Final Project Submission

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BUSINESS UNDERSTANDING

Syria Tel, a telecommunication company, wants to predict customer churn. Identifying customers who are likely to stop using their services soon. Churn represents a major financial challenge, as acquiring new customers is often more expensive than retaining existing ones. By analyzing customer data, Syria Tel can devolop targeted strategies to improve customer retention and reduce revenue loss

Project Overview

In this project we aim to build a classifier to predict whether a customer will ('soon') stop doing business with Syria Tel, a Telecommunications company.

Objective

- Are churned customers more likely to have high or low usage
- The corelation between churn and other variables

DATA UNDERSTANDING

- The dataset has 21 variables with a record of 3,333 records

Import the libraries

- **Data manipulation** : pandas, numpy
- **Visualization** : matplotlib, seaborn
- **Machine learning** : sklearn for Decision Tree, evaluation, and preprocessing
- **Handling Imbalanced Data** : imblearn.SMOTE for oversampling minority classes

In [1]:
```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import  LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix, classifica
from sklearn.metrics import precision_recall_curve
from imblearn.over_sampling import SMOTE

import warnings
warnings.filterwarnings("ignore")
```

Load the dataset

- The dataset is loaded using pd.read_csv().
- It is inspected using .head(), .tail(), .dtypes(), .columns(), .info(), .describe() to understand the data structure.

In [2]:
```
# Load the csv dataset
data = pd.read_csv('churn_dataset.csv')
# Check the top 5
data.head()
```

Out[2]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34

5 rows × 21 columns

In [3]:
```
# Check the bottom 5
data.tail()
```

Out[3]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	t cha
3328	AZ	192	415	414-4276	no	yes	36	156.2	77	26
3329	WV	68	415	370-3271	no	no	0	231.1	57	39
3330	RI	28	510	328-8230	no	no	0	180.8	109	30
3331	CT	184	510	364-6381	yes	no	0	213.8	105	36
3332	TN	74	415	400-4344	no	yes	25	234.4	113	39

5 rows × 21 columns

In [4]:
```
# Check the shape
print(f"The dataset has {data.shape[1]} variables with a record of {data
```

```
The dataset has 21 variables with a record of 21
```

In [5]:
```
# Check the datatype
data.dtypes
```

Out[5]:
```
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
```

In [6]:
```
# Check the data information
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
```

In [7]:
```
# Check column names
data.columns
```

Out[7]:
```
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')
```

In [8]:
```
# Check the statistical summary
data.describe().T
```

Out[8]:

	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

In [9]:
```
# Check the categorical summary
data.describe(include='O').T
```

Out[9]:

	count	unique	top	freq
state	3333	51	WV	106
phone number	3333	3333	382-4657	1
international plan	3333	2	no	3010
voice mail plan	3333	2	no	2411

In [10]:
```
#checking for unique values in each column

for column in data:
    unique_values = data[column].unique()
    print(f"Unique values in column '{column}','\n': {unique_values}", '
```

```
Unique values in column 'state','
': ['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' 'G
A'
 'AK' 'MD' 'AR' 'WI' 'OR' 'MI' 'DE' 'UT' 'CA' 'MN' 'SD' 'NC' 'WA' 'N
M'
 'NV' 'DC' 'KY' 'ME' 'MS' 'TN' 'PA' 'CT' 'ND']

Unique values in column 'account length','
': [128 107 137  84  75 118 121 147 117 141  65  74 168  95  62 161
85  93
  76  73  77 130 111 132 174  57  54  20  49 142 172  12  72  36  78
136
 149  98 135  34 160  64  59 119  97  52  60  10  96  87  81  68 125
116
  38  40  43 113 126 150 138 162  90  50  82 144  46  70  55 106  94
155
  80 104  99 120 108 122 157 103  63 112  41 193  61  92 131 163  91
```

DATA PREPARATION

Data Cleaning

In [11]:
```
# Create a DataFrame copy to be used in data cleaning
data1 = data.copy(deep=True)
data1.head()
```

Out[11]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34

5 rows × 21 columns

In [12]:
```
# Check for missing values
data1.isna().sum()
```

Out[12]:
```
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
```

- Ensures model performance is not affected by null values.

