Building a Machine Learning Classification Model to Predict Customer Churn

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- **Scheduled project review date/time:** 23/12/2024 23.59 Hours
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Introduction

The telco industry is highly competitive with multiple players within any given jurisdiction. Acquiring new customers involves huge marketing costs, that include huge advertising budgets and commissions to sales agents. It therefore becomes imperative to retain those customers once they are acquired. Churn which refers to the number of customers who cease doing business with a company within a given period, is a closely watched metric in the telco industry. It is the motivation of every telco company to understand the features or characteristics of a customer who is likely to 'churn'. With this understanding, the company can get ahead of the problem, and develop initiatives that target these specific customers, to discourage them from ceasing doing business with the company.

In this project, I will use a dataset provided by SyriaTel that is avaialble on https://www.kaggle.com/ that details various call patterns and spend of customers as well as their locations https://www.kaggle.com/datasets/becksddf/churn-in-telecoms-dataset .

Using this data set I will:

- Examine the features and using industry domain knowledge select the features to use in my predictive model.
- Using these features build a classifier model to predict whether a customer will stop doing business with SyriaTel.
- Based on the model metrics, determine if these features have any predictive patterns.
- If the features indeed have predictive patterns, provide SyriaTel with the most optimal version of the model to test new (unseen)customer data and identify those customers that are most likely to churn.
- The company will then use this predicted data to make pro-actice strategies to retain these 'at risk' customers.

Problem Statement

SyriaTel is intentional about reducing the high cost of customer churn. They have hired me to develop a classification model that is able to a higher degree, predict if a customer is likely to churn i.e. terminate their contract. They have provided me with a historical dataset of customers' call and spend characteristics and whether or not they left the network after a period of time. With the optimal model that I develop, their Data Analytics,Marketing and Revenue Assurance departments will be able to test future customers data to predict the likelihood of a customer leaving the network. With these predictions, they will be able to proactively develop retention startegies specifically targeted to these customers to discourage them from leaving.

Business Objectives

- **Goal:**
  - Train a classification model using the provided historical data to determine if and what features are useful in predicting churn.
- **Specific Objectives:**
  - Determine if the data provided has any predictive power on the target (churn) using Logistic regression,Decision tree and Random Frest optimized models
  - Through model optimization, identify the features that have the best predictive power
  - Provide to SyriaTel the most optimal model to deploy on future (new) customers' data to predict "at risk" customers
  - Provide insights on factors affecting customer churn and **suggest** 'data supported' remedies.

1. 0 Industry Background

The SyriaTel data set consist of fairly straightforward and well formated data. It has critical customer usage (minutes/number of calls) as well as customer choices of premium services columns. Based on **industry standards** the following features from the data set are commonly associated with customer churn and will be considered as model features that have an impact on the traget variable 'churn'.

Usage Patterns: 'total day minutes', 'total day calls','total eve calls', 'total eve minutes','total night calls','total night minutes','total intl calls', and 'total intl minutes' are critical columns for determining churn. High usage of calls and minutes can indicate customer engagement and satisfaction, while low usage might suggest dissatisfaction.

Charges: 'total day charge','total eve charge','total night charge', and 'total intl charge' are also important columns. Higher charges can lead to customer distasfaction if they feel they are not getting value for money.

Service Quality: Features like 'International plan' and 'voice mail plan' can reflect a very high expectation from customers who are enrolled in those plans, and can have a direct impact on satisfaction levels and therefore, churn.

Customer Support: 'customer service calls' a high number of customer service calls can indicate issues of service quality or customer dissatisfaction.

Account Length: The 'account length' feature is equally important as longer account lengths generally indicate customer loyalty, while shorter account lengths may suggest a higher likelihood of churn.

Location: Customer location indicated by the 'state' may have an effect on churn due to unique characteristics within the State like income levels, choice of networks etc, and will be tested early in the modeling to assess it's predictive power.If it is found to be having little or no predictive power, this feature will be dropped as multiple locations included in a model can make it very complex and less effecient.

The following features from the data set are deemed to have little or no predicted power and will be excluded from the model right from the start:

- 'area code'
- 'phone number'

2.0 Understanding the Dataset

In [1]:
```
# Import the necessary libraries for data analysis and visualization
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
%matplotlib inline
```

In [2]:
```
# Load the data as a DataFrame and display the first 5 columns
df = pd.read_csv('telco_churn.csv')
df.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 shape of the data
df.shape
print(f"This data set consists of {df.shape[0]} rows")
print(f"This data set consists of {df.shape[1]} columns")
```

```
This data set consists of 3333 rows
This data set consists of 21 columns
```

In [4]:

```
# Get column names
df.columns
```

Out[4]:

```
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')
```

The dataset has 21 columns that can be categorized as follows:-

- **Customer Info:** These clolumns are state, account length(the period when the account has been active), area code, phone number and account length
- **international plan:** This is a binary column (Yes/No) that indicates whether a customer is enrolled for international calls
- **voice mail plan:** This is also a binary column (Yes/No) that indicates whether a customer has enrolled into the Voice Mail service
- **number vmail messages:** This is the number of voice mail messages the customer has received

- **Minutes Info :** These are the number of minutes by each customer with different columns for local day, evening,night minutes, as well as total international minutes
- **Call Info:** These are the number of local calls by each customer with different columns for into day, evening,and night calls, as well as total international calls
- **Charges Info:** These are the charges for local calls made by each customer with different columns for day, evening and night charges, as well as total international charges.
- **customer service calls:** These are the number of calls customers made to customer service
- **churn:** This is a binary column indicating whether or not a customer left the network service. It is our target column.

In [5]:
```
# Get column attributes
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
```

The target column is boolean. This will be converted to integer. The international plan,voice mail plan and state columns are objects and these will be one-hot encoded to integers prior to modeling. There are no missing values in this dataset.

In [6]:
```
# Confirming there are no Null values
df.isnull().values.any()
```

Out[6]: False

In [7]:
```
# Get statistical summary of the numerical columns
df.describe().T
```

Out[7]:

	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

- Average account length in this data set is 101 days which is about 3 months with a maximum of approximately 8 months (243 days).
- While the average day, evening and night calls is similar at around 100, the average duration (minutes) of evening and night calls is significantly higher than day ; 180 minutes for day and 201 minutes for evening/night calls. This is an expected customer call behaviour as people talk more to friends and family outside of the business day hours.
- Also, as per industry standards, tariffs are higher during the day than during the evening and night. The average day charge is 31, while the evening and night is 17 and 9 respectively. This could also explain the longer calls in the evening and night hours.

- The mean for international minutes, calls and charges appear to be low; The minimum is 0: This is because only a few customers enroll for this service as it is a premium service.
- The mean number of voice mail messages is higher than the number of international calls because more people enroll for this service. The minimum is also 0 because not all customers opt into this service.
- The number of calls to customer service are surprisingly low in this network. Average of 1.5 calls with a minimum of 1 and a maximum of 9. This could be due to a generally good service offering by the network or the availability of other mechanisms e.g online chat for resolution of customer issues.

In [8]:
```
# Get statistical summary of the categorical columns
df.describe(include='O').T
```

Out[8]:

	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

- The 'international plan' and 'voice mail plan' columns are binary columns(Yes/No). As expected, only a few customers have opted into these 2 services.(frequency of 'no').These columns will be One-Hot-Encoded and converted to integers.
- There are 51 states, so these will be significant number of feature columns added after one-hot encoding. That is why, it will be imperative to check feature importances early on in the modeling process to check if the states have any significant predictive power. If not, drop the states from the iterative modeling process.

2.1 Data Cleaning and Feature Engineering

In this section I will perform the following tasks:

- Drop columns that are not critical to the model
- Convert column names to CamelCase for easier readability and display
- Convert the target column 'churn' from boolean to integer
- One-Hot Encode the 3 categorical columns 'international plan', 'voice mail plan' and 'state' to numerical.
- Check for, and remove outliers

In [9]:
```
# Making a copy of the DataFrame before data cleaning
df1 = df.copy(deep=True)
df1.head()
```

Out[9]:

	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 [10]:

```
# drop unimportant columns
df1 = df1.drop(columns=['phone number','area code'],axis=1)

# Confirm columns are dropped
df1.columns
```

Out[10]:

```
Index(['state', 'account length', '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')
```

In [11]:

```
# Function to capitalize the first letter of each word in column names
def capitalize_columns(df):
    df1.columns = [' '.join(word.capitalize() for word in col.split()) for col in d
    return df1

# Apply the function to the DataFrame
df1 = capitalize_columns(df1)

# Confirm each column word is Capitalized.
df1.columns
```

Out[11]:

```
Index(['State', 'Account Length', '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')
```

In [12]:
```
#Function to remove the white spaces from column names
def remove_spaces(df1):
    df1.columns = [col.replace(' ', '') for col in df1.columns]
    return df1

#Apply the function to the DataFrame
df1 = remove_spaces(df1)

# Display the updated DataFrame columns
df1.head()
```

Out[12]:

	State	AccountLength	InternationalPlan	VoiceMailPlan	NumberVmailMessages	TotalDa
0	KS	128	no	yes	25	
1	OH	107	no	yes	26	
2	NJ	137	no	no	0	
3	OH	84	yes	no	0	
4	OK	75	yes	no	0	

In [13]:
```
df1.columns
```

Out[13]:
```
Index(['State', 'AccountLength', 'InternationalPlan', 'VoiceMailPlan',
       'NumberVmailMessages', 'TotalDayMinutes', 'TotalDayCalls',
       'TotalDayCharge', 'TotalEveMinutes', 'TotalEveCalls', 'TotalEveCharge',
       'TotalNightMinutes', 'TotalNightCalls', 'TotalNightCharge',
       'TotalIntlMinutes', 'TotalIntlCalls', 'TotalIntlCharge',
       'CustomerServiceCalls', 'Churn'],
      dtype='object')
```

In [14]:
```
# OneHotCode the three categorical columns of interest

df1 = pd.get_dummies(df1, columns=['InternationalPlan','VoiceMailPlan','State'],dro

# Convert the one-hot encoded columns and the target colum 'Churn' from boolean to
for col in df1.columns:
    if df1[col].dtype == 'bool':
          df1[col] = df1[col].astype(int)

df1.head()
```

Out[14]:

	AccountLength	NumberVmailMessages	TotalDayMinutes	TotalDayCalls	TotalDayCharge
0	128	25	265.1	110	45.07
1	107	26	161.6	123	27.47
2	137	0	243.4	114	41.38
3	84	0	299.4	71	50.90
4	75	0	166.7	113	28.34

5 rows × 68 columns

In [15]:

```
# Preview the DataFrame

df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 68 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   AccountLength          3333 non-null   int64  
 1   NumberVmailMessages    3333 non-null   int64  
 2   TotalDayMinutes        3333 non-null   float64
 3   TotalDayCalls          3333 non-null   int64  
 4   TotalDayCharge         3333 non-null   float64
 5   TotalEveMinutes        3333 non-null   float64
 6   TotalEveCalls          3333 non-null   int64  
 7   TotalEveCharge         3333 non-null   float64
 8   TotalNightMinutes      3333 non-null   float64
 9   TotalNightCalls        3333 non-null   int64  
 10  TotalNightCharge       3333 non-null   float64
 11  TotalIntlMinutes       3333 non-null   float64
 12  TotalIntlCalls         3333 non-null   int64  
 13  TotalIntlCharge        3333 non-null   float64
 14  CustomerServiceCalls   3333 non-null   int64  
 15  Churn                  3333 non-null   int32  
 16  InternationalPlan_yes  3333 non-null   int32  
 17  VoiceMailPlan_yes      3333 non-null   int32  
 18  State_AL               3333 non-null   int32  
 19  State_AR               3333 non-null   int32  
 20  State_AZ               3333 non-null   int32  
 21  State_CA               3333 non-null   int32  
 22  State_CO               3333 non-null   int32  
 23  State_CT               3333 non-null   int32  
 24  State_DC               3333 non-null   int32  
 25  State_DE               3333 non-null   int32  
 26  State_FL               3333 non-null   int32  
 27  State_GA               3333 non-null   int32  
 28  State_HI               3333 non-null   int32  
 29  State_IA               3333 non-null   int32  
 30  State_ID               3333 non-null   int32  
 31  State_IL               3333 non-null   int32  
 32  State_IN               3333 non-null   int32  
 33  State_KS               3333 non-null   int32  
 34  State_KY               3333 non-null   int32  
 35  State_LA               3333 non-null   int32  
 36  State_MA               3333 non-null   int32  
 37  State_MD               3333 non-null   int32  
 38  State_ME               3333 non-null   int32  
 39  State_MI               3333 non-null   int32  
 40  State_MN               3333 non-null   int32  
 41  State_MO               3333 non-null   int32  
 42  State_MS               3333 non-null   int32  
 43  State_MT               3333 non-null   int32  
 44  State_NC               3333 non-null   int32  
 45  State_ND               3333 non-null   int32  
 46  State_NE               3333 non-null   int32  
 47  State_NH               3333 non-null   int32  
 48  State_NJ               3333 non-null   int32  
 49  State_NM               3333 non-null   int32  
 50  State_NV               3333 non-null   int32  
```

```
 51  State_NY              3333 non-null   int32
 52  State_OH              3333 non-null   int32
 53  State_OK              3333 non-null   int32
 54  State_OR              3333 non-null   int32
 55  State_PA              3333 non-null   int32
 56  State_RI              3333 non-null   int32
 57  State_SC              3333 non-null   int32
 58  State_SD              3333 non-null   int32
 59  State_TN              3333 non-null   int32
 60  State_TX              3333 non-null   int32
 61  State_UT              3333 non-null   int32
 62  State_VA              3333 non-null   int32
 63  State_VT              3333 non-null   int32
 64  State_WA              3333 non-null   int32
 65  State_WI              3333 non-null   int32
 66  State_WV              3333 non-null   int32
 67  State_WY              3333 non-null   int32
dtypes: float64(8), int32(53), int64(7)
memory usage: 1.1 MB
```

All the columns are now numerical. The columns are now 68 from 21 due to the additional columns from the One-Hot-Encoding

In [16]:

```
def remove_outliers(df1, columns):
    for col in columns:
        # Calculate Q1 (25th percentile) and Q3 (75th percentile)
        Q1 = df1[col].quantile(0.25)
        Q3 = df1[col].quantile(0.75)
        IQR = Q3 - Q1  # Interquartile Range

        # Define lower and upper bounds for detecting outliers
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        # Filter out outliers
        df1 = df1[(df1[col] >= lower_bound) & (df1[col] <= upper_bound)]

    return df1

# List of columns to check for outliers (excluding 'Churn')
feature_columns = [col for col in df1.columns if col != 'Churn' and df1[col].dtype

# Apply the function to remove outliers
df2 = remove_outliers(df1, feature_columns)
df2
```

Out[16]:

	AccountLength	NumberVmailMessages	TotalDayMinutes	TotalDayCalls	TotalDayCha
0	128	25	265.1	110	4!
1	107	26	161.6	123	2'
2	137	0	243.4	114	4'
4	75	0	166.7	113	2!
5	118	0	223.4	98	3'
...	...	...	...	...	
3328	192	36	156.2	77	2(
3329	68	0	231.1	57	3!
3330	28	0	180.8	109	3(
3331	184	0	213.8	105	3(
3332	74	25	234.4	113	3!

