has led to a more balanced performance across the two classes. The model's ability to detect True instances has improved, reducing the bias toward the majority class (False).

Modelling using Decision Trees

In [49]:

```
dt = DecisionTreeClassifier()

dt.fit(X_train,y_train)
```

Out[49]: DecisionTreeClassifier()

In [50]:

```
dt_cv = cross_val_score(dt,X_train,y_train).mean
```

In [51]:

```
#Check for auc of predictions
y_pred = dt.predict(X_test)
fpr,tpr,thresholds = roc_curve(y_test,y_pred)
auc_score = auc(fpr,tpr)
print('AUC Score:', auc_score)
```

```
AUC Score: 0.8384179407340027
```

In [52]:

```
dt_accuracy = accuracy_score(y_test,y_pred)
dt_recall = recall_score(y_test,y_pred)
dt_precision = precision_score(y_test,y_pred)
dt_f1score = f1_score(y_test,y_pred)

print(f"""
Accuracy
Baseline: {baseline_accuracy:1.3f} Fitted Model: {model_accuracy:1.3f} Decisic
Recall
Baseline: {baseline_recall:1.3f} Fitted Model: {model_recall:1.3f} Decision Tr
Precision
Baseline: {baseline_precision:1.3f} Fitted Model: {model_precision:1.3f} Decis
F1_score: {baseline_f1score:.3f} Fitted Model: {model_f1score:.3f} Decision Tr
```

```
Accuracy
Baseline: 0.151 Fitted Model: 0.850 Decision Tree: 0.919
Recall
Baseline: 1.000 Fitted Model: 0.178 Decision Tree: 0.723
Precision
Baseline: 0.151 Fitted Model: 0.514 Decision Tree: 0.737
F1_score: 0.263 Fitted Model: 0.265 Decision Tree: 0.730
```

Based on these metrics:

- **Decision Tree**: Has the highest accuracy (0.919), recall (0.723), precision (0.737), and F1 score (0.730). This indicates that the Decision Tree performs best in terms of balancing these metrics.
- **Fitted Model**: Shows decent precision and recall but lower accuracy and F1 score compared to the Decision Tree.
- **Baseline**: Has very low scores across all metrics, which suggests it is not performing well.

5. Recommendations

1.Model to use

Based on the metrics, the **Decision Tree** model appears to be the best option overall, as it provides the highest scores across accuracy, recall, precision, and F1 score. Decision Tree seems to offer the most balanced performance here.

2.Identify Drivers of Customer Churn

To identify the factors contributing to high customer churn, you can use feature importance scores or coefficients from the model. Feature importance from a Random Forest model or coefficients from a Logistic Regression model can indicate which features most strongly impact churn features most strongly impact churn.

