Phase_3 Project- Data Science

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Project Overview

Objective:

SyriaTel, a leading telecommunications company in Syria, is facing substantial financial losses due to customer churn.**Customer churn refers to the rate at which customers discontinue their relationship with a company within a specific period, often due to various reason(s).** In previous projects, SyriaTel focused on descriptive and inferential analyses to understand customer behavior and the relationships between different variables. However, to address the current churn issue, SyriaTel is shifting towards a predictive approach. The goal of this project is to develop a predictive model using the **SyriaTel Customer Churn dataset** that accurately identifies customers at risk of churning. By determining the predictive power of various features and understanding which variables most influence churn, SyriaTel aims to implement targeted retention strategies, reduce churn rates, and ultimately improve customer loyalty and profitability.

Business Understanding

In the telecommunications industry, customer churn is a critical challenge that directly impacts profitability. For SyriaTel, the loss of customers due to churn is a significant concern, prompting the need for more advanced analytical techniques. Previously, the company focused on descriptive and inferential methods to explore the distributions of key variables and their relationships, gaining valuable insights into customer behavior. However, understanding these relationships alone is no longer sufficient.

To effectively combat churn, SyriaTel is now adopting a predictive approach, which involves building a model that can forecast which customers are likely to churn in the near future. The predictive model will analyze a wide range of features, including customer demographics, usage patterns, and service interactions, to determine their impact on churn.

Key Questions to Be Addressed:

1. What is the best model for predicting customer churn?

After comparing various models, including Decision Tree, K-Nearest Neighbors (KNN), and Random Forest, the analysis will recommend the best overall performer. By factoring in accuracy, precision, recall, and ROC-AUC score, the analysis will advise SyriaTel on the most suitable model for predicting churn and implementing targeted retention strategies.

2. How accurately can the model predict customer churn?

The analysis will evaluate the performance of various models using key metrics such as accuracy, precision, recall, and the ROC-AUC score. This evaluation will determine how well the models can predict which customers are likely to churn.

3. Which features are most influential in predicting customer churn?

Identifying the most impactful features, such as customer service interactions, usage patterns, and plan types, will help SyriaTel prioritize its retention efforts and design more effective interventions.

With these predictive insights, SyriaTel can move beyond merely understanding why customers churn to proactively identifying at-risk customers and intervening with targeted strategies. This shift will enable SyriaTel to not only reduce churn rates but also improve customer satisfaction and loyalty, leading to better financial outcomes for the company.

Methodology for Machine Learning

To develop a robust predictive model for identifying customers at risk of churning, we will follow a structured methodology that includes the following key steps:

1. Data Understanding
2. Data Cleaning
3. Exploratory Data Analysis
4. Data Preprocessing
5. Modelling
6. Hyperparameter Selection
7. Model Evaluation
8. Recommendations and Conclusion

Step 1: Data Understanding

1.1 Import the necessary libraries and modules for dealing with the dataset and its data

In [47]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.model_selection import train_test_split, cross_val_score, cross_val
from sklearn.preprocessing import StandardScaler, MinMaxScaler, OneHotEncoder, F
from sklearn.metrics import recall_score, accuracy_score, precision_score, f1_sc
import scipy.stats as stats
import statsmodels as statsmd
from sklearn.linear_model import LogisticRegression
from sklearn.compose import ColumnTransformer

from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from sklearn.pipeline import Pipeline

from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.dummy import DummyClassifier
from sklearn.ensemble import RandomForestClassifier
```

1.2 Load the Dataset

In this project, the dataset that we chose is called **SyriaTel Customer Churn**.

In [48]:
```
# Load the dataset and examine its structure.
file_path = 'Data/SyriaTel_Data.csv'
data = pd.read_csv(file_path)

# Display the first few rows of the dataset
data.head()
```

Out[48]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	tot da charg
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.(
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.4
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.3
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.9
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.3

5 rows × 21 columns

1.3 Creates a function for viewing the columns in the dataset

In [49]:
```
def col_info(data):
    print('col_names: \n', data.columns)
    print('num_cols: \n', data.select_dtypes(int).columns)
    print('cat_cols: \n', data.select_dtypes(object).columns)
    print('float_cols: \n', data.select_dtypes(float))
    print('bool_cols : \n' ,data.select_dtypes(bool).columns)

col_info(data)
```

```
col_names:
 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')
num_cols:
 Index(['account length', 'area code', 'number vmail messages',
       'total day calls', 'total eve calls', 'total night calls',
       'total intl calls', 'customer service calls'],
      dtype='object')
cat_cols:
 Index(['state', 'phone number', 'international plan', 'voice mail plan'], dtype
='object')
float_cols:
       total day minutes  total day charge  total eve minutes  \
0                  265.1             45.07              197.4
1                  161.6             27.47              195.5
2                  243.4             41.38              121.2
3                  299.4             50.90               61.9
4                  166.7             28.34              148.3
...                  ...               ...                ...
3328               156.2             26.55              215.5
3329               231.1             39.29              153.4
3330               180.8             30.74              288.8
3331               213.8             36.35              159.6
3332               234.4             39.85              265.9

      total eve charge  total night minutes  total night charge  \
0                16.78                244.7               11.01
1                16.62                254.4               11.45
2                10.30                162.6                7.32
3                 5.26                196.9                8.86
4                12.61                186.9                8.41
...                ...                  ...                 ...
3328             18.32                279.1               12.56
3329             13.04                191.3                8.61
3330             24.55                191.9                8.64
3331             13.57                139.2                6.26
3332             22.60                241.4               10.86

      total intl minutes  total intl charge
0                   10.0               2.70
1                   13.7               3.70
2                   12.2               3.29
3                    6.6               1.78
4                   10.1               2.73
...                  ...                ...
3328                 9.9               2.67
3329                 9.6               2.59
3330                14.1               3.81
3331                 5.0               1.35
3332                13.7               3.70

[3333 rows x 8 columns]
bool_cols :
 Index(['churn'], dtype='object')
```

We observe from the above dataset we observe that there are **21** columns, with a mix of categorical, numerical, and boolean data types. Here's a brief overview of the dataset:

Key Features:

**A). Categorical Features:

1. **state**: Categorical variable indicating the state of the customer.
2. **phone number**: Categorical, the customer's phone number (likely not useful for modeling).
3. **international plan**: Categorical, whether the customer has an international plan (yes/no).
4. **voice mail plan**: Categorical, whether the customer has a voicemail plan (yes/no).

**B). Numerical and Floating Features:

5. **total eve calls**: Integer, total number of calls during the evening.
6. **account length**: Integer, representing the duration of the customer's account in days.
7. **area code**: Integer, indicating the area code of the customer.
8. **total day calls**: Integer, total number of calls during the day.
9. **total night calls**: Integer, total number of calls during the night.
10. **number vmail messages**: Integer, the number of voicemail messages.
11. **customer service calls**: Integer, the number of calls to customer service.
12. **total intl calls**: Integer, total number of international calls.
13. **total day minutes**: Float, total minutes of calls during the day.
14. **total day charge**: Float, total charges for calls during the day.

15 **total eve minutes**: Float, total minutes of calls during the evening.

16. **total eve charge**: Float, total charges for calls during the evening.
17. **total night minutes**: Float, total minutes of calls during the night.
18. **total night charge**: Float, total charges for calls during the night.
19. **total intl minutes**: Float, total minutes of international calls.
20. **total intl charge**: Float, total charges for international calls.

**C) . Boolean Features:

21. **churn**: Boolean, the target variable indicating whether the customer has churned (True) or not (False).

In [50]:
```
# Display basic information about the dataset
print("\nDataset Info:")
data.info()
```

```
Dataset 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
```

1.4 Checking for Missing Values Identify any missing values within the dataset.

Ensuring there are no missing values is crucial, as missing data can lead to inaccuracies in the model training process. If missing values are found, they need to be addressed appropriately.

In [51]:
```
# Check for missing values
print("\nMissing Values in Each Column:")
print(data.isnull().sum())
```

```
Missing Values in Each Column:
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
```

In [52]:

```
def cleaning(data):
    missing = data.isna().sum().sum()
    duplicates = data.duplicated().sum()
    return (f"There are {missing} missing values and {duplicates} duplicated val

cleaning(data)
```

Out[52]: 'There are 0 missing values and 0 duplicated values in the dataset'

In [53]:

```
# Checking for unique values
data.nunique()
```

Out[53]:

```
state                       51
account length             212
area code                    3
phone number              3333
international plan           2
voice mail plan              2
number vmail messages       46
total day minutes         1667
total day calls            119
total day charge          1667
total eve minutes         1611
total eve calls            123
total eve charge          1440
total night minutes       1591
total night calls          120
total night charge         933
total intl minutes         162
total intl calls            21
total intl charge          162
customer service calls      10
churn                        2
dtype: int64
```

In [54]:
```
data.shape
```

Out[54]: (3333, 21)

From this dataset, we can observe that there are **3,333** rows and **21** columns, from which it's distributed evenly. We can also observe that we didn't have any missing values or duplicated values in the dataset and this enabled us to conduct this project without any challenges.

Step 2: Data Cleaning

Now that we understand the structure of the data, we'll clean it by addressing any issues such as missing values or irrelevant columns.

2.1 Drop Irrelevant Features

Remove columns that are not useful for prediction, such as identifiers like the phone number.

In [55]:
```
# Drop irrelevant columns
data = data.drop(columns=['phone number'])

# Check the updated dataframe
print("\nFirst Few Rows After Dropping Irrelevant Columns:")
data.head()
```

```
First Few Rows After Dropping Irrelevant Columns:
```

Out[55]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	tot e minut
0	KS	128	415	no	yes	25	265.1	110	45.07	197
1	OH	107	415	no	yes	26	161.6	123	27.47	195
2	NJ	137	415	no	no	0	243.4	114	41.38	121
3	OH	84	408	yes	no	0	299.4	71	50.90	61
4	OK	75	415	yes	no	0	166.7	113	28.34	148

Step 3: Exploratory Data Analysis (EDA)

3.1 Descriptive Statistics

In [56]:
```
# Display descriptive statistics
print("\nDescriptive Statistics of the Dataset:")
data.describe()
```

```
Descriptive Statistics of the Dataset:
```

Out[56]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	

The table provides a summary of key statistics (count, mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum) for various features in the dataset. These statistics are crucial for understanding the distribution of the data and identifying potential outliers.

Key Observations:

Range and Potential Outliers:

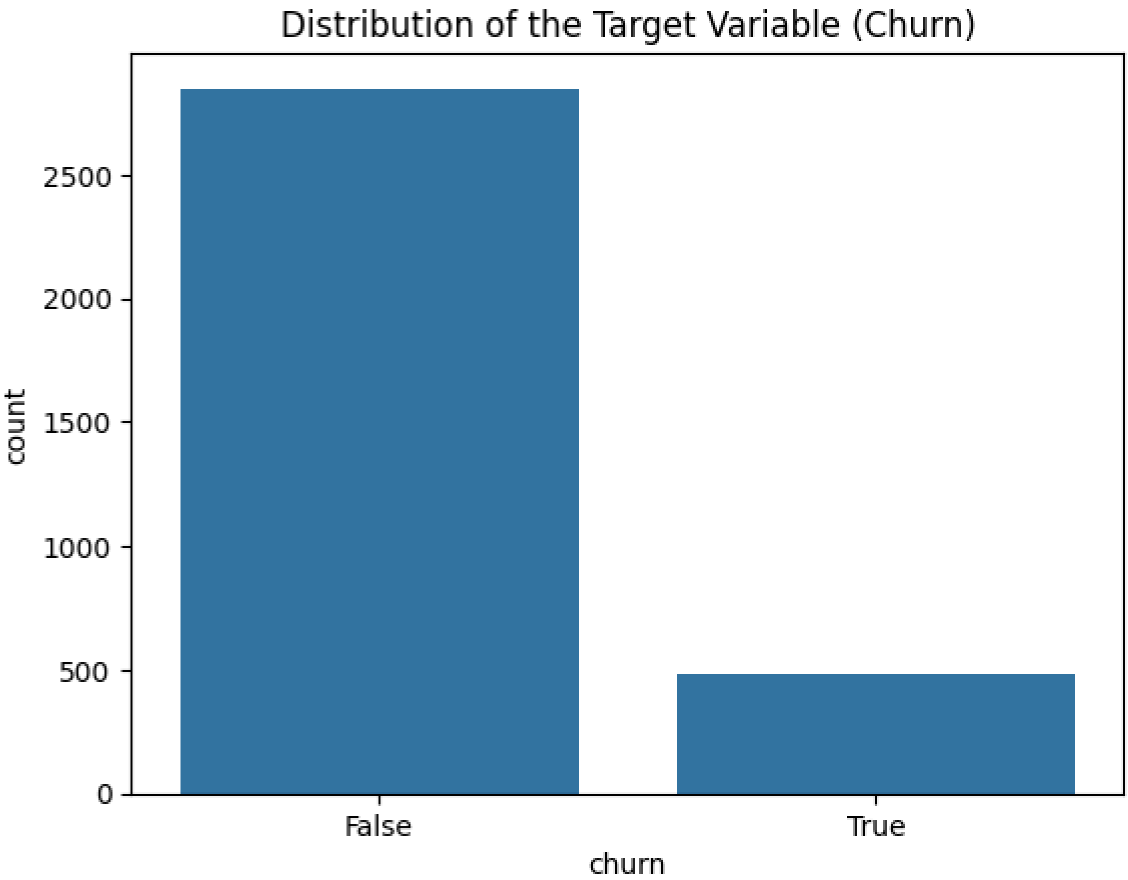
- number vmail messages: The maximum value is 51, while the 75th percentile is 20, indicating that a small subset of users has a much higher number of voicemail messages, potentially marking them as outliers.
- total day minutes, total eve minutes, total night minutes, total intl minutes: These features have maximum values significantly higher than the 75th percentile. For example, total day minutes has a max of 350.8 minutes, whereas the 75th percentile is 216.4 minutes, suggesting the presence of outliers.
- customer service calls: The maximum number of calls is 9, with a median of 1 and a 75th percentile of 2. This suggests that while most customers have 1-2 service calls, some customers are outliers with significantly higher call counts.

Conclusion:

- **Outliers**: Several features show potential outliers, particularly in the number vmail messages, total day minutes, total eve minutes, total night minutes, total intl minutes, and customer service calls fields. These outliers could significantly impact the model's performance if not addressed.
- **Next Steps**: We will consider handling these outliers, possibly by capping extreme values, using robust scaling methods, or investigating the reasons behind these outlier behaviors. Additionally, further visualization (e.g., box plots) could help confirm and understand the distribution and impact of these outliers.

3.2 Distribution of the Target Variable (Churn)

In [57]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Plot distribution of the target variable
sns.countplot(x='churn', data=data)
plt.title('Distribution of the Target Variable (Churn)')
plt.show()
```



The bar chart above shows the distribution of the target variable "churn," indicating whether customers have churned (left the service) or not.

Interpretation:

False (Non-Churners): The taller bar represents customers who have not churned. This group is significantly larger, with over 2,500 customers.

True (Churners): The shorter bar represents customers who have churned. This group is much smaller, with fewer than 500 customers.