In [13]:
```
# Fix the column names by replacing spaces with underscore and convertin
data1.columns = data1.columns.str.replace(" ", "_").str.lower()
# Check the updated columns
data1.columns
```

Out[13]:
```
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')
```

In [14]:
```
# Check for duplicates
data1.duplicated().sum()
```

Out[14]:
```
0
```

In [15]:
```
# Drop irrelevant columns
data1 = data1.drop(columns=["phone_number", "state"])
```

Feature Engineering

In [16]:
```
# Encode categorical variables
data1["international_plan"] = data1["international_plan"].map({"yes":1,
data1["voice_mail_plan"] = data1["voice_mail_plan"].map({"yes":1, "no":0
data1["churn"] = data1["churn"].astype(int) # Convert churn to integer
```

Statistical testing

In [17]:
```
# Example: Chi-Square Test for 'international_plan' vs. 'churn'
combine_table = pd.crosstab(data1['international_plan'], data1['churn'])
chi2, p, dof, expected = stats.chi2_contingency(combine_table)

print(f"Chi-Square Test Statistic: {chi2:.2f}")
print(f"P-value: {p:.2f}")

if p < 0.05:
    print("Significant: 'international_plan' affects churn.")
else:
    print("No significant: 'international_plan' does not affect churn.")
```

```
Chi-Square Test Statistic: 222.57
P-value: 0.00
Significant: 'international_plan' affects churn.
```

Observation

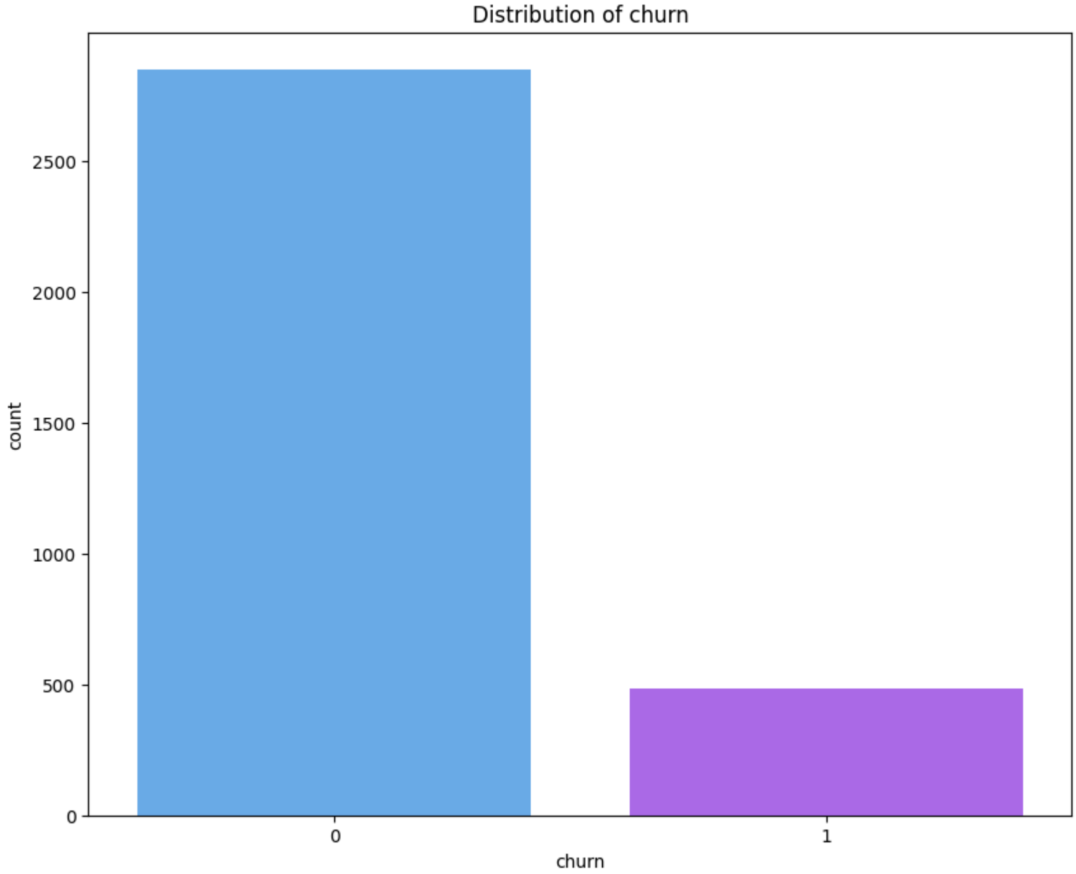
- A high test statistic indicates a strong deviation from the null hypothesis, suggesting a significant association between international_plan and churn.
- p = 0, meaning we reject the null hypothesis that international_plan and churn are independent.