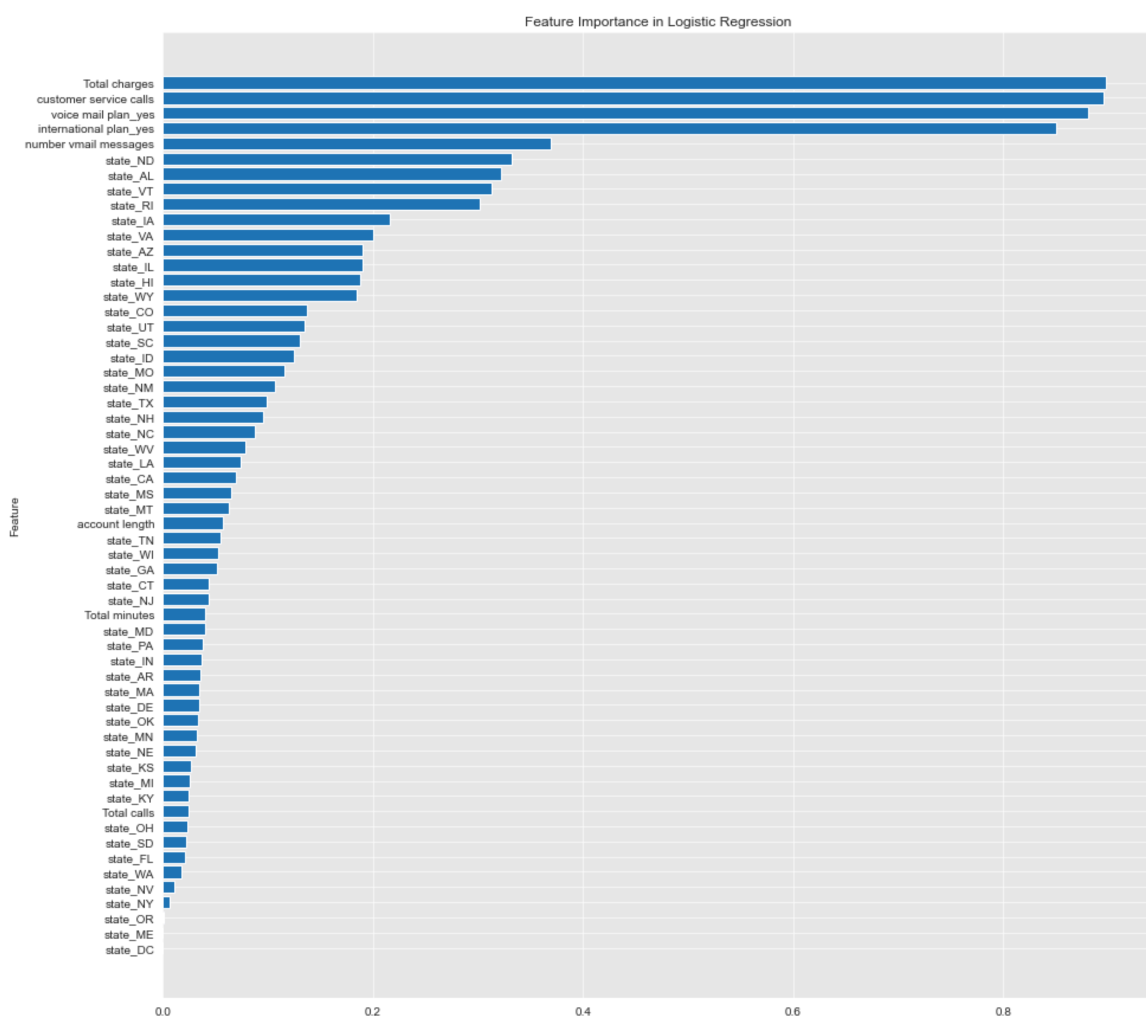
In [53]:

```
# Getting the coefficients of the model
coefficients = model.coef_[0]  # For binary classification, it's a 1D array

# Creating a DataFrame for better visualization
feature_importance_df = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': np.abs(coefficients)
})

# Sorting by the most important features
feature_importance_df = feature_importance_df.sort_values(by='Importance', asc

plt.figure(figsize=(15,15))
plt.barh(feature_importance_df['Feature'], feature_importance_df['Importance']
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title('Feature Importance in Logistic Regression')
plt.gca().invert_yaxis()
plt.show()
```



Key Drivers likely to lead to customer Churn are;

Total Charges: This is the most important feature. Customers with higher total charges

Total Charges: This is the most important feature. Customers with higher total charges are more likely to churn. **Action**: Implement targeted discounts or loyalty rewards for high-billing customers. Offer bundled services at a reduced rate to decrease the perceived cost.

Customer Service Calls: A high number of customer service calls indicates dissatisfaction or unresolved issues. **Action**: Improve customer service quality by training staff, reducing response times, and resolving issues on the first call. Implement a proactive approach by contacting customers with high call volumes to check their satisfaction levels.

Voice Mail Plan and International Plan: The presence of a voice mail plan or international plan correlates with churn. **Action**: Re-evaluate the pricing or value of these plans. Consider offering better value-added services or bundles that encourage customers to keep these plans.

Number of Voicemail Messages: A higher number of voicemail messages could indicate that customers are not using modern communication features or are facing issues. **Action**: Educate customers about newer, more efficient communication methods and offer incentives for switching to them.

Geographic Factors (States): Several states (e.g., ND, AL, VT) have a higher importance in predicting churn. **Action**: Conduct state-specific market research to understand the unique reasons for churn in these areas. Tailor marketing strategies, service improvements, or special offers to address local needs.