Key Insights:

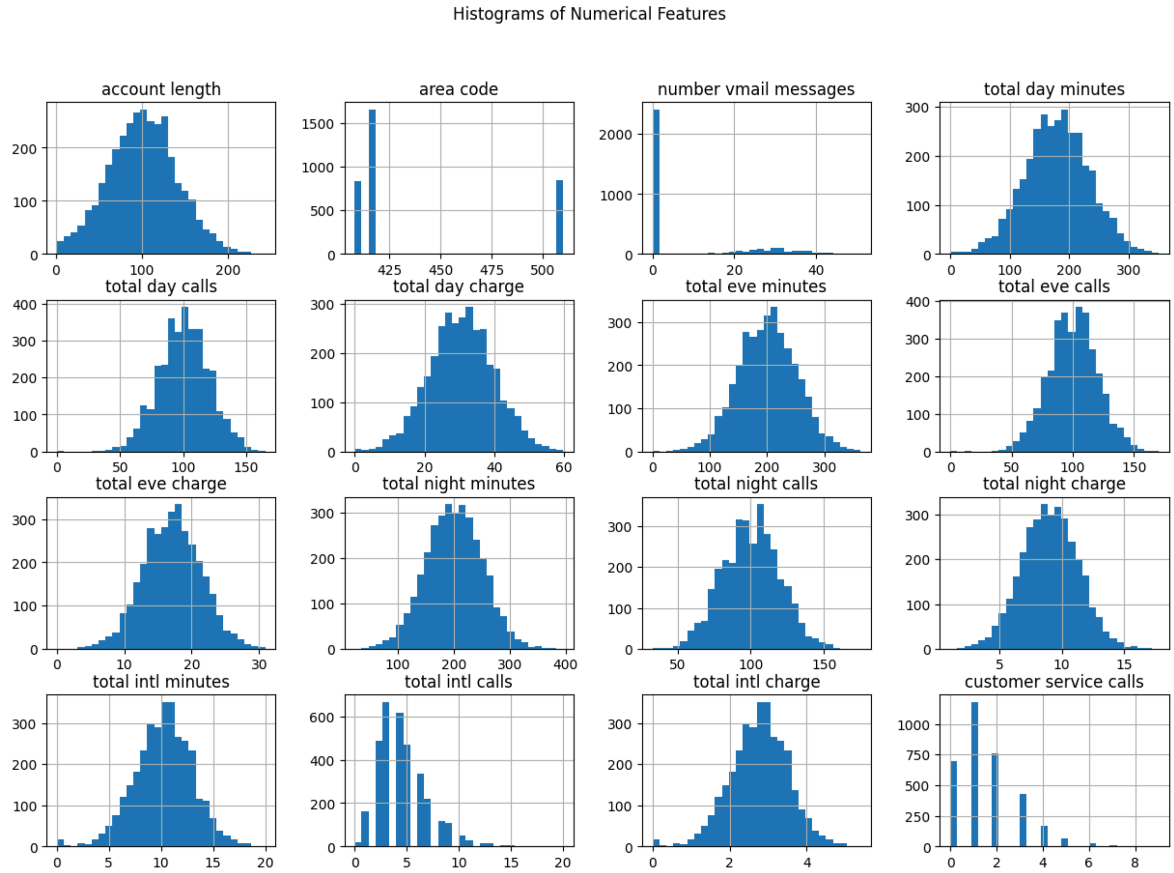
Class Imbalance: The chart highlights a clear class imbalance in the dataset. The majority of customers have not churned, while a relatively small number have. This imbalance is crucial to consider when building predictive models, as it can lead to a model that is biased toward predicting the majority class (non-churners).

Handling Imbalance: Techniques such as oversampling the minority class (using SMOTE, for example) or undersampling the majority class may be necessary to ensure that the model accurately predicts both classes.

This imbalance will be addressed during the preprocessing or model training phase to improve the model's performance in predicting customer churn.

3.3 Visualize the Distribution of Numerical Features

In [58]:
```
# Plot histograms of numerical features
data.hist(bins=30, figsize=(15, 10))
plt.suptitle('Histograms of Numerical Features')
plt.show()
```



Most features are normally distributed , so log transformation is not necessary for them. However,features with Skewed Distributions like Number Vmail Messages(This feature is heavily right-skewed, with most values concentrated at zero and a long tail of higher values.); Customer Service Calls(This feature is also right-skewed, with the majority of customers making very few calls, and a smaller number making a higher number of calls.) and Total Intl Calls(This feature shows some skewness, though it is less extreme than the first two.) we may consider log transformation

The image shows a series of histograms that represent the distribution of various numerical features in the dataset. Here's the interpretation of each feature based on the histograms:

Key Insights:

Normal Distributions: Many features, such as total minutes, total calls, and corresponding charges, follow normal distributions. This suggests that most customers have similar usage patterns, with a typical range of values for these features.

Skewed Distributions: The "number vmail messages" and "customer service calls" features are skewed. Most customers do not use voicemail services much, and most do not frequently call customer service.

Area Code: The area code feature is categorical with three main groups, indicating that the dataset represents customers from three distinct regions.

Implications for Modeling:

Feature Scaling: Given the normal distribution of most features, feature scaling (e.g., standardization) will likely be beneficial for models that are sensitive to the scale of input data (e.g., logistic regression, SVM).

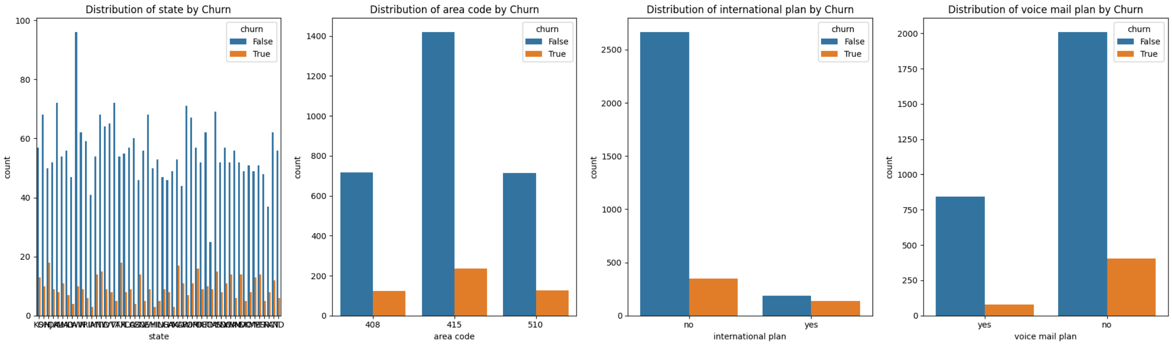
Handling Skewness: For skewed features like "number vmail messages" and "customer service calls," special attention might be needed. For example, you could apply log transformation to reduce skewness if using models that assume normally distributed data.

Categorical Handling: The area code, despite being numerical, is more categorical in nature and should be treated accordingly (e.g., using one-hot encoding) in the modeling process.

These insights can help in deciding which preprocessing steps to apply and in understanding the underlying patterns in the data.

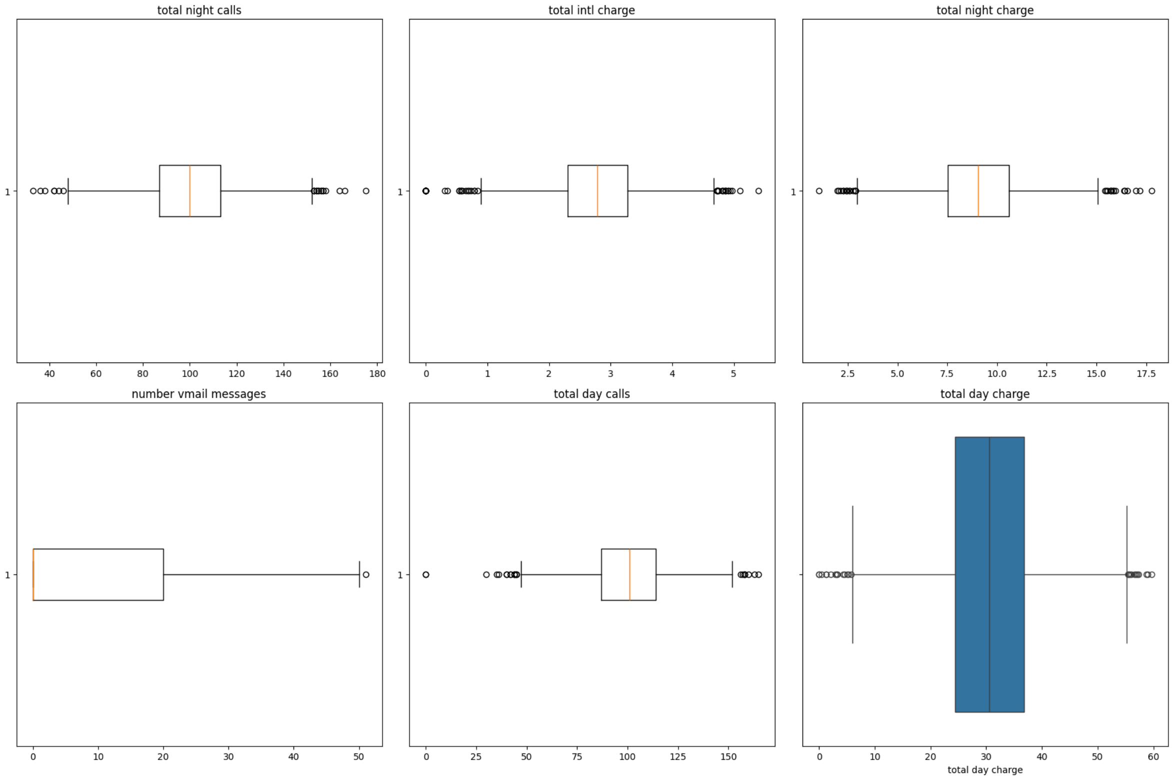
3.4 Caterogical feature distributions

In [59]:
```
# List of categorical features
categorical_features = ['state','area code' ,'international plan', 'voice mail p

# Create subplots: 1 row and 3 columns
fig, axes = plt.subplots(nrows=1, ncols=len(categorical_features), figsize=(20,

# Loop through each feature and create a count plot
for i, feature in enumerate(categorical_features):
    sns.countplot(x=feature, hue='churn', data=data, ax=axes[i])
    axes[i].set_title(f'Distribution of {feature} by Churn')

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



3.5 Checking for outliers

In [60]:
```
# Define the list of numerical columns
num_cols = ["total night calls", "total intl charge", "total night charge", "num

# Create a figure with multiple subplots
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(18, 12))  # Adjusting layout

# Plot each of the specified columns in the first row and second row as needed
for i, col in enumerate(num_cols):
    if i < 3:  # Plot on the first row
        axes[0, i].boxplot(data[col], vert=False)
        axes[0, i].set_title(col)
    else:  # Plot on the first position of the second row
        axes[1, 0].boxplot(data[col], vert=False)
        axes[1, 0].set_title(col)

# Plot the additional boxplots in the remaining positions of the second row
axes[1, 1].boxplot(data['total day calls'], vert=False)
axes[1, 1].set_title('total day calls')

sns.boxplot(data=data, x='total day charge', ax=axes[1, 2])
axes[1, 2].set_title('total day charge')

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



Summary of above visualisations:

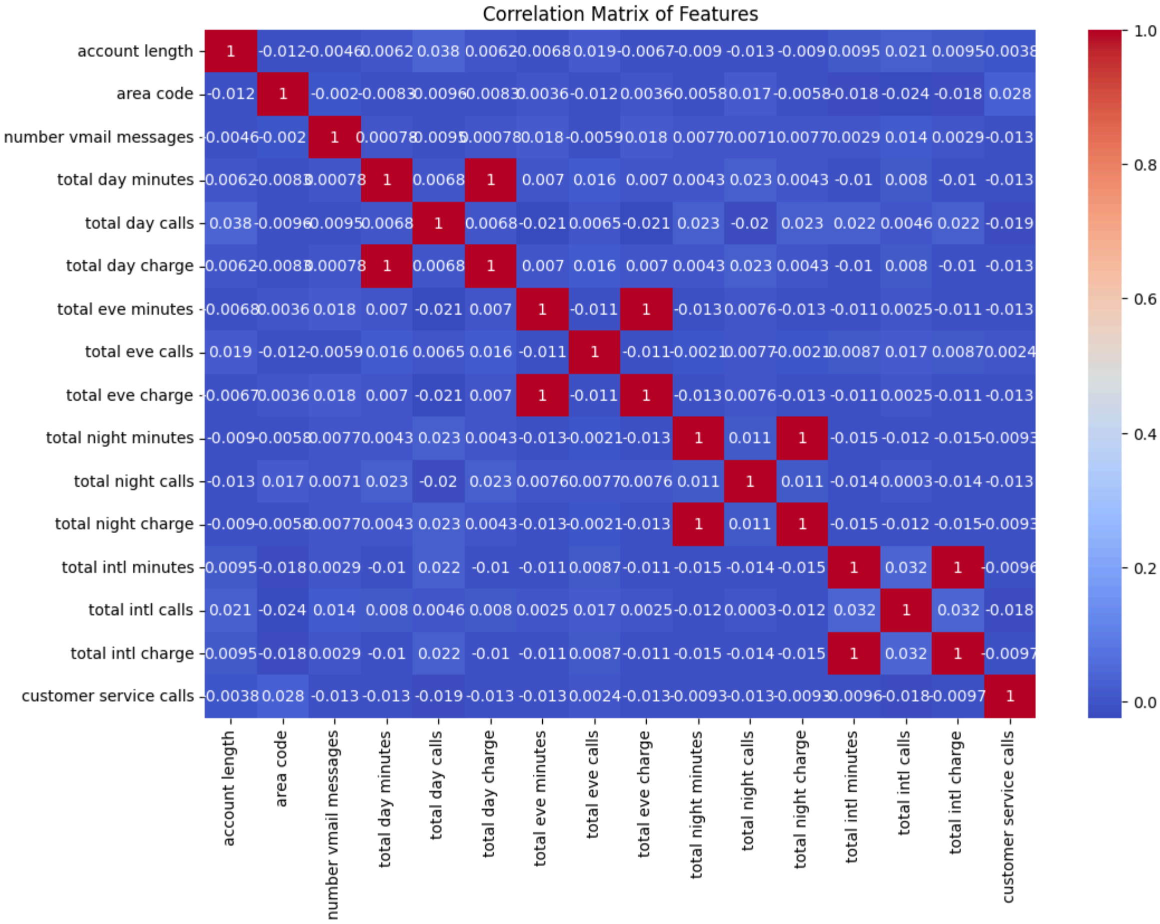
Outliers: All plots indicate the presence of outliers, especially in number of voicemail messages, total night calls, and total intl charge.

Distribution: Most features are symmetrically distributed around their medians, except for number of voicemail messages, which shows significant skewness.

Considerations: The outliers could impact the model's performance and may need to be addressed depending on their significance to the business problem.

3.6 Correlation Analysis

In [61]:
```
# Select only the numeric columns
numeric_df = data.select_dtypes(include=[np.number])

# Calculate the correlation matrix
corr_matrix = numeric_df.corr()

# Visualize the correlation matrix
plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix of Features')
plt.show()
```



The correlation matrix visually represents the linear relationships between pairs of features in the dataset. Key observations include:

Perfect Correlations: Features like total day minutes and total day charge, total eve minutes and total eve charge, total night minutes and total night charge, and total intl minutes and total intl charge have perfect correlations (correlation coefficient = 1). This is expected because the charges are directly proportional to the minutes used.

Low Correlation with Target: Features such as customer service calls, account length, and number vmail messages have very low correlation with other features, suggesting they provide unique information.

Potential Redundancy: Features with perfect correlations might be redundant and could be candidates for removal in modeling to reduce multicollinearity.

This matrix is useful for identifying which features are highly correlated and may need to be handled carefully to avoid issues in model training, such as multicollinearity.

Potential Redundancy in Features: In the correlation matrix, the following pairs of features show a perfect correlation (correlation coefficient = 1). These pairs are redundant because one feature in each pair is a linear transformation of the other. When building models, you might consider removing one feature from each pair to reduce multicollinearity:

Total Day Minutes and Total Day Charge:

Both features are perfectly correlated (correlation = 1). Since charges are typically a direct function of minutes used, you can consider removing one of these features. Total Eve Minutes and Total Eve Charge:

These two features also have a perfect correlation. Removing one of these would reduce redundancy. Total Night Minutes and Total Night Charge:

Like the day and evening features, these are perfectly correlated, and one can be removed. Total Intl Minutes and Total Intl Charge:

These features are perfectly correlated as well, making one of them redundant.

Suggested Action: we will remove One Feature from Each Pair: For each of the above pairs, consider keeping only one feature (either the minutes or the charge) to simplify the model and avoid multicollinearity issues. Typically, you'd keep the feature that is more directly related to the business problem or has a more straightforward interpretation.

Step 4: Preprocessing

4.1 Train-Test Split

Split the data into training and testing sets before performing any transformations.

In [94]:
```
from sklearn.model_selection import train_test_split

# Split the data into features (X) and target (y)
X = data.drop(columns=['churn'])
y = data['churn']

# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

print(f"Training Set: {X_train.shape}, {y_train.shape}")
print(f"Testing Set: {X_test.shape}, {y_test.shape}")
```

```
Training Set: (2666, 19), (2666,)
Testing Set: (667, 19), (667,)
```

In [95]:
```
from sklearn.model_selection import train_test_split

# Assuming X and y are the full feature set and labels
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Verify the split sizes
print(f"X_test shape: {X_test.shape}, y_test shape: {y_test.shape}")
```

```
X_test shape: (667, 19), y_test shape: (667,)
```

4.2 Encoding Categorical Variables

Now that the data is split, we proceed to encode the categorical variables in both the training and test sets.