2797 rows × 68 columns

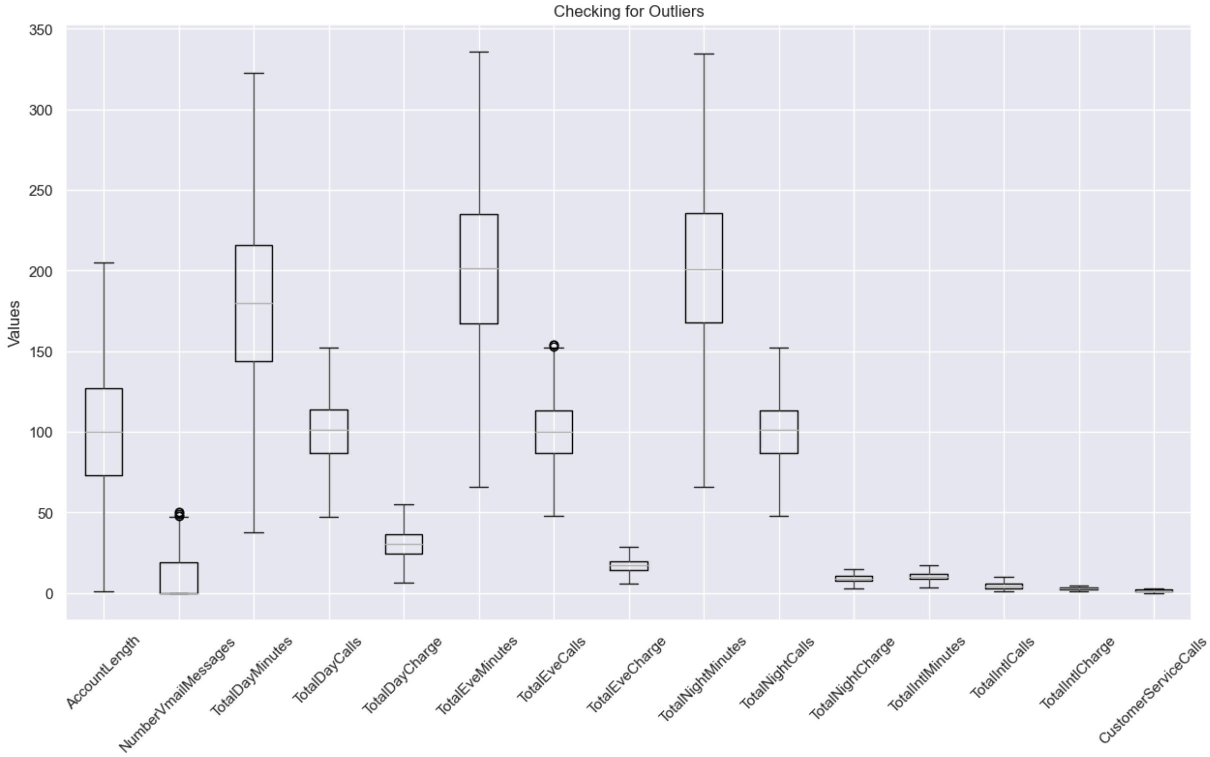
In [17]:

```
# check the shape of the data after removing outliers
df2.shape
print(f"This data set consists of {df2.shape[0]} rows")
print(f"This data set consists of {df2.shape[1]} columns")

# The number of rows have reduced from 3333 to 2797.
```

```
This data set consists of 2797 rows
This data set consists of 68 columns
```

In [18]:

```
# Generate boxplots for cleaned columns to confirm outliers have been dropped
plt.figure(figsize=(15,8))
df2.boxplot(feature_columns, boxprops=dict(linewidth=1 ))
plt.title('Checking for Outliers')
plt.ylabel('Values')
plt.xticks(rotation=45)


plt.show();

# No values outside the IQR showing outliers have been removed
```



The outliers are now eliminated, and the columns are cleaned; we can go ahead and start EDA. But first we save the clean dataframe to a CSV and make a copy of the same.

In [19]:
```
# save the clean dataframe in csv format
df2.to_csv('telco_churn_clean.csv',index=False)
```

In [20]:
```
# create a copy of the clean dataframe
df2=df2.copy(deep=True)
```

2.2 Exploratory Data Analysis

I will perform various univariate, bivariate and multivariate data analysis to better understand the data, These will include:-

- **Summary Statistics:** To get a quick overview of the central tendency and dispersion of the dataset's distribution.
- **Correlation Matrix:** To understand the relationships between nemerical features
- **Histograms:** To understand numerical features distributions
- **Class Distribution:** Analyze the distribution of the target variable churn

In [21]:
```
# Load the clean dataset and create a new dataframe
data = pd.read_csv('telco_churn_clean.csv')
data.head()
```

Out[21]:

	AccountLength	NumberVmailMessages	TotalDayMinutes	TotalDayCalls	TotalDayCharge
0	128	25	265.1	110	45.07
1	107	26	161.6	123	27.47
2	137	0	243.4	114	41.38
3	75	0	166.7	113	28.34
4	118	0	223.4	98	37.98

5 rows × 68 columns

In [22]:

```
print(data.columns)

print("\nThis data set consists of {} rows".format(data.shape[0]))
print("\nThis data set consists of {} columns".format(data.shape[1]))
```

```
Index(['AccountLength', 'NumberVmailMessages', 'TotalDayMinutes',
       'TotalDayCalls', 'TotalDayCharge', 'TotalEveMinutes', 'TotalEveCalls',
       'TotalEveCharge', 'TotalNightMinutes', 'TotalNightCalls',
       'TotalNightCharge', 'TotalIntlMinutes', 'TotalIntlCalls',
       'TotalIntlCharge', 'CustomerServiceCalls', 'Churn',
       'InternationalPlan_yes', 'VoiceMailPlan_yes', 'State_AL', 'State_AR',
       'State_AZ', 'State_CA', 'State_CO', 'State_CT', 'State_DC', 'State_DE',
       'State_FL', 'State_GA', 'State_HI', 'State_IA', 'State_ID', 'State_IL',
       'State_IN', 'State_KS', 'State_KY', 'State_LA', 'State_MA', 'State_MD',
       'State_ME', 'State_MI', 'State_MN', 'State_MO', 'State_MS', 'State_MT',
       'State_NC', 'State_ND', 'State_NE', 'State_NH', 'State_NJ', 'State_NM',
       'State_NV', 'State_NY', 'State_OH', 'State_OK', 'State_OR', 'State_PA',
       'State_RI', 'State_SC', 'State_SD', 'State_TN', 'State_TX', 'State_UT',
       'State_VA', 'State_VT', 'State_WA', 'State_WI', 'State_WV', 'State_WY'],
      dtype='object')

This data set consists of 2797 rows

This data set consists of 68 columns
```

The number of columns have increased exponetially because of one-hot encoding the State columns which has many unique values

2.2.1 Summary Statistics

In [23]:

```
# Get descriptive statistics for the non-binary nemeric columns
desc_columns = data[['AccountLength','NumberVmailMessages','TotalDayMinutes','Total
                     'TotalEveMinutes','TotalEveCalls','TotalEveCharge','TotalNightMi
                      'TotalNightCharge','TotalIntlMinutes','TotalIntlCalls','TotalIn



desc_columns.describe().T
```

Out[23]:

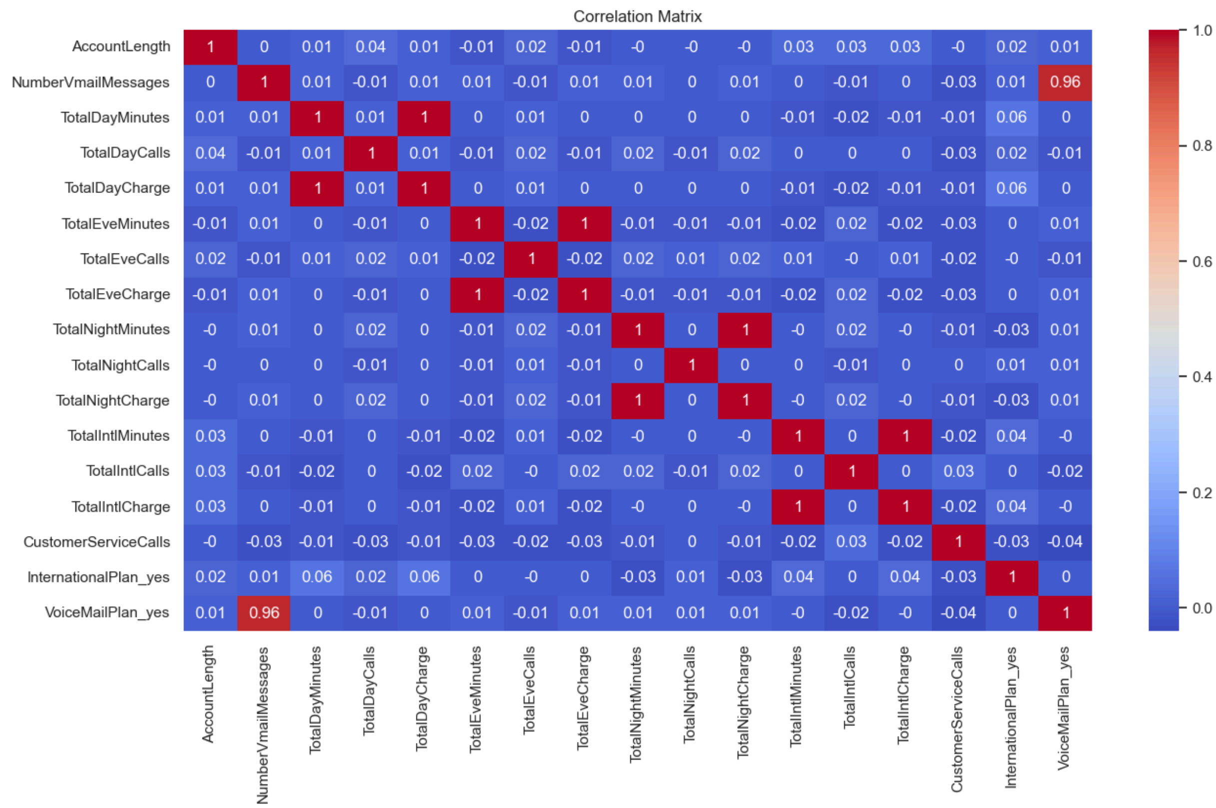
	count	mean	std	min	25%	50%	75%	max
AccountLength	2797.0	100.392206	39.329033	1.00	73.00	100.00	127.00	205.00
NumberVmailMessages	2797.0	8.131212	13.707224	0.00	0.00	0.00	19.00	50.00
TotalDayMinutes	2797.0	179.995817	52.589516	37.70	144.00	179.80	216.00	322.50
TotalDayCalls	2797.0	100.577047	19.284581	47.00	87.00	101.00	114.00	152.00
TotalDayCharge	2797.0	30.599828	8.940156	6.41	24.48	30.57	36.72	54.83
TotalEveMinutes	2797.0	201.288059	49.042830	66.00	167.20	201.40	235.10	336.00
TotalEveCalls	2797.0	100.020379	19.225656	48.00	87.00	100.00	113.00	154.00
TotalEveCharge	2797.0	17.109714	4.168704	5.61	14.21	17.12	19.98	28.56
TotalNightMinutes	2797.0	201.175366	48.827301	65.70	167.60	201.10	235.80	334.70
TotalNightCalls	2797.0	100.047193	19.052069	48.00	87.00	101.00	113.00	152.00
TotalNightCharge	2797.0	9.052942	2.197284	2.96	7.54	9.05	10.61	15.06
TotalIntlMinutes	2797.0	10.310976	2.594138	3.40	8.60	10.30	12.10	17.30
TotalIntlCalls	2797.0	4.311763	2.073932	1.00	3.00	4.00	6.00	10.00
TotalIntlCharge	2797.0	2.784483	0.700338	0.92	2.32	2.78	3.27	4.67
CustomerServiceCalls	2797.0	1.306400	0.975453	0.00	1.00	1.00	2.00	3.00

- The maximum values have changed because the outliers have been removed.
- The charactestics and patterns of usage and charges are still as described in the first summary.
- There is significant variability in the local minutes/calls as well as in the number voicemail messages, with significantly lower variation in charges. The network could be penalizing low usage customers with higher tariffs.

2.2.2 Correlation Matrix

In [24]:

```
# Calculate the correlation matrix
corr_matrix_columns = data[['AccountLength','NumberVmailMessages','TotalDayMinutes'
                   'TotalEveMinutes','TotalEveCalls','TotalEveCharge','TotalNightMi
                    'TotalNightCharge','TotalIntlMinutes','TotalIntlCalls','TotalIn
                    'InternationalPlan_yes','VoiceMailPlan_yes']]
corr_matrix = corr_matrix_columns.corr().round(2)

plt.figure(figsize=(15, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')

plt.show()
```

