1 1. BUSINESS UNDERSTANDING ¶

1.1 1.1 Project Overview

This project aim to build a model that will predict whether a customer is likely to leave SyriaTel soon

1.2 1.2 Problem Statement

SyriaTel, a telecommunications company, is dealing with a critical concern which is customer churn. This poses threats to revenue, and deepens the issue of long-term sustainability. They are presented with the task of determining which customers are most likely to stop using their services, as well as understanding the reasons why these choices are made so that the company can address these concerns.

1.3 1.3 Objectives

1.3.1 1.4 Main Objectives

To analyze customer behaviour,call usage and the interaction with customer services inorder to discover factors contributing to customer churn behaviour

1.3.2 1.5 Specific Objectives

Other specific objectives include:

1. Identify how the number of customer service interactions relates to the probabilities of customer churn for your business.
2. Examine the elements that lead to customer churn and estimate the clients poised to exit.
3. To examine customer behavour by analyzing day,night calls and their correlation to churn
4. To identify the relationship between the charge and the charge both during the day and the night
5. To identify if customers from international calls are likely to churn more
6. To identify the relationship between the day/night minutes and there charge

2 2. DATA UNDERSTANDING

2.1 2.0 Import Libraries

In [2]:

```
##Import libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings('ignore')


from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score,confusion_matrix,classifi
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.metrics import classification_report

from imblearn.over_sampling import SMOTE

from sklearn import tree
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score, confusion_matrix, classi
```

2.2 2.1 Load DataSet

In [3]:
```
##Load the csv data set
df=pd.read_csv("bigml.csv")
df
```

Out[3]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	ch
0	KS	128	415	382-4657	no	yes	25	265.1	110	4
1	OH	107	415	371-7191	no	yes	26	161.6	123	2
2	NJ	137	415	358-1921	no	no	0	243.4	114	4
3	OH	84	408	375-9999	yes	no	0	299.4	71	5
4	OK	75	415	330-6626	yes	no	0	166.7	113	2
...	...	...	...	...	...	...	...	...	...	
3328	AZ	192	415	414-4276	no	yes	36	156.2	77	2
3329	WV	68	415	370-3271	no	no	0	231.1	57	3
3330	RI	28	510	328-8230	no	no	0	180.8	109	3
3331	CT	184	510	364-6381	yes	no	0	213.8	105	3
3332	TN	74	415	400-4344	no	yes	25	234.4	113	3

3333 rows × 21 columns

In [4]:
```
##Check the head
df.head()
```

Out[4]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	tota da charg
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.0
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.4
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.3
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.9
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.3

5 rows × 21 columns

In [5]:
```
##Check the tail
df.tail()
```

Out[5]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	ch
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	:

5 rows × 21 columns

Observation:The dataset is not corrupted hence it is uniform from Top to bottom

In [6]:
```
##Check the shape attribute
df.shape
```

Out[6]: (3333, 21)

In [7]:
```
print(f"The dataset has row of {df.shape[0]} and columns of {df.shap
```

```
The dataset has row of 3333 and columns of 21
```

In [8]:
```
##checking the datatypes
df.dtypes
```

Out[8]:
```
state                      object
account length              int64
area code                   int64
phone number               object
international plan         object
voice mail plan            object
number vmail messages       int64
total day minutes         float64
total day calls             int64
total day charge          float64
total eve minutes         float64
total eve calls             int64
total eve charge          float64
total night minutes       float64
total night calls           int64
total night charge        float64
total intl minutes        float64
total intl calls            int64
total intl charge         float64
customer service calls      int64
churn                        bool
dtype: object
```

OBSERVATION:We can see that the churn column is boolean meaning that it has two unique values

In [9]:

```
##checking the info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   state                   3333 non-null   object 
 1   account length          3333 non-null   int64  
 2   area code               3333 non-null   int64  
 3   phone number            3333 non-null   object 
 4   international plan      3333 non-null   object 
 5   voice mail plan         3333 non-null   object 
 6   number vmail messages   3333 non-null   int64  
 7   total day minutes       3333 non-null   float64
 8   total day calls         3333 non-null   int64  
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64  
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64  
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64  
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64  
 20  churn                   3333 non-null   bool   
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

In [10]:

```
##Checking the columns
df.columns
```

Out[10]:

```
Index(['state', 'account length', 'area code', 'phone number',
       'international plan', 'voice mail plan', 'number vmail message
s',
       '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 charg
e',
       'total intl minutes', 'total intl calls', 'total intl charge',
       'customer service calls', 'churn'],
      dtype='object')
```

Observation:The columns are well written with no mixture of upper and lowercase

In [11]:
```
##Checking the statistical summary and transpose
df.describe().T
```

Out[11]:

	count	mean	std	min	25%	50%	75%	max
account length	3333.0	101.064806	39.822106	1.00	74.00	101.00	127.00	243.00
area code	3333.0	437.182418	42.371290	408.00	408.00	415.00	510.00	510.00
number vmail messages	3333.0	8.099010	13.688365	0.00	0.00	0.00	20.00	51.00
total day minutes	3333.0	179.775098	54.467389	0.00	143.70	179.40	216.40	350.80
total day calls	3333.0	100.435644	20.069084	0.00	87.00	101.00	114.00	165.00
total day charge	3333.0	30.562307	9.259435	0.00	24.43	30.50	36.79	59.64
total eve minutes	3333.0	200.980348	50.713844	0.00	166.60	201.40	235.30	363.70
total eve calls	3333.0	100.114311	19.922625	0.00	87.00	100.00	114.00	170.00
total eve charge	3333.0	17.083540	4.310668	0.00	14.16	17.12	20.00	30.91
total night minutes	3333.0	200.872037	50.573847	23.20	167.00	201.20	235.30	395.00
total night calls	3333.0	100.107711	19.568609	33.00	87.00	100.00	113.00	175.00
total night charge	3333.0	9.039325	2.275873	1.04	7.52	9.05	10.59	17.77
total intl minutes	3333.0	10.237294	2.791840	0.00	8.50	10.30	12.10	20.00
total intl calls	3333.0	4.479448	2.461214	0.00	3.00	4.00	6.00	20.00
total intl charge	3333.0	2.764581	0.753773	0.00	2.30	2.78	3.27	5.40
customer service calls	3333.0	1.562856	1.315491	0.00	1.00	1.00	2.00	9.00

3 3. DATA PREPARATION

3.1 3.0 Data Cleaning

In [12]:
```
##Checking for unique values in the categorical values
df.groupby("churn")["churn"].count()
```

Out[12]:
```
churn
False    2850
True      483
Name: churn, dtype: int64
```

In [13]:
```
##Checking for unique values in the categorical values
df.groupby("international plan")["international plan"].count()
```

Out[13]:
```
international plan
no     3010
yes     323
Name: international plan, dtype: int64
```

In [14]:
```
df.groupby("voice mail plan")["voice mail plan"].count()
```

Out[14]:
```
voice mail plan
no     2411
yes     922
Name: voice mail plan, dtype: int64
```

In [15]:
```
##Checking for missing values
df.isnull().sum()
```

Out[15]:
```
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:No missing values