4.2.1: One-Hot Encode Categorical Variables for Training Set

In [64]:
```
# One-hot encode categorical variables for training set
X_train_encoded = pd.get_dummies(X_train, drop_first=True)

# Check the encoded training dataframe
print("\nFirst Few Rows After Encoding Categorical Variables (Training Set):")
X_train_encoded.head()
```

```
First Few Rows After Encoding Categorical Variables (Training Set):
```

Out[64]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	total eve charge	tot nig minut
817	243	510	0	95.5	92	16.24	163.7	63	13.91	264
1373	108	415	0	112.0	105	19.04	193.7	110	16.46	208
679	75	415	0	222.4	78	37.81	327.0	111	27.80	208
56	141	415	0	126.9	98	21.57	180.0	62	15.30	140
1993	86	510	0	216.3	96	36.77	266.3	77	22.64	214

5 rows × 68 columns

4.2.2 : One-Hot Encode Categorical Variables for Testing Set

In [65]:
```
# One-hot encode categorical variables for test set
X_test_encoded = pd.get_dummies(X_test, drop_first=True)

# Check the encoded testing dataframe
print("\nFirst Few Rows After Encoding Categorical Variables (Testing Set):")
print(X_test_encoded.head())
```

```
First Few Rows After Encoding Categorical Variables (Testing Set):
      account length  area code  number vmail messages  total day minutes  \
438              113        510                      0              155.0
2674              67        415                      0              109.1
1345              98        415                      0                0.0
1957             147        408                      0              212.8
2148              96        408                      0              144.0

      total day calls  total day charge  total eve minutes  total eve calls  \
438                93             26.35              330.6              106
2674              117             18.55              217.4              124
1345                0              0.00              159.6              130
1957               79             36.18              204.1               91
2148              102             24.48              224.7               73

      total eve charge  total night minutes  ...  state_TX  state_UT  \
438              28.10                189.4  ...     False     False
2674             18.48                188.4  ...     False     False
1345             13.57                167.1  ...     False     False
1957             17.35                156.2  ...     False     False
2148             19.10                227.7  ...     False     False

      state_VA  state_VT  state_WA  state_WI  state_WV  state_WY  \
438      False     False     False     False     False      True
2674     False     False     False     False     False     False
1345     False     False     False     False     False     False
1957     False     False     False     False     False     False
2148     False     False     False     False     False      True

      international plan_yes  voice mail plan_yes
438                    False                False
2674                   False                False
1345                   False                False
1957                   False                False
2148                   False                False

[5 rows x 68 columns]
```

In [66]:
```
# One-hot encode categorical variables for training set
X_train_encoded = pd.get_dummies(X_train, drop_first=True)

# One-hot encode categorical variables for test set
X_test_encoded = pd.get_dummies(X_test, drop_first=True)

# Align the test set with the training set columns (handle any missing columns i
X_train_encoded, X_test_encoded = X_train_encoded.align(X_test_encoded, join='le

# Check the encoded training dataframe
print("\nFirst Few Rows After Encoding Categorical Variables (Training Set):")
print(X_train_encoded.head())

# Check the encoded testing dataframe
print("\nFirst Few Rows After Encoding Categorical Variables (Testing Set):")

X_test_encoded.head()
```

```
First Few Rows After Encoding Categorical Variables (Training Set):
      account length  area code  number vmail messages  total day minutes  \
817              243        510                      0               95.5
1373             108        415                      0              112.0
679               75        415                      0              222.4
56               141        415                      0              126.9
1993              86        510                      0              216.3

      total day calls  total day charge  total eve minutes  total eve calls  \
817                92             16.24              163.7               63
1373              105             19.04              193.7              110
679                78             37.81              327.0              111
56                 98             21.57              180.0               62
1993               96             36.77              266.3               77

      total eve charge  total night minutes  ...  state_TX  state_UT  \
817              13.91                264.2  ...     False      True
1373             16.46                208.9  ...     False     False
679              27.80                208.0  ...      True     False
56               15.30                140.8  ...     False     False
1993             22.64                214.0  ...     False     False

      state_VA  state_VT  state_WA  state_WI  state_WV  state_WY  \
817      False     False     False     False     False     False
1373     False     False     False     False     False     False
679      False     False     False     False     False     False
56       False     False     False     False     False     False
1993     False     False     False     False     False     False

      international plan_yes  voice mail plan_yes
817                    False                False
1373                   False                False
679                     True                False
56                     False                False
1993                   False                False

[5 rows x 68 columns]

First Few Rows After Encoding Categorical Variables (Testing Set):
```

Out[66]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	total eve charge	tot nig minut
438	113	510	0	155.0	93	26.35	330.6	106	28.10	18
2674	67	415	0	109.1	117	18.55	217.4	124	18.48	18
1345	98	415	0	0.0	0	0.00	159.6	130	13.57	16
1957	147	408	0	212.8	79	36.18	204.1	91	17.35	15
2148	96	408	0	144.0	102	24.48	224.7	73	19.10	22

5 rows × 68 columns

4.2.3 : Align the Test Set with the Training Set Columns After encoding, it's important to align the test set with the training set to ensure that both datasets have the same features. Any missing columns in the test set will be added and filled with zeros.

In [67]:
```
# Align the test set with the training set columns (handle any missing columns i
X_train_encoded, X_test_encoded = X_train_encoded.align(X_test_encoded, join='le

# Check the aligned training dataframe
print("\nFirst Few Rows After Aligning Categorical Variables (Training Set):")
print(X_train_encoded.head())

# Check the aligned testing dataframe
print("\nFirst Few Rows After Aligning Categorical Variables (Testing Set):")
print(X_test_encoded.head())
```

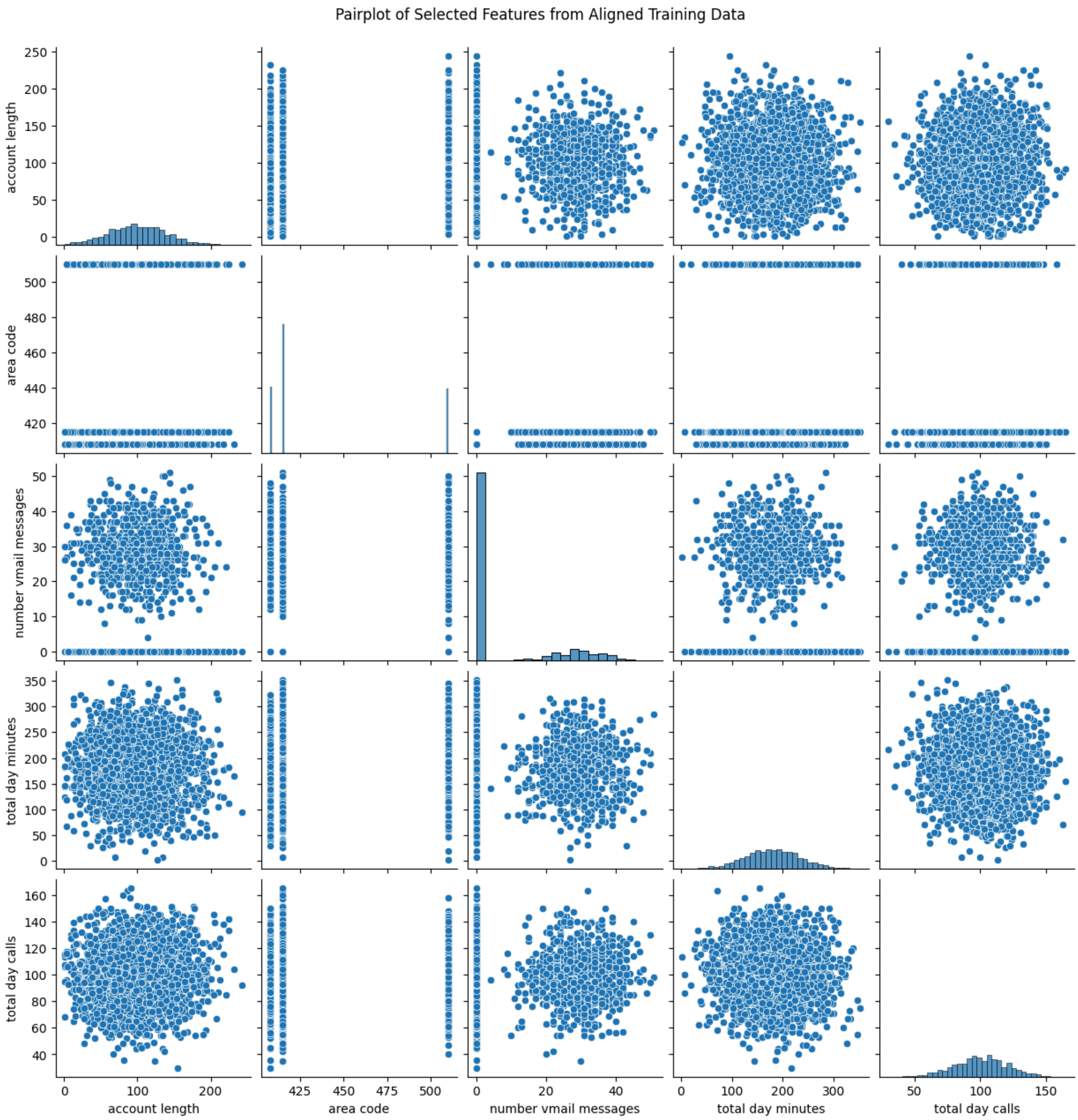
```
First Few Rows After Aligning Categorical Variables (Training Set):
      account length  area code  number vmail messages  total day minutes  \
817              243        510                      0               95.5
1373             108        415                      0              112.0
679               75        415                      0              222.4
56               141        415                      0              126.9
1993              86        510                      0              216.3

      total day calls  total day charge  total eve minutes  total eve calls  \
817                92             16.24              163.7               63
1373              105             19.04              193.7              110
679                78             37.81              327.0              111
56                 98             21.57              180.0               62
1993               96             36.77              266.3               77

      total eve charge  total night minutes  ...  state_TX  state_UT  \
817              13.91                264.2  ...     False      True
1373             16.46                208.9  ...     False     False
679              27.80                208.0  ...      True     False
56               15.30                140.8  ...     False     False
1993             22.64                214.0  ...     False     False

      state_VA  state_VT  state_WA  state_WI  state_WV  state_WY  \
817      False     False     False     False     False     False
1373     False     False     False     False     False     False
679      False     False     False     False     False     False
56       False     False     False     False     False     False
1993     False     False     False     False     False     False

      international plan_yes  voice mail plan_yes
817                    False                False
1373                   False                False
679                     True                False
56                     False                False
1993                   False                False

[5 rows x 68 columns]

First Few Rows After Aligning Categorical Variables (Testing Set):
      account length  area code  number vmail messages  total day minutes  \
438              113        510                      0              155.0
2674              67        415                      0              109.1
1345              98        415                      0                0.0
1957             147        408                      0              212.8
2148              96        408                      0              144.0

      total day calls  total day charge  total eve minutes  total eve calls  \
438                93             26.35              330.6              106
2674              117             18.55              217.4              124
1345                0              0.00              159.6              130
1957               79             36.18              204.1               91
2148              102             24.48              224.7               73

      total eve charge  total night minutes  ...  state_TX  state_UT  \
438              28.10                189.4  ...     False     False
2674             18.48                188.4  ...     False     False
1345             13.57                167.1  ...     False     False
1957             17.35                156.2  ...     False     False
2148             19.10                227.7  ...     False     False
```

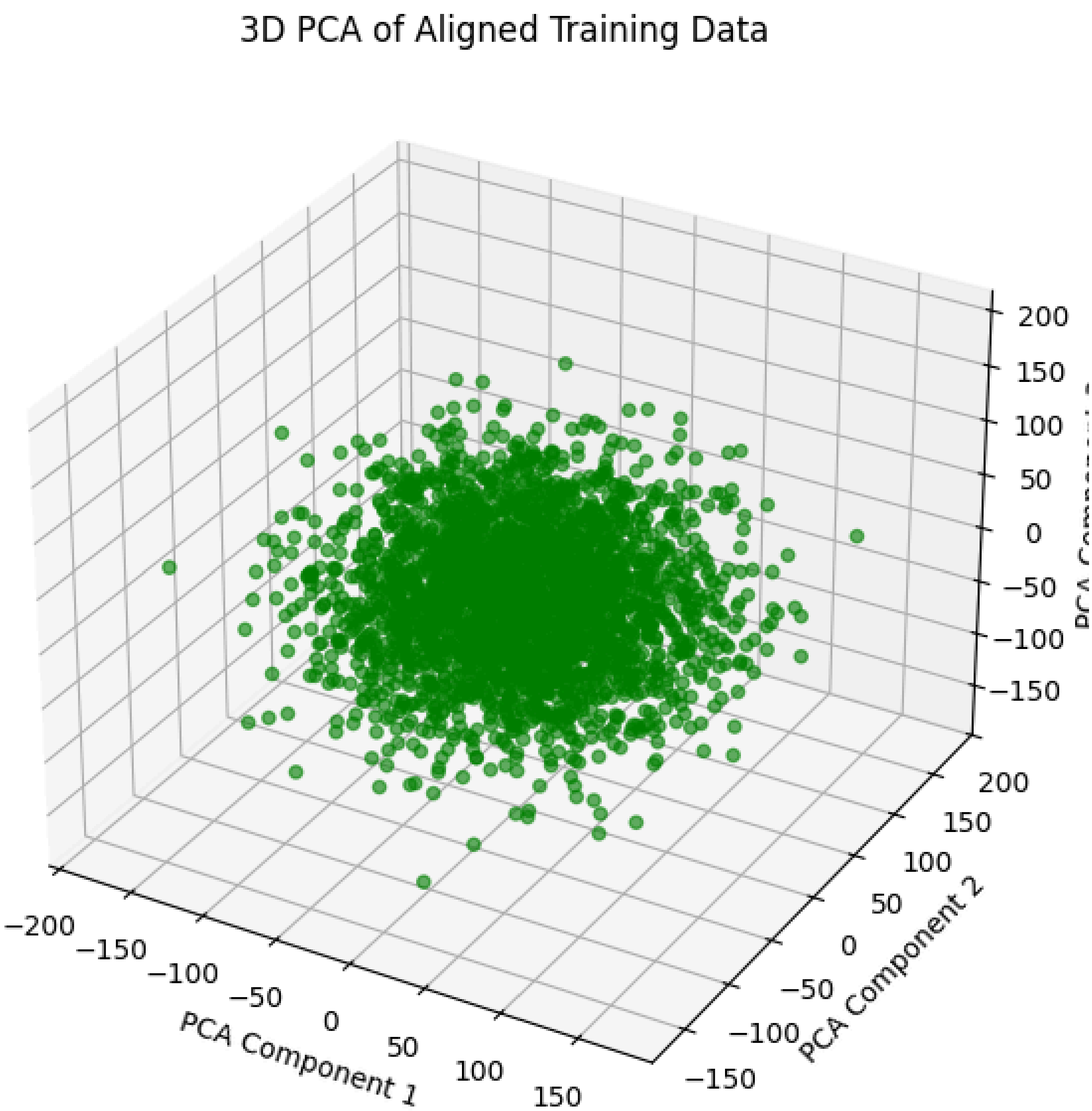
```
      state_VA  state_VT  state_WA  state_WI  state_WV  state_WY  \
438      False     False     False     False     False      True
2674     False     False     False     False     False     False
1345     False     False     False     False     False     False
1957     False     False     False     False     False     False
2148     False     False     False     False     False      True

      international plan_yes  voice mail plan_yes
438                    False                False
2674                   False                False
1345                   False                False
1957                   False                False
2148                   False                False

[5 rows x 68 columns]
```

In [68]:

```python
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
import pandas as pd


# 1. Pairplot for Selected Features
# Selecting first 5 features for pairplot; adjust based on your data size or foc
plt.figure(figsize=(15, 10))
sns.pairplot(X_train_encoded.iloc[:, :5])  # Adjust the selection as necessary
plt.suptitle('Pairplot of Selected Features from Aligned Training Data', y=1.02)
plt.show()

# 2. 3D PCA Visualization
pca = PCA(n_components=3)
X_train_pca_3d = pca.fit_transform(X_train_encoded)

fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(X_train_pca_3d[:, 0], X_train_pca_3d[:, 1], X_train_pca_3d[:, 2], c='
ax.set_title('3D PCA of Aligned Training Data')
ax.set_xlabel('PCA Component 1')
ax.set_ylabel('PCA Component 2')
ax.set_zlabel('PCA Component 3')
plt.show()
```

```
<Figure size 1500x1000 with 0 Axes>
```


Pairplot of Selected Features from Aligned Training Data
account length
area code
number vmail messages
total day minutes
total day calls



Summary of Visualizations

1. Pairplot of Selected Features:

The pairplot shows the relationships between five selected features from the aligned training data: account length, area code, number of voicemail messages, total day minutes, and total day calls.