EDA

Univariate

- Analyze the distribution of the churn variable

In [18]:
```
# plot churn distribution
plt.figure(figsize=(10,8))
sns.countplot(x="churn", data=data1, palette="cool")
plt.title("Distribution of churn")
plt.xlabel("churn")
plt.ylabel("count");
```



Observation

- **Business Imlication**, Since churn is relatively low, retaining customers could be a key business strategy.

In [19]:
```
# Display churn percentage
churn_count = data1["churn"].value_counts(normalize='True') * 100
print(churn_count.round(1))
```

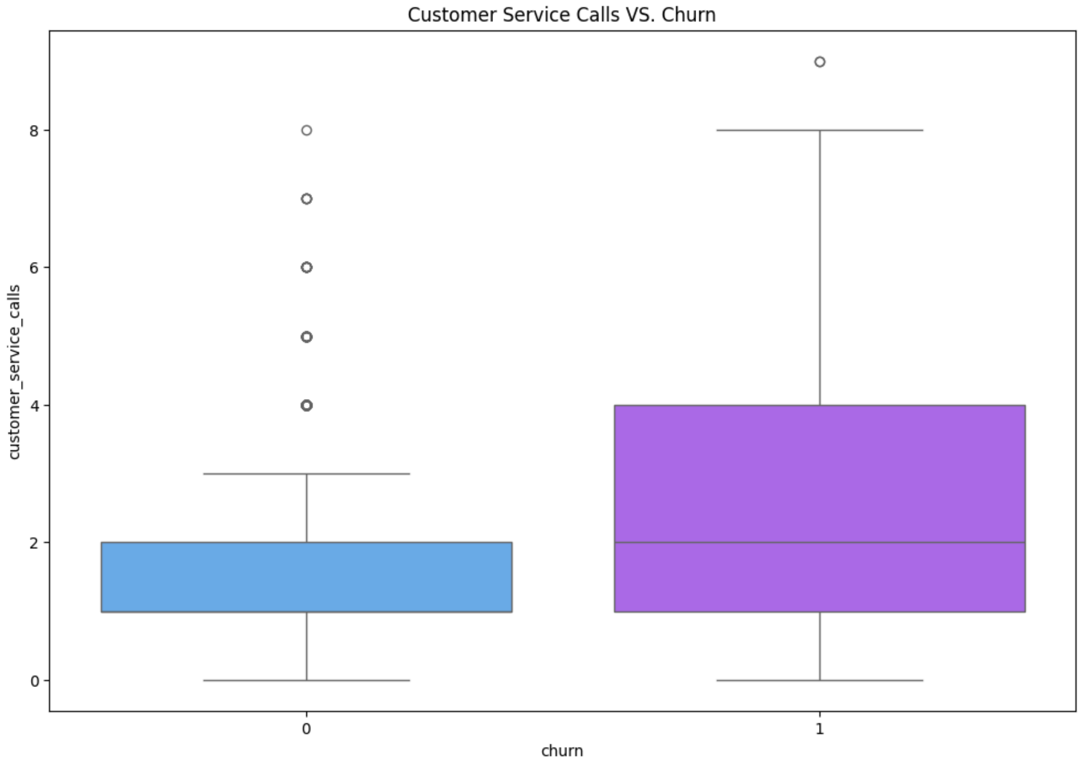
```
churn
0    85.5
1    14.5
Name: proportion, dtype: float64
```