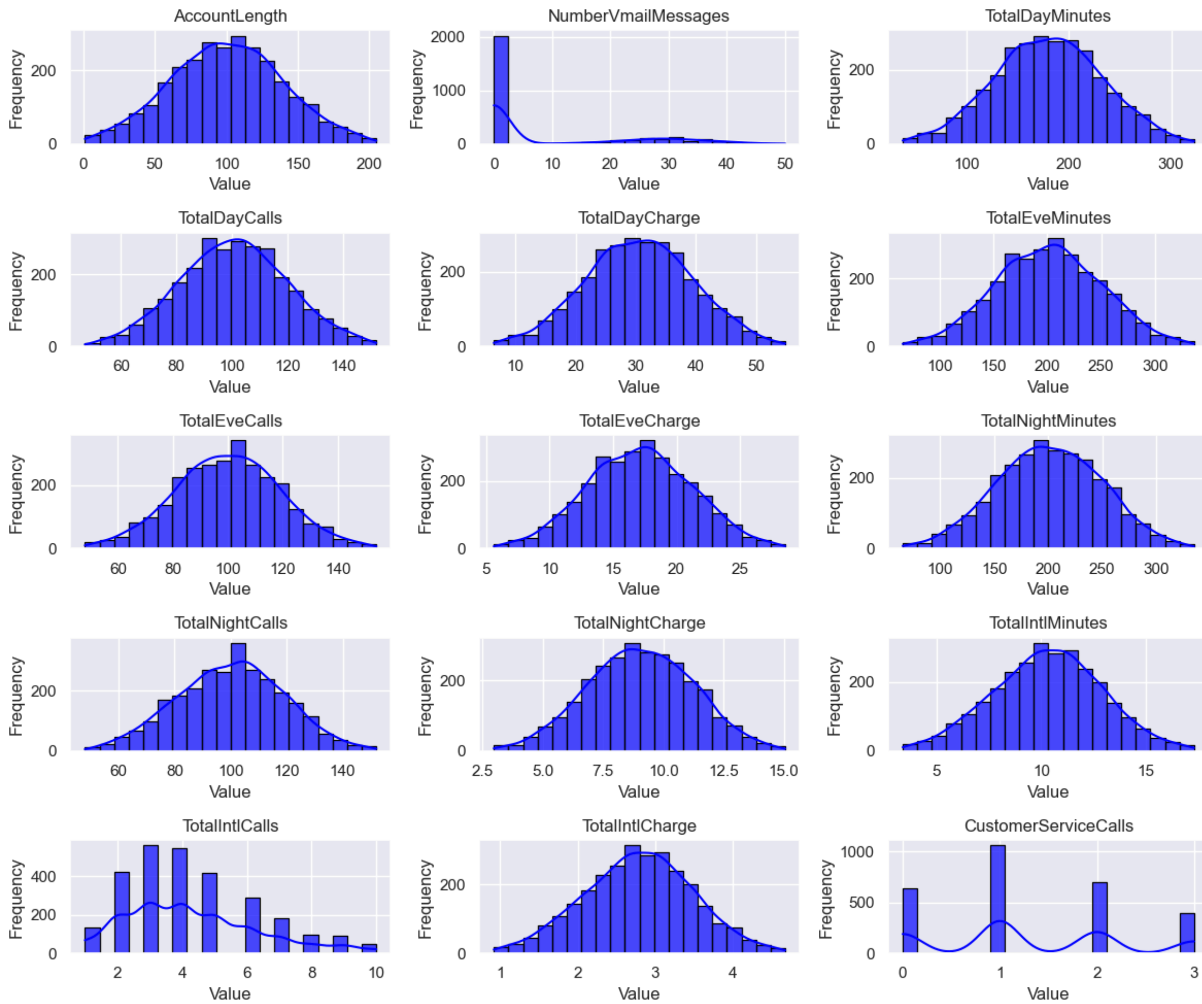


- Not surprisingly, the total (day,evening,night international) minutes have a perfect linear relationship with the total(day,evening,night,international) charges. This is because charges are based on minutes.
- Being on a voice plan is also very correlated to the number of voice mail minutes.
- This **multicollinearity** can impact model performance and interpretability. Highly correlated predictors can contribute to overfitting where the model performs well on training data but poorly on unseen data.
- Proposed remedy is to drop one of the correlated predictors form the model.

2.2.3 Histograms

In [25]:
```
# List of continous columns to plot
continous_cols = data[['AccountLength','NumberVmailMessages','TotalDayMinutes','Tot
                   'TotalEveMinutes','TotalEveCalls','TotalEveCharge','TotalNightMi
                    'TotalNightCharge','TotalIntlMinutes','TotalIntlCalls','TotalIn

# Create subplots
plt.figure(figsize=(12,10))

for i,col in enumerate (continous_cols):
    plt.subplot(5,3,i+1)
    sns.histplot(data[col],bins=20,kde=True,color='blue',alpha=0.7,edgecolor='black
    plt.title(col)
    plt.xlabel('Value')
    plt.ylabel('Frequency')
```

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



- The charts show that the number of calls and charges for local calls are approximately normally distributed;
- International calls distribution is right-skewed with with most customers in this plan making between 2 and 6 calls, and a few extending to 10;
- The total international charge distribution is approximately normal.
- The Customer Service Calls show distinct peaks at 1,2, indicating that these values are more frequent.A significant number of customers have not mae any calls to Customer Service,
- Number of Voice Mail Messages is highly skewed to the right, with most values concentrated around 0 and a few exceeding 20.This is because VM is an opt-in service and most customers in the network are not using the service.

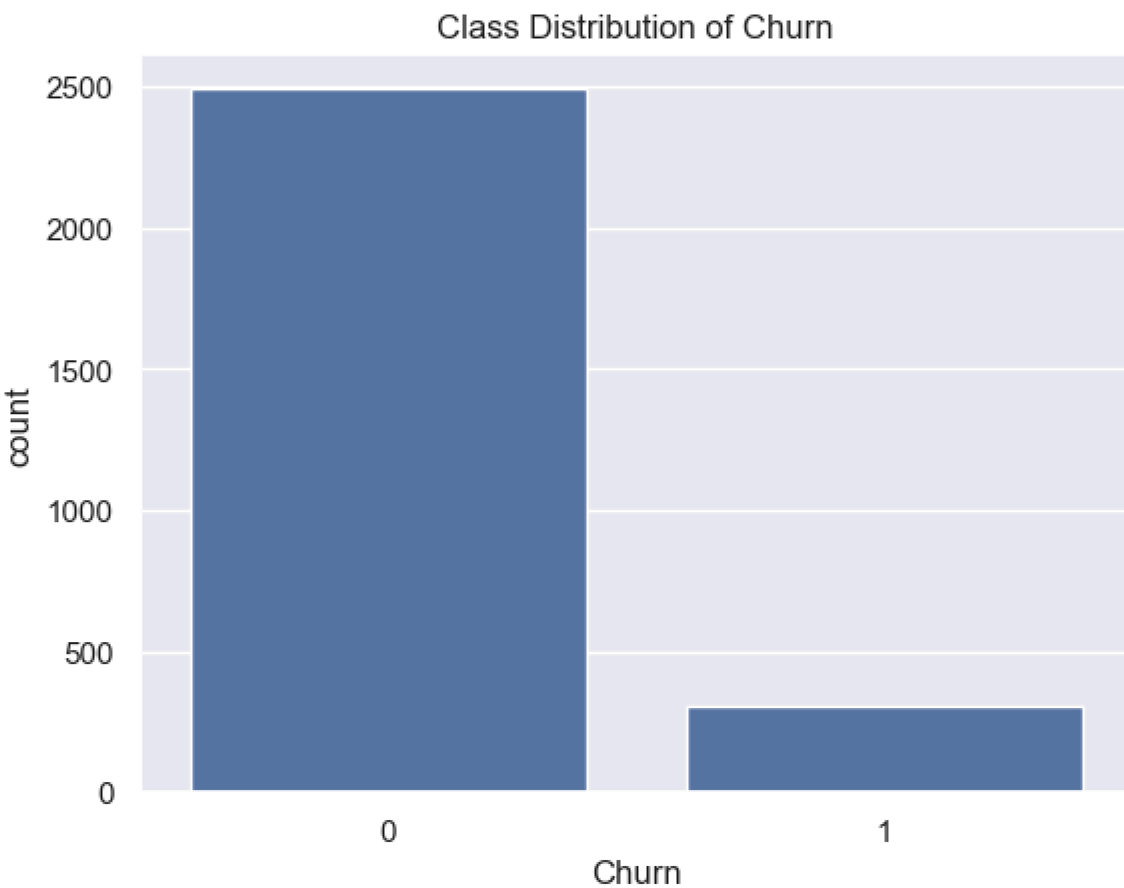
2.2.4 Class distribution of the target variable

In [26]:
```
# Check the value counts of the target variable
```

```
print(data['Churn'].value_counts())
print(data['Churn'].value_counts(normalize=True))
```

```
Churn
0    2493
1     304
Name: count, dtype: int64
Churn
0    0.891312
1    0.108688
Name: proportion, dtype: float64
```

In [27]:
```
# Plot the classes
sns.countplot(x='Churn', data=data)
plt.title('Class Distribution of Churn')
plt.show()
```



The output indicates that 89% of the customers did not leave while 11% left. This is significant class imbalance. This can impact the reliability of the model in the following ways:-

- **Bias:** A model trained on imbalanced data may become biased biased toward the majority class. The bias may lead to a high accuracy score, but fail to correctly predict the minority class.
- **Poor Performance on Minority Class:** Where detecting the minority class is of critical class, like in our case, the model may have poor performance in detecting the minority

class i.e. incorrectly fail to predict churn.

I will address the class problem using **SMOTE** (Synthetic Minority Over-Sampling Technique) an oversampling technique that increases the number of instances in the minority class during the modeling process below.

4.0 Modeling

In this section I will follow a model iteration plan that addresses class imbalance and leverages feature importance and hyperparameters tuning. The following is a step by step plan to build and improve the model, starting with a baseline logistic model and incorporating SMOTE for oversampling, Random Forest for feature selection,and GridSearchCV and RandomSearchCV for hyperparameter tuning:-

- **Data Preparation:** In this section, I will prepare the data for modeling. Since I have alredy handled data cleaning and one-hot encoding, I will address multicollinearity, standardize the data and split the data into train and test sets. I will use the correlation matrix in section 2.2.2 above and remove highly correlated features.
- **Baseline Logistic Regression Model:** I will train the logistic regression model on the training data and evaluate the baseline model using appropriate metrics.
- **Handle Class Imbalance:** I will use **SMOTE** to oversample the minority class in the training set. I will re-train the model on the oversampled training data and evaluate the model on the original test set. I will compare the performance metrics before and after SMOTE application.
- **Feature Selection:** I will use **Random Forest** to calculate feature importances and identify and retain the most important features. I will then retrain the model with these features and compare the results with those obtained above.
- **Cross-Validation:** I will use cross-validation to ensure the model's performance is consistent and not dependent on a specific train-test split.
- **Hyperparameter Tuning:** I will use **GridSearchCV** to find the optimal hyperparameters for the logistic regression model, and may include regularization (L1/L2) to handle overfitting. I will re-train the model with optimal hyperparameters and optimal features obtained in feature selection and evaluate and compare performance metrics with previous iterations.
- **Use other Modeling Algorithms**: I will train a different model algorithms - a hyperparameter pruned Decision Tree Model and a Random Forest Ensemble Model - and compare their performance with the Hyperparameter tuned logistic regression
- **Final Model Selection:** I will select the model with the best performance based on validation metrics, interpret this final model's results, and generate a report on model performance, feature importance and othe insights from the modeling process.

4.1 Data Preparation

In this section:

- I will use the correlation heat map to remove highly correlated features.
- Split the data into train and test sets
- Standardize the data for modeling

In [28]:
```
# Making a copy of the DataFrame before we clean
data1 = data.copy(deep=True)
data1
```

Out[28]:

	AccountLength	NumberVmailMessages	TotalDayMinutes	TotalDayCalls	TotalDayCha
0	128	25	265.1	110	4!
1	107	26	161.6	123	2
2	137	0	243.4	114	4
3	75	0	166.7	113	2
4	118	0	223.4	98	3
...	...	...	...	...	
2792	192	36	156.2	77	2
2793	68	0	231.1	57	3
2794	28	0	180.8	109	3
2795	184	0	213.8	105	3
2796	74	25	234.4	113	3

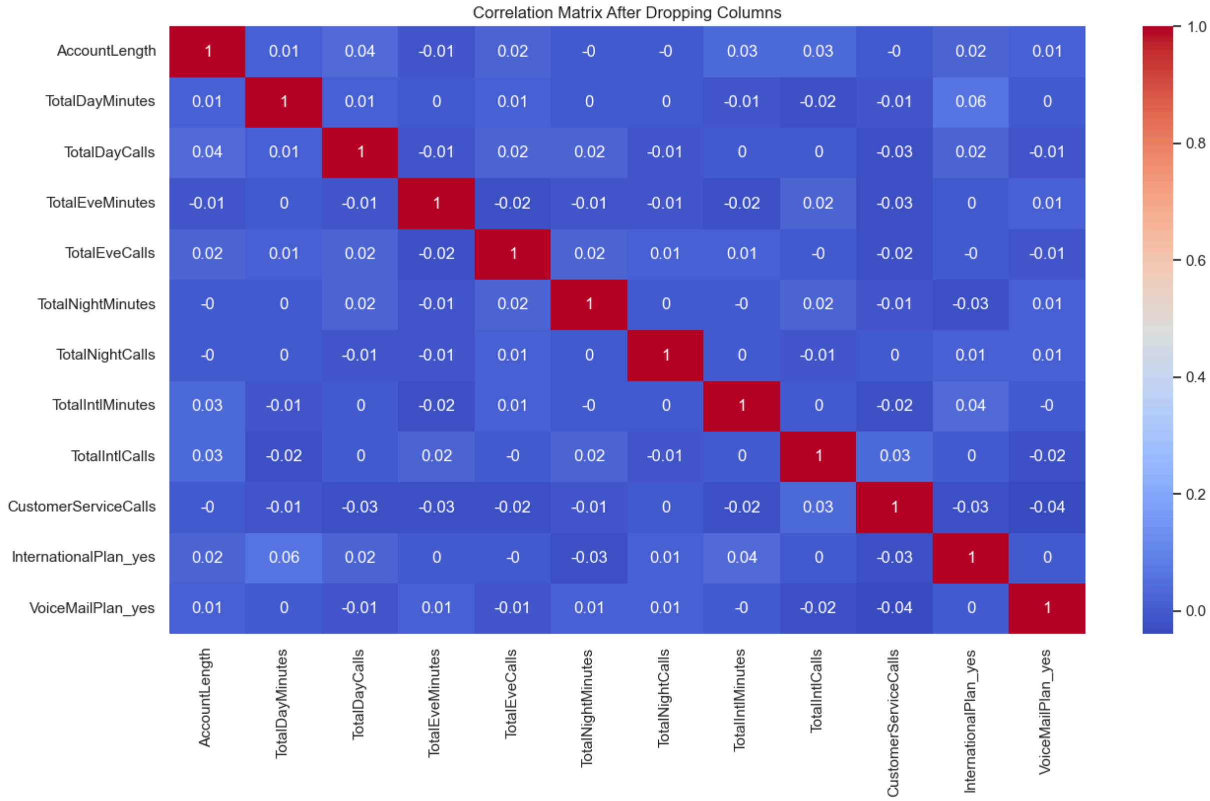
2797 rows × 68 columns

4.1.1 Remove Correlated Columns

In [29]:
```
# List of columns to drop
col_to_drop = ['NumberVmailMessages', 'TotalDayCharge', 'TotalEveCharge', 'TotalNig

# Drop the columns from the DataFrame
corr_df = corr_matrix_columns.drop(columns=col_to_drop)

# Print the remaining columns in the DataFrame
print(corr_df.columns)

# Confirm multicollinearity as been eliminated
# Visualize the correlation matrix
corr_matrix1 = corr_df.corr().round(2)

plt.figure(figsize=(15, 8))
sns.heatmap(corr_matrix1, annot=True, cmap='coolwarm')
```

```
plt.title('Correlation Matrix After Dropping Columns')
plt.show()
```

```
Index(['AccountLength', 'TotalDayMinutes', 'TotalDayCalls', 'TotalEveMinutes',
       'TotalEveCalls', 'TotalNightMinutes', 'TotalNightCalls',
       'TotalIntlMinutes', 'TotalIntlCalls', 'CustomerServiceCalls',
       'InternationalPlan_yes', 'VoiceMailPlan_yes'],
      dtype='object')
```



We no longer have features that are highly correlated and we can proceed to create the baseline logistic regression model.