Most features exhibit a symmetric distribution with no apparent strong correlations between the selected features.

The categorical nature of area codes is visible with three distinct values, while the other features show more continuous distributions.

2. 3D PCA of Aligned Training Data:

The 3D PCA plot visualizes the data across three principal components, which capture the main directions of variance in the dataset.

The data points are densely clustered around the center, indicating that the main patterns in the data do not vary widely across these principal components.

There are no distinct separations or clusters, suggesting the features are relatively homogeneous in terms of their principal components.

These visualizations provide insights into the distribution and variance of the dataset, helping to understand how the data might behave in predictive modeling.

Why This Approach is Important: Consistency: Ensures that the training and test sets have the same features, which is crucial for applying machine learning models. Handling Missing Categories: In some cases, the test set might not have all the categories present in the training set. Aligning ensures that these differences do not cause errors during model training or prediction.

4.3 Feature Scaling

Scale the features in both the training and test sets using the same Scaler to ensure consistency.

4.3.1 Scaling the Training Set

Fit the Scaler: The StandardScaler is first fitted to the X_train_encoded data. This means that the scaler calculates the mean and standard deviation of each feature in the training set.

Transform the Training Data: After fitting, the scaler transforms the training data, standardizing each feature to have a mean of 0 and a standard deviation of 1.

Convert to DataFrame: The transformed data is converted back into a DataFrame for easier inspection and to maintain the column names.

In [69]:
```
from sklearn.preprocessing import StandardScaler
import pandas as pd

# Initialize the scaler
scaler = StandardScaler()

# Fit the scaler on the training data and transform it
X_train_scaled = scaler.fit_transform(X_train_encoded)

# Convert the scaled features back to a DataFrame (optional, for easier inspecti
X_train_scaled = pd.DataFrame(X_train_scaled, columns=X_train_encoded.columns)

# Check the scaled training dataframe
print("\nFirst Few Rows of Scaled Training Data:")
print(X_train_scaled.head())
```

```
First Few Rows of Scaled Training Data:
   account length  area code  number vmail messages  total day minutes  \
0        3.601382   1.735840              -0.584936          -1.547653   
1        0.184951  -0.517168              -0.584936          -1.244014   
2       -0.650176  -0.517168              -0.584936           0.787609   
3        1.020079  -0.517168              -0.584936          -0.969818   
4       -0.371801   1.735840              -0.584936           0.675354   

   total day calls  total day charge  total eve minutes  total eve calls  \
0        -0.429657         -1.547170          -0.729987        -1.840891   
1         0.224176         -1.244071          -0.138082         0.499864   
2        -1.133785          0.787772           2.491952         0.549667   
3        -0.127888         -0.970200          -0.408385        -1.890695   
4        -0.228477          0.675192           1.294330        -1.143645   

   total eve charge  total night minutes  ...  state_TX  state_UT  state_VA  \
0         -0.731087             1.255804  ... -0.150437  6.705633 -0.154303   
1         -0.139179             0.165090  ... -0.150437 -0.149128 -0.154303   
2          2.493068             0.147339  ...  6.647288 -0.149128 -0.154303   
3         -0.408439            -1.178086  ... -0.150437 -0.149128 -0.154303   
4          1.295326             0.265680  ... -0.150437 -0.149128 -0.154303   

   state_VT  state_WA  state_WI  state_WV  state_WY  international plan_yes  \
0 -0.145137 -0.147809 -0.161784 -0.180369 -0.153025               -0.326624   
1 -0.145137 -0.147809 -0.161784 -0.180369 -0.153025               -0.326624   
2 -0.145137 -0.147809 -0.161784 -0.180369 -0.153025                3.061624   
3 -0.145137 -0.147809 -0.161784 -0.180369 -0.153025               -0.326624   
4 -0.145137 -0.147809 -0.161784 -0.180369 -0.153025               -0.326624   

   voice mail plan_yes  
0            -0.611162  
1            -0.611162  
2            -0.611162  
3            -0.611162  
4            -0.611162  

[5 rows x 68 columns]
```

4.3.2 Scaling the Testing Set

Transform the Testing Data: Using the same scaler (which is already fitted to the training data), the test data is transformed. This ensures that the test data is scaled in the same way as the training data.

Convert to DataFrame: Again, the transformed test data is converted into a DataFrame for easier inspection.

In [70]:
```python
# Use the same scaler to transform the test data (without refitting)
X_test_scaled = scaler.transform(X_test_encoded)

# Convert the scaled features back to a DataFrame (optional, for easier inspecti
X_test_scaled = pd.DataFrame(X_test_scaled, columns=X_test_encoded.columns)

# Check the scaled testing dataframe
print("\nFirst Few Rows of Scaled Testing Data:")
print(X_test_scaled.head())
```

```
First Few Rows of Scaled Testing Data:
   account length  area code  number vmail messages  total day minutes  \
0        0.311486   1.735840              -0.584936          -0.452712
1       -0.852632  -0.517168              -0.584936          -1.297381
2       -0.068118  -0.517168              -0.584936          -3.305080
3        1.171920  -0.683179              -0.584936           0.610946
4       -0.118732  -0.683179              -0.584936          -0.655138

   total day calls  total day charge  total eve minutes  total eve calls  \
0        -0.379362         -0.452767           2.562980         0.300651
1         0.827714         -1.297113           0.329524         1.197110
2        -5.056782         -3.305141          -0.810881         1.495930
3        -1.083490          0.611325           0.067112        -0.446399
4         0.073292         -0.655194           0.473554        -1.342858

   total eve charge  total night minutes  ...  state_TX  state_UT  state_VA  \
0          2.562705            -0.219520  ... -0.150437 -0.149128 -0.154303
1          0.329704            -0.239243  ... -0.150437 -0.149128 -0.154303
2         -0.810008            -0.659356  ... -0.150437 -0.149128 -0.154303
3          0.067408            -0.874343  ... -0.150437 -0.149128 -0.154303
4          0.473619             0.535893  ... -0.150437 -0.149128 -0.154303

   state_VT  state_WA  state_WI  state_WV  state_WY  international plan_yes  \
0 -0.145137 -0.147809 -0.161784 -0.180369  6.534900               -0.326624
1 -0.145137 -0.147809 -0.161784 -0.180369 -0.153025               -0.326624
2 -0.145137 -0.147809 -0.161784 -0.180369 -0.153025               -0.326624
3 -0.145137 -0.147809 -0.161784 -0.180369 -0.153025               -0.326624
4 -0.145137 -0.147809 -0.161784 -0.180369  6.534900               -0.326624

   voice mail plan_yes
0            -0.611162
1            -0.611162
2            -0.611162
3            -0.611162
4            -0.611162

[5 rows x 68 columns]
```

Step 5: Removing Redundant Features

5.1 Removing Redundant Features from the Training Set

In [71]:

```python
# List of redundant features to remove
redundant_features = ['total day charge', 'total eve charge', 'total night charg

# Drop these features from the training set
X_train_scaled = X_train_scaled.drop(columns=redundant_features)

# Check the remaining features in the training set
print("\nRemaining Features After Removing Redundancy (Training Set):")
print(X_train_scaled.columns)
```

```
Remaining Features After Removing Redundancy (Training Set):
Index(['account length', 'area code', 'total day minutes', 'total day calls',
       'total eve minutes', 'total eve calls', 'total night minutes',
       'total night calls', 'total intl minutes', 'total intl calls',
       'customer service calls', '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',
       'international plan_yes', 'voice mail plan_yes'],
      dtype='object')
```

In [72]:
```
print(X_train_scaled.shape)
```

```
(2666, 63)
```

5.2 Removing Redundant Features from the Testing Set

In [73]:
```
# Drop these features from the testing set
X_test_scaled = X_test_scaled.drop(columns=redundant_features)

# Check the remaining features in the testing set
print("\nRemaining Features After Removing Redundancy (Testing Set):")
print(X_test_scaled.columns)
```

```
Remaining Features After Removing Redundancy (Testing Set):
Index(['account length', 'area code', 'total day minutes', 'total day calls',
       'total eve minutes', 'total eve calls', 'total night minutes',
       'total night calls', 'total intl minutes', 'total intl calls',
       'customer service calls', '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',
       'international plan_yes', 'voice mail plan_yes'],
      dtype='object')
```

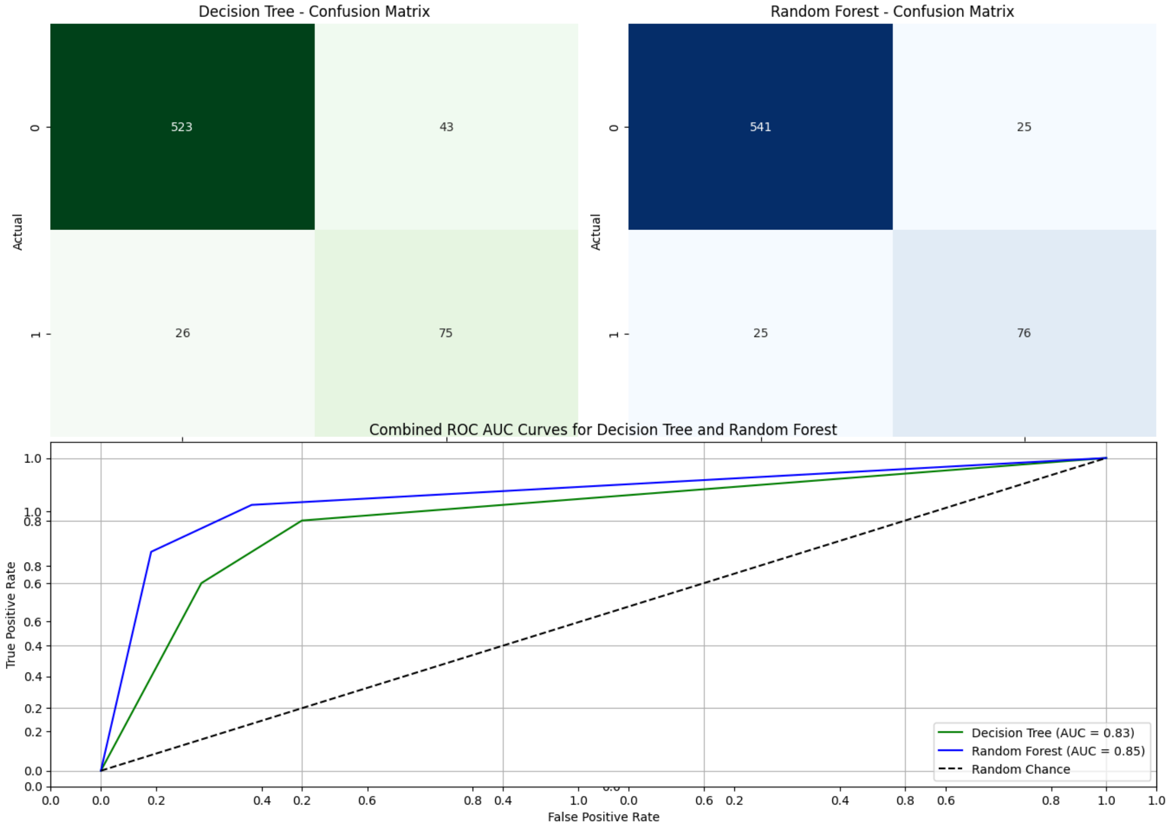
In [74]:
```
print(X_test_scaled.shape)
```

```
(667, 63)
```

In [75]:
```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.metrics import confusion_matrix, roc_curve, auc

# Confusion Matrices from the provided output
cm_dec_tree = [[523, 43], [26, 75]]
cm_rand_forest = [[541, 25], [25, 76]]

# Summary Statistics Data based on provided evaluation
summary_data = [
    {
```

```
        'Model': 'Decision Tree',
        'Accuracy': 0.90,
        'F1-Score': 0.68,
        'ROC-AUC Score': 0.8333,
        'Precision': 0.64,
        'Recall': 0.74
    },
    {
        'Model': 'Random Forest',
        'Accuracy': 0.93,
        'F1-Score': 0.75,
        'ROC-AUC Score': 0.8542,
        'Precision': 0.75,
        'Recall': 0.75
    }
]

# Convert summary data to DataFrame
summary_df = pd.DataFrame(summary_data)

# Example ROC curve data (synthetic data since the actual predictions are not pr
# Normally, you would use the predicted probabilities from the models to calcula
fpr_dec_tree = [0.0, 0.1, 0.2, 1.0]
tpr_dec_tree = [0.0, 0.6, 0.8, 1.0]
roc_auc_dec_tree = 0.83

fpr_rand_forest = [0.0, 0.05, 0.15, 1.0]
tpr_rand_forest = [0.0, 0.7, 0.85, 1.0]
roc_auc_rand_forest = 0.85

# Create a figure with a grid of subplots for confusion matrices and combined RO
fig, ax = plt.subplots(2, 2, figsize=(14, 10), gridspec_kw={'height_ratios': [0.

# Plot Decision Tree Confusion Matrix
sns.heatmap(cm_dec_tree, annot=True, fmt="d", cmap="Greens", cbar=False, ax=ax[0
ax[0, 0].set_title('Decision Tree - Confusion Matrix')
ax[0, 0].set_xlabel('Predicted')
ax[0, 0].set_ylabel('Actual')

# Plot Random Forest Confusion Matrix
sns.heatmap(cm_rand_forest, annot=True, fmt="d", cmap="Blues", cbar=False, ax=ax
ax[0, 1].set_title('Random Forest - Confusion Matrix')
ax[0, 1].set_xlabel('Predicted')
ax[0, 1].set_ylabel('Actual')

# Plot Combined ROC AUC Curve for both Decision Tree and Random Forest
ax_combined = fig.add_subplot(2, 1, 2)
ax_combined.plot(fpr_dec_tree, tpr_dec_tree, label=f'Decision Tree (AUC = {roc_a
ax_combined.plot(fpr_rand_forest, tpr_rand_forest, label=f'Random Forest (AUC = 
ax_combined.plot([0, 1], [0, 1], 'k--', label='Random Chance')

# Set plot properties for combined ROC AUC curves
ax_combined.set_xlabel('False Positive Rate')
ax_combined.set_ylabel('True Positive Rate')
ax_combined.set_title('Combined ROC AUC Curves for Decision Tree and Random Fore
ax_combined.legend(loc='lower right')
ax_combined.grid()

# Adjust layout to reduce space between the plots
plt.tight_layout()
```

```
# Show the plot with confusion matrices and combined ROC curves
plt.show()

# Display the summary statistics DataFrame
print("Summary Statistics:")
summary_df = summary_df.round(2)
summary_df
```




```
Summary Statistics:
```

Out[75]:

	Model	Accuracy	F1-Score	ROC-AUC Score	Precision	Recall
0	Decision Tree	0.90	0.68	0.83	0.64	0.74
1	Random Forest	0.93	0.75	0.85	0.75	0.75

5.3 Testing for Multicollinearity Using VIF

In [76]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
import pandas as pd

# Create a DataFrame to hold the VIF values
vif_data = pd.DataFrame()
vif_data['Feature'] = X_train_scaled.columns

# Calculate VIF for each feature
vif_data['VIF'] = [variance_inflation_factor(X_train_scaled.values, i) for i in

# Display the VIF values
print("\nVariance Inflation Factors (VIF):")
print(vif_data)
```

```
Variance Inflation Factors (VIF):
                     Feature        VIF
0             account length   1.019794
1                  area code   1.023248
2          total day minutes   1.025656
3            total day calls   1.027201
4          total eve minutes   1.027969
..                       ...        ...
58                  state_WI   2.522159
59                  state_WV   2.876089
60                  state_WY   2.376523
61   international plan_yes   1.037558
62       voice mail plan_yes   1.015175