In [16]:
```
##Check for duplicates
df.duplicated().sum()
```

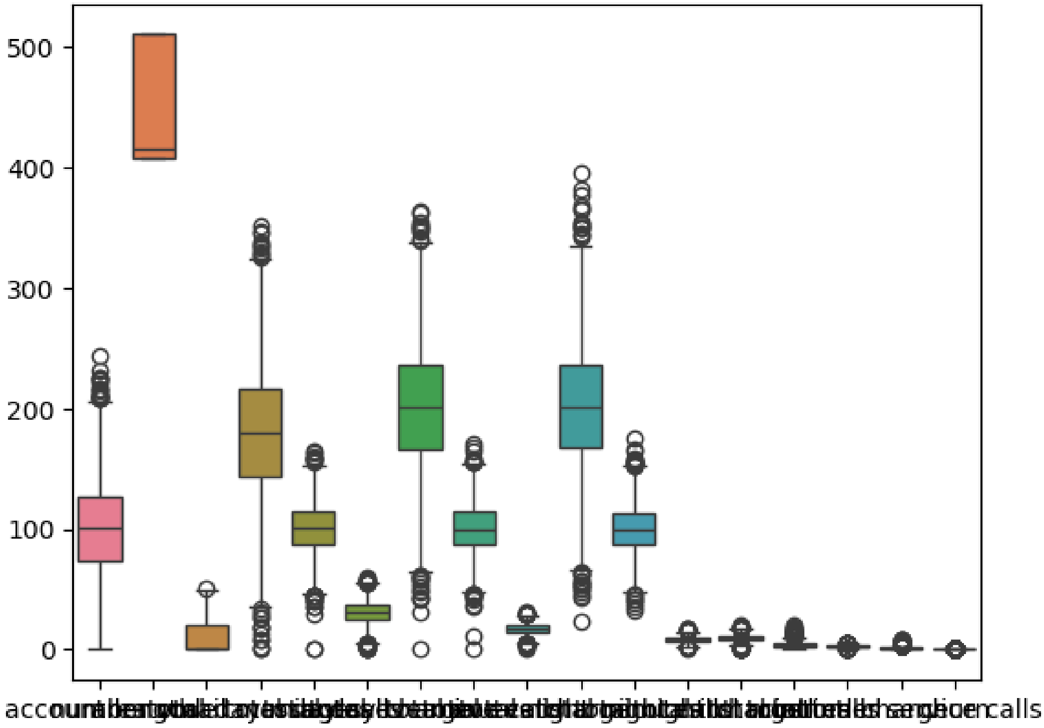
Out[16]:
```
0
```

Note:No duplicates

In [17]:
```
##Drop unnecessary column
del df["phone number"]
```

Type *Markdown* and LaTeX: α^2

In [18]:
```
##Check for outliers
sns.boxplot(df);
```



NOTE : I will remove outliers from numerical data only eg account length Some outliers are healthy while others are not

In [19]:
```
##identify numerical columns except area code
numerical_cols = df.select_dtypes(include=['number']).columns.drop("
numerical_cols
```

Out[19]:
```
Index(['account length', 'number vmail messages', 'total day minute
s',
       '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 minute
s',
       'total intl calls', 'total intl charge', 'customer service cal
ls'],
      dtype='object')
```

NOTE:I want to perform iqr in all columns in order to remove outliers except from area code which i consider that Applying IQR could remove valid data, which is not desirable for identifiers

In [20]:

```
# Compute Q1 (25th percentile) and Q3 (75th percentile) for all nume
Q1 = df[numerical_cols].quantile(0.25)
Q3 = df[numerical_cols].quantile(0.75)

# Compute IQR
IQR = Q3 - Q1

# Define the lower and upper bounds for outlier removal
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Remove outliers (keeping "area code" unchanged)
df_cleaned = df[~((df[numerical_cols] < lower_bound) | (df[numerical

# Display the shape before and after removing outliers
print(f"Original dataset shape {df.shape[0]} rows and {df.shape[1]}
print(f"Cleaned dataset shape {df_cleaned.shape[0]} rows and {df_cle
```

```
Original dataset shape 3333 rows and 20 columns
Cleaned dataset shape 2804 rows and 20 columns
```

In [21]:

```
# Save the cleaned dataset
df_cleaned.to_csv("cleaned_bigml.csv", index=False)
df_cleaned.head()
## I have used index=False Avoids an extra, unnecessary column in th
```

Out[21]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	tot ev minute
0	KS	128	415	no	yes	25	265.1	110	45.07	197
1	OH	107	415	no	yes	26	161.6	123	27.47	195
2	NJ	137	415	no	no	0	243.4	114	41.38	121
4	OK	75	415	yes	no	0	166.7	113	28.34	148
5	AL	118	510	yes	no	0	223.4	98	37.98	220

4 4. EDA

4.1 Here i will be able to perform the following activities

- Univariate analysis
- Bivarite analysis
- Multivariate analysis

In [22]:

```
##Load the clean data set
df5=pd.read_csv("cleaned_bigml.csv")
df5
```

Out[22]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	mi
0	KS	128	415	no	yes	25	265.1	110	45.07	
1	OH	107	415	no	yes	26	161.6	123	27.47	
2	NJ	137	415	no	no	0	243.4	114	41.38	
3	OK	75	415	yes	no	0	166.7	113	28.34	
4	AL	118	510	yes	no	0	223.4	98	37.98	
...	...	...	...	...	...	...	...	...	...	
2799	AZ	192	415	no	yes	36	156.2	77	26.55	
2800	WV	68	415	no	no	0	231.1	57	39.29	
2801	RI	28	510	no	no	0	180.8	109	30.74	
2802	CT	184	510	yes	no	0	213.8	105	36.35	
2803	TN	74	415	no	yes	25	234.4	113	39.85	