4.1.2 Standardize the features columns

In [30]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

# Split data1 into X an y
y = data1['Churn']
X = data1.drop(columns=['Churn','NumberVmailMessages', 'TotalDayCharge', 'TotalEveC
                        'TotalIntlCharge'],axis=1)

# Split the data into a training and a test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_st

# Intitialize the StandardScaler
scaler = StandardScaler()

# Fit the scaler on the training data and transform both the training and test data
X_train_standardized = scaler.fit_transform(X_train)
X_test_standardized = scaler.transform(X_test)
```

```
# Retain feature names and convert back to DataFrame
X_train = pd.DataFrame(X_train_standardized, columns=X_train.columns)
X_test = pd.DataFrame(X_test_standardized,columns=X_test.columns)
```

In [31]:
```
# Display first five columns of the Standardized X_train
X_train.head()
```

Out[31]:

	AccountLength	TotalDayMinutes	TotalDayCalls	TotalEveMinutes	TotalEveCalls	TotalNig
0	-0.260348	-1.953549	1.068323	1.796482	-1.419285	
1	-2.030083	-0.876027	-0.348210	0.059342	0.042856	
2	-0.542480	-2.439006	-2.027065	-0.005522	-0.688215	
3	-0.234700	-0.375340	0.438753	1.082977	2.183849	
4	1.227255	1.259981	2.589785	-1.696041	1.974972	

5 rows × 62 columns

In [32]:
```
# Display first five columns of the Standardized X_test
X_test.head()
```

Out[32]:

	AccountLength	TotalDayMinutes	TotalDayCalls	TotalEveMinutes	TotalEveCalls	TotalNig
0	1.175958	0.037774	-0.977781	-0.567002	-0.531557	
1	0.303915	-0.192580	0.071503	1.952561	0.878366	
2	-0.362942	-0.712304	-1.502423	-0.960240	-0.270460	
3	-0.003865	0.664107	1.383109	-0.522408	-0.949311	
4	0.150025	-1.133033	2.170072	0.541768	2.027191	

5 rows × 62 columns

In [33]:
```
# Check the shape of the standardized X_datasets
print(f"The y_train data set consists of {y_train.shape[0]} rows")
print(f"The X_train data set consists of {X_train.shape[0]} rows")
print(f"The X_train data set consists of {X_train.shape[1]} columns\n")

print(f"The y_test data set consists of {y_test.shape[0]} rows")
print(f"The X_test data set consists of {X_test.shape[0]} rows")
print(f"The X_train data set consists of {X_test.shape[1]} columns")
```

```
The y_train data set consists of 2097 rows
The X_train data set consists of 2097 rows
The X_train data set consists of 62 columns

The y_test data set consists of 700 rows
The X_test data set consists of 700 rows
The X_train data set consists of 62 columns
```

Both the training and test features have been standardized in order to make the model training and evaluation more reliable and effective. The two data sets have a 75.25 split.

4.2 Baseline Logistic Regression Model

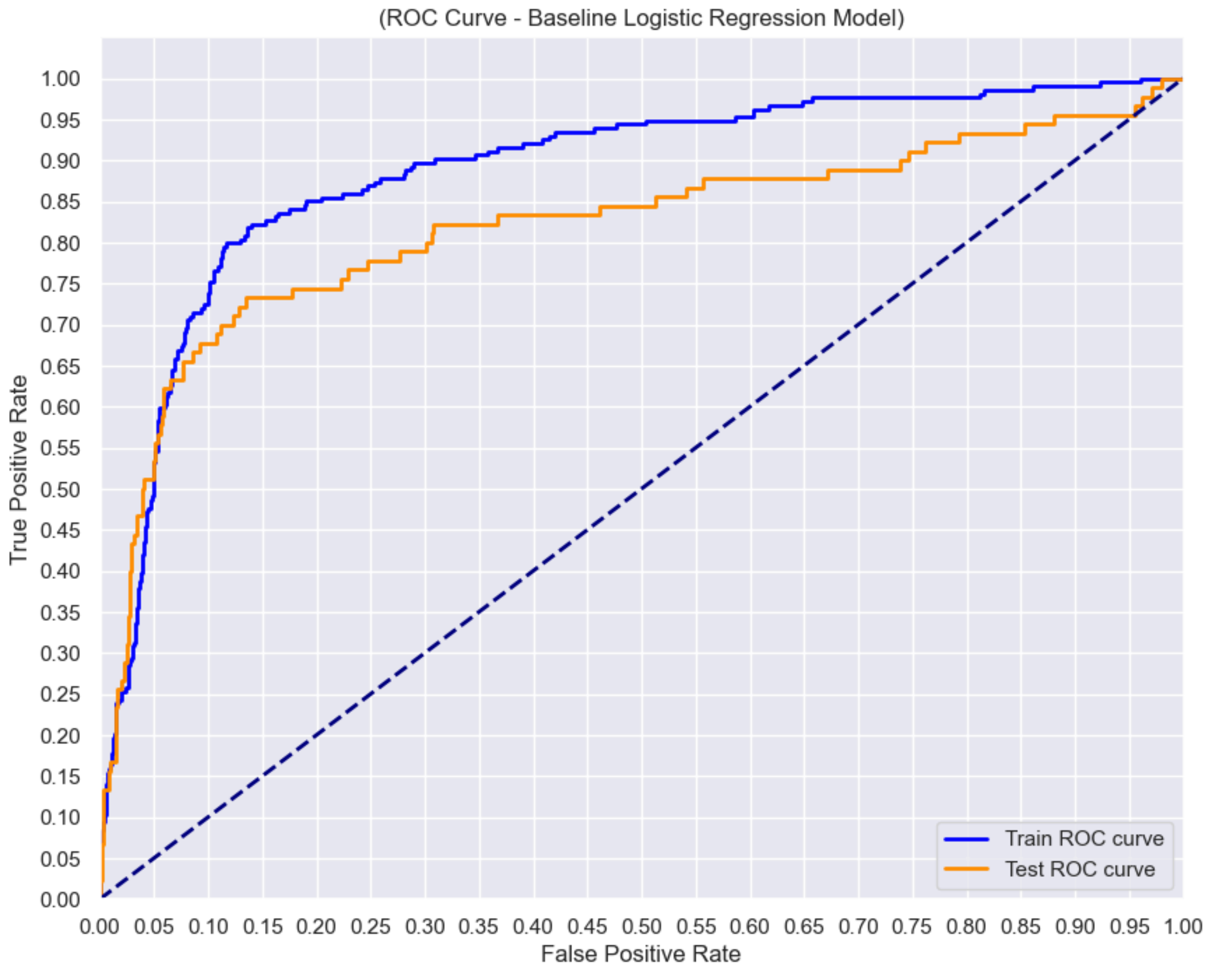
- Train and evaluate a Baseline Model using Accuracy score, the AUC (Area Under the Curve) and ROC (Receiver Operator Characteristic) Curve.
- Accuracy is a measure of how often the model gets the predictions right;
- AUC evaluates the ability of the model to differentiate between classes,across all possible threshold settings.
- The ROC Curve is a graph that helps us visualize how well a classification model distinguishes between 2 classes. The X-axis represents the False Positive Rate (FPR) while the Y-axis represents the True Positive Rate(TPR).
- A good model curves up towards the top=left corner, indicating high TPR and low FPR

The same metrics will be used for all subsequent model iterations and the results compared

In [34]:
```
# import the necessary libaries

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score,roc_curve,auc,roc_auc_score

# Instantiate LogisticRegression
logreg = LogisticRegression(fit_intercept=False, solver='liblinear',C=1e12)

# Fit to training data
base_log_model = logreg.fit(X_train,y_train)

# Predict on train and test sets
y_hat_train = logreg.predict(X_train)
y_hat_test = logreg.predict (X_test)

# Get Accuracy Score
base_train_accuracy = round(accuracy_score(y_train,y_hat_train),2)
base_test_accuracy = round(accuracy_score(y_test,y_hat_test),2)
print(f"Training Accuracy: {base_train_accuracy}")
print(f"Test Accuracy: {base_test_accuracy}")

# Create the ROC Curve for both the train and test sets

# Calculate the probability scores of each point for the train and test sets
y_train_score = base_log_model.decision_function(X_train)
```

```
y_test_score = base_log_model.decision_function(X_test)

# Calculate the fpr,tpr, and thresholds for the train and test sets
train_fpr, train_tpr, train_thresholds = roc_curve(y_train,y_train_score)
test_fpr, test_tpr, test_thresholds = roc_curve(y_test,y_test_score)

# Print the AUC for the train and test sets
base_train_AUC = round(auc(train_fpr,train_tpr),2)
base_test_AUC = round(auc(test_fpr,test_tpr),2)
print(f"Train AUC: {base_train_AUC}")
print(f"Test AUC: {base_test_AUC}")

# Plot the ROC curves for the train and test sets

plt.figure(figsize=(10, 8))
lw = 2

plt.plot(train_fpr, train_tpr, color='blue',
         lw=lw, label='Train ROC curve')
plt.plot(test_fpr, test_tpr, color='darkorange',
         lw=lw, label='Test 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('(ROC Curve - Baseline Logistic Regression Model)')
plt.legend(loc='lower right')
plt.show()
```

```
Training Accuracy: 0.64
Test Accuracy: 0.57
Train AUC: 0.89
Test AUC: 0.82
```



4.2.1 Evaluate the baseline model results

In [35]:
```
# Data for the models
Metrics = ['Training Accuracy', 'Testing Accuracy', 'Train AUC', 'Test AUC']
base_scores = [base_train_accuracy,base_test_accuracy,base_train_AUC,base_test_AUC]

# Create a data Frame for the results
results_base = {'Metric':Metrics,'Score':base_scores}
base_model_metrics = pd.DataFrame(results_base)
base_model_metrics
```

Out[35]:

	Metric	Score
0	Training Accuracy	0.64
1	Testing Accuracy	0.57
2	Train AUC	0.89
3	Test AUC	0.82

- The high AUC scores compared to the lower accuracy scores suggest that while the model performs well in distinguishing between the classes, it's accuracy is low implying the model's threshold for classification might not be optimal(accuracy is calculated on a fixed threshold, often 0.5)

- **Class Imbalance**: The significant discrepancy between accuracy and AUC scores could be due to class imbalance. The model might be predicting the majority class more often (misclassification of the minority class), leading to lower accuracy but still achieving high AUC because it gets the ranking of probabilities right.
- **Next Steps:** Addressing class imbalance and further tuning the model should help in improving both accuracy and AUC, leading to a more robust and reliable model.

4.3 Handle Class Imbalance with SMOTE

4.3.1 Compare the Classes Before and After SMOTE

In [36]:
```
# Import the library
from imblearn.over_sampling import SMOTE

# Compare the classes before and after SMOTE
print('Original class distribution: \n')
print(y.value_counts())

# Instantiate SMOTE and fit into the training set
smote = SMOTE()
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)

# Preview synthetic sample class distribution
print('-----------------------------------------')
print('SMOTE sample class distribution: \n')
print(pd.Series(y_train_resampled).value_counts())
```

```
Original class distribution:

Churn
0    2493
1     304
Name: count, dtype: int64
-----------------------------------------
SMOTE sample class distribution:

Churn
0    1883
1    1883
Name: count, dtype: int64
```

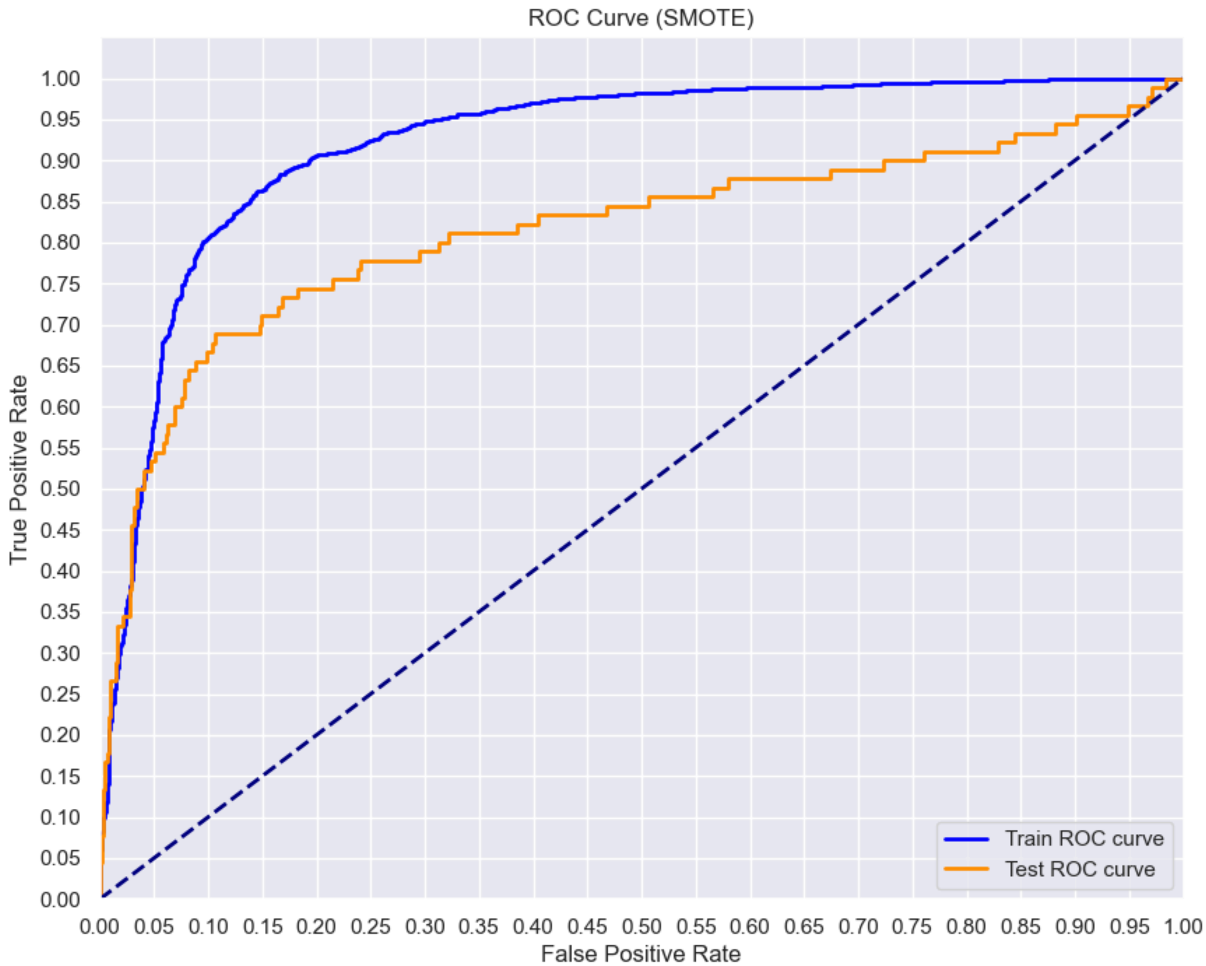
In [37]:
```
# Get the shape of the resampled X_train and y_train
print(f"X_train resampled has {X_train_resampled.shape[0]} rows and {X_train_resamp
print(f"y train resampled has {y_train_resampled.shape[0]} rows")
```