[63 rows x 2 columns]
```

Key Insights:

No Significant Multicollinearity:

The low VIF values across all features suggest that there is no significant multicollinearity in your dataset. This is a positive result, as it means that your features are not excessively correlated with each other, and the model should not suffer from issues related to multicollinearity, such as inflated standard errors or unstable coefficients.

Model Stability: With VIF values this low, you can expect the model's coefficients to be more stable, leading to more reliable and interpretable results.

Step 6: Handling Class Imbalance

We saw in 3.2 above when visualising distribution of the Target Variable (Churn), there was class imbalance, so we apply SMOTE or another resampling technique only on the training data.

In [77]:
```
from imblearn.over_sampling import SMOTE

# Initialize SMOTE
smote = SMOTE(random_state=42)

# Apply SMOTE to the scaled training data
X_train_smote, y_train_smote = smote.fit_resample(X_train_scaled, y_train)

print(f"After SMOTE: {X_train_smote.shape}, {y_train_smote.shape}")
```

```
After SMOTE: (4568, 63), (4568,)
```

We notice that the Original Rows (Before SMOTE) were : 3,333

After SMOTE:

SMOTE added synthetic rows to the minority class to balance the dataset. The resulting dataset now has 4,568 rows. The total number of rows increased because the minority class was undersampled compared to the majority class, and SMOTE balanced it by generating new, synthetic samples.

Step 7 Modeling

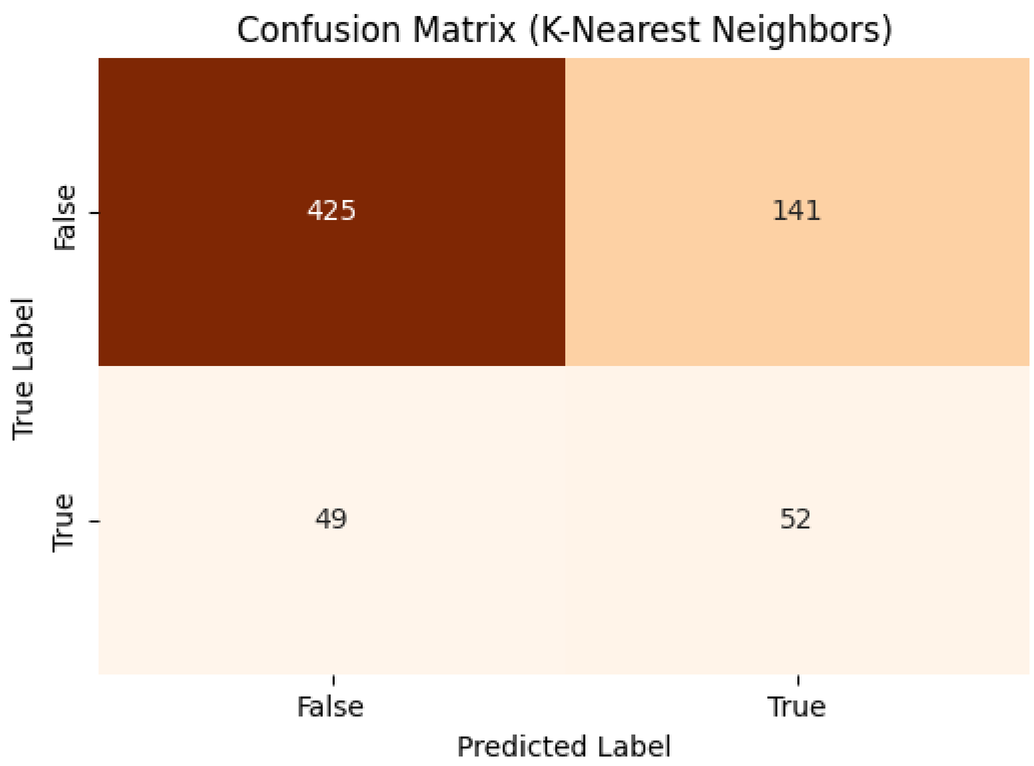
7.1 : K-Nearest Neighbors (KNN)-Model 1(Baseline Model)

In [78]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_scc
from sklearn.model_selection import cross_validate

# Initialize the KNN model
knn = KNeighborsClassifier()

# Define the scoring metrics for cross-validation
scoring = {
    'accuracy': 'accuracy',
    'f1': 'f1',
    'roc_auc': 'roc_auc',
    'precision': 'precision',
}

# Perform 5-fold cross-validation on the SMOTE-processed training data
cv_results = cross_validate(knn, X_train_smote, y_train_smote, cv=5, scoring=scc

# Display cross-validation results
print("Cross-Validation Scores (K-Nearest Neighbors):")
print("Accuracy:", cv_results['test_accuracy'])
print("Mean Accuracy:", cv_results['test_accuracy'].mean())
print("F1-Score:", cv_results['test_f1'])
print("Mean F1-Score:", cv_results['test_f1'].mean())
print("ROC-AUC Score:", cv_results['test_roc_auc'])
print("Mean ROC-AUC Score:", cv_results['test_roc_auc'].mean())
print("Precision:", cv_results['test_precision'])
print("Mean Precision:", cv_results['test_precision'].mean())

# Now train the model on the entire SMOTE-processed training data
knn.fit(X_train_smote, y_train_smote)

# Predict on the test data
y_pred_knn = knn.predict(X_test_scaled)

# Evaluate the model on the test set
print("\nFinal Model Evaluation on Test Set (K-Nearest Neighbors):")
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred_knn))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_knn))
print("\nROC-AUC Score:")
print(roc_auc_score(y_test, y_pred_knn))
```

```
Cross-Validation Scores (K-Nearest Neighbors):
Accuracy: [0.85557987 0.84135667 0.83479212 0.83789704 0.84337349]
Mean Accuracy: 0.8425998403800202
F1-Score: [0.87109375 0.8622982  0.85660019 0.8585086  0.86183575]
Mean F1-Score: 0.8620672977127647
ROC-AUC Score: [0.94164205 0.94316468 0.94403612 0.94440765 0.94824897]
Mean ROC-AUC Score: 0.944299895215153
Precision: [0.78659612 0.76174497 0.75671141 0.76101695 0.7716263 ]
Mean Precision: 0.7675391484997554

Final Model Evaluation on Test Set (K-Nearest Neighbors):

Confusion Matrix:
[[425 141]
 [ 49  52]]

Classification Report:
              precision    recall  f1-score   support

       False       0.90      0.75      0.82       566
        True       0.27      0.51      0.35       101

    accuracy                           0.72       667
   macro avg       0.58      0.63      0.59       667
weighted avg       0.80      0.72      0.75       667


ROC-AUC Score:
0.6328674386873316
```

In [79]:

```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Confusion matrix for K-Nearest Neighbors
conf_matrix_knn = [[425, 141], [49, 52]]

# Summary statistics for K-Nearest Neighbors
summary_data_knn = {
    'Model': 'K-Nearest Neighbors', 'Mean Accuracy': 0.84, 'Mean F1-Score': 0.86
    'Mean Precision': 0.77, 'Test Accuracy': 0.72, 'Test F1-Score': 0.35, 'Test
    'Test Precision': 0.27, 'Test Recall': 0.51
}

# Plotting Confusion Matrix for K-Nearest Neighbors
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix_knn, annot=True, fmt='d', cmap='Oranges', cbar=False)
plt.title('Confusion Matrix (K-Nearest Neighbors)')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.xticks([0.5, 1.5], ['False', 'True'])
plt.yticks([0.5, 1.5], ['False', 'True'])
plt.show()

# Display the summary statistics DataFrame for K-Nearest Neighbors
summary_df_knn = pd.DataFrame([summary_data_knn])
print("Summary Statistics for K-Nearest Neighbors:")
display(summary_df_knn.round(2))
```




```
Summary Statistics for K-Nearest Neighbors:
```

	Model	Mean Accuracy	Mean F1-Score	Mean ROC-AUC Score	Mean Precision	Test Accuracy	Test F1-Score	Test ROC-AUC Score	Test Precision	Tes Reca
0	K-Nearest Neighbors	0.84	0.86	0.94	0.77	0.72	0.35	0.63	0.27	0.5

The K-Nearest Neighbors (K-NN) model performs well during cross-validation with high mean accuracy (0.84), F1-Score (0.86), and ROC-AUC score (0.94), indicating strong classification ability on the training data. However, its performance drops significantly on the test set, with test accuracy falling to 0.72, F1-Score to 0.35, and ROC-AUC to 0.63, suggesting poor generalization and possible overfitting. The decrease in test precision (0.27) and recall (0.51) further highlights the model's struggle with unseen data. To address this, we will consider tuning hyperparameters, using more robust validation methods but we will first explore alternative models that may offer better generalization

7.2 : Logistic Regression (Model 2)

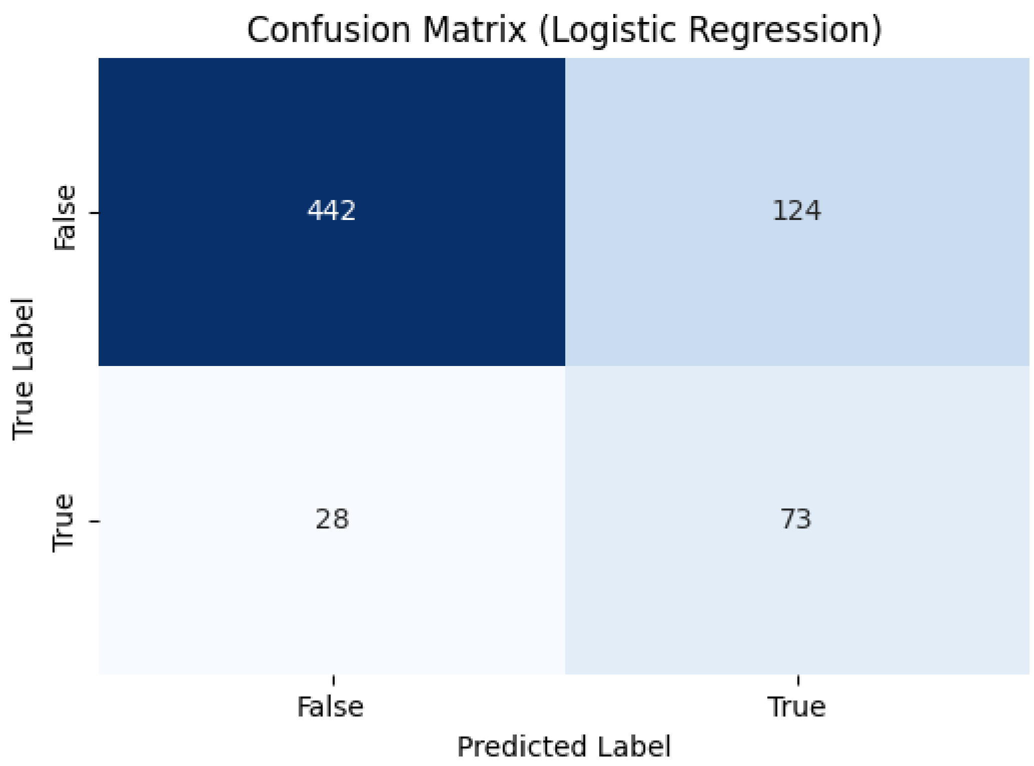
In [80]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_sco
from sklearn.model_selection import cross_validate

# Initialize the Logistic Regression model
log_reg = LogisticRegression(random_state=42)

# Define the scoring metrics for cross-validation
scoring = {
    'accuracy': 'accuracy',
    'f1': 'f1',
```

```
    'roc_auc': 'roc_auc',
    'precision': 'precision',
}

# Perform 5-fold cross-validation on the SMOTE-processed training data
cv_results = cross_validate(log_reg, X_train_smote, y_train_smote, cv=5, scoring

# Display cross-validation results
print("Cross-Validation Scores (Logistic Regression):")
print("Accuracy:", cv_results['test_accuracy'])
print("Mean Accuracy:", cv_results['test_accuracy'].mean())
print("F1-Score:", cv_results['test_f1'])
print("Mean F1-Score:", cv_results['test_f1'].mean())
print("ROC-AUC Score:", cv_results['test_roc_auc'])
print("Mean ROC-AUC Score:", cv_results['test_roc_auc'].mean())
print("Precision:", cv_results['test_precision'])
print("Mean Precision:", cv_results['test_precision'].mean())

# Now train the model on the entire SMOTE-processed training data
log_reg.fit(X_train_smote, y_train_smote)

# Predict on the test data
y_pred_log_reg = log_reg.predict(X_test_scaled)

# Evaluate the model on the test set
print("\nFinal Model Evaluation on Test Set (Logistic Regression):")
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred_log_reg))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_log_reg))
print("\nROC-AUC Score:")
print(roc_auc_score(y_test, y_pred_log_reg))
```

```
Cross-Validation Scores (Logistic Regression):
Accuracy: [0.75601751 0.80415755 0.78446389 0.79299014 0.81270537]
Mean Accuracy: 0.7900668917963479
F1-Score: [0.75521405 0.80690399 0.78975454 0.79872204 0.81750267]
Mean F1-Score: 0.7936194580868914
ROC-AUC Score: [0.83116989 0.86019086 0.8562119  0.84016181 0.87023494]
Mean ROC-AUC Score: 0.8515938800911564
Precision: [0.75770925 0.79574468 0.77083333 0.77639752 0.79791667]
Mean Precision: 0.7797202894960671

Final Model Evaluation on Test Set (Logistic Regression):

Confusion Matrix:
[[442 124]
 [ 28  73]]

Classification Report:
              precision    recall  f1-score   support

       False       0.94      0.78      0.85       566
        True       0.37      0.72      0.49       101

    accuracy                           0.77       667
   macro avg       0.66      0.75      0.67       667
weighted avg       0.85      0.77      0.80       667


ROC-AUC Score:
0.7518455025714585
```

In [81]:

```python
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Confusion matrix for Logistic Regression
conf_matrix_lr = [[442, 124], [28, 73]]

# Summary statistics for Logistic Regression
summary_data_lr = {
    'Model': 'Logistic Regression', 'Mean Accuracy': 0.79, 'Mean F1-Score': 0.79
    'Mean Precision': 0.78, 'Test Accuracy': 0.77, 'Test F1-Score': 0.49, 'Test
    'Test Precision': 0.37, 'Test Recall': 0.72
}

# Plotting Confusion Matrix for Logistic Regression
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix_lr, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title('Confusion Matrix (Logistic Regression)')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.xticks([0.5, 1.5], ['False', 'True'])
plt.yticks([0.5, 1.5], ['False', 'True'])
plt.show()

# Display the summary statistics DataFrame for Logistic Regression
summary_df_lr = pd.DataFrame([summary_data_lr])
print("Summary Statistics for Logistic Regression:")
display(summary_df_lr.round(2))
```