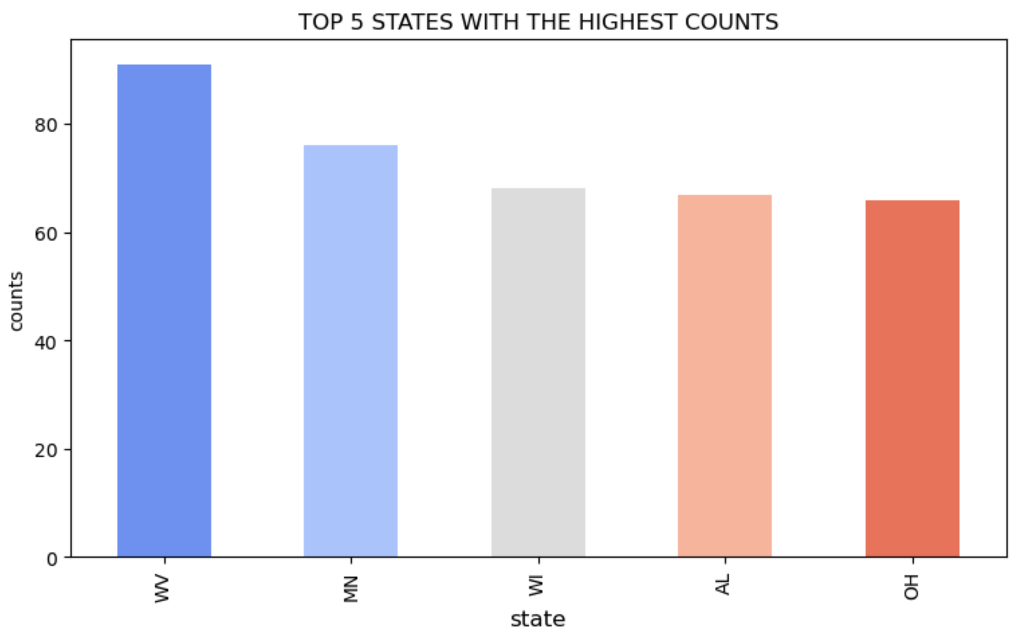
2804 rows × 20 columns

4.2 4.1 UNIVARIATE ANALYSIS

4.2.1 4.1.1 Analysis on top 5 states with the highest Counts

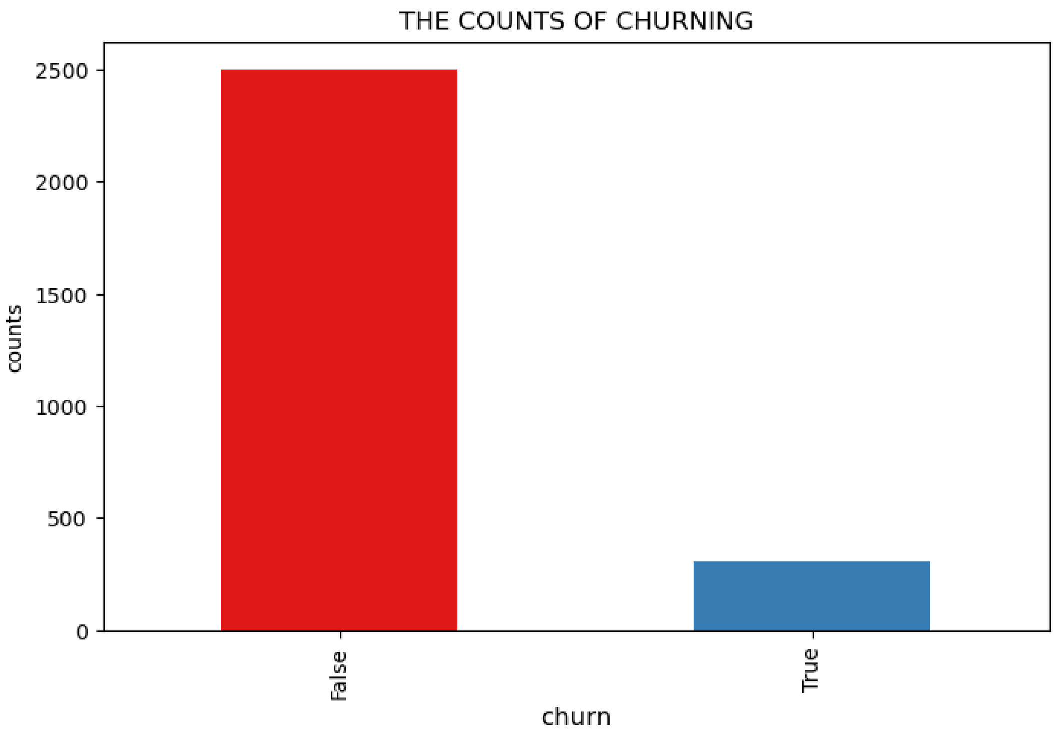
In [23]:

```
TOP_5_States=df5["state"].value_counts().head(5).plot(kind='bar',fig
sns.set_palette('Blues')
plt.title("TOP 5 STATES WITH THE HIGHEST COUNTS")
plt.ylabel("counts")
plt.xlabel('state',fontsize=12)
plt.show;
```



4.2.2 4.1.2 Analysis on the counts of churn

In [24]:
```
df5["churn"].value_counts().plot(kind='bar',figsize=(8,5),color=sns.
sns.set_palette('Set1')
plt.title("THE COUNTS OF CHURNING")
plt.ylabel("counts")
plt.xlabel('churn',fontsize=12)
plt.show;
```



OBSERVATION: People who are likely to churn are less than the others

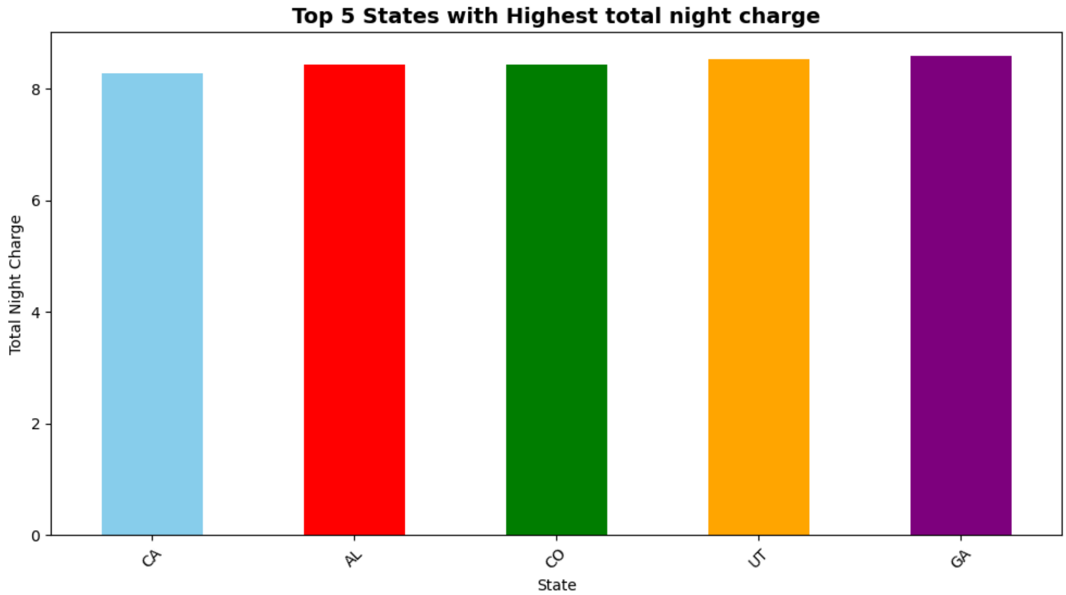
4.3 4.2 BIVARIATE ANALYSIS

This is the analysis of two variable

4.3.1 4.2.1 Analysis on top 5 states with the highest total night charge

In [25]:

```
colors = ['skyblue', 'red', 'green', 'orange', 'purple']

plt.figure(figsize=(12, 6))

df5.groupby("state")["total night charge"].mean().sort_values(ascend
.plot(kind='bar', color=colors)

plt.title("Top 5 States with Highest total night charge", fontsize=1

plt.ylabel("Total Night Charge")

plt.xlabel("State")

plt.xticks(rotation=45)

plt.show()
```



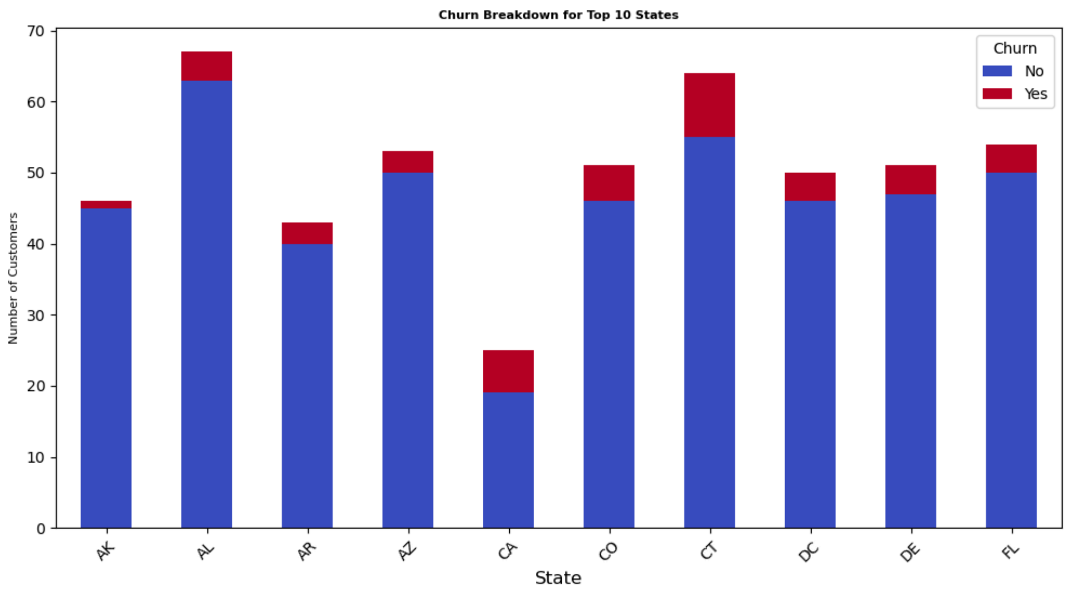
OBSERVATION:

- The night charge values appear to be very similar across the states, with minimal variation.