3. Analyze Churn Trends across Different States

To analyze churn trends across different states, you can group the data by state and compute the churn rate for each state.

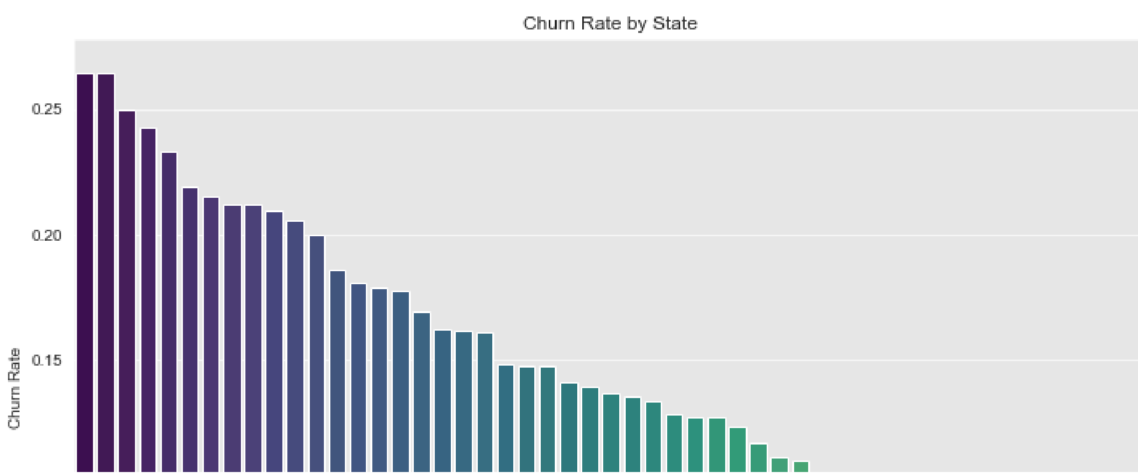
In [54]:

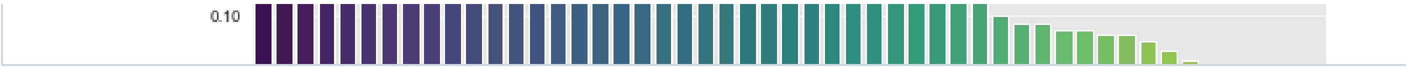
```
# Group by state and calculate churn rate
churn_by_state = data.groupby('state')['churn'].mean().reset_index()
churn_by_state = churn_by_state.sort_values(by='churn', ascending=False)
print(churn_by_state)

# Plotting churn rates by state
plt.figure(figsize=(12, 8))
sns.barplot(data=churn_by_state, x='state', y='churn', palette='viridis')
plt.xticks(rotation=90)
plt.title('Churn Rate by State')
plt.xlabel('State')
plt.ylabel('Churn Rate')
plt.show()
```

```
   state     churn
31    NJ  0.264706
4     CA  0.264706
43    TX  0.250000
20    MD  0.242857
40    SC  0.233333
```

22	MI	0.219178
25	MS	0.215385
33	NV	0.212121
47	WA	0.212121
21	ME	0.209677
26	MT	0.205882
2	AR	0.200000
16	KS	0.185714
34	NY	0.180723
23	MN	0.178571
38	PA	0.177778
19	MA	0.169231
6	CT	0.162162
27	NC	0.161765
30	NH	0.160714
10	GA	0.148148
8	DE	0.147541
36	OK	0.147541
37	OR	0.141026
44	UT	0.138889
5	CO	0.136364
17	KY	0.135593
41	SD	0.133333
35	OH	0.128205
9	FL	0.126984
15	IN	0.126761
13	ID	0.123288
50	WY	0.116883
24	MO	0.111111
46	VT	0.109589
1	AL	0.100000
32	NM	0.096774
28	ND	0.096774
49	WV	0.094340
42	TN	0.094340
7	DC	0.092593
39	RI	0.092308
48	WI	0.089744
14	IL	0.086207
29	NE	0.081967
18	LA	0.078431
12	IA	0.068182
45	VA	0.064935
3	AZ	0.062500
0	AK	0.057692
11	HI	0.056604




0.10