```
X_train resampled has 3766 rows and 62 columns
y train resampled has 3766 rows
```

4.3.2 Train and Evaluate Logistic Regression Model on Oversampled Data

In [38]:
```
# Train logistic regression model on oversampled data

# Fit to training data
smote_log_model = logreg.fit(X_train_resampled,y_train_resampled)

# Predict on train and test sets
y_hat_train = logreg.predict(X_train_resampled)
y_hat_test = logreg.predict (X_test)

# Get Accuracy Score
smote_train_accuracy = round(accuracy_score(y_train_resampled, y_hat_train),2)
smote_test_accuracy= round(accuracy_score(y_test, y_hat_test),2)
print(f"Training Accuracy: {smote_train_accuracy}")
print(f"Test Accuracy: {smote_test_accuracy}")

# Calculate the probability scores of each point for the train and test sets
y_train_score = smote_log_model.decision_function(X_train_resampled)
y_test_score = smote_log_model.decision_function(X_test)

# Calculate the fpr,tpr and thresholds for the train and test sets
train_fpr, train_tpr, train_thresholds = roc_curve(y_train_resampled,y_train_score)
test_fpr, test_tpr, test_thresholds = roc_curve(y_test,y_test_score)

# Print the AUC for the train and test sets
smote_train_AUC = round(auc(train_fpr, train_tpr),2)
smote_test_AUC = round(auc(test_fpr, test_tpr),2)
print(f"Train AUC: {smote_train_AUC}")
print(f"Test AUC: {smote_test_AUC}")

# Plot the ROC curves for the train and test sets

plt.figure(figsize=(10, 8))
lw = 2

plt.plot(train_fpr, train_tpr, color='blue',
         lw=lw, label='Train ROC curve')
plt.plot(test_fpr, test_tpr, color='darkorange',
         lw=lw, label='Test 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('ROC Curve (SMOTE)')
plt.legend(loc='lower right')
plt.show()
```

```
Training Accuracy: 0.78
Test Accuracy: 0.57
Train AUC: 0.92
Test AUC: 0.81
```



4.3.2 Compare the results of the baseline model with the oversampled SMOTE model

In [39]:
```
# # Data for the models
smote_scores =[smote_train_accuracy,smote_test_accuracy,smote_train_AUC,smote_test_
results_base_smote = {
    'Metric':Metrics,
    'Baseline Model': base_scores,
    'Smote Model':smote_scores}

# Create a DataFrame
base_smote_metrics = pd.DataFrame(results_base_smote)
base_smote_metrics
```

Out[39]:

	Metric	Baseline Model	Smote Model
0	Training Accuracy	0.64	0.78
1	Testing Accuracy	0.57	0.57
2	Train AUC	0.89	0.92
3	Test AUC	0.82	0.81

- **Training Improvement:** The model showed improved training accuracy and AUC after applying SMOTE, indicating better learning from the resampled data and improved discrimination power on the training set.
- **Testing Performance:** The testing accuracy and the test AUC remained relatively stable, suggesting that while the model became better at learning from the training data, it did not generalize as well to the test data.
- **Conclusion :** Potential overfitting due to the synthetic samples from SMOTE.
- **Next Steps:** Feature Selection, cross-validation, and Hyperparameter tuning techniques to further optimize model performance .

4.4 Feature Selection with Random Forest

In this section, I will try to further optimize the model through feature selection using Random Forest.

- Train Random Forest to determine feature importances
- Select Top Features based on importances
- Retrain Logistic Regression Model Using Selected Features

4.4.1 Train Random Forest to Determine Feature Importances

In [40]:

```
# Import the Random Forest Clasifier
from sklearn.ensemble import RandomForestClassifier

# Train a Random Forest Model to calculate feature importances
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train_resampled, y_train_resampled)

# Get feature importances
feature_importances = rf_model.feature_importances_
importance_df = pd.DataFrame({'Feature':X_train.columns,'Importance':feature_import

# Sort features by importance
importance_df = importance_df.sort_values(by='Importance', ascending=False)
importance_df.head(15)
```

Out[40]:

	Feature	Importance
1	TotalDayMinutes	0.221904
10	InternationalPlan_yes	0.144069
3	TotalEveMinutes	0.089532
11	VoiceMailPlan_yes	0.076552
9	CustomerServiceCalls	0.061465
8	TotalIntlCalls	0.055961
5	TotalNightMinutes	0.052950
7	TotalIntlMinutes	0.042700
2	TotalDayCalls	0.035896
4	TotalEveCalls	0.034088
6	TotalNightCalls	0.033112
0	AccountLength	0.032736
60	State_WV	0.008582
46	State_OH	0.007242
54	State_TX	0.006510

- It is clear that the States have very little predictive power as they all appear below all the other features.
- I will model top features ranging from top 5 to top 20 and compare results

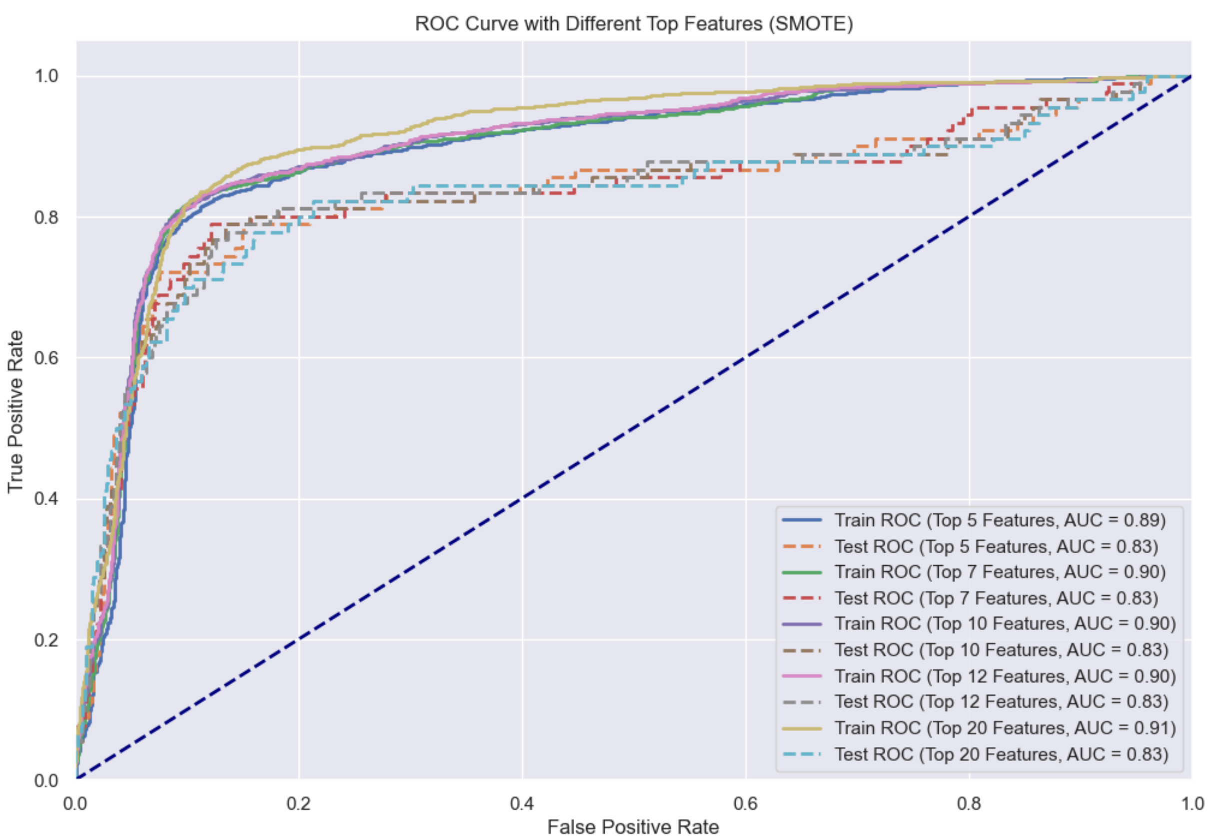
4.4.2 Select Top Features Based on Importances and evaluate their model results

In [41]:

```
top_features_list = [5, 7,10,12,20]

# Define a function to evaluate models with different top features
def evaluate_model_with_top_features(top_features_count):
    top_features = importance_df['Feature'].head(top_features_count)
    X_train_top = X_train_resampled[top_features]
    X_test_top = X_test[top_features]

    # Train Logistic Regression model
    logreg.fit(X_train_top, y_train_resampled)

   # Calculate the probability scores of each point for the train and test sets
    y_train_score = logreg.decision_function(X_train_top)
    y_test_score = logreg.decision_function(X_test_top)

    # Calculate accuracy
    y_train_pred = logreg.predict(X_train_top)
```

```
    y_test_pred = logreg.predict(X_test_top)

    train_accuracy = accuracy_score(y_train_resampled, y_train_pred)
    test_accuracy = accuracy_score(y_test, y_test_pred)

    # Calculate ROC Curve
    train_fpr, train_tpr, _ = roc_curve(y_train_resampled, y_train_score)
    test_fpr, test_tpr, _ = roc_curve(y_test, y_test_score)

    # Calculate AUC
    train_auc = auc(train_fpr, train_tpr)
    test_auc = auc(test_fpr, test_tpr)



    return {
        'top_features': top_features_count,
        'train_accuracy': round(train_accuracy,2),
        'test_accuracy': round(test_accuracy,2),
        'train_auc': round(train_auc,2),
        'test_auc': round(test_auc,2),
        'train_fpr': train_fpr,
        'train_tpr': train_tpr,
        'test_fpr': test_fpr,
        'test_tpr': test_tpr
    }

# Evaluate models
results = [evaluate_model_with_top_features(n) for n in top_features_list]

# Print results
for result in results:
    print(f"Top {result['top_features']} Features")
    print(f"Train Accuracy: {result['train_accuracy']}")
    print(f"Test Accuracy: {result['test_accuracy']}")
    print(f"Train AUC: {result['train_auc']}")
    print(f"Test AUC: {result['test_auc']}\n")

# Plot ROC Curves
plt.figure(figsize=(12, 8))
for result in results:
    plt.plot(result['train_fpr'], result['train_tpr'], lw=2, label=f"Train ROC (Top
    plt.plot(result['test_fpr'], result['test_tpr'], lw=2, linestyle='--', label=f"

plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve with Different Top Features (SMOTE)')
plt.legend(loc='lower right')
plt.show()
```

```
Top 5 Features
Train Accuracy: 0.76
Test Accuracy: 0.59
Train AUC: 0.89
Test AUC: 0.83

Top 7 Features
Train Accuracy: 0.76
Test Accuracy: 0.58
Train AUC: 0.9
Test AUC: 0.83

Top 10 Features
Train Accuracy: 0.76
Test Accuracy: 0.59
Train AUC: 0.9
Test AUC: 0.83

Top 12 Features
Train Accuracy: 0.76
Test Accuracy: 0.58
Train AUC: 0.9
Test AUC: 0.83

Top 20 Features
Train Accuracy: 0.77
Test Accuracy: 0.58
Train AUC: 0.91
Test AUC: 0.83
```



4.4.3 Compare the results of the features against Baseline and SMOTE models

In [42]:
```
# Data for the models
data = {'Metric': Metrics,
    'Baseline Model':base_scores,
    'SMOTE Model': smote_scores,
    'Top 5 Features':[0.77,0.6,0.90,0.83],
    'Top 7 Features':[0.76,0.58,0.91,0.83],
    'Top 10 Features':[0.76,0.59,0.91,0.83],
    'Top 12 Features': [0.76,0.58,0.91,0.83],
    'Top 20 Features':[0.77,0.58,0.92,0.83]}


# Create a DataFrame
base_smote_features_df = pd.DataFrame(data)
base_smote_features_df
```

Out[42]:

	Metric	Baseline Model	SMOTE Model	Top 5 Features	Top 7 Features	Top 10 Features	Top 12 Features	Top 20 Features
0	Training Accuracy	0.64	0.78	0.77	0.76	0.76	0.76	0.77
1	Testing Accuracy	0.57	0.57	0.60	0.58	0.59	0.58	0.58
2	Train AUC	0.89	0.92	0.90	0.91	0.91	0.91	0.92
3	Test AUC	0.82	0.81	0.83	0.83	0.83	0.83	0.83

- **Training Accuracy and AUC:** Selected features show no improvements from the SMOTE model
- **Testing Performance:** Testing accuracy shows minor improvements with selected features.
- **Optimal Feature Selection:** Top 10 to 12 features offer a balance between improving model performance and avoiding overfitting.Adding more features while increasing model complexity doea not add much to model improvement.
- **Next Steps:** I will subset the features to the top 12 and then perform cross-validation to evaluate if the model is overfitting the training data, and Hyperparameter tuning to optimize the model.

4.4.3 Subset the X_train_resampled and X_test_resampled to the 12 top features

In [43]:
```
# Subset the top 12 best columns
top_features_cols = ['AccountLength', 'TotalDayMinutes', 'TotalDayCalls', 'TotalEve
       'TotalEveCalls', 'TotalNightMinutes', 'TotalNightCalls',
       'TotalIntlMinutes', 'TotalIntlCalls', 'CustomerServiceCalls',
       'InternationalPlan_yes', 'VoiceMailPlan_yes']
```

```
X_train_resampled= X_train_resampled[top_features_cols]
X_test = X_test[top_features_cols]

print(f"This X_train_resampled with top 12 best features data set consists of {X_tr
print(f"This X_train_resampled with top 12 best features data set consists of {X_tr

print(f"This X_test with top 12 best features data set consists of {X_test.shape[0]
print(f"This X_test with top 12 best features data set consists of {X_test.shape[1]
```

```
This X_train_resampled with top 12 best features data set consists of 3766 rows
This X_train_resampled with top 12 best features data set consists of 12 columns

This X_test with top 12 best features data set consists of 700 rows
This X_test with top 12 best features data set consists of 12 columns
```

4.5 Cross-Validation

I will now perform cross-validation to assess how the model generalizes to an independent dataset. I will use the SMOTE resampled data with the top 12 best features

In [44]:

```
# Import the necessary library
from sklearn.model_selection import cross_validate

# Define the number of folds and scoring metric
cv_folds = 5
scoring_metrics = {'accuracy':'accuracy', 'auc':'roc_auc'}

# Perform cross-validation
cv_results = cross_validate(logreg,X_train_resampled,y_train_resampled, cv=cv_folds
            return_train_score=True)

# Evaluate cross-validation

# Evaluate cross-validation results with rounding print("Cross-Validation Results:"
for metric in scoring_metrics:
    train_scores = [round(score, 2) for score in cv_results['train_' + metric]]
    test_scores = [round(score, 2) for score in cv_results['test_' + metric]]
    mean_train_score = round(cv_results['train_' + metric].mean(), 2)
    mean_test_score = round(cv_results['test_' + metric].mean(), 2)
    std_train_score = round(cv_results['train_' + metric].std(), 2)
    std_test_score = round(cv_results['test_' + metric].std(), 2)

    print(f"{metric.capitalize()} - Train: {train_scores}")
    print(f"{metric.capitalize()} - Test: {test_scores}")
    print(f"Mean {metric.capitalize()} - Train: {mean_train_score}")
    print(f"Mean {metric.capitalize()} - Test: {mean_test_score}")
    print(f"Standard Deviation {metric.capitalize()} - Train: {std_train_score}")
    print(f"Standard Deviation {metric.capitalize()} - Test: {std_test_score}")
    print()
```

```
Accuracy - Train: [0.76, 0.76, 0.75, 0.76, 0.76]
Accuracy - Test: [0.74, 0.76, 0.78, 0.75, 0.75]
Mean Accuracy - Train: 0.76
Mean Accuracy - Test: 0.76
Standard Deviation Accuracy - Train: 0.0
Standard Deviation Accuracy - Test: 0.02

Auc - Train: [0.91, 0.9, 0.9, 0.9, 0.9]
Auc - Test: [0.87, 0.91, 0.92, 0.9, 0.9]
Mean Auc - Train: 0.9
Mean Auc - Test: 0.9
Standard Deviation Auc - Train: 0.0
Standard Deviation Auc - Test: 0.02
```

Accuracy: The training and testing accuracies are relatively close, indicating the model does not significantly overfit or underfit the data. However the slight testing accuracy variability indicates that the model's performance can vary based on the data split.

AUC: Both training and test AUC values are high, showing the model's strong ability to distinguish between classes. The train results are quite consistent across folds while the variability in testing AUC suggests the need for careful interpretation.

Overall the results show that the model performs well and generalizes effectively across different folds.

4.6 Hyperparameter Tuning

Hyperparameter tuning will further optimize the model and potentially reduce variability in performance. I will use GridSearchCV for tuning the following hyperparameters:

- **max_iter:** This parameter specifies the maximum number of iterations taken for the solvers to converge. Our models so far have use 100, the default value.
- **C:** This is the inverse of the regularization strength; smaller values specify stronger regularization. Our models have used a very high value of C=1e12 (very small regularization). The default when not specified is 1.0.
- **solver:** This parameter determines the algorithm to use in the optimization problem. In our models, we ahave been using 'liblinear'. The default value when not specified is 'lbfgs'.
- **penalty:** This parameter specifies the norm of the penalty. Our models so far, have used the deafaul L2 norm which is the Ridge Regularization.

4.6.1 Tune the model to find the best hyperparameters

In [45]:

```
# Import the necessary library
from sklearn.model_selection import GridSearchCV

# Define the parameter grid
param_grid = {
```

```
    'C': [0.01, 0.1, 1, 10, 100],
    'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'],
    'penalty': ['l2'],
    'fit_intercept':[True, False],
    'max_iter': [100,200,300,500,1000]}

# Initialize GridSearchCV with scoring metrics
grid_search = GridSearchCV(LogisticRegression(max_iter=1000, random_state=42), para
              cv=5, scoring=['accuracy', 'roc_auc'], refit='roc_auc', return_train_

# Fit the model
grid_search.fit(X_train_resampled, y_train_resampled)

# Evaluate the results
best_params = grid_search.best_params_
best_score = grid_search.best_score_
print("Best Hyperparameters:", best_params)
print("Best AUC Score from Cross-Validation:", best_score)

# Get results for both metrics
results_df = pd.DataFrame(grid_search.cv_results_)
accuracy_scores = results_df[results_df['mean_test_accuracy'].notnull()][['mean_tes
print("Grid Search Results for Accuracy and AUC:")
print(accuracy_scores)
```

```
Best Hyperparameters: {'C': 0.01, 'fit_intercept': True, 'max_iter': 100, 'penalty':
'l2', 'solver': 'newton-cg'}
Best AUC Score from Cross-Validation: 0.9020203140299724
Grid Search Results for Accuracy and AUC:
     mean_test_accuracy  mean_test_roc_auc
0              0.841486           0.902020
1              0.841486           0.902020
2              0.832459           0.901630
3              0.841486           0.902020
4              0.841486           0.902016
..                  ...                ...
245            0.755183           0.899564
246            0.755183           0.899564
247            0.755183           0.899566
248            0.755183           0.899561
249            0.755183           0.899566

[250 rows x 2 columns]
```

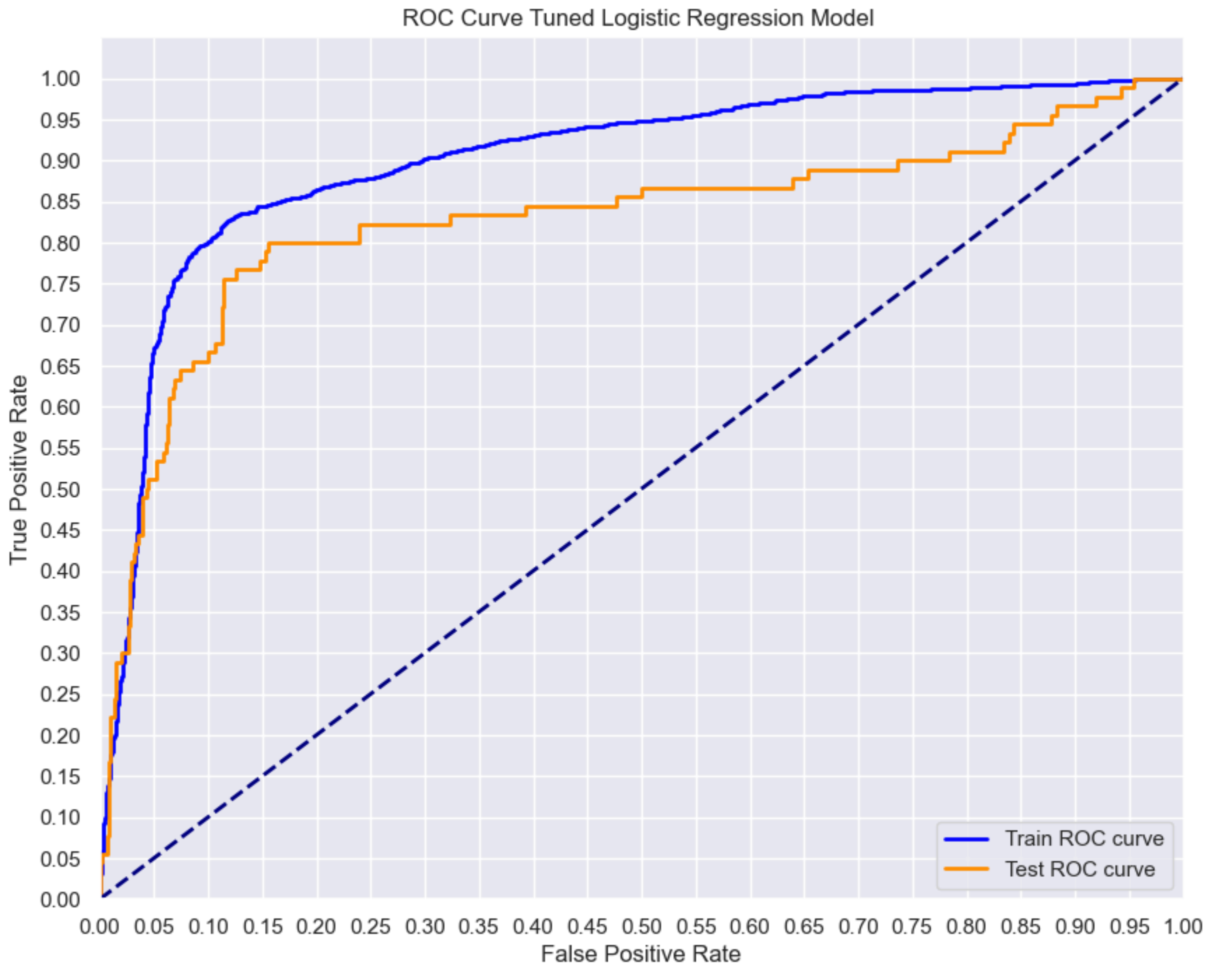
In [46]:
```
# Best Hyperparameters
best_params
```

Out[46]:
```
{'C': 0.01,
 'fit_intercept': True,
 'max_iter': 100,
 'penalty': 'l2',
 'solver': 'newton-cg'}
```

4.6.2 Retrain the model with the best parameters

In [47]:
```
# Retrain the model with the best parameters
best_model = LogisticRegression(random_state=42, **best_params)
best_model.fit(X_train_resampled, y_train_resampled)

# Predict on train and test sets
y_hat_train = best_model.predict(X_train_resampled)
y_hat_test = best_model.predict(X_test)

# Get Accuracy Score
tuned_train_accuracy = round(accuracy_score(y_train_resampled, y_hat_train), 2)
tuned_test_accuracy = round(accuracy_score(y_test, y_hat_test), 2)
print(f"Training Accuracy: {tuned_train_accuracy}")
print(f"Test Accuracy: {tuned_test_accuracy}")

# Calculate the probability scores of each point for the train and test sets
y_train_score = best_model.decision_function(X_train_resampled)
y_test_score = best_model.decision_function(X_test)

# Calculate the fpr, tpr and thresholds for the train and test sets
train_fpr, train_tpr, train_thresholds = roc_curve(y_train_resampled, y_train_score
test_fpr, test_tpr, test_thresholds = roc_curve(y_test, y_test_score)

# Print the AUC for the train and test sets
tuned_train_AUC = round(auc(train_fpr, train_tpr), 2)
tuned_test_AUC = round(auc(test_fpr, test_tpr), 2)
print(f"Train AUC: {tuned_train_AUC}")
print(f"Test AUC: {tuned_test_AUC}")

# Plot the ROC curve
plt.figure(figsize=(10, 8))
lw = 2

plt.plot(train_fpr, train_tpr, color='blue', lw=lw, label='Train ROC curve')
plt.plot(test_fpr, test_tpr, color='darkorange', lw=lw, label='Test 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('ROC Curve Tuned Logistic Regression Model ')
plt.legend(loc='lower right')
plt.show()
```

```
Training Accuracy: 0.84
Test Accuracy: 0.83
Train AUC: 0.9
Test AUC: 0.83
```



4.6.3 Analyze the hyperparameter Tuning Results

I will compare the Hyperparameter Tuned Model (with only the top 12 features), with the SMOTE resampled model and the Baseline Model

In [48]:
```
# Data for the models
tuned_scores = [tuned_train_accuracy,tuned_test_accuracy,tuned_train_AUC,tuned_test
results_base_smote_tuned = {
    'Metric':Metrics,
    'Baseline Model': base_scores,
    'Smote Model':smote_scores,
    'Hyperparameter Tuned Model':tuned_scores
   }
three_models_analysis_df= pd.DataFrame(results_base_smote_tuned)
three_models_analysis_df
```

Out[48]:

	Metric	Baseline Model	Smote Model	Hyperparameter Tuned Model
0	Training Accuracy	0.64	0.78	0.84
1	Testing Accuracy	0.57	0.57	0.83
2	Train AUC	0.89	0.92	0.90
3	Test AUC	0.82	0.81	0.83

- All metrics improved after hyperparameter tuning, which suggests that the tuning process successfully enhanced the model's performance.
- Both the testing accuracy and test AUC improvements indicate better generalization to new data, reducing the risk of overfitting.
- The improvements are consistent accross both training and testing datasets, which is a positive sign that the model's enhancements are not just resticted to training data
- Hyperparameter tuning has greatly enhanced the models accuracy
- **Next Steps** Train a different algorithm to assess the model performance against the best Logistic Regression Model- the Hyperparameter tuned Model.

A Different Modeling Algorithm - Decision Tree, Random Forest

In the next section I will model the following:-

- Baseline Decision Tree
- Hyperparameter Tuned Decision Tree
- Random Forest Ensemble Model

These 3 model results will be compared with those of the best performing Logistic Regression Model - The Hyperparameter Tuned Model.

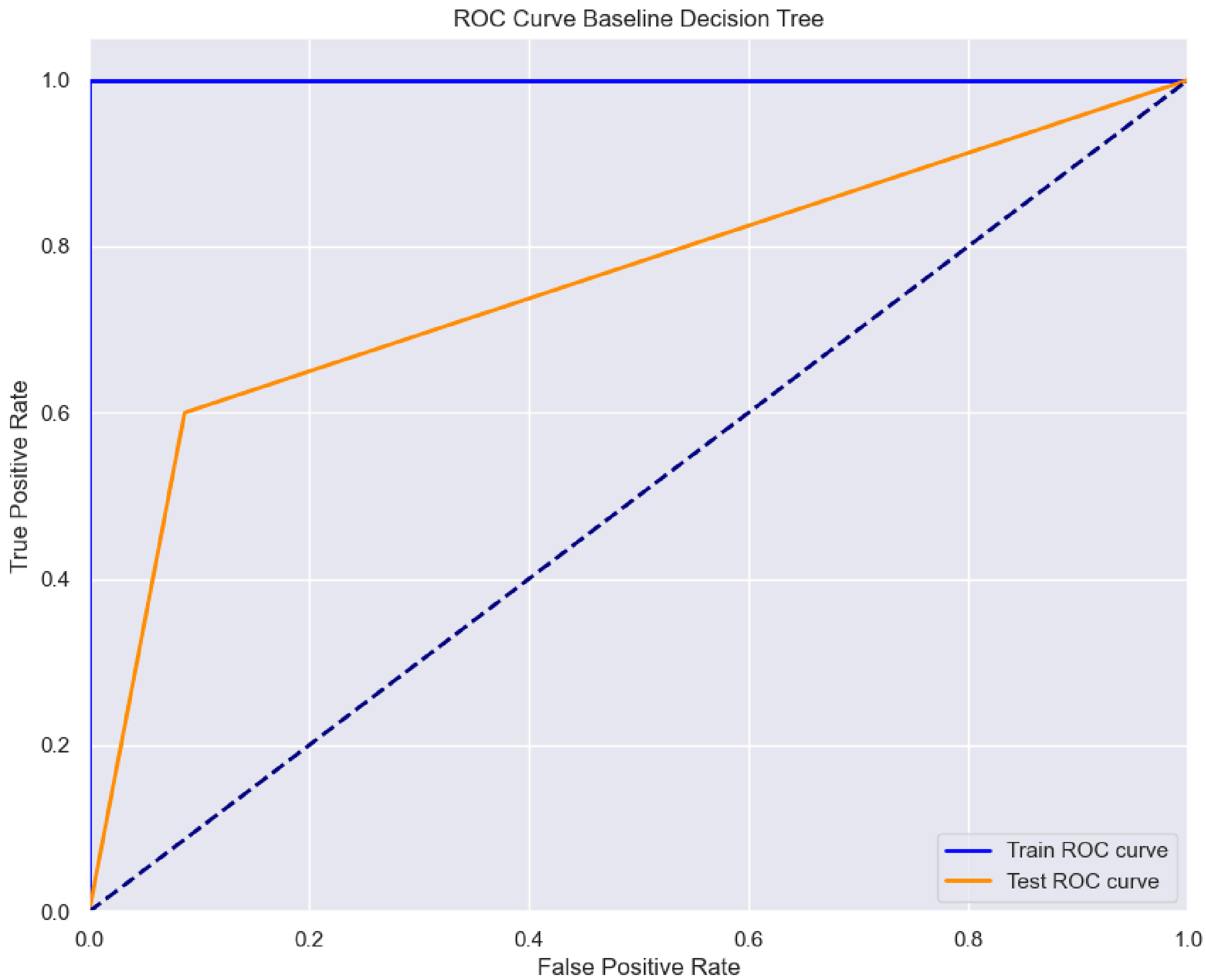
4. 7 Baseline Decision Tree

In [49]:

```
from sklearn.tree import DecisionTreeClassifier

# Initialize the Decision Tree Classifier
dt_clf = DecisionTreeClassifier(random_state=42)

# Fit the model on the SMOTE-resampled training data
dt_clf.fit(X_train_resampled, y_train_resampled)

# Predict on the resampled training and testing sets
y_hat_train = dt_clf.predict(X_train_resampled)
y_hat_test = dt_clf.predict(X_test)

# Get accuracy scores
basedt_train_accuracy = round(accuracy_score(y_train_resampled, y_hat_train), 2)
```

```
basedt_test_accuracy = round(accuracy_score(y_test, y_hat_test), 2)
print('Training Accuracy:', basedt_train_accuracy)
print('Testing Accuracy:', basedt_test_accuracy)

# Calculate the probability scores for the ROC curve
y_train_prob = dt_clf.predict_proba(X_train_resampled)[:, 1]
y_test_prob = dt_clf.predict_proba(X_test)[:, 1]

# Calculate the fpr, tpr, and thresholds for the ROC curve
train_fpr, train_tpr, _ = roc_curve(y_train_resampled, y_train_prob)
test_fpr, test_tpr, _ = roc_curve(y_test, y_test_prob)

# Calculate the AUC scores
basedt_train_AUC = round(auc(train_fpr, train_tpr), 2)
basedt_test_AUC = round(auc(test_fpr, test_tpr), 2)
print('Train AUC:', basedt_train_AUC)
print('Test AUC:', basedt_test_AUC)

# Plot the ROC curves for the train and test sets
plt.figure(figsize=(10, 8))
lw = 2

plt.plot(train_fpr, train_tpr, color='blue', lw=lw, label='Train ROC curve')
plt.plot(test_fpr, test_tpr, color='darkorange', lw=lw, label='Test 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.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Baseline Decision Tree')
plt.legend(loc='lower right')
plt.show()
```

```
Training Accuracy: 1.0
Testing Accuracy: 0.87
Train AUC: 1.0
Test AUC: 0.76
```



4.7.1 Analyze the Baseline Decision Tree Model against the Tuned Logistics Model

In [50]:
```
# Data for the models
basedt_scores = [basedt_train_accuracy,basedt_test_accuracy,basedt_train_AUC,basedt
results_bestlog_basedt = {
    'Metric':Metrics,
    'Best Logistic Model':tuned_scores,
    'Baseline Decision Tree Model': basedt_scores
   }
log_dt_analysis_df= pd.DataFrame(results_bestlog_basedt)
log_dt_analysis_df
```

Out[50]:

	Metric	Best Logistic Model	Baseline Decision Tree Model
0	Training Accuracy	0.84	1.00
1	Testing Accuracy	0.83	0.87
2	Train AUC	0.90	1.00
3	Test AUC	0.83	0.76

- **Overfitting:** The Baseline Decision Tree model shows signs of overfitting with perfect training metrics but much lower test metrics.
- **Generalization:** The Hyperparameter Tuned model, while having lower training and testing accuracies, demonstrates better generalization capability. The test scores do not vary too much from the training scores.
- **Balanced Performance:** The Hyperparameter Tuned model balances bias and variance better, resulting in more consistent and reliable performance across different datasets.
- **Next Steps:** Prune the Decision Tree to improve performance using RandomizedSearchCV.

4.8 Pruned Decision Tree

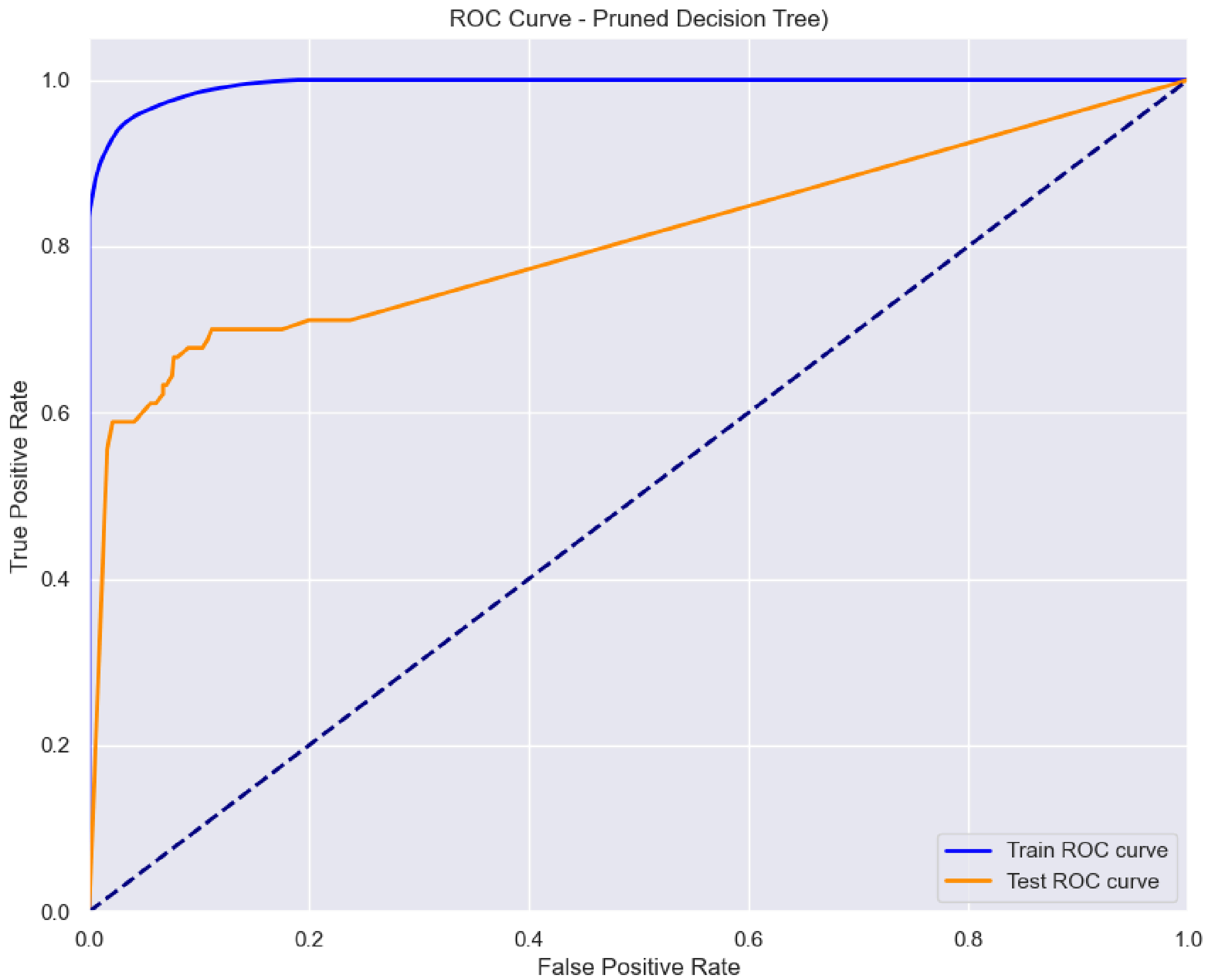
I will prune the following parameters to get the best Decision Tree Model using **RandomizedSearchCV**:

- **min_samples_split:** The minimum number of samples required to split an internal node. Default is 2.
- **min_samples_leaf:** The minimum number of samples required to be at a leaf node. A split point at any depth will only be considered if it leaves at least min_samples_leaf training samples in each of the left and right branches. Default is 1
- **max_depth:** The maximum depth of a tree. If None, the nodes are expanded until all leaves are pure or until leaves contain less than min_samples_split samples
- **criterion:** This function measures the quality of a split. The default is 'gini' for the Gini impurity and 'entropy' for the information gain.

In [51]:
```
from sklearn.model_selection import RandomizedSearchCV
import warnings

# Suppress warnings
warnings.filterwarnings('ignore')

# Define the hyperparameters for tuning the Decision Tree
param_grid = {
    'max_depth': [3, 5, 7, 10, 15, None],
    'min_samples_split': [2, 5, 10, 15, 20],
    'min_samples_leaf': [1, 2, 4, 6, 8, 10],
    'criterion': ['gini', 'entropy']}

# Initialize the Decision Tree Classifier
dt_clf = DecisionTreeClassifier(random_state=42)

# Use RandomizedSearchCV to search over the defined parameter grid
random_search = RandomizedSearchCV(dt_clf, param_distributions=param_grid, n_iter=1
                                   scoring='roc_auc', n_jobs=-1, random_state=42)
```

```python
# Fit RandomizedSearchCV to the SMOTE-resampled training data
random_search.fit(X_train_resampled, y_train_resampled)

# Evaluate the Best Model
best_dt_model = random_search.best_estimator_
print("Best Parameters:", random_search.best_params_)
print("Best AUC Score from Cross-Validation:", random_search.best_score_)

# Predict on the resampled training and testing sets
y_hat_train = best_dt_model.predict(X_train_resampled)
y_hat_test = best_dt_model.predict(X_test)

# Get accuracy scores
prunedt_train_accuracy = round(accuracy_score(y_train_resampled, y_hat_train), 2)
prunedt_test_accuracy = round(accuracy_score(y_test, y_hat_test), 2)
print('Training Accuracy:', prunedt_train_accuracy)
print('Testing Accuracy:', prunedt_test_accuracy)

# Calculate the probability scores for the ROC curve
y_train_prob = best_dt_model.predict_proba(X_train_resampled)[:, 1]
y_test_prob = best_dt_model.predict_proba(X_test)[:, 1]

# Calculate the fpr, tpr, and thresholds for the ROC curve
train_fpr, train_tpr, _ = roc_curve(y_train_resampled, y_train_prob)
test_fpr, test_tpr, _ = roc_curve(y_test, y_test_prob)

# Calculate the AUC scores
prunedt_train_AUC = round(auc(train_fpr, train_tpr), 2)
prunedt_test_AUC = round(auc(test_fpr, test_tpr), 2)
print('Train AUC:', prunedt_train_AUC)
print('Test AUC:', prunedt_test_AUC)

# Plot the ROC curves for the train and test sets
plt.figure(figsize=(10, 8))
lw = 2

plt.plot(train_fpr, train_tpr, color='blue', lw=lw, label='Train ROC curve')
plt.plot(test_fpr, test_tpr, color='darkorange', lw=lw, label='Test 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.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - Pruned Decision Tree)')
plt.legend(loc='lower right')
plt.show()
```

```
Best Parameters: {'min_samples_split': 5, 'min_samples_leaf': 10, 'max_depth': None,
'criterion': 'entropy'}
Best AUC Score from Cross-Validation: 0.9598001077983845
Training Accuracy: 0.96
Testing Accuracy: 0.89
Train AUC: 0.99
Test AUC: 0.81
```



4.8.1 Anlalyze the Pruned Decision Tree Model against the Baseline Decision Tree and Hyperparameter Tuned Logistics Model

In [52]:
```
# Data for the models
prunedt_scores = [prunedt_train_accuracy,prunedt_test_accuracy,prunedt_train_AUC,pr
results_bestlog_basedt_prunedt = {
    'Metric':Metrics,
    'Best Logistic Model':tuned_scores,
    'Baseline Decision Tree Model': basedt_scores,
    'Pruned Decision Tree Model':prunedt_scores
   }
log_dt_prune_analysis_df= pd.DataFrame(results_bestlog_basedt_prunedt)
log_dt_prune_analysis_df
```

Out[52]:

	Metric	Best Logistic Model	Baseline Decision Tree Model	Pruned Decision Tree Model
0	Training Accuracy	0.84	1.00	0.96
1	Testing Accuracy	0.83	0.87	0.89
2	Train AUC	0.90	1.00	0.99
3	Test AUC	0.83	0.76	0.81

- **Baseline Decision Tree:** Exhibits overfitting with perfect training metrics but lower test performance.
- **Pruned Decision Tree:** Balances the trade-off between bias and variance well, achieving high test accuracy and AUC, indicating better generalization.
- **Hyperparameter Tuned Decision Tree:** Avoids overfitting, with reasonable training and test performance, making it a reliable but not the best choice.
- **Conclusion:** Among the three models, the Pruned Decision Tree stands out with the best generalization ability and highest test performance.
- **Next Steps:** Perform a parameter grid search for the **Random Forest Ensemble Model** using RandomizedSearchCV

4.8 Random Forest Ensemble Model

I will tune the following parameters to get the best possible hyperparameters to optimize the Random Forest Ensemble Model:

- **n_estimators:** This refers to the number of trees the model will build during training. More trees improves the model's accuracy but it can lead to overfitting and increase in computational time.
- **min_samples_split:** The minimum number of samples required to split an internal node. Default is 2.
- **min_samples_leaf:** The minimum number of samples required to be at a leaf node. A split point at any depth will only be considered if it leaves at least min_samples_leaf training samples in each of the left and right branches. Default is 1
- **max_features:** Controls the number of features considered when splitting a node. This may help with overfitting.
- **max_depth:** The maximum depth of a tree. If None, the nodes are expanded until all leaves are pure or until leaves contain less than min_samples_split samples

- **criterion:** This function measures the quality of a split. The default is 'gini' for the Gini impurity and 'entropy' for the information gain.

4.8.1 Finding the the best parameters

In [53]:
```
# Import necessary libraries
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import RandomizedSearchCV
import warnings
warnings.filterwarnings('ignore')

# Define the hyperparameters for tuning the Random Forest
param_grid = {
    'n_estimators': [10, 20, 100,200],
    'criterion': ['gini', 'entropy'],
    'max_depth': [None, 3, 5, 7,10, 15, 20],
    'min_samples_split': [2, 5, 10,15,20],
    'min_samples_leaf': [1, 2, 4,6,8,10],
    'max_features': ['auto', 'sqrt', 'log2']
}

# Initialize the Random Forest Classifier
rf_clf = RandomForestClassifier(random_state=42)

# Use RandomizedSearchCV to search over the defined parameter grid
random_search = RandomizedSearchCV(rf_clf, param_distributions=param_grid, n_iter=1
                                   scoring='roc_auc', n_jobs=-1, random_state=42)

# Fit RandomizedSearchCV to the training data
random_search.fit(X_train_resampled, y_train_resampled)

# Evaluate the Best Model
best_rf_model = random_search.best_estimator_
print("Best Parameters:", random_search.best_params_)
print("Best AUC Score from Cross-Validation:", random_search.best_score_)
```

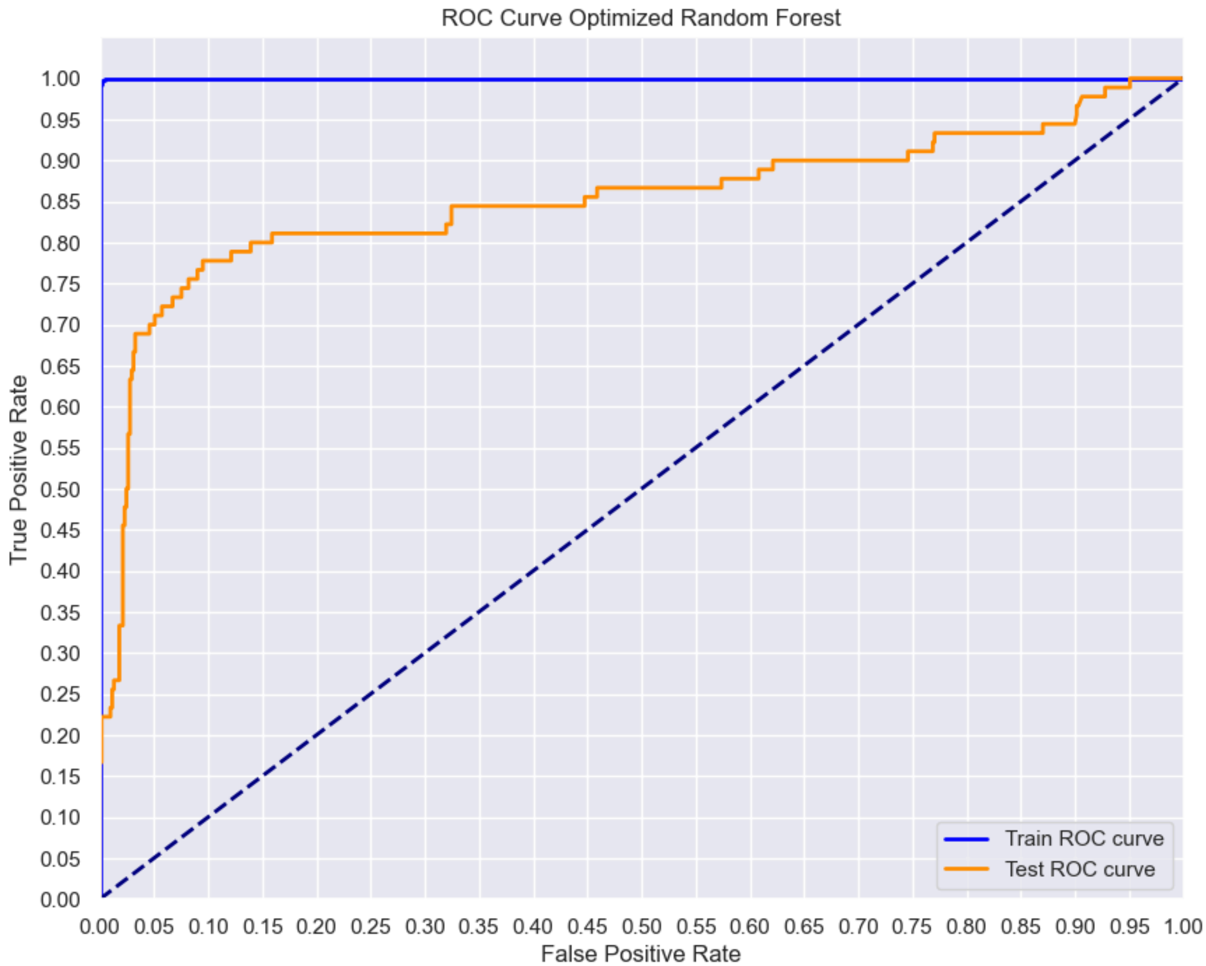
```
Best Parameters: {'n_estimators': 100, 'min_samples_split': 5, 'min_samples_leaf':
1, 'max_features': 'sqrt', 'max_depth': 15, 'criterion': 'gini'}
Best AUC Score from Cross-Validation: 0.9898748559706696
```

4.8.2 Retrain the model with the best parameters

In [54]:
```
# Predict on train and test sets
y_hat_train = best_rf_model.predict(X_train_resampled)
y_hat_test = best_rf_model.predict(X_test)

# Get Accuracy Score
rf_train_accuracy = round(accuracy_score(y_train_resampled, y_hat_train), 2)
rf_test_accuracy = round(accuracy_score(y_test, y_hat_test), 2)
print('Training Accuracy:', rf_train_accuracy)
print('Testing Accuracy:', rf_test_accuracy)

# Calculate the probability scores of each point for the train and test sets
y_train_score_tree = best_rf_model.predict_proba(X_train_resampled)[:,1]
```

```
y_train_pred = best_rf_model.predict(X_train_resampled)
y_test_score_tree = best_rf_model.predict_proba(X_test)[:,1]
y_test_pred = best_rf_model.predict(X_test)

# Calculate the fpr,tpr and thresholds for the train and test sets
train_fpr, train_tpr, train_thresholds = roc_curve(y_train_resampled,y_train_score_
test_fpr, test_tpr, test_thresholds = roc_curve(y_test,y_test_score_tree)

# Print the AUC for the train and test sets
rf_train_AUC = round(auc(train_fpr, train_tpr), 2)
rf_test_AUC = round(auc(test_fpr, test_tpr), 2)
print('Train AUC:', rf_train_AUC)
print('Test AUC:', rf_test_AUC)

# Plot the ROC curve
plt.figure(figsize=(10, 8))
lw = 2

plt.plot(train_fpr, train_tpr, color='blue',
         lw=lw, label='Train ROC curve')
plt.plot(test_fpr, test_tpr, color='darkorange',
         lw=lw, label='Test 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('ROC Curve Optimized Random Forest')
plt.savefig('ROC_Curve_Optimized_Random_Forest')
plt.legend(loc='lower right')
plt.show()
```

```
Training Accuracy: 1.0
Testing Accuracy: 0.92
Train AUC: 1.0
Test AUC: 0.85
```



4.8.3 Analyze the Random Forest Model against Pruned Decision Tree and the Tuned Logistic Regression Model

In [55]:

```
# Data for the models
rf_scores = [rf_train_accuracy,rf_test_accuracy,rf_train_AUC,rf_test_AUC]
best_log_dt_rf = {
    'Metric':Metrics,
    'Best Logistic Model':tuned_scores,
    'Pruned Decision Tree Model':prunedt_scores,
    'Random Forest Ensemble Model':rf_scores
   }
log_dt_rf_analysis = pd.DataFrame(best_log_dt_rf)
log_dt_rf_analysis
```

Out[55]:

	Metric	Best Logistic Model	Pruned Decision Tree Model	Random Forest Ensemble Model
0	Training Accuracy	0.84	0.96	1.00
1	Testing Accuracy	0.83	0.89	0.92
2	Train AUC	0.90	0.99	1.00
3	Test AUC	0.83	0.81	0.85

In [56]:

```
# Create a markdown table for README Summary
!pip install tabulate

from tabulate import tabulate

# Convert DataFrame to Markdown table
markdown_table = tabulate(log_dt_rf_analysis, headers='keys', tablefmt='pipe', show

print(markdown_table)
```

```
Requirement already satisfied: tabulate in c:\users\wambu\anaconda3\envs\learn-env\l
ib\site-packages (0.9.0)
| Metric            |   Best Logistic Model |   Pruned Decision Tree Model |   Rando
m Forest Ensemble Model |
|:------------------|----------------------:|-----------------------------:|--------
-----------------------:|
| Training Accuracy |                  0.84 |                         0.96 |
1    |
| Testing Accuracy  |                  0.83 |                         0.89 |
0.92 |
| Train AUC         |                  0.9  |                         0.99 |
1    |
| Test AUC          |                  0.83 |                         0.81 |
0.85 |
```

- **Logistic Regression Hyperparameter Tuned Model:**
  - Both training and testing accuracy are close (0.84 and 0.83), which indicates the model generalizes well to unseen data and has a balanced performance.
  - The Train and Test AUC scores (0.90 and 0.83) show that the model has good discriminative power without overfitting.
  - Logistic Regression has a consistent performance between training and testing, reflecting a balanced model.
- **Decision Tree Pruned Model:**
  - The Training Accuracy and Train AUC are 0.96 and 0.99, indicating the model fits the training data very well.
  - The Testing Accuracy (0.89) is higher than the Best Logistics Model and Test AUC (0.81) is alower. This model also shows good generalizing on the test data.

- **Random Forest Emsemble Model:**
- This model has perfect scores on both The Training and Test AUC.
- It also exhibits high accuracy and AUC, scores on the testing data, showing that it also generalizes well on unseen data. This model has the best metrics.
- **Conclusion**

The **Random Forest Ensemble** model outperforms all the other model terms of accuracy and AUC on both the training and test sets. Though it has perfect training scores, it still has very good testing scores, which is an indication of a good generalization to unseen data.The Random Forest Ensemble model is the best model, from my analysis.

5.0 Summary and Recomendations

5.1 Predictive power of the Data Set

The provided historical data indeed has predictive power in determing customer churn. The Hyperparameter tuned Logistic regression model, the Pruned Decision Tree Model and the Random Forest Ensemble Model have shown the ability to predict churn with high to very high accuracy and AUC scores.

Accuracy is a measure of how often the model gets the prediction right, and in this case measures how often the model correctly predicts whether a customer will churn or not. A test accuracy score of 0.92 from the best Random Forest Ensemble Model means that our model was able to predict correctly 92% of the time.

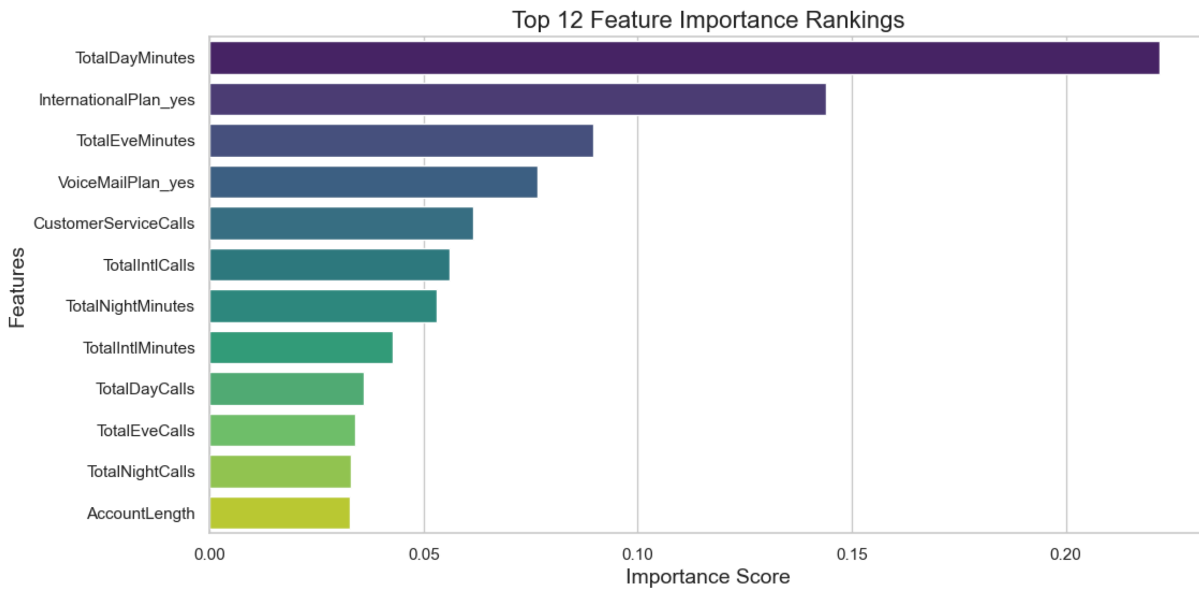
AUC evaluates the ability of the model to differentiate between customers who churn and those who don't,across all possible threshold settings - ranging from conservative (label fewer ccustomers as churners) to more aggressive (label more customers as churners). An AUC of 0.5 means the model is no better than random guessing while an AUC of 1.0 means the model perfectly distinguishes between churners and non-churners. The test AUC of 0.85 from the best model means that there is an 85% chance that the model will correctly rank a randomly chosen churner higher than a randomly chosen non-churner.

5.2 Feature Importance

The top-12 features and their importance are detailed in the barplot below.

In [58]:
```
importance_df = importance_df.sort_values(by='Importance', ascending=False).head(12

# Set the plot style
sns.set(style="whitegrid")

# Create a barplot for the top 12 features
plt.figure(figsize=(12, 6))
```

```
sns.barplot(x='Importance', y='Feature', data=importance_df, palette="viridis")

# Add title and labels
plt.title('Top 12 Feature Importance Rankings', fontsize=16)
plt.xlabel('Importance Score', fontsize=14)
plt.ylabel('Features', fontsize=14)

# Show the plot
plt.savefig('Feature_Importance_Rankings')
plt.show()
```



6.2.1 Actionable Insights from feature importance

- Customers with high usage as indicated by Total Day Minutes and Total Evening Minutes are at a higher risk of churn. The usage patterns during the day give the highest predictive power.
- Premium customers indicated by enrolment into the International Call Plan also has significant impact on churn. Voice Mail Plan enrolment also has a strong impact.
- Customer Service Calls also have an impact on churn, meaning a customer calling customer service more is more likely to churn.
- The frequency or number of calls as indicated by the number of calls also has an impact, though to a lower extent that the actual time spent on the call.

SyriaTel should closely watch customers with high usage, and those who enroll into premium services. From the data analysis and modeling, these factors have a high impact on churn. Customer care calls and complaints should also be followed through to ensure customers' issues are resolved to avoid the risk of churn.

5.3 Model Selection and Optimization

- **Random Forest Ensemble Model:** Given its high performance on test data, it is recommended for deployment on future company data.

- **Feature Selection** Focus on the most impactful features identified above to reduce the complexity of the model and make it more effective and efficient. Drop less impact features like State.
- **Model Updates** Regularly update the model with new data to maintain accuracy and adapt to any changes in customer behavior.

While both the pruned Decision Tree Model and the Random Forest Model show good results, the Random Forest Model has better metrics and should be deployed on SyriaTel unseen customers' data to predict churn. However, the model should be revised by training on new data periodically. This will help in adapting the model to any changes in customer behavior. These updates may result in a new choice of model selection.

5.4 Proposed Retention Strategies based on the model results

- **Proactive Engagement:** Regularly check in with high-usage customers and premium customers (those enrolled into International and Voice Mail plans) to address any potential issues and enhance their experience.

- **Personalized Offers:** Provide targeted offers and discounts to high-risk customers based on their usage patterns and preferences.

- **Customer Service Improvement:** Analyze customer service interactions to identify common pain points and address them promptly.