4.3.2 4.2.3 Analysis on top 10 states with the highest churn

In [26]:

```
# Count churn by state
churn_state = df5.groupby(["state", "churn"]).size().unstack()

# Plot
churn_state.head(10).plot(kind='bar', stacked=True, figsize=(12, 6),

# Titles and labels
plt.title("Churn Breakdown for Top 10 States", fontsize=8, fontweigh
plt.xlabel("State", fontsize=12)
plt.ylabel("Number of Customers", fontsize=8)
plt.xticks(rotation=45)
plt.legend(title="Churn", labels=["No", "Yes"])

# Show plot
plt.show()
```



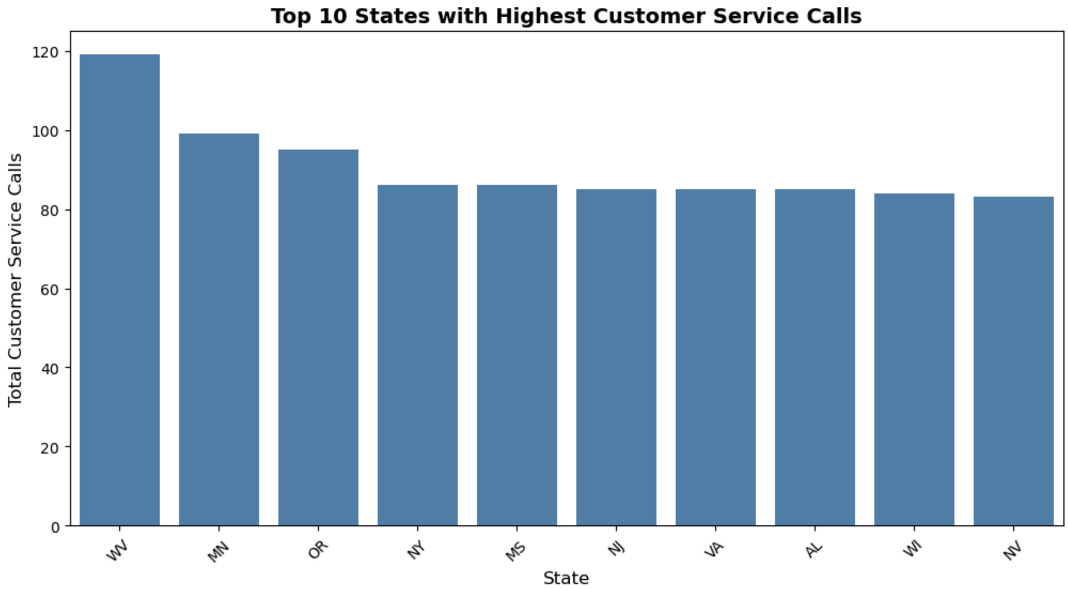
OBSERVATION:

- The blue portion represents customers who have not churned, while the red portion represents those who have churned.
- The state with the highest total number of customers also has one of the highest numbers of customer churn, which indicates that having a high number of customers does not hinder or reduce the process of customer churn.
- There are some states with a relatively lower rate of churn, indicating greater customer retention within those specific states.

4.3.3 4.2.4 Analysis on top 10 states with the highest customer srvice calls

In [27]:

```
# Count customer service calls per state
top_service_calls = df5.groupby("state")["customer service calls"].s

# Plot
plt.figure(figsize=(12, 6))
sns.barplot(x=top_service_calls.index, y=top_service_calls.values, c

# Titles and labels
plt.title("Top 10 States with Highest Customer Service Calls", fonts
plt.xlabel("State", fontsize=12)
plt.ylabel("Total Customer Service Calls", fontsize=12)
plt.xticks(rotation=45)

# Show plot
plt.show()
```

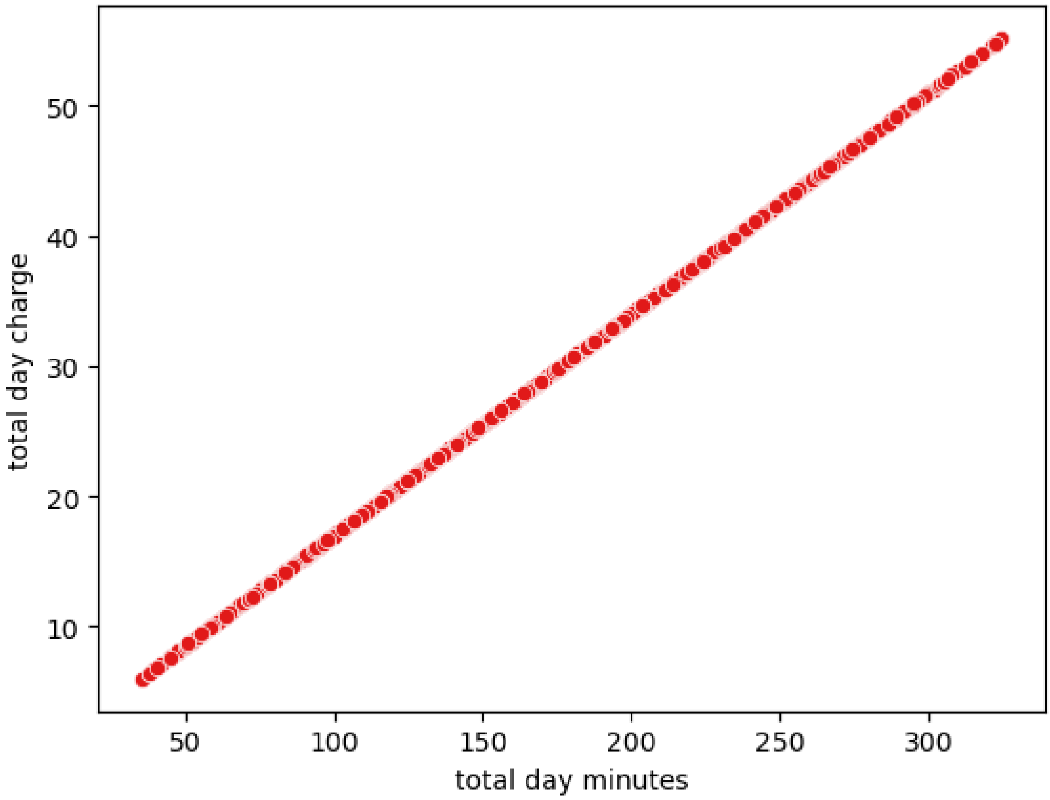


OBSERVATION: West Virginia (WV) has the highest number of customer service calls, followed by Minnesota (MN) and Oregon (OR)

4.3.4 4.2.5 Analysis on total day minutes and total day charge

In [28]:

```
##using scatter plot
sns.scatterplot(data=df5, x='total day minutes', y='total day charge
```

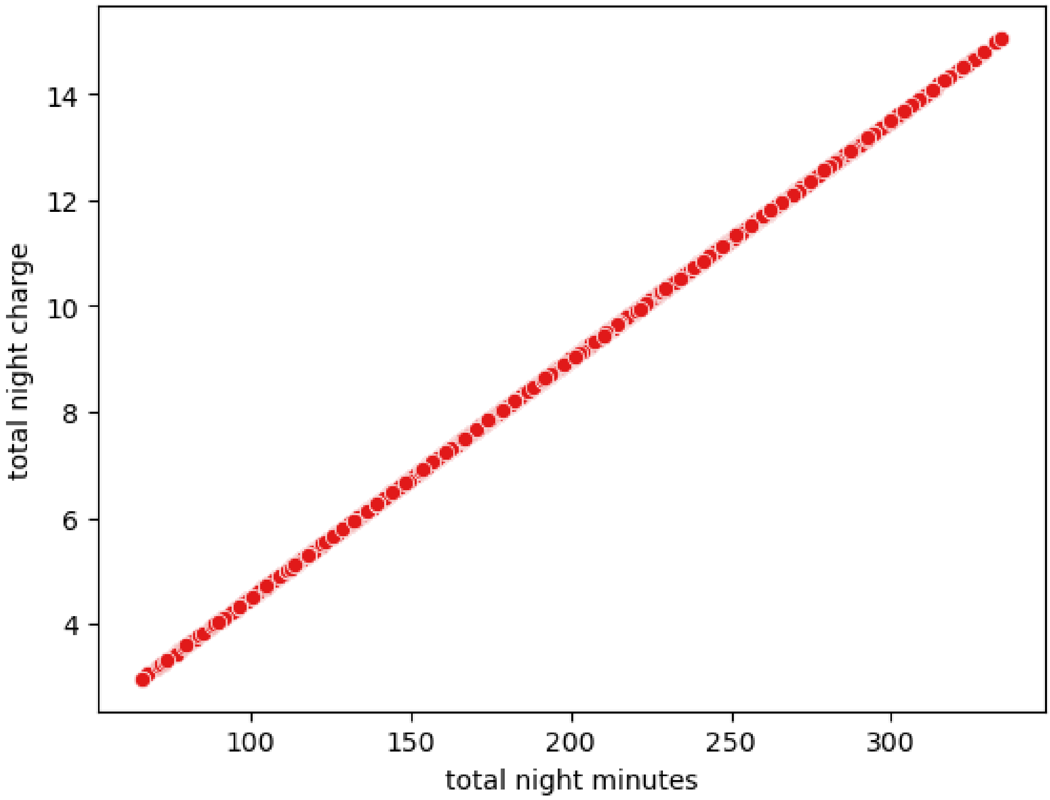


OBSERVATION:This shows a positive correlation between total day minutes and total day charge¶ which means that if one variable increases the other one will also increase