- 85.5% of customers did not churn, while 14.5% churned
- The above barchart shows that the dataset is imbalanced, meaning the model may predict "No_Churn" more often by default

Bivariate

- Check impact of customer_service_calls on churn

In [20]:
```
# plot customer_sercice_calls vs churn
plt.figure(figsize=(12, 8))
sns.boxplot(x='churn', y='customer_service_calls', data=data1, palette='
plt.title("Customer Service Calls VS. Churn");
```



Observation

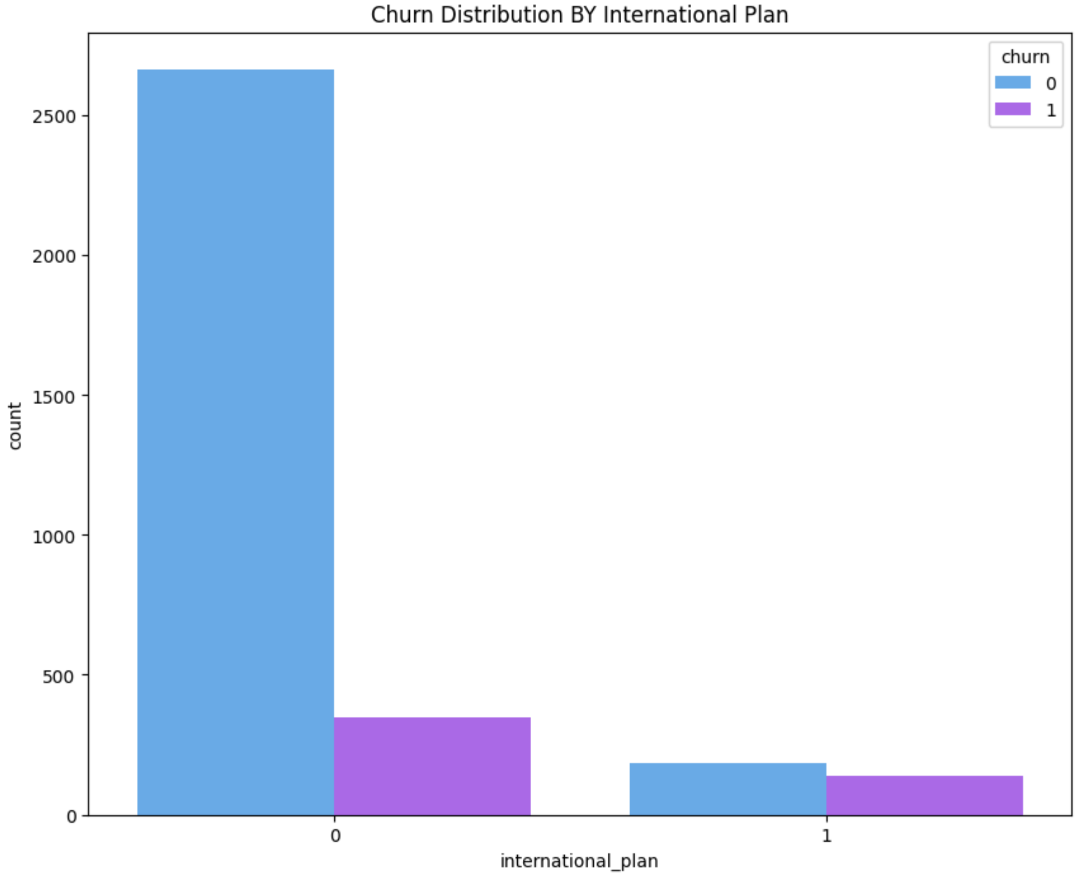
- A high number of customer_service_calls might indicate unresolved issues or dissatisfaction.
- The median number of customer_service_calls is higher for churn = 1, suggests that customers who call the customer service frequently are more likely to churn.