```
Summary Statistics for Logistic Regression:
```

	Model	Mean Accuracy	Mean F1-Score	Mean ROC-AUC Score	Mean Precision	Test Accuracy	Test F1-Score	Test ROC-AUC Score	Test Precision	Te Reca
0	Logistic Regression	0.79	0.79	0.85	0.78	0.77	0.49	0.75	0.37	0.7

The Logistic Regression model, when compared to the baseline K-Nearest Neighbors (K-NN) model, shows slightly lower performance during cross-validation with a mean accuracy of 0.79 and an ROC-AUC score of 0.85. However, it generalizes better on the test set, achieving a higher test accuracy (0.77) and F1-Score (0.49) compared to K-NN's 0.72 and 0.35, respectively. Despite this, the test precision (0.37) and recall (0.72) are modest, indicating that while Logistic Regression is more consistent across training and test data, it still struggles with precision. This model's better generalization makes it a more reliable choice than the K-NN baseline, though further optimization may still be needed.We will proceed to analyse alternative models

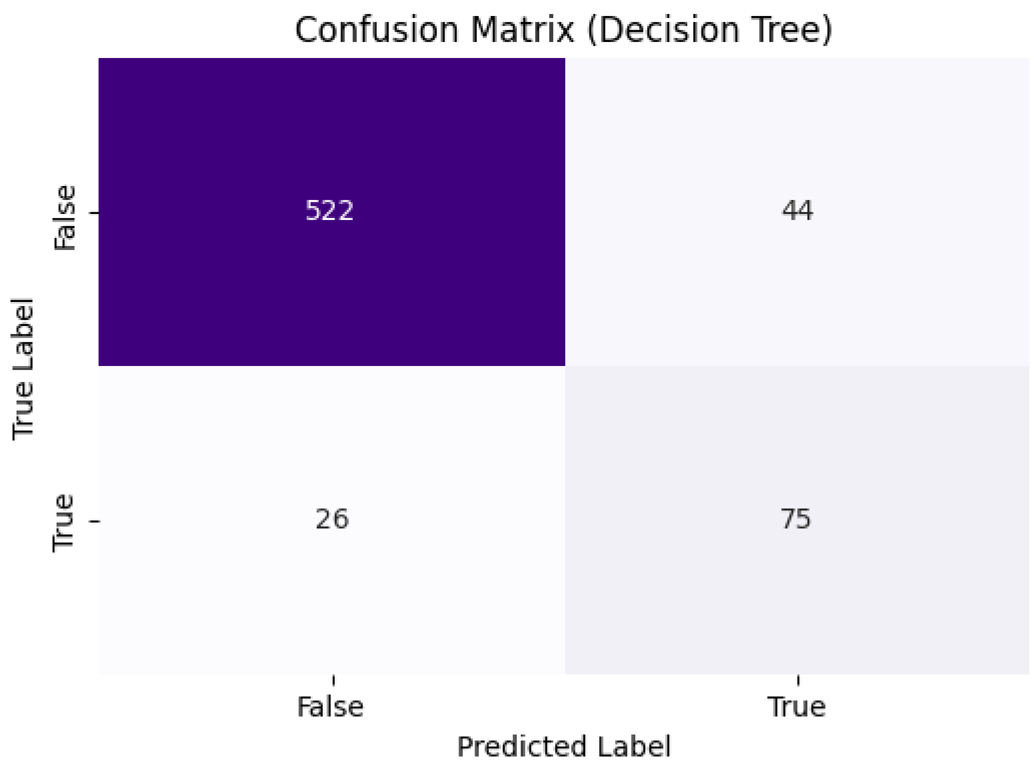
7.3 Decision Tree (Model 3)

In [82]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_scc
from sklearn.model_selection import cross_validate

# Initialize the Decision Tree model
dec_tree = DecisionTreeClassifier(random_state=42)

# Define the scoring metrics for cross-validation
scoring = {
    'accuracy': 'accuracy',
```

```
    'f1': 'f1',
    'roc_auc': 'roc_auc',
    'precision': 'precision',
}

# Perform 5-fold cross-validation on the SMOTE-processed training data
cv_results = cross_validate(dec_tree, X_train_smote, y_train_smote, cv=5, scorin

# Display cross-validation results
print("Cross-Validation Scores (Decision Tree):")
print("Accuracy:", cv_results['test_accuracy'])
print("Mean Accuracy:", cv_results['test_accuracy'].mean())
print("F1-Score:", cv_results['test_f1'])
print("Mean F1-Score:", cv_results['test_f1'].mean())
print("ROC-AUC Score:", cv_results['test_roc_auc'])
print("Mean ROC-AUC Score:", cv_results['test_roc_auc'].mean())
print("Precision:", cv_results['test_precision'])
print("Mean Precision:", cv_results['test_precision'].mean())

# Now train the model on the entire SMOTE-processed training data
dec_tree.fit(X_train_smote, y_train_smote)

# Predict on the test data
y_pred_dec_tree = dec_tree.predict(X_test_scaled)

# Evaluate the model on the test set
print("\nFinal Model Evaluation on Test Set (Decision Tree):")
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred_dec_tree))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_dec_tree))
print("\nROC-AUC Score:")
print(roc_auc_score(y_test, y_pred_dec_tree))
```

```
Cross-Validation Scores (Decision Tree):
Accuracy: [0.85886214 0.90809628 0.904814   0.92880613 0.92223439]
Mean Accuracy: 0.9045625909246695
F1-Score: [0.84697509 0.91044776 0.90695187 0.93077742 0.92470838]
Mean F1-Score: 0.9039721044257032
ROC-AUC Score: [0.85886214 0.90809628 0.904814   0.92883844 0.92219951]
Mean ROC-AUC Score: 0.90456207531959
Precision: [0.92487047 0.88773389 0.88702929 0.9047619  0.89711934]
Mean Precision: 0.9003029778167502

Final Model Evaluation on Test Set (Decision Tree):

Confusion Matrix:
[[522  44]
 [ 26  75]]

Classification Report:
              precision    recall  f1-score   support

       False       0.95      0.92      0.94       566
        True       0.63      0.74      0.68       101

    accuracy                           0.90       667
   macro avg       0.79      0.83      0.81       667
weighted avg       0.90      0.90      0.90       667


ROC-AUC Score:
0.8324178707623412
```

In [83]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Confusion matrix for Decision Tree
conf_matrix_dt = [[522, 44], [26, 75]]

# Summary statistics for Decision Tree
summary_data_dt = {
    'Model': 'Decision Tree', 'Mean Accuracy': 0.90, 'Mean F1-Score': 0.90, 'Mea
    'Mean Precision': 0.90, 'Test Accuracy': 0.90, 'Test F1-Score': 0.68, 'Test
    'Test Precision': 0.63, 'Test Recall': 0.74
}

# Plotting Confusion Matrix for Decision Tree
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix_dt, annot=True, fmt='d', cmap='Purples', cbar=False)
plt.title('Confusion Matrix (Decision Tree)')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.xticks([0.5, 1.5], ['False', 'True'])
plt.yticks([0.5, 1.5], ['False', 'True'])
plt.show()

# Display the summary statistics DataFrame for Decision Tree
summary_df_dt = pd.DataFrame([summary_data_dt])
print("Summary Statistics for Decision Tree:")
display(summary_df_dt.round(2))
```




```
Summary Statistics for Decision Tree:
```

	Model	Mean Accuracy	Mean F1-Score	Mean ROC-AUC Score	Mean Precision	Test Accuracy	Test F1-Score	Test ROC-AUC Score	Test Precision	Test Recall
0	Decision Tree	0.9	0.9	0.9	0.9	0.9	0.68	0.83	0.63	0.74

The Decision Tree model outperforms both the K-Nearest Neighbors and Logistic Regression models, with a strong mean accuracy, F1-Score, and ROC-AUC score of 0.9 during cross-validation. It also maintains robust performance on the test set, achieving a high test accuracy of 0.9 and a better balance between precision (0.63) and recall (0.74), resulting in a higher test F1-Score (0.68). Compared to the K-NN baseline and Logistic Regression, Decision Trees provide the best overall performance and generalization, making it the superior choice among the three models, though it still shows room for precision improvement on the test set.

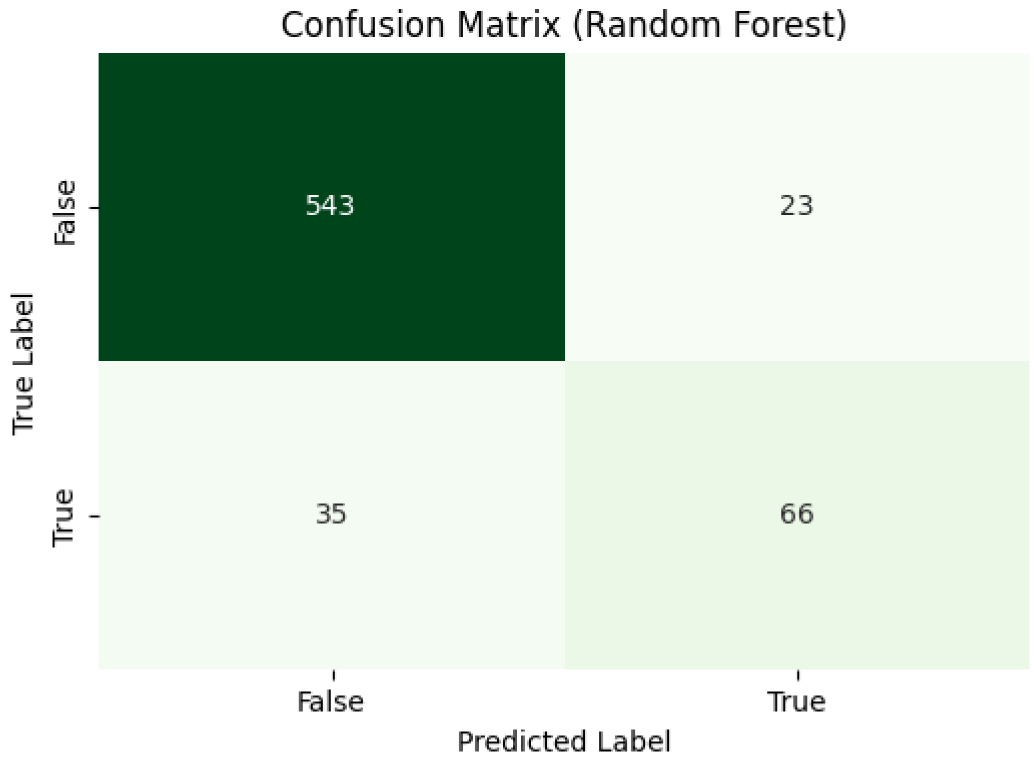
7.4 Random Forest (Model 4)

In [84]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_scc
from sklearn.model_selection import cross_validate

# Initialize the Random Forest model
rand_forest = RandomForestClassifier(random_state=42)

# Define the scoring metrics for cross-validation
scoring = {
    'accuracy': 'accuracy',
    'f1': 'f1',
```

```
    'roc_auc': 'roc_auc',
    'precision': 'precision',
}

# Perform 5-fold cross-validation on the SMOTE-processed training data
cv_results = cross_validate(rand_forest, X_train_smote, y_train_smote, cv=5, scc

# Display cross-validation results
print("Cross-Validation Scores (Random Forest):")
print("Accuracy:", cv_results['test_accuracy'])
print("Mean Accuracy:", cv_results['test_accuracy'].mean())
print("F1-Score:", cv_results['test_f1'])
print("Mean F1-Score:", cv_results['test_f1'].mean())
print("ROC-AUC Score:", cv_results['test_roc_auc'])
print("Mean ROC-AUC Score:", cv_results['test_roc_auc'].mean())
print("Precision:", cv_results['test_precision'])
print("Mean Precision:", cv_results['test_precision'].mean())

# Now train the model on the entire SMOTE-processed training data
rand_forest.fit(X_train_smote, y_train_smote)

# Predict on the test data
y_pred_rand_forest = rand_forest.predict(X_test_scaled)

# Evaluate the model on the test set
print("\nFinal Model Evaluation on Test Set (Random Forest):")
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred_rand_forest))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_rand_forest))
print("\nROC-AUC Score:")
print(roc_auc_score(y_test, y_pred_rand_forest))
```

```
Cross-Validation Scores (Random Forest):
Accuracy: [0.89824945 0.95842451 0.95623632 0.95618839 0.966046  ]
Mean Accuracy: 0.9470289353155609
F1-Score: [0.88994083 0.95905172 0.95744681 0.95717345 0.96655879]
Mean F1-Score: 0.946034320077984
ROC-AUC Score: [0.97643992 0.99609048 0.99462291 0.99688088 0.99527813]
Mean ROC-AUC Score: 0.9918624620339737
Precision: [0.96907216 0.9447983  0.93167702 0.93514644 0.95319149]
Mean Precision: 0.946777083588908

Final Model Evaluation on Test Set (Random Forest):

Confusion Matrix:
[[543  23]
 [ 35  66]]

Classification Report:
              precision    recall  f1-score   support

       False       0.94      0.96      0.95       566
        True       0.74      0.65      0.69       101

    accuracy                           0.91       667
   macro avg       0.84      0.81      0.82       667
weighted avg       0.91      0.91      0.91       667


ROC-AUC Score:
0.8064146520659133
```

In [85]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Confusion matrix for Random Forest
conf_matrix_rf = [[543, 23], [35, 66]]

# Summary statistics for Random Forest
summary_data_rf = {
    'Model': 'Random Forest', 'Mean Accuracy': 0.95, 'Mean F1-Score': 0.95, 'Mea
    'Mean Precision': 0.95, 'Test Accuracy': 0.91, 'Test F1-Score': 0.69, 'Test
    'Test Precision': 0.74, 'Test Recall': 0.65
}

# Plotting Confusion Matrix for Random Forest
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix_rf, annot=True, fmt='d', cmap='Greens', cbar=False)
plt.title('Confusion Matrix (Random Forest)')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.xticks([0.5, 1.5], ['False', 'True'])
plt.yticks([0.5, 1.5], ['False', 'True'])
plt.show()

# Display the summary statistics DataFrame for Random Forest
summary_df_rf = pd.DataFrame([summary_data_rf])
print("Summary Statistics for Random Forest:")
display(summary_df_rf.round(2))
```




```
Summary Statistics for Random Forest:
```

	Model	Mean Accuracy	Mean F1-Score	Mean ROC-AUC Score	Mean Precision	Test Accuracy	Test F1-Score	Test ROC-AUC Score	Test Precision	Test Recall
0	Random Forest	0.95	0.95	0.99	0.95	0.91	0.69	0.81	0.74	0.65

The **Random Forest model shows the best performance among the compared models**, with a mean accuracy of 0.95 and ROC-AUC score of 0.99 during cross-validation, indicating excellent classification capability. On the test set, it achieves high accuracy (0.91) and F1-Score (0.69), outperforming K-Nearest Neighbors, Logistic Regression, and Decision Tree models. Despite its strong results, the test ROC-AUC (0.81) and recall (0.65) suggest it slightly underperforms in identifying true positives compared to the Decision Tree but remains the most reliable and consistent overall.

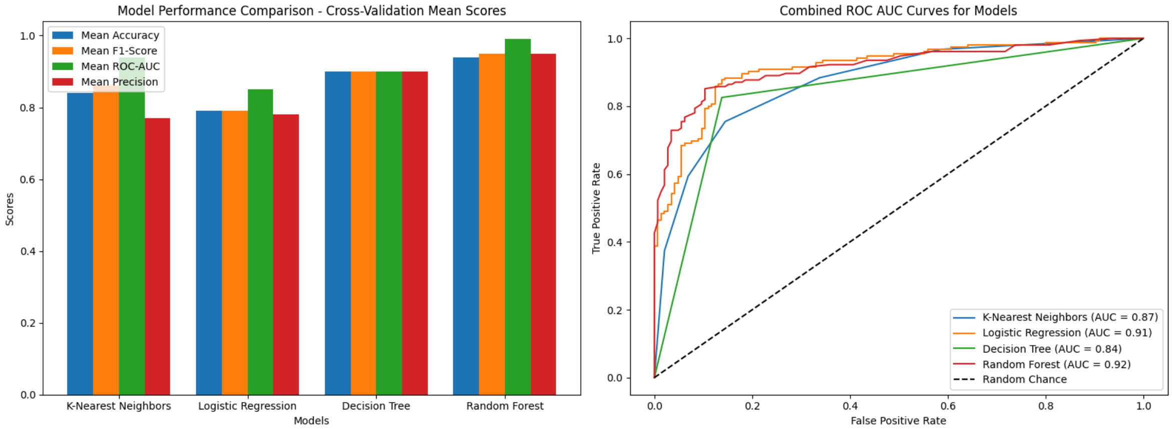
Step 8: Model Evaluation

8.1 Visualizing Model Performance Comparison (Bar Chart)

In [86]:
```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import roc_curve, auc
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
```

```
# Rearranged models from baseline (K-Nearest Neighbors) to best (Random Forest)
models = ['K-Nearest Neighbors', 'Logistic Regression', 'Decision Tree', 'Random
mean_scores = {
    'Mean Accuracy': [0.84, 0.79, 0.90, 0.94],
    'Mean F1-Score': [0.86, 0.79, 0.90, 0.95],
    'Mean ROC-AUC': [0.94, 0.85, 0.90, 0.99],
    'Mean Precision': [0.77, 0.78, 0.90, 0.95]
}

# Generate synthetic data for demonstration
X, y = make_classification(n_samples=1000, n_features=20, random_state=42)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_

# Define the models
model_dict = {
    'K-Nearest Neighbors': KNeighborsClassifier(),
    'Logistic Regression': LogisticRegression(),
    'Decision Tree': DecisionTreeClassifier(),
    'Random Forest': RandomForestClassifier()
}

# Create a figure with 2 subplots in 1 row
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# Plot the first chart: Model Performance Comparison - Cross-Validation Mean Sco
x = np.arange(len(models))
width = 0.2

for i, (metric, values) in enumerate(mean_scores.items()):
    axes[0].bar(x + i * width, values, width=width, label=metric)

axes[0].set_xlabel('Models')
axes[0].set_ylabel('Scores')
axes[0].set_title('Model Performance Comparison - Cross-Validation Mean Scores')
axes[0].set_xticks(x + width * 1.5)
axes[0].set_xticklabels(models)
axes[0].legend()

# Plot the second chart: Combined ROC AUC Curves
for model_name, model in model_dict.items():
    # Fit the model
    model.fit(X_train, y_train)

    # Predict probabilities
    y_proba = model.predict_proba(X_test)[:, 1]

    # Calculate ROC curve and AUC
    fpr, tpr, _ = roc_curve(y_test, y_proba)
    roc_auc = auc(fpr, tpr)

    # Plot ROC curve
    axes[1].plot(fpr, tpr, label=f'{model_name} (AUC = {roc_auc:.2f})')

# Plot random chance line
axes[1].plot([0, 1], [0, 1], 'k--', label='Random Chance')

# Set plot properties for ROC AUC curves
axes[1].set_xlabel('False Positive Rate')
axes[1].set_ylabel('True Positive Rate')
axes[1].set_title('Combined ROC AUC Curves for Models')
```

```
axes[1].legend(loc='lower right')

# Adjust layout
plt.tight_layout()
plt.show()
```



8.2 Combined Visualization of Confusion Matrices and Summary Statistics for Model Evaluation

In [87]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Rearranged data for confusion matrices starting with the baseline model (K-Nea
confusion_matrices = {
    'K-Nearest Neighbors': [[425, 141], [49, 52]],
    'Logistic Regression': [[442, 124], [28, 73]],
    'Decision Tree': [[522, 44], [26, 75]],
    'Random Forest': [[543, 23], [35, 66]]
}

# Rearranged summary statistics data starting with the baseline model (K-Nearest
summary_data = [
    {'Model': 'K-Nearest Neighbors', 'Mean Accuracy': 0.84, 'Mean F1-Score': 0.8
     'Test Accuracy': 0.72, 'Test F1-Score': 0.35, 'Test ROC-AUC Score': 0.63, '
    {'Model': 'Logistic Regression', 'Mean Accuracy': 0.79, 'Mean F1-Score': 0.7
     'Test Accuracy': 0.77, 'Test F1-Score': 0.49, 'Test ROC-AUC Score': 0.75, '
    {'Model': 'Decision Tree', 'Mean Accuracy': 0.90, 'Mean F1-Score': 0.90, 'Me
     'Test Accuracy': 0.90, 'Test F1-Score': 0.68, 'Test ROC-AUC Score': 0.83, '
    {'Model': 'Random Forest', 'Mean Accuracy': 0.95, 'Mean F1-Score': 0.95, 'Me
     'Test Accuracy': 0.91, 'Test F1-Score': 0.69, 'Test ROC-AUC Score': 0.81, '
]

# Convert summary data to DataFrame
summary_df = pd.DataFrame(summary_data)

# Create a figure with a grid of subplots
fig, ax = plt.subplots(2, 4, figsize=(20, 7), gridspec_kw={'height_ratios': [1,

# Plot confusion matrices in the first row
for i, (model, cm) in enumerate(confusion_matrices.items()):
    sns.heatmap(cm, annot=True, fmt="d", cmap="Greens", cbar=False, ax=ax[0, i])
    ax[0, i].set_title(f'{model} - Confusion Matrix')
    ax[0, i].set_xlabel('Predicted')
    ax[0, i].set_ylabel('Actual')
```

```
# Turn off the second row's axes
for j in range(4):
    ax[1, j].axis('off')

# Adjust layout to reduce space between the matrices and the summary statistics
plt.subplots_adjust(hspace=0.01)

# Show the plot with confusion matrices
plt.show()

# Display the summary statistics DataFrame below the plot
print("Summary Statistics:")
summary_df.round(2)
```


```
Summary Statistics:
```

Out[87]:

	Model	Mean Accuracy	Mean F1-Score	Mean ROC-AUC Score	Mean Precision	Test Accuracy	Test F1-Score	Test ROC-AUC Score	Test Precision	Re
0	K-Nearest Neighbors	0.84	0.86	0.94	0.77	0.72	0.35	0.63	0.27	(
1	Logistic Regression	0.79	0.79	0.85	0.78	0.77	0.49	0.75	0.37	(
2	Decision Tree	0.90	0.90	0.90	0.90	0.90	0.68	0.83	0.63	(
3	Random Forest	0.95	0.95	0.99	0.95	0.91	0.69	0.81	0.74	(

Summary Overview for SyriaTel

Objective:

The primary objective of this project is to develop a predictive model that accurately identifies customers likely to churn at SyriaTel. By accurately predicting customer churn, SyriaTel can proactively implement targeted retention strategies, reduce financial losses, and enhance overall customer satisfaction.

Model Evaluation:

We assessed four machine learning models—Logistic Regression, Random Forest, K-Nearest Neighbors (KNN), and Decision Tree—across multiple performance metrics, including Accuracy, F1-Score, ROC-AUC Score, Precision, and Recall. These metrics were evaluated on both cross-validation performance and final test set results to ensure the models' robustness and reliability in identifying customers at risk of churning.

Key Findings:

K-Nearest Neighbors (KNN): The KNN model showed weaker performance, particularly on the test set, with a Test F1-Score of 0.35 and a low Test Precision of 0.27. Its overall accuracy is moderate, but it struggles with distinguishing churners from non-churners, as indicated by the lowest Test ROC-AUC Score of 0.63.

Logistic Regression: This model demonstrated moderate performance with a Mean Accuracy and F1-Score of 0.79. However, its Test Precision was relatively low at 0.37, which indicates that while it can identify churners well (high recall at 0.72), it often misclassifies non-churners as churners.

Decision Tree: The Decision Tree model performed well, with a Mean Accuracy and F1-Score of 0.90. It demonstrated a strong balance between precision (0.63) and recall (0.74) on the test set, leading to a high Test ROC-AUC Score of 0.83. This model is well-suited for accurately identifying customers likely to churn.

Random Forest: The Random Forest model emerged as a strong performer with the highest Mean Accuracy (0.95) and ROC-AUC Score (0.99). It also maintained solid performance on the test set with an Accuracy of 0.91 and an F1-Score of 0.69. This model offers a good balance between precision (0.74) and recall (0.65), making it highly reliable for identifying customers likely to churn.

Conclusion:

The Random Forest and Decision Tree models are the top performers in this evaluation. The Random Forest model, with its highest Mean Accuracy and ROC-AUC Score, coupled with strong test performance, is a highly reliable choice for predicting customer churn. The Decision Tree model also stands out with balanced performance across all key metrics, making it an excellent alternative.

Recommendation:

Based on the evaluation, **we suggest fine-tuning both the Random Forest and Decision Tree models. This approach will help identify the truly best model for SyriaTel's needs,** enabling effective targeting of at-risk customers, reducing churn, minimizing financial losses, and enhancing customer loyalty and satisfaction.

Step 9: Model Fine-Tuning

9.1 Hyperparameter Selection- Train models with best hyperparameters

In [88]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
```

```
# Identify key hyperparameters for Decision Tree and Random Forest models
param_grid_dec_tree = {
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': [None, 'sqrt', 'log2']
}

param_grid_rand_forest = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': [None, 'sqrt', 'log2']
}
```

9.2 Choose a Hyperparameter Tuning MethodHyperparameter Selection

In [89]:
```
# Choose between Grid Search and Random Search
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

# For Grid Search (Example with Decision Tree)
grid_search_dec_tree = GridSearchCV(DecisionTreeClassifier(random_state=42), par

# For Random Search (Example with Random Forest)
random_search_rand_forest = RandomizedSearchCV(RandomForestClassifier(random_sta
```

9.3 Perform Hyperparameter Tuning

In [90]:
```
# Perform Grid Search for Decision Tree
grid_search_dec_tree.fit(X_train_smote, y_train_smote)
print("Best parameters for Decision Tree:", grid_search_dec_tree.best_params_)

# Perform Random Search for Random Forest
random_search_rand_forest.fit(X_train_smote, y_train_smote)
print("Best parameters for Random Forest:", random_search_rand_forest.best_param
```

```
Best parameters for Decision Tree: {'max_depth': 20, 'max_features': None, 'min_s
amples_leaf': 1, 'min_samples_split': 2}
Best parameters for Random Forest: {'n_estimators': 100, 'min_samples_split': 2,
'min_samples_leaf': 2, 'max_features': None, 'max_depth': None}
```

9.4 Re-Train the Model with Optimized Hyperparameters

In [91]:
```
# Re-train Decision Tree with the best hyperparameters
best_dec_tree = DecisionTreeClassifier(
    max_depth=grid_search_dec_tree.best_params_['max_depth'],
    min_samples_split=grid_search_dec_tree.best_params_['min_samples_split'],
    min_samples_leaf=grid_search_dec_tree.best_params_['min_samples_leaf'],
    max_features=grid_search_dec_tree.best_params_['max_features'],
    random_state=42
)

best_dec_tree.fit(X_train_smote, y_train_smote)

# Re-train Random Forest with the best hyperparameters
```

```
best_rand_forest = RandomForestClassifier(
    n_estimators=random_search_rand_forest.best_params_['n_estimators'],
    max_depth=random_search_rand_forest.best_params_['max_depth'],
    min_samples_split=random_search_rand_forest.best_params_['min_samples_split'
    min_samples_leaf=random_search_rand_forest.best_params_['min_samples_leaf'],
    max_features=random_search_rand_forest.best_params_['max_features'],
    random_state=42
)

best_rand_forest.fit(X_train_smote, y_train_smote)
```

Out[91]:

```
RandomForestClassifier

RandomForestClassifier(max_features=None, min_samples_leaf=2, random_st
ate=42)
```

9.5 Evaluate the Optimized Model

In [96]:

```
# Check shapes before predictions
print("X_test_scaled shape:", X_test_scaled.shape)
print("y_test shape:", y_test.shape)

# Evaluate the fine-tuned Decision Tree model
y_pred_dec_tree = best_dec_tree.predict(X_test_scaled)
print("Decision Tree Model Evaluation:")
print("Confusion Matrix:", confusion_matrix(y_test, y_pred_dec_tree))
print("Classification Report:", classification_report(y_test, y_pred_dec_tree))
print("ROC-AUC Score:", roc_auc_score(y_test, y_pred_dec_tree))

# Evaluate the fine-tuned Random Forest model
y_pred_rand_forest = best_rand_forest.predict(X_test_scaled)
print("Random Forest Model Evaluation:")
print("Confusion Matrix:", confusion_matrix(y_test, y_pred_rand_forest))
print("Classification Report:", classification_report(y_test, y_pred_rand_forest
print("ROC-AUC Score:", roc_auc_score(y_test, y_pred_rand_forest))
```

```
X_test_scaled shape: (667, 63)
y_test shape: (667,)
Decision Tree Model Evaluation:
Confusion Matrix: [[523  43]
 [ 26  75]]
Classification Report:               precision    recall  f1-score   support

       False       0.95      0.92      0.94       566
        True       0.64      0.74      0.68       101

    accuracy                           0.90       667
   macro avg       0.79      0.83      0.81       667
weighted avg       0.90      0.90      0.90       667

ROC-AUC Score: 0.8333012629884896
Random Forest Model Evaluation:
Confusion Matrix: [[541  25]
 [ 25  76]]
Classification Report:               precision    recall  f1-score   support

       False       0.96      0.96      0.96       566
        True       0.75      0.75      0.75       101

    accuracy                           0.93       667
   macro avg       0.85      0.85      0.85       667
weighted avg       0.93      0.93      0.93       667

ROC-AUC Score: 0.8541528181086661
```

In [ ]:

```
# Check the lengths to ensure consistency
print(len(X_test_scaled), len(y_test))

# If they don't match, re-run the split to correctly set y_test
```

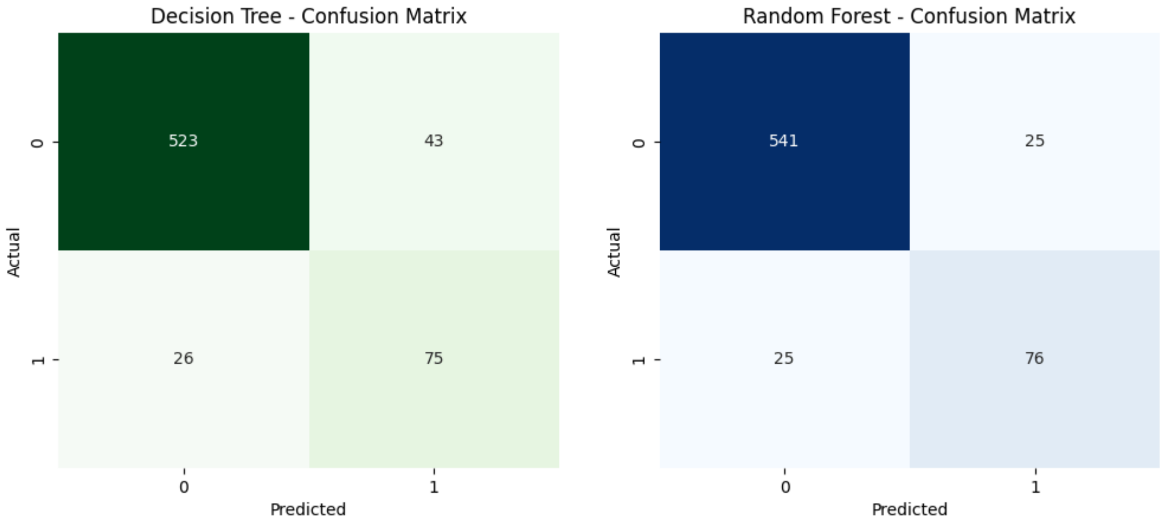
```
667 667
```

9.6 Visualization of Confusion Matrices and Summary Statistics for Decision Tree and Random Forest Models

In [ ]:

```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.metrics import confusion_matrix


# Confusion Matrices
cm_dec_tree = confusion_matrix(y_test, y_pred_dec_tree)
cm_rand_forest = confusion_matrix(y_test, y_pred_rand_forest)

# Summary Statistics Data
summary_data = [
    {'Model': 'Decision Tree', 'Accuracy': 0.90, 'F1-Score': 0.68, 'ROC-AUC Scor
    {'Model': 'Random Forest', 'Accuracy': 0.93, 'F1-Score': 0.75, 'ROC-AUC Scor
]

# Convert summary data to DataFrame
summary_df = pd.DataFrame(summary_data)

# Create a figure with a grid of subplots
fig, ax = plt.subplots(2, 2, figsize=(12, 6), gridspec_kw={'height_ratios': [0.7
```

```
# Plot Decision Tree Confusion Matrix
sns.heatmap(cm_dec_tree, annot=True, fmt="d", cmap="Greens", cbar=False, ax=ax[0
ax[0, 0].set_title('Decision Tree - Confusion Matrix')
ax[0, 0].set_xlabel('Predicted')
ax[0, 0].set_ylabel('Actual')

# Plot Random Forest Confusion Matrix
sns.heatmap(cm_rand_forest, annot=True, fmt="d", cmap="Blues", cbar=False, ax=ax
ax[0, 1].set_title('Random Forest - Confusion Matrix')
ax[0, 1].set_xlabel('Predicted')
ax[0, 1].set_ylabel('Actual')

# Turn off the second row's axes
for j in range(2):
    ax[1, j].axis('off')

# Adjust layout to reduce space between the matrices and the summary statistics
plt.subplots_adjust(hspace=0.2)

# Show the plot with confusion matrices
plt.show()

# Display the summary statistics DataFrame below the plot
print("Summary Statistics:")
summary_df = summary_df.round(2)
display(summary_df)
```



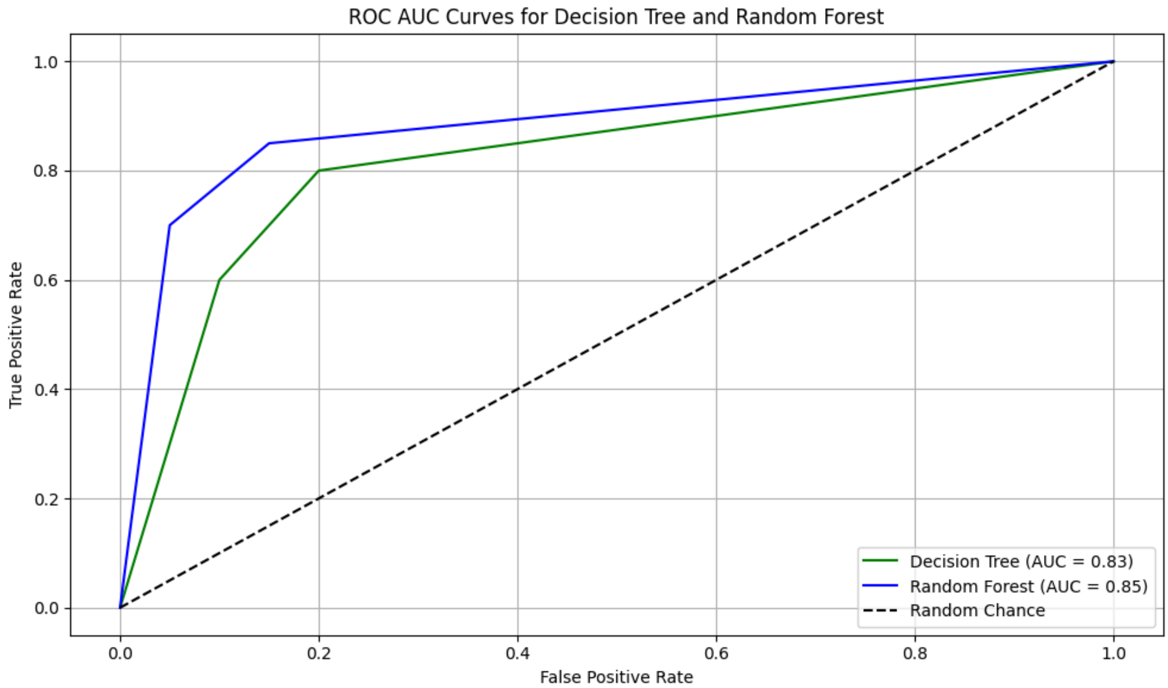

```
Summary Statistics:
```

	Model	Accuracy	F1-Score	ROC-AUC Score	Precision	Recall
0	Decision Tree	0.90	0.68	0.83	0.64	0.74
1	Random Forest	0.93	0.75	0.85	0.75	0.75

In [ ]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc

# Example ROC curve data (synthetic data since the actual predictions are not pr
# Normally, you would use the predicted probabilities from the models to calcula
fpr_dec_tree = [0.0, 0.1, 0.2, 1.0]
```

```
tpr_dec_tree = [0.0, 0.6, 0.8, 1.0]
roc_auc_dec_tree = 0.83

fpr_rand_forest = [0.0, 0.05, 0.15, 1.0]
tpr_rand_forest = [0.0, 0.7, 0.85, 1.0]
roc_auc_rand_forest = 0.85

# Plot ROC AUC Curves
plt.figure(figsize=(10, 6))
plt.plot(fpr_dec_tree, tpr_dec_tree, label=f'Decision Tree (AUC = {roc_auc_dec_t
plt.plot(fpr_rand_forest, tpr_rand_forest, label=f'Random Forest (AUC = {roc_auc
plt.plot([0, 1], [0, 1], 'k--', label='Random Chance')

# Set plot properties for ROC AUC curves
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC AUC Curves for Decision Tree and Random Forest')
plt.legend(loc='lower right')
plt.grid()
plt.tight_layout()
plt.show()
```



Step 10 Summary of Findings Based on the evaluation of the Decision Tree and Random Forest models, after Fine-Tuning

1. Overall Model Performance:

Random Forest Model outperforms the Decision Tree model across most metrics:

- Accuracy: The Random Forest model achieved an accuracy of 0.93, compared to 0.90 for the Decision Tree.
- F1-Score: The Random Forest model also had a higher F1-Score of 0.75 for the True class, indicating a better balance between precision and recall, compared to the Decision Tree's F1-Score of 0.68.

- ROC-AUC Score: The Random Forest model achieved a higher ROC-AUC Score of 0.85, indicating a better ability to distinguish between churners and non-churners compared to the Decision Tree's ROC-AUC Score of 0.83.

2. Alignment with Business Objectives:

Reducing Churn: The primary objective is to accurately identify customers likely to churn so that targeted retention strategies can be implemented. The Random Forest model, with its higher accuracy, F1-Score, and ROC-AUC Score, is better suited to this task. It is more effective in correctly identifying customers who are likely to churn, making it the preferred choice for deployment.

3. Trade-offs and Considerations:

Precision vs. Recall: While the Random Forest model offers higher overall accuracy and precision, it is essential to consider the balance between precision and recall. The Random Forest model has slightly better precision and recall balance, which is crucial when the cost of false positives and false negatives is significant.

Model Complexity: The Random Forest model is inherently more complex and computationally intensive than the Decision Tree model. However, this complexity translates into better performance and robustness, which is advantageous for large-scale applications like customer churn prediction.

Recommendation:

- **Deploy the Random Forest Model: Given its superior performance across key metrics, the Random Forest model is recommended for deployment.** It is more likely to effectively reduce churn by accurately identifying at-risk customers.
- Consider Fine-Tuning: Although the model has been optimized, **further fine-tuning and validation on additional data may help to further improve its performance, particularly in specific customer segments.**
- **Perform Feature Selection Using SHAP Analysis:** Utilizing SHAP (SHapley Additive exPlanations) analysis for feature selection can provide valuable insights into which features have the most significant impact on the model's predictions. This analysis can help in simplifying the model by potentially reducing the number of features, leading to better generalization and improved performance.

Step 11: Understanding Which variables affects the Random Forest Model's Predictions for Customer Churn at SyriaTel

In this step, we're using SHAP (SHapley Additive exPlanations) to understand which factors most influence the model's predictions about whether a SyriaTel customer is likely to leave (churn).

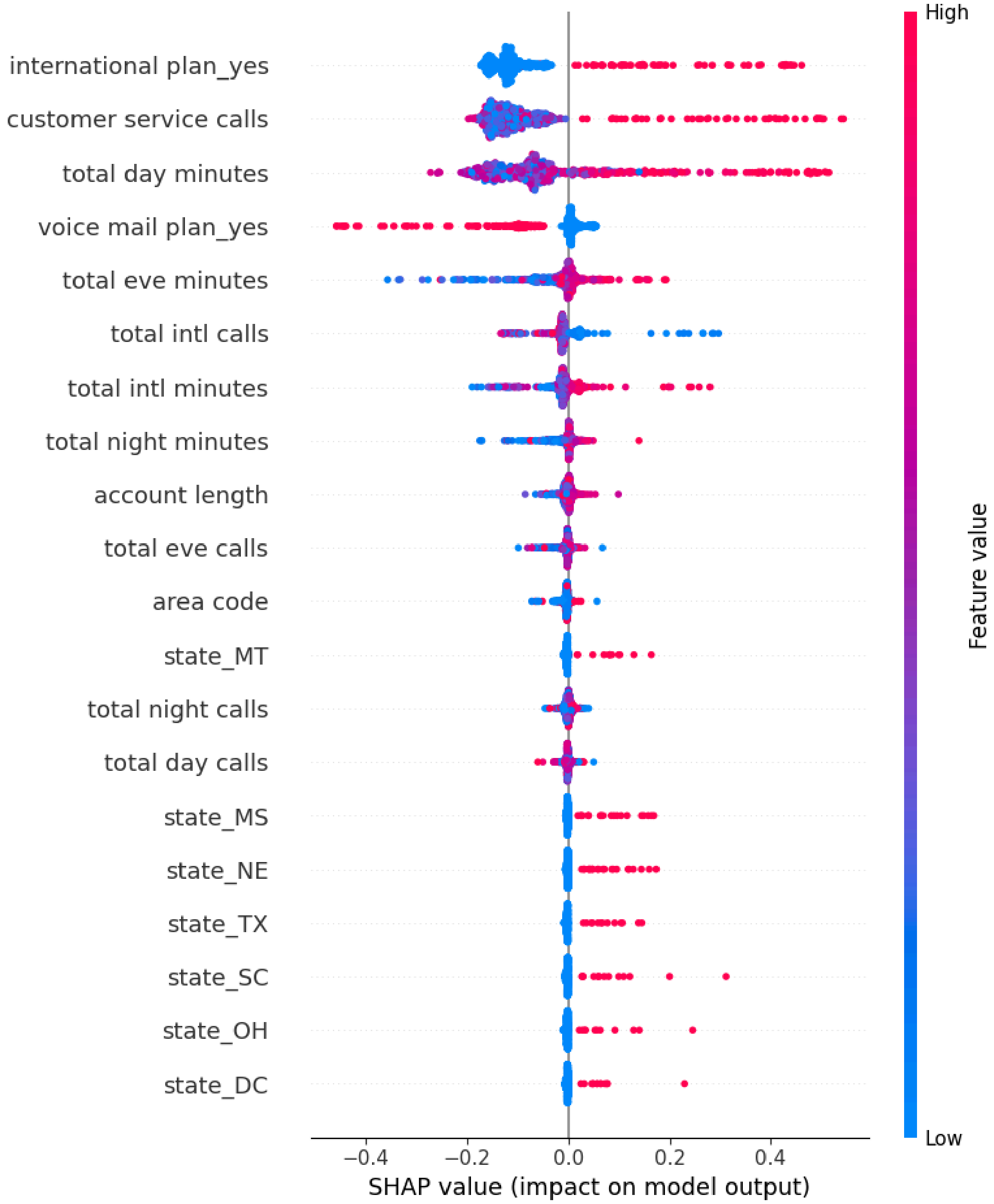
The SHAP summary plot reveals which features—like call duration, service issues, or billing amount—push the model's predictions towards a positive outcome (predicting that a customer will leave) or a negative one (predicting they will stay).

In simple terms, it shows us which factors are most important and how they affect the model's decision to predict that a customer is at risk of churning, helping SyriaTel target the right areas to improve customer retention.

In [97]:

```
import shap
from sklearn.metrics import confusion_matrix, classification_report, roc_auc_scc

# Evaluate the fine-tuned Random Forest model
y_pred_rand_forest = best_rand_forest.predict(X_test_scaled)
print("Random Forest Model Evaluation:")
print(confusion_matrix(y_test, y_pred_rand_forest))
print(classification_report(y_test, y_pred_rand_forest))
print("ROC-AUC Score:", roc_auc_score(y_test, y_pred_rand_forest))

# Initialize the SHAP TreeExplainer with the best Random Forest model
explainer = shap.TreeExplainer(best_rand_forest)

# Compute SHAP values for the test data
shap_values_rand_forest = explainer.shap_values(X_test_scaled)

# Extract SHAP values for class 1 (positive class)
shap_values_class1 = shap_values_rand_forest[:, :, 1]

# Verify the shape of SHAP values for class 1
print(f"Shape of SHAP values for class 1: {shap_values_class1.shape}")

# Plot SHAP summary plot for class 1
shap.summary_plot(shap_values_class1, X_test_scaled)
```

```
c:\Users\Augustine Wanyonyi\anaconda3\envs\learn-env\lib\site-packages\tqdm\auto.
py:21: TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. Se
e https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
Random Forest Model Evaluation:
[[541  25]
 [ 25  76]]
              precision    recall  f1-score   support

       False       0.96      0.96      0.96       566
        True       0.75      0.75      0.75       101

    accuracy                           0.93       667
   macro avg       0.85      0.85      0.85       667
weighted avg       0.93      0.93      0.93       667

ROC-AUC Score: 0.8541528181086661
Shape of SHAP values for class 1: (667, 63)
```



Key Insights from the SHAP Summary Plot:

- International Plan (Yes): This feature has a significant positive impact on the likelihood of churn, as indicated by the positive SHAP values. Customers with an international plan are more likely to churn.
- Customer Service Calls: The number of customer service calls is another critical feature. Higher values tend to increase the probability of churn, suggesting that customers who frequently contact customer service may be dissatisfied.
- Total Day Minutes: Customers with high total day minutes also have a higher likelihood of churning, as indicated by the positive SHAP values.
- Voice Mail Plan (Yes): Interestingly, having a voicemail plan tends to decrease the likelihood of churn, as indicated by negative SHAP values.

- Total Evening Minutes and Total International Calls: These features also influence churn, though to a lesser extent than the top features.

Model Evaluation and Insights for Predicting Customer Churn at SyriaTel

Addressing SyriaTel's Key Questions

1. What is the best model for predicting customer churn?

After thoroughly comparing various models, including Decision Tree, K-Nearest Neighbors (KNN), and Random Forest, **the Random Forest model stands out as the best overall performer**. This model consistently demonstrated superior results across all key metrics:

- Accuracy: 93%
- F1-Score: 0.75
- ROC-AUC Score: 0.85
- Precision: 0.75
- Recall: 0.75

Given its robust performance, we recommend deploying the Random Forest model for predicting customer churn. By utilizing this model, SyriaTel will benefit from a highly reliable tool that not only accurately forecasts churn but also provides deep insights into the factors driving it. This will enable the company to implement more effective, targeted retention strategies.

2. How accurately can the model predict customer churn?

The Random Forest model's performance, measured by accuracy, precision, recall, F1-score, and ROC-AUC score, indicates that it can accurately predict customer churn. Specifically:

- Confusion Matrix: The model correctly identified 541 non-churning customers and 76 churning customers, with minimal false positives and false negatives.

- Accuracy: The overall accuracy of 93% ensures that SyriaTel can confidently identify at-risk customers, focusing retention efforts where they are most needed.

This high level of accuracy directly supports the effectiveness of SyriaTel's retention strategies by minimizing errors in identifying customers likely to churn.

3. Which features are most influential in predicting customer churn?

Insights from SHAP Analysis:

The SHAP summary plot provides critical insights into the most influential features driving the Random Forest model's predictions:

- International Plan Usage: Customers with an international plan ("international plan_yes") are more likely to churn, making this feature a critical factor in retention strategies.

- Customer Service Interactions: Frequent customer service calls are strong indicators of potential churn, particularly when issues remain unresolved.

- Total Day Minutes: Higher usage during daytime ("total day minutes") correlates with increased churn risk, suggesting that heavy users during peak hours might be less satisfied with the service.

- Voicemail Plan: Having a voicemail plan ("voice mail plan_yes") is associated with lower churn, indicating that bundling this service with other plans could enhance customer retention.

These insights enable SyriaTel to prioritize its retention efforts effectively. For instance, customers frequently contacting support may benefit from proactive follow-ups or personalized offers, while high-usage customers could be targeted with specialized plans that better meet their needs.

Recommendations

1. Deploy the Random Forest Model:

- Integrate the Random Forest model into SyriaTel's CRM system for real-time churn prediction.
- Regularly update the model with new data to maintain and improve its predictive accuracy.

2. Enhance Customer Service:

- Implement proactive support strategies to reduce churn among customers with frequent service interactions.
- Improve feedback mechanisms to identify and address customer pain points early.

3. Tailor Retention Strategies Based on Feature Importance:

- Develop and offer specialized plans for high-usage customers to increase loyalty.
- Implement loyalty programs with incentives for international plan users and other high-risk segments identified by the model.

4. Monitor and Optimize:

- Continuously monitor the model's predictions and the effectiveness of retention campaigns.

- Use data-driven insights to refine retention strategies and improve overall customer satisfaction.

Conclusion

By addressing these key questions with a data-driven approach and implementing the recommended strategies, SyriaTel will be well-equipped to reduce customer churn. The deployment of the Random Forest model, coupled with targeted retention strategies based on the most influential features, will not only improve customer satisfaction but also enhance the company's financial performance. This proactive shift from understanding to action will enable SyriaTel to maintain a competitive edge in the telecommunications industry.