4.3.5 4.2.6 Analysis on total night minutes and total night charge

In [29]:

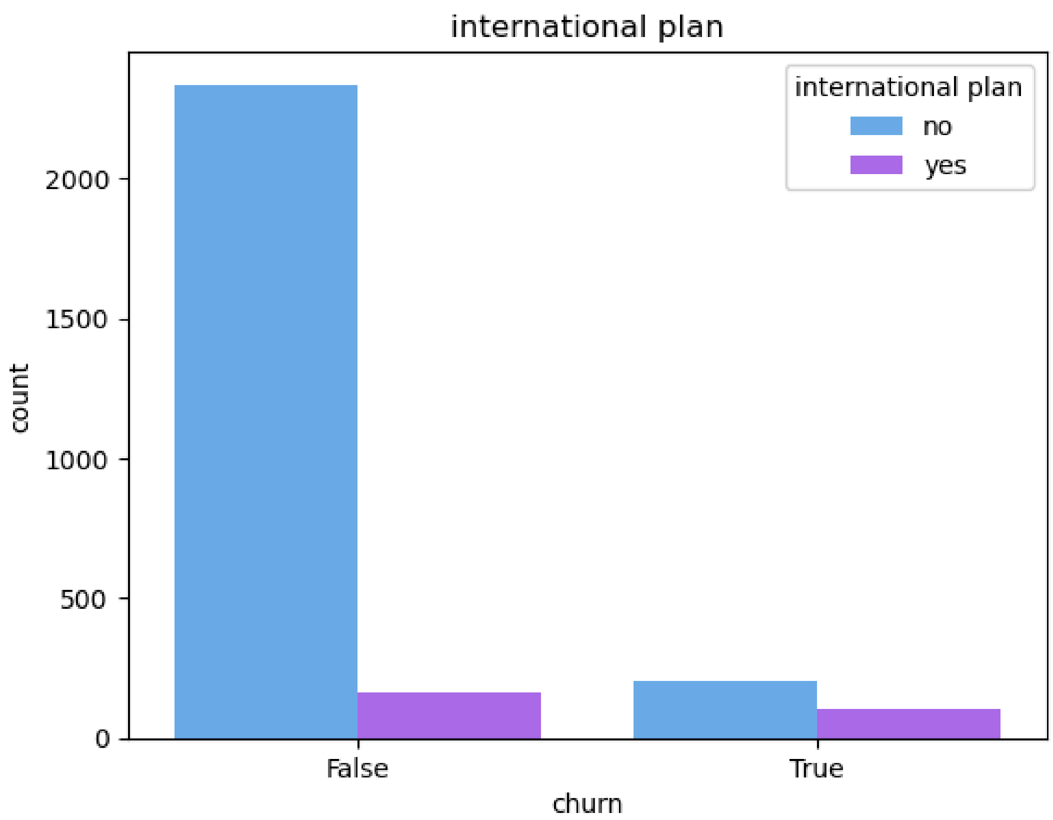
```
##using scatter plot
sns.scatterplot(data=df5, x='total night minutes', y='total night ch
```



OBSERVATION: This shows a positive correlation between total night minutes and total night charge which means that if one variable increases the other one will also increase

4.3.6 4.2.6 Analysis on international plan and churn

In [30]:
```
##using count plot
sns.countplot(x=df5["churn"],hue=df5["international plan"], palette=
plt.title("international plan")
plt.show()
cort=pd.crosstab(df5["churn"],df5["international plan"])
cort
```



Out[30]:

international plan	no	yes
churn		
False	2335	164
True	201	104

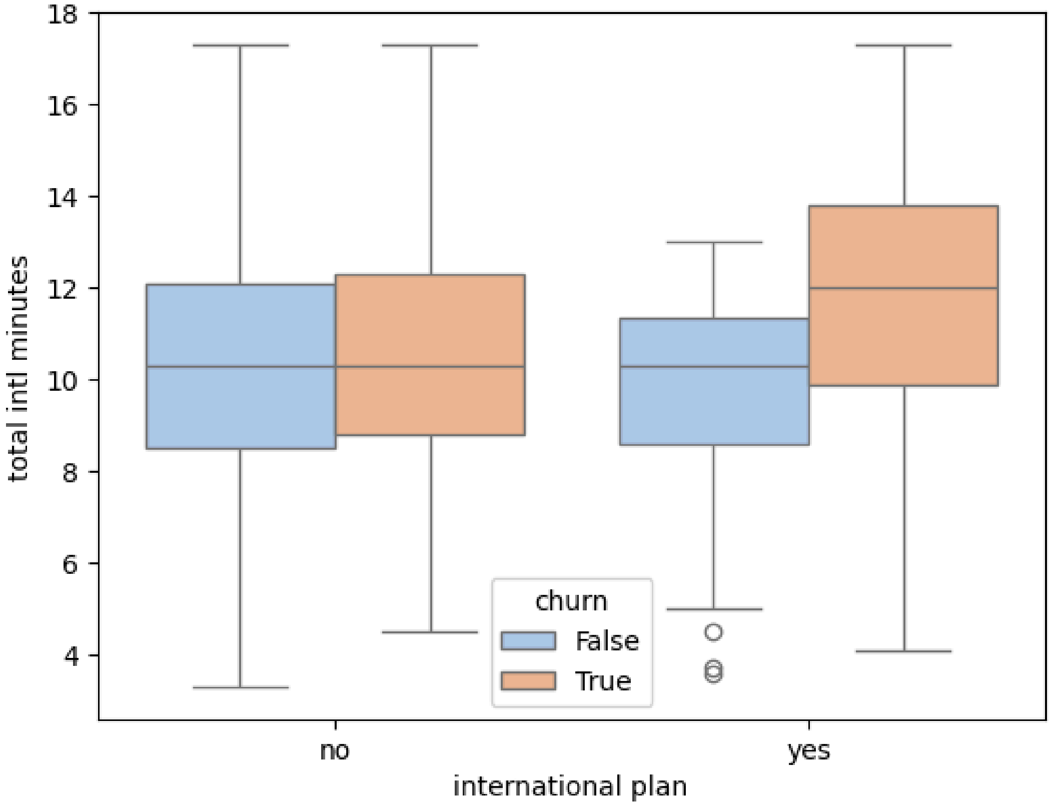
OBSERVATION: A majority (2335) of customers who did not churn have no international plan. Only 164 non-churn customers have an international plan. A significant number of churned customers (201) do not have an international plan. However, 104 churned customers do have an international plan, which indicates that some customers with an international plan still ended up churning.

4.4 4.3 MULTIVARIATE ANALYSIS

This is the analysis of more than two variable

4.4.1 4.3.1 Analyzing Relationship Between international plan,total intl minutes' and churn

In [31]:
```
sns.boxplot(data=df5, x='international plan', y='total intl minutes'
plt.legend
plt.show()
```



OBSERVATION:

- The box plot visualizes the relationship between having an international plan (0 = No, 1 = Yes) and total international minutes, categorized by customer churn (True/False).
- Customers with an international plan (1) tend to have a higher median total international minutes compared to those without a plan.
- Churned customers tend to have a higher total international minutes, especially for those with an international plan.