Multivariate

- Anliyze import of international plan on the distribution of churn

In [21]:

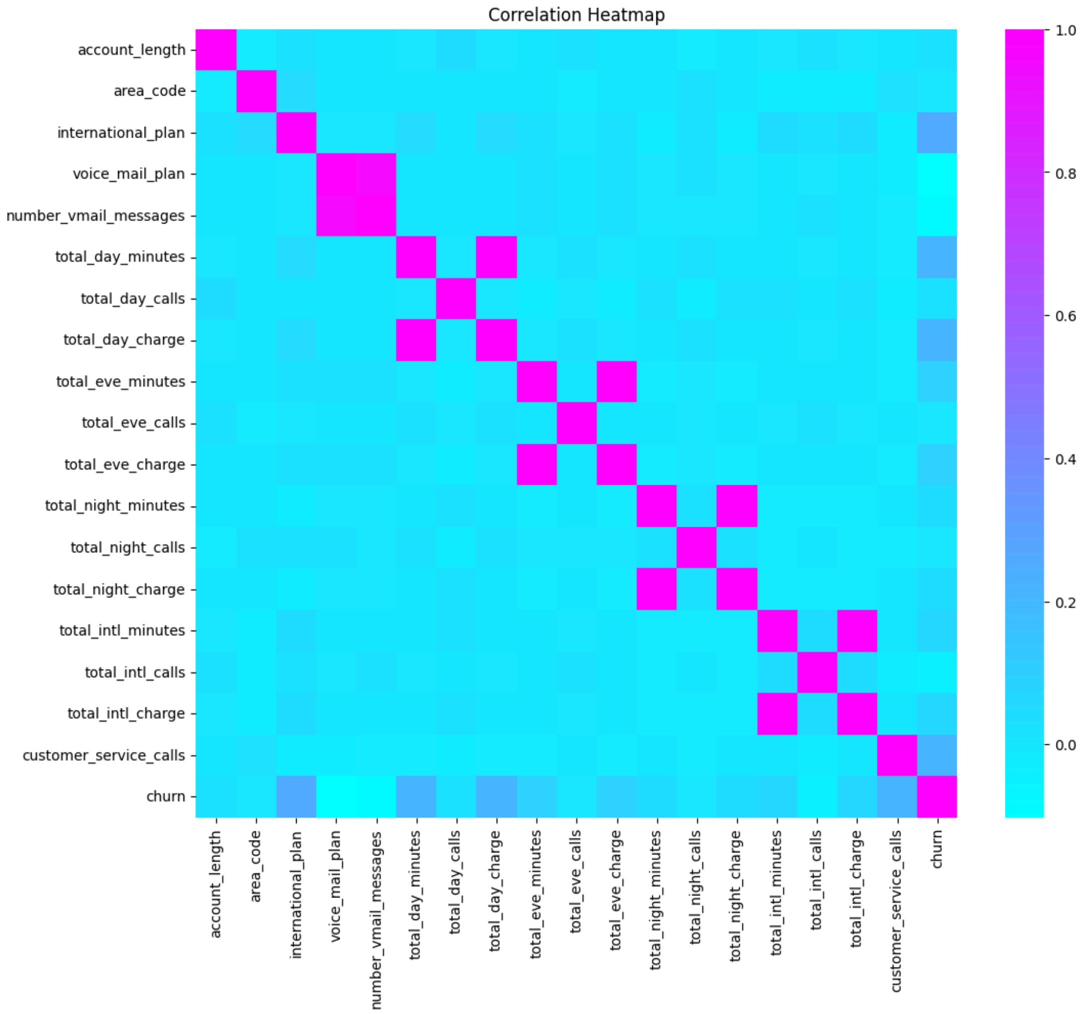
```
# Plot churn VS. International plan
plt.figure(figsize=(10, 8))
sns.countplot(x='international_plan', hue='churn', data=data1, palette='
plt.title("Churn Distribution BY International Plan");
```



Observation

- The chart shows that customers with an international plan (international_plan = 1) have a relatively higher proportion of churned users compared to those without an international plan (international_plan = 0).
- Even though fewer customers have an international plan overall, their churn count is almost as high as those without an international plan.

In [22]:
```
# Compute correlation matrix
# Plot heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(data1.corr(), cmap="cool")
plt.title("Correlation Heatmap")
plt.show()
```



Observation

Strongly Correlated Features (Multicollinearity)

- Features like total_day_minutes, total_day_charge, total_eve_minutes, and total_eve_charge show high correlation (values close to 1).

Correlation with Churn

- customer_service_calls appears to have a noticeable positive correlation with churn, reinforcing our earlier observation that frequent customer service calls are linked to customer dissatisfaction.
- international_plan also shows some correlation with churn, which aligns with our previous analysis.

MODEL

1 LogisticRegression

Splitting

- **Split the dataset** into training (`X_train, y_train`) and testing (`X_test, y_test`) sets.
- 80% training ** Used to train the model.
- 20% testing ** Used to evaluate model performance.

In [23]:
```
# Split features and target variable
x = data1.drop(columns=["churn"])
y = data1["churn"]
```

In [24]:
```
# Split data into training and testing sets(80% train, 20% test)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,
print("x_test shape:", x_test.shape)
print("y_test shape:", y_test.shape)
```

```
x_test shape: (667, 18)
y_test shape: (667,)
```

- The test set contains 667 rows (samples) and 18 features (independent variables).

Fixing the imbalance class

- Balances the dataset -- Helps models learn equally from churned & non-churned customers.
- Improves model performance -- Especially recall (True Positives) for churn.

In [25]:
```
print("Before SMOTE: \n", y_train.value_counts())  # Original
```

```
Before SMOTE:
 churn
0    2280
1     386
Name: count, dtype: int64
```

In [26]:
```
# Apply SMOTE to oversample the minority class
smote = SMOTE(random_state=42)
x_train_resampled, y_train_resampled = smote.fit_resample(x_train, y_tra
```

- Ensures the model does not ignore the minority class (churners).
- Prevents biased predictions towards the majority class.

In [27]:
```
# Check new class distribution
print("After SMOTE: \n", pd.Series(y_train_resampled).value_counts())  #
```

```
After SMOTE:
 churn
0    2280
1    2280
Name: count, dtype: int64
```

feature scaling using `StandardScaler` :

- Standardization is important to ensure all numerical features are on a similar scale.
- It improves numerical stability and model performance.

In [28]:
```
# Standardize numerical feature
s_scaler = StandardScaler()
x_train_scaled = s_scaler.fit_transform(x_train_resampled)
x_test_scaled = s_scaler.transform(x_test)
```

Train the baseline Logistic Regression

- Train a Logistic Regression model using all available features.
- Make predictions on the test set.
- **Evaluate performance** using: - **Accuracy** (general performance) - **Recall** for churn prediction
- This serves as a **baseline model**.

In [29]:
```
# Create the model
lr = LogisticRegression()

# Train the model
lr.fit(x_train_scaled, y_train_resampled)
```

Out[29]:
```
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.

In [30]:
```
# Prediction
y_pred = lr.predict(x_test)
y_pred_bal = lr.predict(x_test_scaled)
```

- y_pred is the prediction on the original class
- y_pred_bal is the prediction on the balanced class

Evaluating the baseline model

In [31]:
```
# Report on model with imbalanced data
print("classification_report - LogisticRegression Imbalanced")
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
```

```
classification_report - LogisticRegression Imbalanced
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       570
           1       0.15      1.00      0.25        97

    accuracy                           0.15       667
   macro avg       0.07      0.50      0.13       667
weighted avg       0.02      0.15      0.04       667

[[  0 570]
 [  0  97]]
```

Observation(imbalanced data)

- The dataset is highly imbalanced, with 570 non-churned (class 0) and 97 churned (class 1) customers.
- The model is performing poorly due to the imbalance, significantly favoring the minority class (churned customers).
- Recall: **class 0** 0.00 : The model is completely missing non-churned customers.
- Recall: **class 1** 1.00 : The model classifies all customers as churned to maximize recall, leading to 100% recall but poor precision.

In [32]:
```
# Report on balanced churn
print("classification_report - LogisticRegression Balanced")
print(classification_report(y_test, y_pred_bal))
print(confusion_matrix(y_test, y_pred_bal))
```

```
classification_report - LogisticRegression Balanced
              precision    recall  f1-score   support

           0       0.93      0.71      0.81       570
           1       0.29      0.70      0.41        97

    accuracy                           0.71       667
   macro avg       0.61      0.71      0.61       667
weighted avg       0.84      0.71      0.75       667

[[405 165]
 [ 29  68]]
```

Observation(balanced data)

- After applying class weighting (class_weight='balanced'), the model now provides better performance across both classes, compared to the previous imbalanced version.
- Recall: **class 0** 0.71 : The model correctly identifies 71% of non-churned customers.

In [39]:
```
# Check the training accuracy score
print(round(lr.score(x_train_scaled, y_train_resampled),2))
```

```
0.75
```

In [40]:
```
# Check the test accuracy score
print(round(lr.score(x_test_scaled, y_test),2))
```

```
0.71
```

Obsersavation

- The training and test accuracies are very close, meaning the model is not overfitting or underfitting(75% vs. 71%)
- Recall for class 1 is low at 71%
- lets improve on our recall
- The difference of 0.04 accuracy suggest the model perfome similarly on unseen data

2 Decision Tree Classifier

In [41]:
```
# Training decision tree classifier model
dt = DecisionTreeClassifier()
dt.fit(x_train_scaled, y_train_resampled)
```

Out[41]:
```
DecisionTreeClassifier()
```

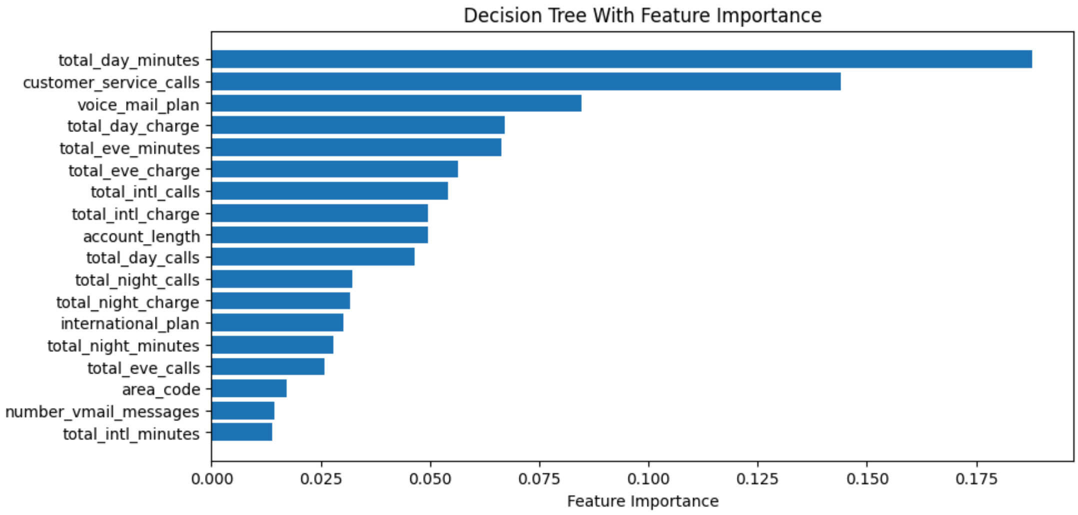
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Check feature importance

- Which features contribute the most to your model's predictions

In [42]:
```
# train a decision tree as `dt`
feature_importance = dt.feature_importances_
feature_names = x.columns  # Ensure X is your feature matrix

# Sort features by importance
sorted_idx = np.argsort(feature_importance)
plt.figure(figsize=(10, 5))
plt.barh(range(len(sorted_idx)), feature_importance[sorted_idx], align='
plt.yticks(range(len(sorted_idx)), np.array(feature_names)[sorted_idx])
plt.xlabel("Feature Importance")
plt.title("Decision Tree With Feature Importance")
plt.show()
```



Observation:

- The above graph align the variable in descending order of their importance on the model decision
- Top features have the most impact on the predictions
- The graph identified total day charge as the most predictor of customer churns, with a score of 0.2.Then followed by the customer_service_calls and total_eve_charge as the next influential features.
- The relatively low importance of features like total_eve_call and total_night_charge indicates these features plays a small role in prediction

Evaluate the dt model

In [43]:
```
# Check accuracy on the training data
dt.score(x_train_scaled, y_train_resampled)
```

Out[43]: 1.0

In [47]:
```
# Check accuracy on the test data
print(round(dt.score(x_test_scaled, y_test),2))
```

0.81

Observation

- Training Accuracy = 1.0 (100%) : The model perfectly classifies the training data, which is highly suspicious.

- Test Accuracy = 0.82 (82%) : While this is a good accuracy score on the test set, the gap between training and test performance indicates overfitting.
- The model memorized only on training data rather than learning the pattern

In [48]:
```
# Classification report
y_pred_dt = dt.predict(x_test_scaled)
print("Classification report - Decision Tree")
print(classification_report(y_test, y_pred_dt))
print(confusion_matrix(y_test, y_pred_dt))
```

```
Classification report - Decision Tree
              precision    recall  f1-score   support

           0       0.94      0.83      0.88       570
           1       0.41      0.68      0.51        97

    accuracy                           0.81       667
   macro avg       0.67      0.76      0.70       667
weighted avg       0.86      0.81      0.83       667

[[474  96]
 [ 31  66]]
```

Findings

- Since the training accuracy is higher than the test accuracy, overfitting may be occuring hence we need to reduce the overfitting.
- Recall: ** class 0 ** 0.83 : 83% of actual non-churned customers are correctly classified
- Recall: ** class 1 ** 0.68 : 68% of actual churned customers are identified, which is an improvement over Logistic Regression.
- To reduce overfitting, we limit the tree depth.
- **Max_Depth = 7** ovoids the tree from growing too more complex
- Decision Tree captures more complex relationships in the data but may still be prone to overfitting.

Training Pruned Decision Tree

In [75]:
```
# Training the decision tree while specifying the maximum depth to be 8
dt1 = DecisionTreeClassifier(max_depth=7, random_state=42 )
dt1.fit(x_train_scaled, y_train_resampled)
```

Out[75]:
```
DecisionTreeClassifier(max_depth=7, random_state=42)
```

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.

In [76]:
```
# Evaluating the results
print("training data score: " + str(dt1.score(x_train_scaled, y_train_re
print('test data score ' + str(dt1.score(x_test_scaled, y_test)))
```

```
training data score: 0.8725877192982456
test data score 0.8575712143928036
```

Observation

The Traing accuracy is higher than the test accuracy, which is normal and hence no Overfitting.

In [77]:
```
y_pred_dt1 = dt1.predict(x_test_scaled)
print("Classification Report - Pruned Decision Tree:")
print(classification_report(y_test, y_pred_dt1))
print(confusion_matrix(y_test, y_pred_dt1))
```

```
Classification Report - Pruned Decision Tree:
              precision    recall  f1-score   support

           0       0.95      0.88      0.91       570
           1       0.51      0.72      0.60        97

    accuracy                           0.86       667
   macro avg       0.73      0.80      0.75       667
weighted avg       0.88      0.86      0.87       667

[[502  68]
 [ 27  70]]
```

Observation

- The model now performs well on both training and test data.
- my recall now is 72% for class 1.
- No clear overfitting or underfitting, as both scores are reasonably close.
- Class 0 (Non-Churn) has 95% precision and 88% recall (good).
- Class 1 (Churn) has 51% precision and 72% recall (low).
- The model is biased towards the majority class (class 0)

finding

Class 0 (Non-churn

- Precision: 95% (Very high, meaning low false positives).
- Recall: 88% (Most non-churn customers are correctly classified).

Class 1 (churn)

- Precision 51%
- Recall 72% (More churners are correctly detected).

Confusion matrix

- 27 False Negative (Missed churn customers)
- 68 False Positive (non-churn wrongly predicted as churn)

The model is now detecting churn well (72% recall for class 1) while keeping overall accuracy high (86%). It’s a good balance between detecting churners and avoiding too many false alarms.