5 5. MODELLING

In this section of modelling i will be able to conduct two model that is:

- Logistic Regression
- Decision Tree

5.1 5.1 LOGISTIC REGRESSION

5.1.1 A. WITHOUT ADRESSING CLASS IMBALANCE

5.2 Activities i will conduct

- I will be able to perform one hot encoding on the Predictor Variable or the Feature(preprocessing)
- I will also convert the target variable which is categorical variable into 0,1,2 etc
- Divide the data into target and predictor
- Split the data into train and test
- scalling
- Modelling
- Getting the shapes
- Predict
- Check the accuracy
- confusion matrix
- Classification Report

In [34]:
```
##Import the relevant libraries

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt


from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score,confusion_matrix,classifi
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.metrics import classification_report
from imblearn.over_sampling import SMOTE
```

In [35]:
```
##Load our dataset
df10=pd.read_csv("cleaned_bigml.csv")
df10
```

Out[35]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	mi
0	KS	128	415	no	yes	25	265.1	110	45.07	
1	OH	107	415	no	yes	26	161.6	123	27.47	
2	NJ	137	415	no	no	0	243.4	114	41.38	
3	OK	75	415	yes	no	0	166.7	113	28.34	
4	AL	118	510	yes	no	0	223.4	98	37.98	
...	...	...	...	...	...	...	...	...	...	
2799	AZ	192	415	no	yes	36	156.2	77	26.55	
2800	WV	68	415	no	no	0	231.1	57	39.29	
2801	RI	28	510	no	no	0	180.8	109	30.74	
2802	CT	184	510	yes	no	0	213.8	105	36.35	
2803	TN	74	415	no	yes	25	234.4	113	39.85	

2804 rows × 20 columns

In [36]:
```
df10 = pd.read_csv("cleaned_bigml.csv", dtype={"international plan":
```

5.2.0.1 5.1.1 Preprocessing

- I will Convert categorical variables (international plan, voice mail plan) into numerical format.
- I will Convert churn (target variable) into a binary numerical format (False → 0, True → 1).
- I will also drop state because it has too many categorical variables

In [37]:
```
##From the data set lets drop state because it has too many categori
df10.drop(columns=['state'], inplace=True)

# Convert categorical variables to numeric
df10['international plan'] = df10['international plan'].map({'no': 0
df10['voice mail plan'] = df10['voice mail plan'].map({'no': 0, 'yes
df10['churn'] = df['churn'].astype(int)  # Convert False/True to 0/1
```

In [38]:
```
##The state column has been removed
df10
```

Out[38]:

	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes
0	128	415	0	1	25	265.1	110	45.07	197.4
1	107	415	0	1	26	161.6	123	27.47	195.5
2	137	415	0	0	0	243.4	114	41.38	121.2
3	75	415	1	0	0	166.7	113	28.34	148.3
4	118	510	1	0	0	223.4	98	37.98	220.6
...	...	...	...	...	...	...	...	...	...
2799	192	415	0	1	36	156.2	77	26.55	215.5
2800	68	415	0	0	0	231.1	57	39.29	153.4
2801	28	510	0	0	0	180.8	109	30.74	288.8
2802	184	510	1	0	0	213.8	105	36.35	159.6
2803	74	415	0	1	25	234.4	113	39.85	265.9

2804 rows × 19 columns

OBSERVATION:It has been converted to numeric

5.2.0.2 5.1.2 Split the data into target and Predictor

In [39]:
```
#Split the data into target and predictor
x=df10.drop("churn",axis=1)
y=df10["churn"]
```

5.2.0.3 5.1.3 Split the data into train,test and split

In [40]:
```
##split the data into train,test and split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.1,ran
```

5.2.0.4 5.1.4 Scalling

In [41]:
```
##Scalling
##We scale only the features not target
##We perform it on the features only and not target both the x_train
sc = StandardScaler()
x_train_sc = sc.fit_transform(x_train)
x_test_sc = sc.transform(x_test)
```

5.2.0.5 5.1.5 Build Model

In [42]:
```
#Build the model
model = LogisticRegression()
model.fit (x_train_sc,y_train)
```

Out[42]:
```
LogisticRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

5.2.0.6 5.1.6 Predict

In [43]:
```
#Predict
y_predict=model.predict(x_test_sc)
y_predict
```

Out[43]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

In [44]:
```
##the original
y
```

Out[44]:
```
0       0
1       0
2       0
3       0
4       0
       ..
2799    0
2800    1
2801    0
2802    0
2803    0
Name: churn, Length: 2804, dtype: int32
```

5.2.0.7 5.1.7 Accuracy

In [45]:
```
##We can check the model evaluation and round off to the nearest 2 d
round(accuracy_score(y_test,y_predict),2) *100
```

Out[45]:
```
89.0
```

In [46]:
```
##using print function
print(f"The accuracy score is {round(accuracy_score(y_test, y_predic
```

```
The accuracy score is 89.32 %
```

OBSERVATION:It is a better model perfomance since it is closer to 100 %

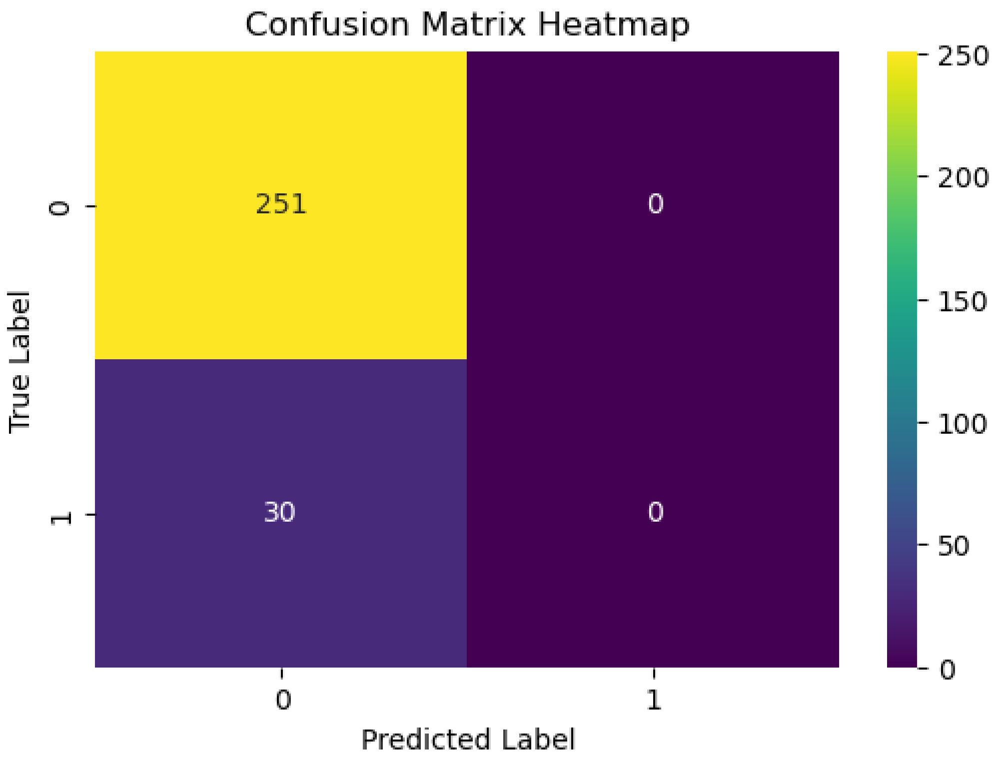
5.2.0.8 5.1.8 Confusion matrix

In [47]:
```
##confusion matrix
logistic_matrix=confusion_matrix(y_test,y_predict)
logistic_matrix
```

Out[47]:
```
array([[251,   0],
       [ 30,   0]], dtype=int64)
```

In [48]:

```
#In a heat maps
logistic_matrix=confusion_matrix(y_test,y_predict)

plt.figure(figsize=(6, 4))
logistic_matrix=sns.heatmap(logistic_matrix, annot=True, fmt='g', cm
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix Heatmap')
plt.show()
```



OBSERVATION: 251 is true positive,0True Negative,30 is False Negative, 0 is False positive

5.2.1 B.ADRESSING CLASS IMBALANCE

- I will use smote technique

In [49]:
```
# call SMOTE
smote = SMOTE(random_state=42)

# Apply SMOTE to the training data
x_train_smote, y_train_smote = smote.fit_resample(x_train, y_train)

# Check the new class distribution
print('Class distribution after SMOTE:')
print(pd.Series(y_train_smote).value_counts())
```

```
Class distribution after SMOTE:
churn
0    2153
1    2153
Name: count, dtype: int64
```

OBSERVATION:The class is balanced

In [50]:
```
# call the Logistic Regression model
smote_model = LogisticRegression()
```

In [51]:
```
# Train the model on the SMOTE data
model = LogisticRegression( max_iter=50000)

smote_model.fit(x_train_smote, y_train_smote)
```

Out[51]:
```
LogisticRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [52]:
```

# Make predictions
y_pred_smote = smote_model.predict(x_test)
```

In [53]:
```
# Accuracy
accuracy_smote = accuracy_score(y_test, y_pred_smote)
accuracy_smote
```

Out[53]:
```
0.4875444839857651
```

In [54]:
```
##using print
print(f"The accuracy score of the SMOTE model is {accuracy_score(y_t
```

```
The accuracy score of the SMOTE model is 0.49
```

In [55]:
```
# Classification Report
print('SMOTE Model Classification Report:')
print(classification_report(y_test, y_pred_smote))
```

```
SMOTE Model Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.49      0.63       251
           1       0.10      0.47      0.16        30

    accuracy                           0.49       281
   macro avg       0.49      0.48      0.40       281
weighted avg       0.80      0.49      0.58       281
```

OBSERVATION:

- Decreased Overall Accuracy (from 89% to 49%):

This is because the model is currently making a larger proportion of errors on class 0, which represents non-churn customers. Precision by itself has now been shown to be an unsatisfactory metric in the present scenario, primarily because it used to get artificially boosted and biased previously due to the natural skewness present in the data.

- Decreased precision for Class 1 (0.10):

The model currently believes that some customers will depart, but most of those predictions are incorrect. Precision indicates the number of customers we predicted would churn who actually churned. Low precision reflects high false positives (predicted churn when there isn't any)

5.3 5.2 DECISON TREES

5.3.1 WITH A TUNED HYPERPARAMETER(max_depth)

I will be able to perform the following activities:

- preprocessing
- Divide the data into target and predictor
- Split the data into train and split
- Cheking the shape
- Modelling
- Predict
- Accuracy checking
- Confusion_matrix
- Report
- Visualization

In [57]:
```
#import libraries relevant libraries in decision trees
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score, confusion_matrix, classi
```

In [58]:
```
##Load our dataset
df20=pd.read_csv("cleaned_bigml.csv")
df20
```

Out[58]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	mi
0	KS	128	415	no	yes	25	265.1	110	45.07	
1	OH	107	415	no	yes	26	161.6	123	27.47	
2	NJ	137	415	no	no	0	243.4	114	41.38	
3	OK	75	415	yes	no	0	166.7	113	28.34	
4	AL	118	510	yes	no	0	223.4	98	37.98	
...	...	...	...	...	...	...	...	...	...	
2799	AZ	192	415	no	yes	36	156.2	77	26.55	
2800	WV	68	415	no	no	0	231.1	57	39.29	
2801	RI	28	510	no	no	0	180.8	109	30.74	
2802	CT	184	510	yes	no	0	213.8	105	36.35	
2803	TN	74	415	no	yes	25	234.4	113	39.85	

2804 rows × 20 columns

5.3.1.1 5.2.1 Preprocessing

- I will Convert categorical variables (international plan, voice mail plan) into numerical format.
- I will Convert churn (target variable) into a binary numerical format (False → 0, True → 1).
- I will also drop state because it has too many categorical variables

In [59]:
```
##Ensures that "international plan" and "voice mail plan" columns ar
df20= pd.read_csv("cleaned_bigml.csv", dtype={"international plan":
```

In [60]:
```
##check the head
df20.head()
```

Out[60]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	tot ev minute
0	KS	128	415	no	yes	25	265.1	110	45.07	197
1	OH	107	415	no	yes	26	161.6	123	27.47	195
2	NJ	137	415	no	no	0	243.4	114	41.38	121
3	OK	75	415	yes	no	0	166.7	113	28.34	148
4	AL	118	510	yes	no	0	223.4	98	37.98	220

In [61]:
```
#From the data set lets drop state because it has too many categoric
df20.drop(columns=['state'], inplace=True)

# Convert categorical variables to numeric using map
df20['international plan'] = df20['international plan'].map({'no': 0
df20['voice mail plan'] = df20['voice mail plan'].map({'no': 0, 'yes
df20['churn'] = df20['churn'].astype(int)  # Convert False/True to 0
```

In [62]:
```
##Confirm if international plan ,churn and voice mail plan have been
df20.head()
```

Out[62]:

	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	tot ev call
0	128	415	0	1	25	265.1	110	45.07	197.4	9
1	107	415	0	1	26	161.6	123	27.47	195.5	10
2	137	415	0	0	0	243.4	114	41.38	121.2	11
3	75	415	1	0	0	166.7	113	28.34	148.3	12
4	118	510	1	0	0	223.4	98	37.98	220.6	10

5.3.1.2 5.2.2 Split the data into target and Predictor

In [63]:
```
#Split the data into target and predictor
x=df10.drop("churn",axis=1)      ### we use axis=1 because it is in
y=df10["churn"]
```

In [64]:
```
##Confirm if churn has been removed
x
```

Out[64]:

	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes
0	128	415	0	1	25	265.1	110	45.07	197.4
1	107	415	0	1	26	161.6	123	27.47	195.5
2	137	415	0	0	0	243.4	114	41.38	121.2
3	75	415	1	0	0	166.7	113	28.34	148.3
4	118	510	1	0	0	223.4	98	37.98	220.6
...	...	...	...	...	...	...	...	...	...
2799	192	415	0	1	36	156.2	77	26.55	215.5
2800	68	415	0	0	0	231.1	57	39.29	153.4
2801	28	510	0	0	0	180.8	109	30.74	288.8
2802	184	510	1	0	0	213.8	105	36.35	159.6
2803	74	415	0	1	25	234.4	113	39.85	265.9

2804 rows × 18 columns

5.3.1.3 5.2.3 Split the data into train and test

In [65]:
```
#split dataset into train and test
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=.
```

observation:i have used test_size of 20% and random state of 42 because it gives high accuracy eg 42 and 30% gives accuracy of 73% which is low comapred to 75

5.3.1.4 5.2.4 Check the shape

In [66]:
```
##Checking the shape
print(x_train.shape,x_test.shape)
print(y_train.shape, y_test.shape)
```

```
(2243, 18) (561, 18)
(2243,) (561,)
```

observation:The shape is the same in x_test and y_test,x_train and y_train

5.3.1.5 5.2.5 Modelling

In [67]:
```
#modeling
model = DecisionTreeClassifier(max_depth=6,criterion='entropy')
#train
model.fit(x_train, y_train)
```

Out[67]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=6)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

5.3.1.6 5.2.6 Predict

In [68]:
```
#predict
y_pred = model.predict(x_test)
y_pred
```

Out[68]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
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, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 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, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 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, 0, 0, 0,
0,
       0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

In [69]:
```
#The original values
y
```

Out[69]:
```
0       0
1       0
2       0
3       0
4       0
       ..
2799    0
2800    1
2801    0
2802    0
2803    0
Name: churn, Length: 2804, dtype: int32
```

5.3.1.7 5.2.7 Accuracy

In [70]:
```
#accuracy in 2 dp
print(f"The accuracy score is {accuracy_score(y_test, y_pred)*100:.2
```

```
The accuracy score is 86.27 %
```

5.3.1.8 5.2.8 Confusion matrix

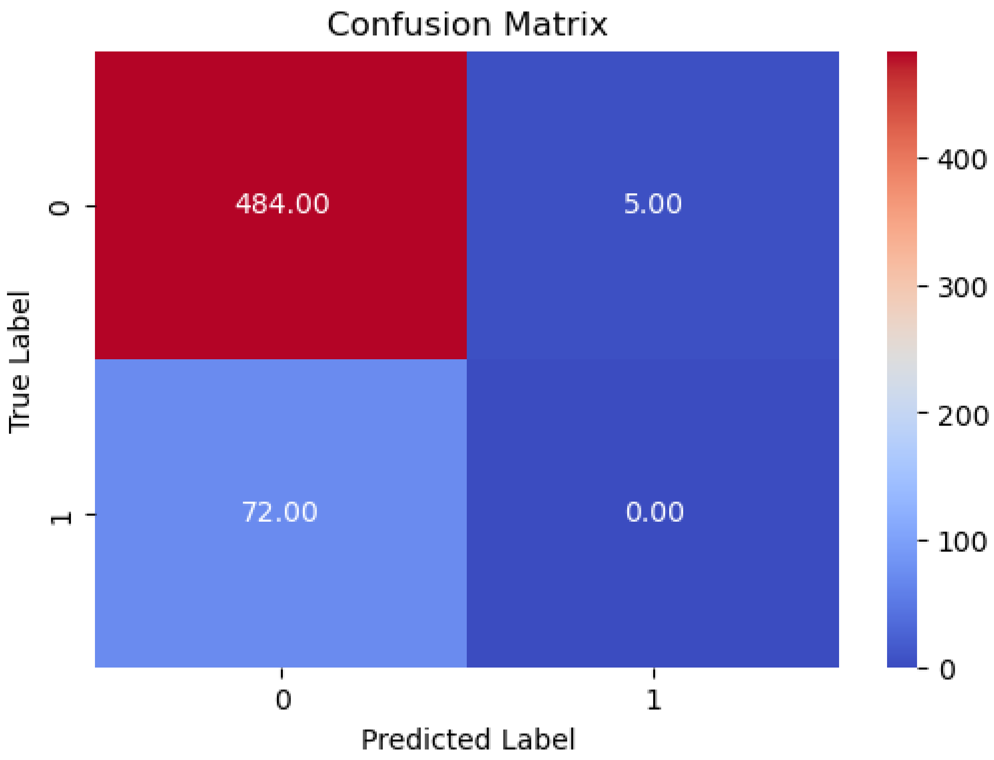
In [71]:
```
#confusion matrix
print(confusion_matrix(y_test, y_pred))
```

```
[[484   5]
 [ 72   0]]
```

In [72]:
```
Decisiontree_matrix = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(6, 4))
sns.heatmap(Decisiontree_matrix, annot=True, fmt='.2f', cmap='coolwa

plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```



5.3.1.9 5.2.9 classification report

In [73]:
```
# classification report
print(classification_report(y_test, y_pred))
```

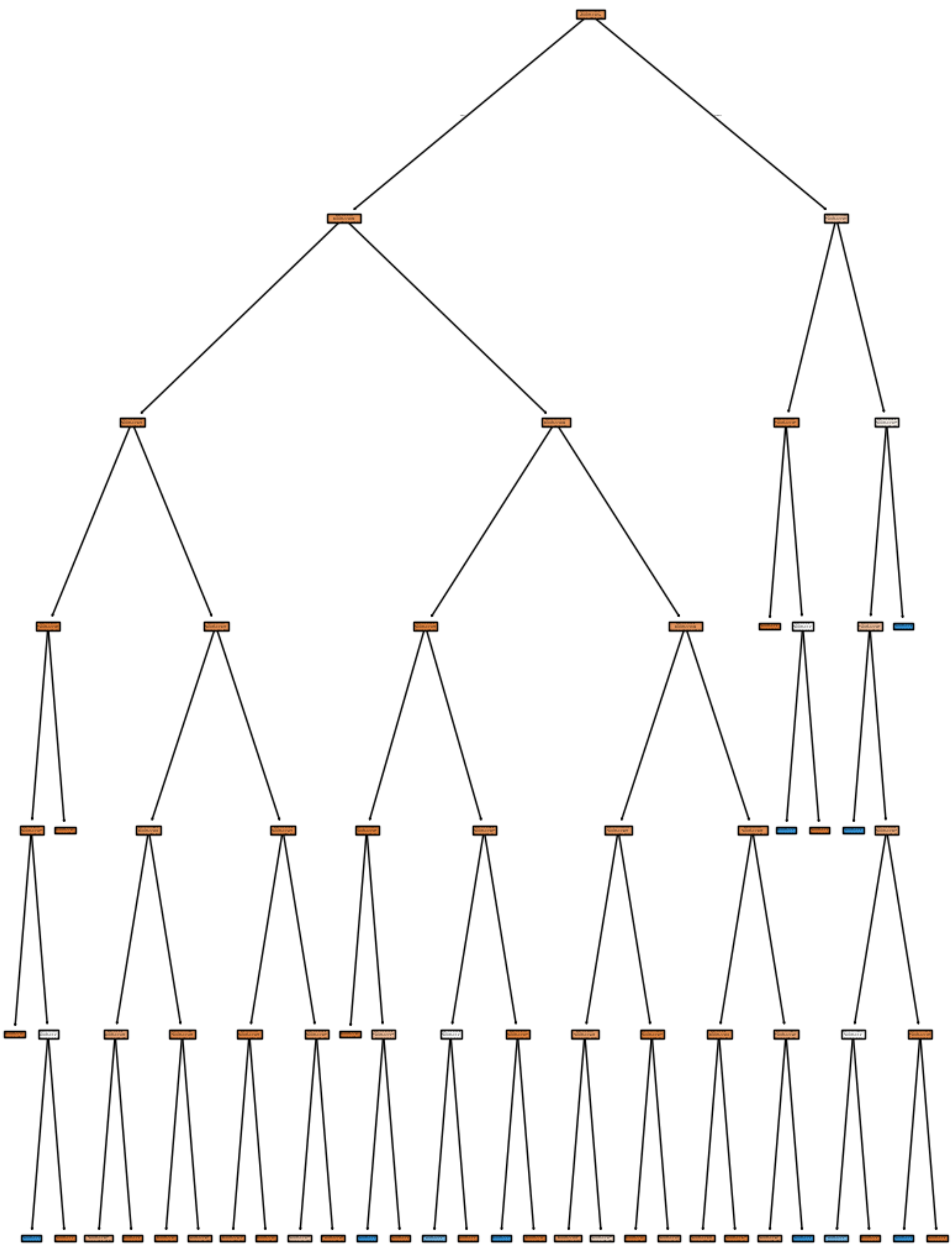
```
              precision    recall  f1-score   support

           0       0.87      0.99      0.93       489
           1       0.00      0.00      0.00        72

    accuracy                           0.86       561
   macro avg       0.44      0.49      0.46       561
weighted avg       0.76      0.86      0.81       561
```

5.3.1.10 5.3 Visualization

In [74]:
```
#visualizations
plt.figure(figsize= (10,15))
tree.plot_tree(model, filled= True)
plt.show()
```



OBSERVATION BEFORE HYPER PARAMETER

- There is much splitting
- When entropy is zero is considered pure hence no more splitting is required
- The accuracy score is 75 % which may be misleading because of class imbalanced
- Precision: 0.88 – When the model predicts class 0, it's correct 88% of the time.

- Recall: 0.82 – The model correctly identifies 82% of the actual class 0 instances.
- F1-score: 0.85 – The harmonic mean of precision and recall indicates a balanced performance for class 0.

OBSERVATION BEFORE HYPER PARAMETER TUNING(max_depth)

- The accuracy score raises to 89%. Higher overall accuracy due to the overwhelming correct classification of class 0.
- There is less splitting after using hyper parameter(max_depth)
- Precision: 0.87 – Remains similar to before.
- Recall: 0.99 – Nearly all actual class 0 instances are now correctly identified.
- F1-score: 0.93 – Indicates very strong performance on class 0.

6 6.EVALUATION

- The best performing model is decision tree because it has the highest accuracy level keeping in mind that i have compared it when the class is balance
- Also it has the highest number of true positive

In [ ]:

In [ ]:

In [ ]: