SyriaTel Customer Churn Prediction

Business Understanding

This project aims to help SyriaTel identify customers at risk of leaving so the company can take proactive steps to retain them. By accurately predicting customer churn, SyriaTel can take proactive measures to retain these customers, thereby reducing revenue loss and increasing customer lifetime value.The management and marketing teams can implement targeted strategies like personalized offers and improved service, reducing customer loss and boosting profitability.

Problem Statement ¶

SyriaTel has been experiencing a high churn rate leading to losses for the company.This project aims to create a predictive model that accurately identifies customers at risk of churning for SyriaTel, a telecommunications company.

By proactively identifying customers who may discontinue their services, the objective is to decrease customer attrition and retain a higher number of customers. Ultimately, the project seeks to support SyriaTel in reducing financial losses caused by customer churn, improving overall customer retention rates, and optimizing business strategies to enhance profitability.

Objectives

The primary business objectives of this project for SyriaTel are to reduce customer churn, improve customer retention rates, and enhance overall customer satisfaction.

We will focus on the following questions to achieve our objectives;

1. Identify Key Predictors of Customer Churn: Determine which features most significantly influence customer churn at SyriaTel.
2. Provide Actionable Insights for Customer Retention by translating the findings from the predictive models into actionable recommendations for the management and marketing teams at SyriaTel.
3. Build and compare different machine learning models that is, logistic regression and decision trees to predict customer churn with high accuracy.

Data understanding

In [19]:
```
#Import relevant libraries

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

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from imblearn.over_sampling import SMOTE
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_
score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier


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

Loading data

In [20]:
```
#Importing dataset
pd.set_option('display.max_columns', None)
df = pd.read_csv('customer_churn.csv')
df.head()
```

Out[20]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	tota ev minute
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	197.
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	195.
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	121.
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	61.
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	148.

In [21]:
```
df.describe()
```

Out[21]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total ev minute
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.00000
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	200.98034
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50.71384
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0.00000
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166.60000
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201.40000
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235.30000
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363.70000

In [22]:
```
df.info()
```

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

Data cleaning

In [23]:
```
#Check for missing data
df.isnull().sum()
```

Out[23]:

	0
state	0
account length	0
area code	0
phone number	0
international plan	0
voice mail plan	0
number vmail messages	0
total day minutes	0
total day calls	0
total day charge	0
total eve minutes	0
total eve calls	0
total eve charge	0
total night minutes	0
total night calls	0
total night charge	0
total intl minutes	0
total intl calls	0
total intl charge	0
customer service calls	0
churn	0

dtype: int64

There is no missing data in the dataset

Handling duplicates

In [24]:
```
#Checking for duplicates
df.duplicated().sum()
```

Out[24]: 0

Appears like there are no duplicates in the data set|

Exploratory Data Analysis

In [25]:
```
# Convert the "churn" column to integer type
df["churn"] = df["churn"].astype(int)
```

We split the data into categorical and numerical data

In [26]:
```
# seperating categorical from numerical data
categorical_df = df.select_dtypes("object")
categorical_df = categorical_df.drop("phone number", axis=1)
categorical_df.head()
```

Out[26]:

	state	international plan	voice mail plan
0	KS	no	yes
1	OH	no	yes
2	NJ	no	no
3	OH	yes	no
4	OK	yes	no

In [27]:
```
# numerical data
numeric_df =  df.select_dtypes("number")
numeric_df.head()
```

Out[27]:

	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	total night minutes	total night calls	t n cha
0	128	415	25	265.1	110	45.07	197.4	99	16.78	244.7	91	1
1	107	415	26	161.6	123	27.47	195.5	103	16.62	254.4	103	1
2	137	415	0	243.4	114	41.38	121.2	110	10.30	162.6	104	
3	84	408	0	299.4	71	50.90	61.9	88	5.26	196.9	89	
4	75	415	0	166.7	113	28.34	148.3	122	12.61	186.9	121	

Univariate Analysis

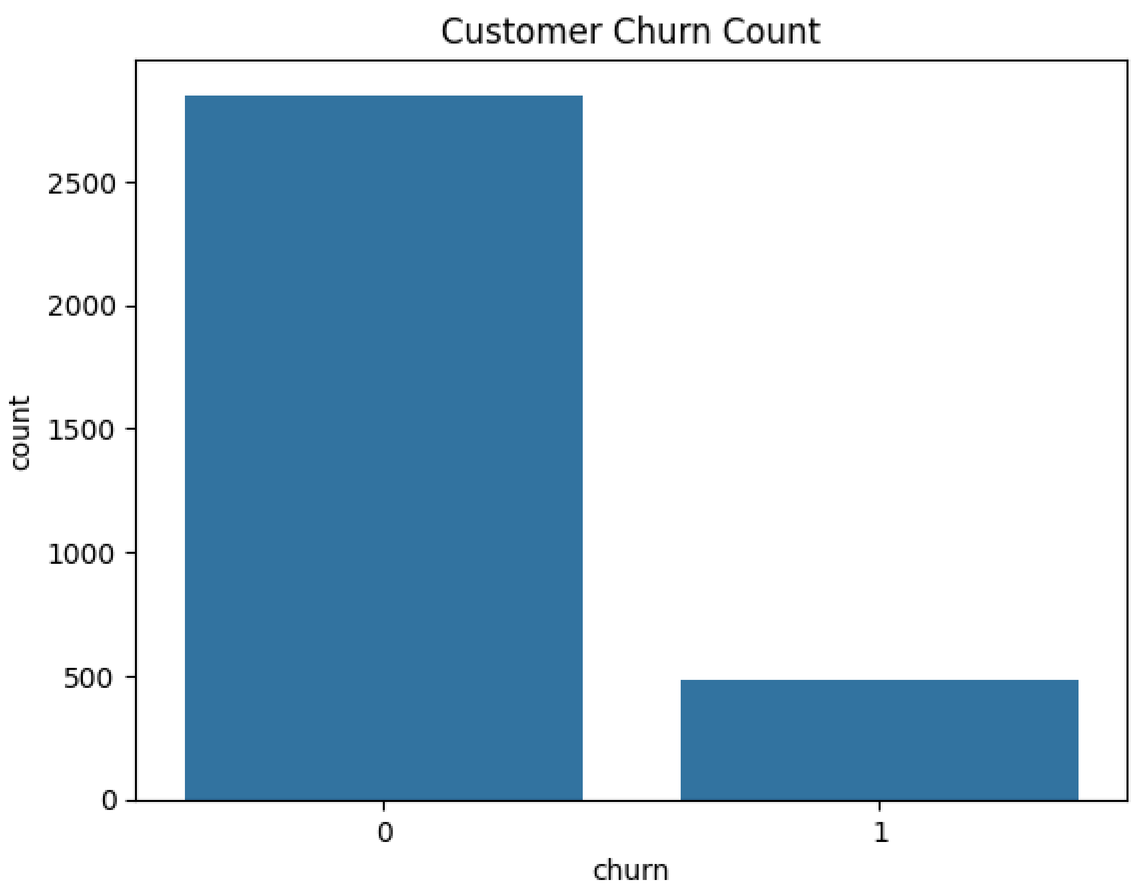
Let us check the distribution of the target variable

Checking the target variable's count helps us understand the class distribution, revealing the number of customers who churned versus those who stayed.

BIvariate analysis

In [28]:
```
# Count of churn (target variable)

print(df['churn'].value_counts())

# Visualize the churn distribution using a count plot
sns.countplot(data=df, x='churn')
plt.title('Customer Churn Count')
plt.show()
```

```
churn
0    2850
1     483
Name: count, dtype: int64
```

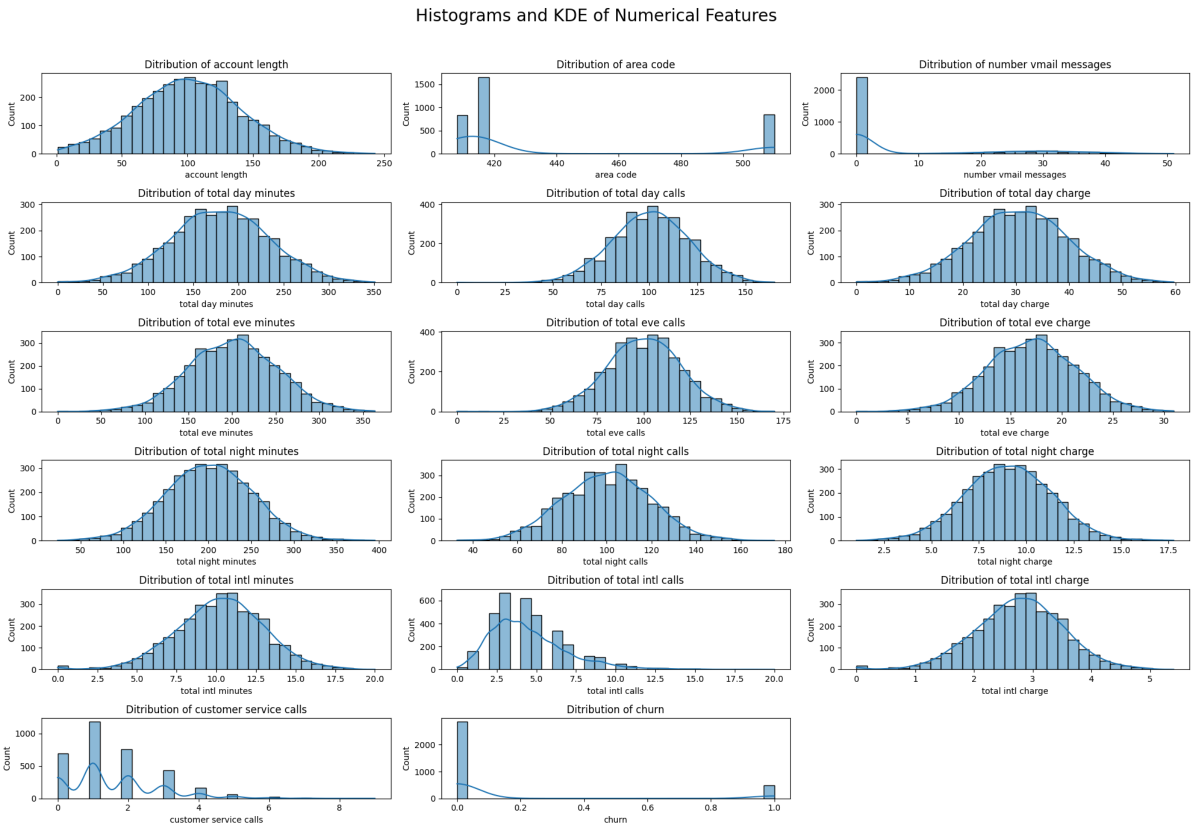


There is an inbalance between the classes

Histograms and KDE of Numerical Features

To identify the shape, skewness, and spread of the data we plotted histograms combined with Kernel Density Estimation (KDE).

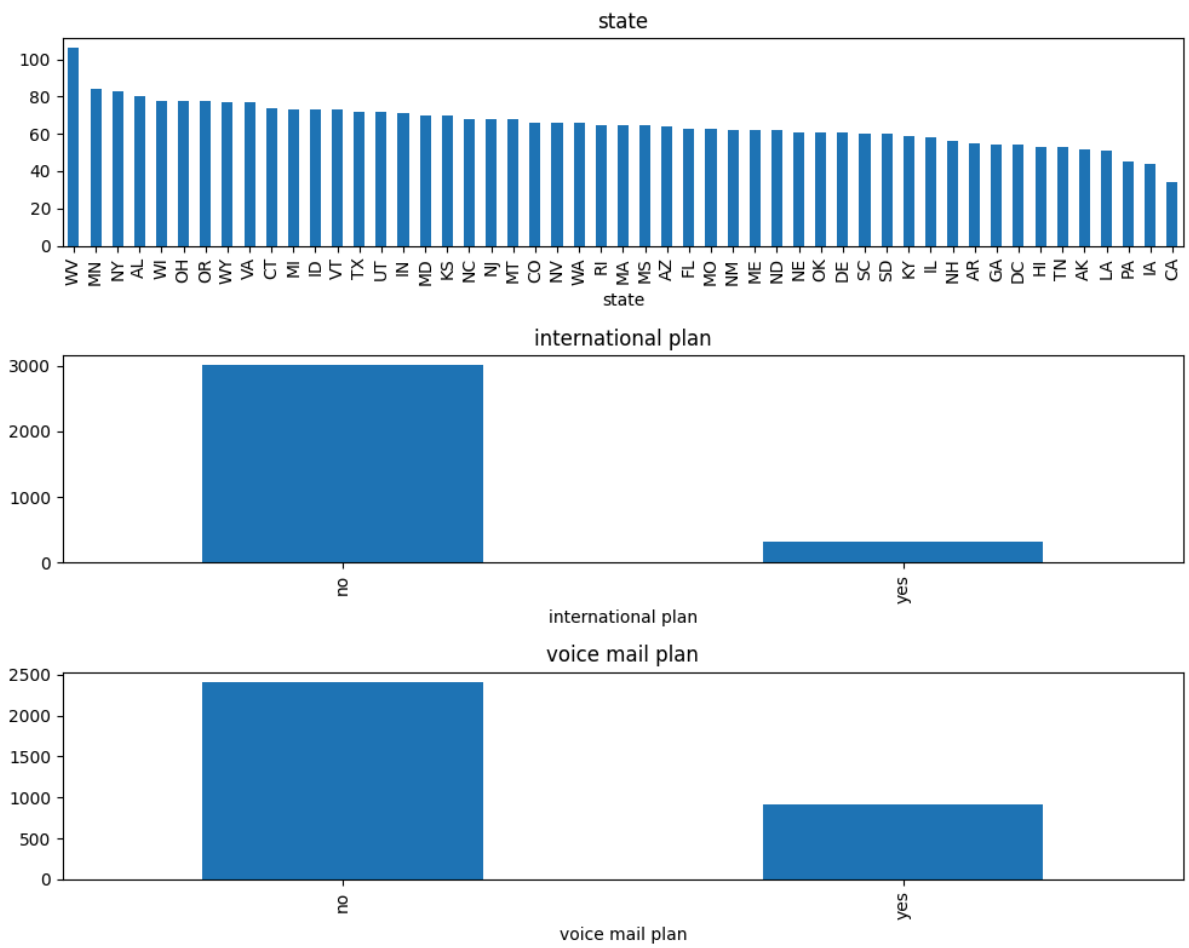
In [29]:
```
# Visualizing the distributions of numerical features using histograms with KD
E

plt.figure(figsize=(20, 14))

for i, column in enumerate(numeric_df.columns):
    plt.subplot(len(numeric_df.columns) // 3 + 1, 3, i + 1)
    sns.histplot(numeric_df[column], kde=True, bins=30)
    plt.title(f'Ditribution of {column}')

plt.suptitle('Histograms and KDE of Numerical Features', fontsize=20)
plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
```



Visualizing Categorical Features

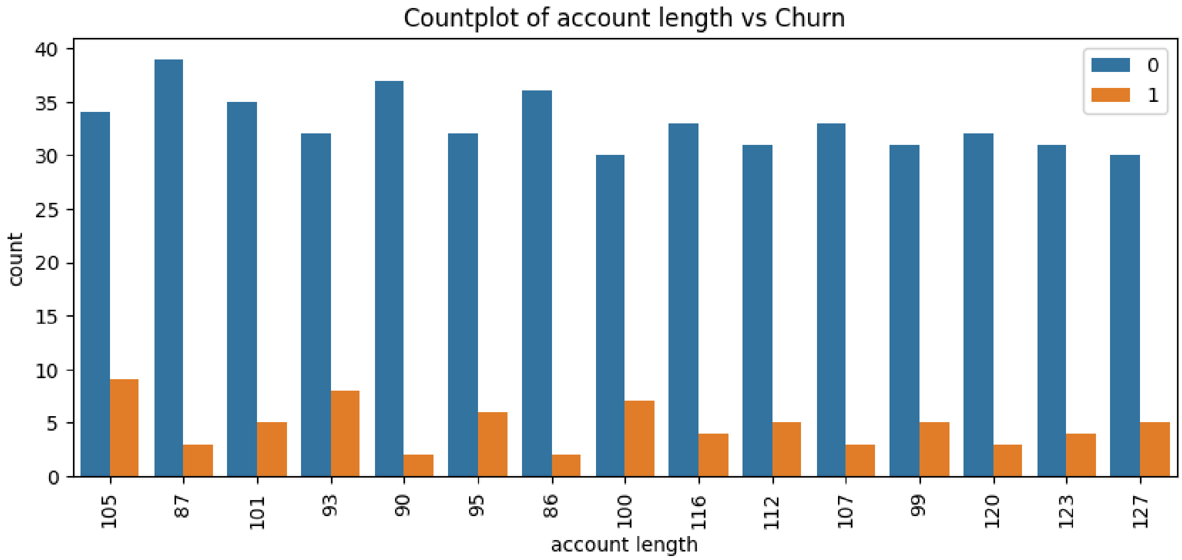
We use bar plots to visualize categorical data, which display the frequency of each category in the data.

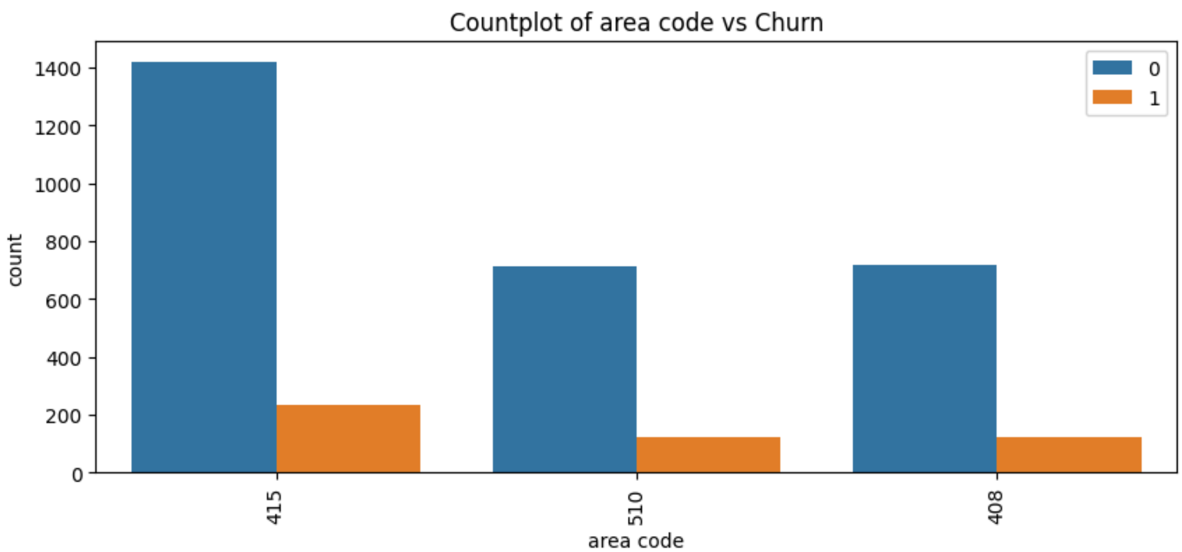
In [30]:
```
# Visualizing categorical features

# Create the figure and axis objects
fig, ax = plt.subplots(nrows= 3, ncols= 1, figsize=(10, 8))

# Flatten the axis array so that it can be iterated over easily
ax = ax.flatten()

# Loop over the columns and plot a density graph for each one

columns = categorical_df.columns.tolist()

for i, col in enumerate (columns):
    categorical_df[col].value_counts().plot(kind="bar", ax=ax[i])
    ax[i].set_title(col)

# Adjust the spacing between the subplots
fig.tight_layout()
```

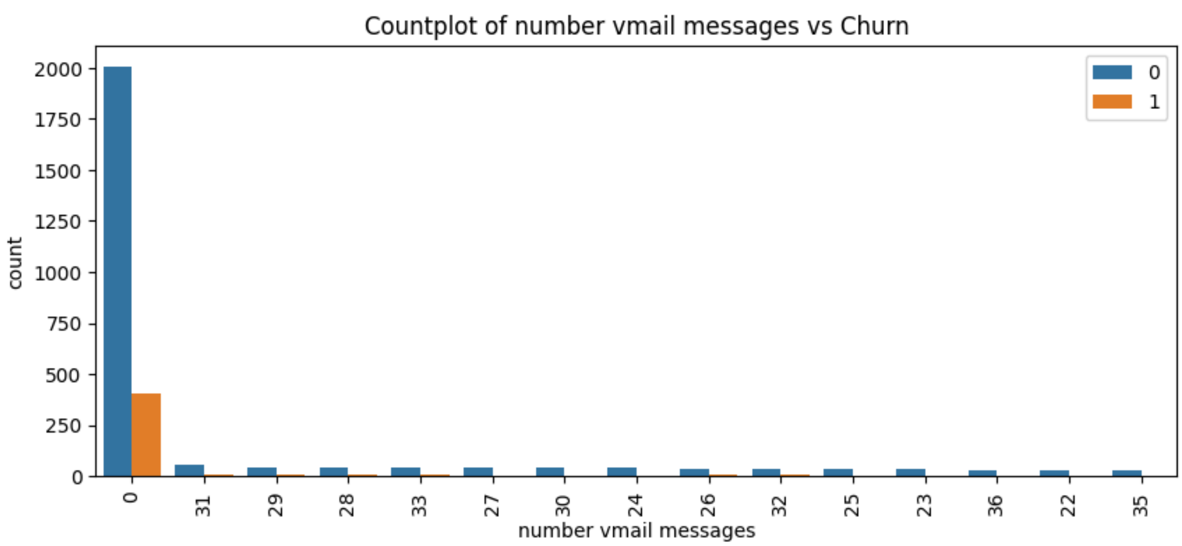


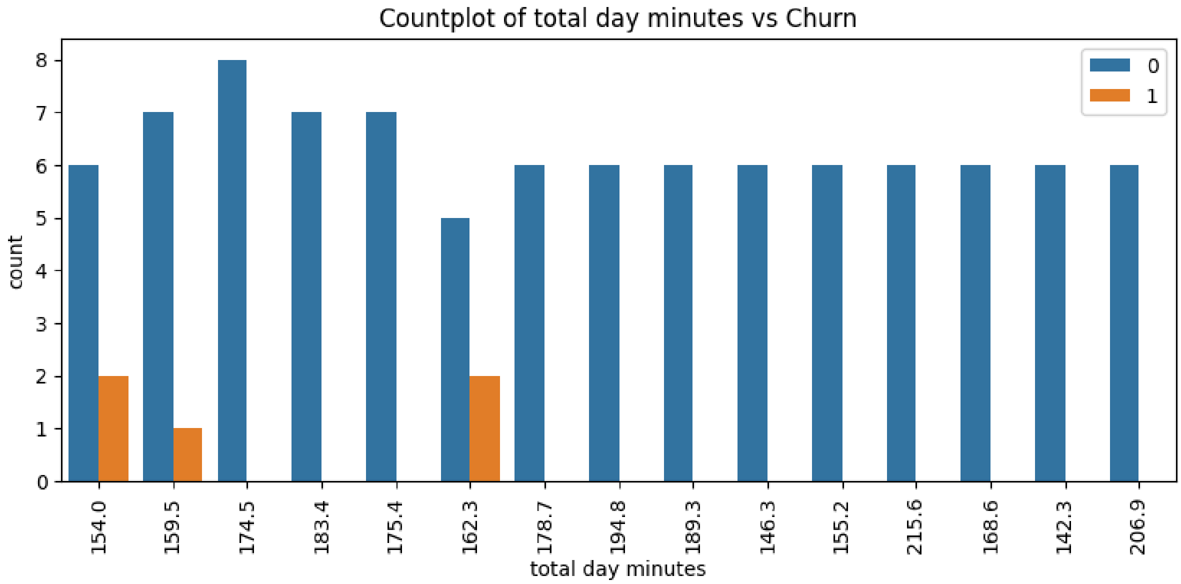
Bivariate Analysis: Relationship Between Categorical Variables, Numerical Variables, and Churn This was done to understand how each feature individually relates to the target variable. The churn column was removed from numeric_df to focus on the relationships between the other numerical features and churn.

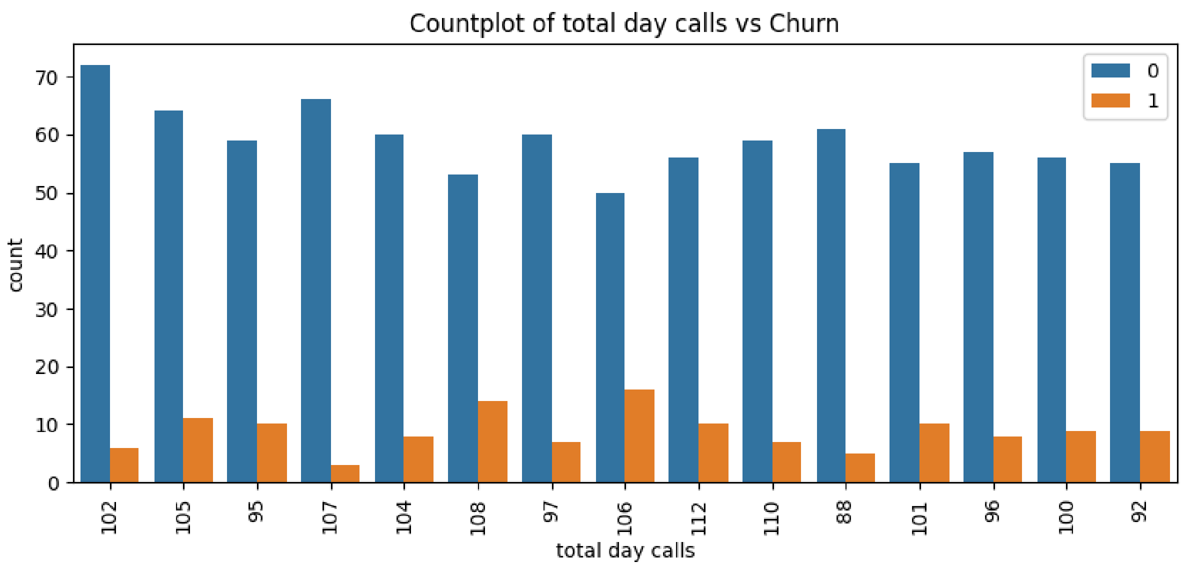
In [31]:
```
# Dropping the churn column from numeric_df
numeric_df = numeric_df.drop("churn", axis=1)

# Comparing numeric data to churn using countplots
for i in numeric_df:
    plt.figure(figsize=(10, 4))
    sns.countplot(x=i, hue="churn", data=df, order=df[i].value_counts().iloc
[0:15].index)
    plt.xticks(rotation=90)
    plt.legend(loc="upper right")
    plt.title(f'Countplot of {i} vs Churn')
    plt.show()
```

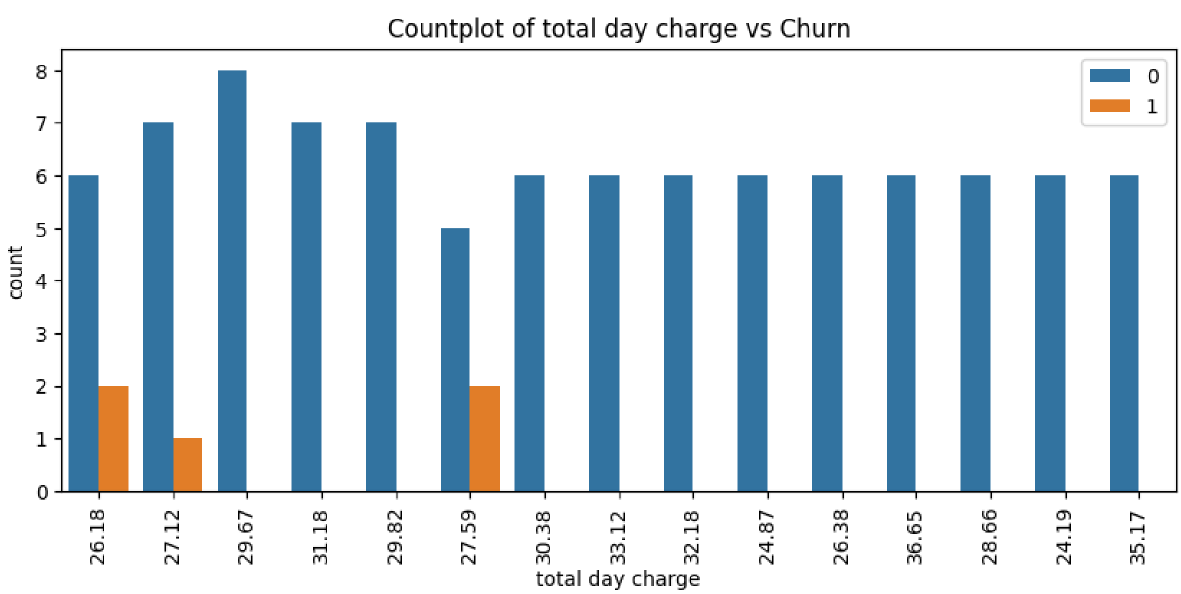

Countplot of account length vs Churn
count
account length
0
1
105
87
101
93
90
95
86
100
116
112
107
99
120
123
127

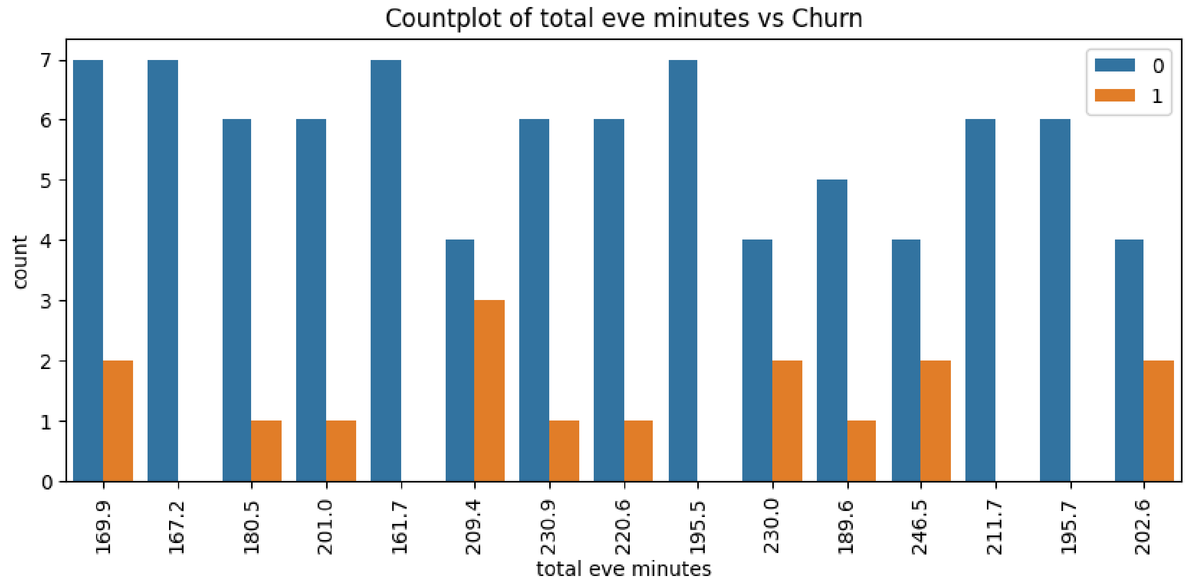

Countplot of area code vs Churn
count
area code
0
1
415
510
408

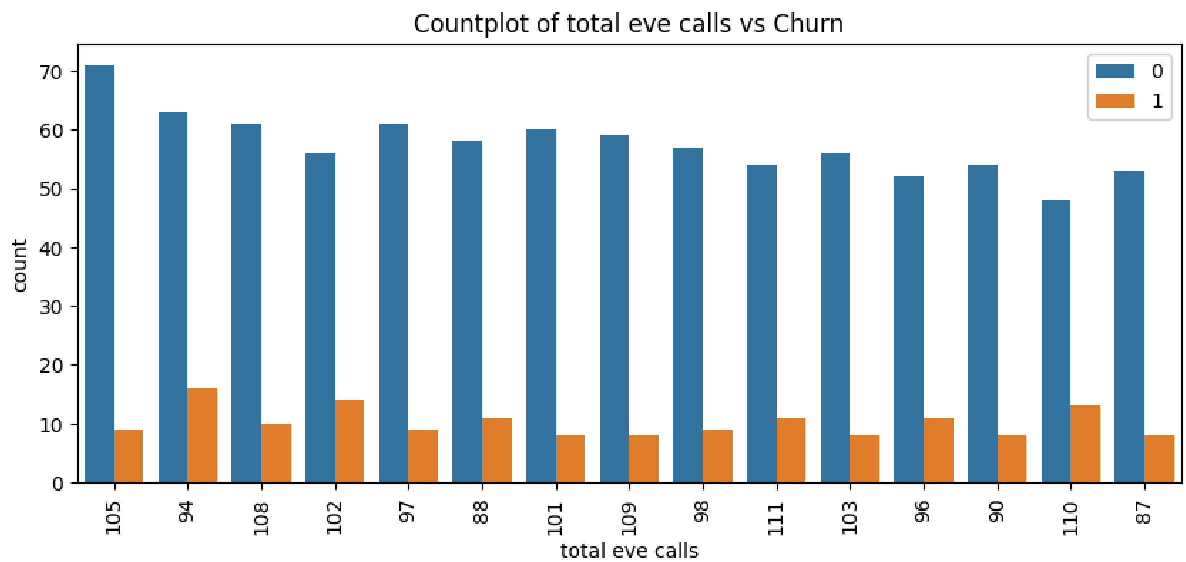

Countplot of number vmail messages vs Churn
count
number vmail messages
0
1
0
31
29
28
33
27
30
24
26
32
25
23
36
22
35

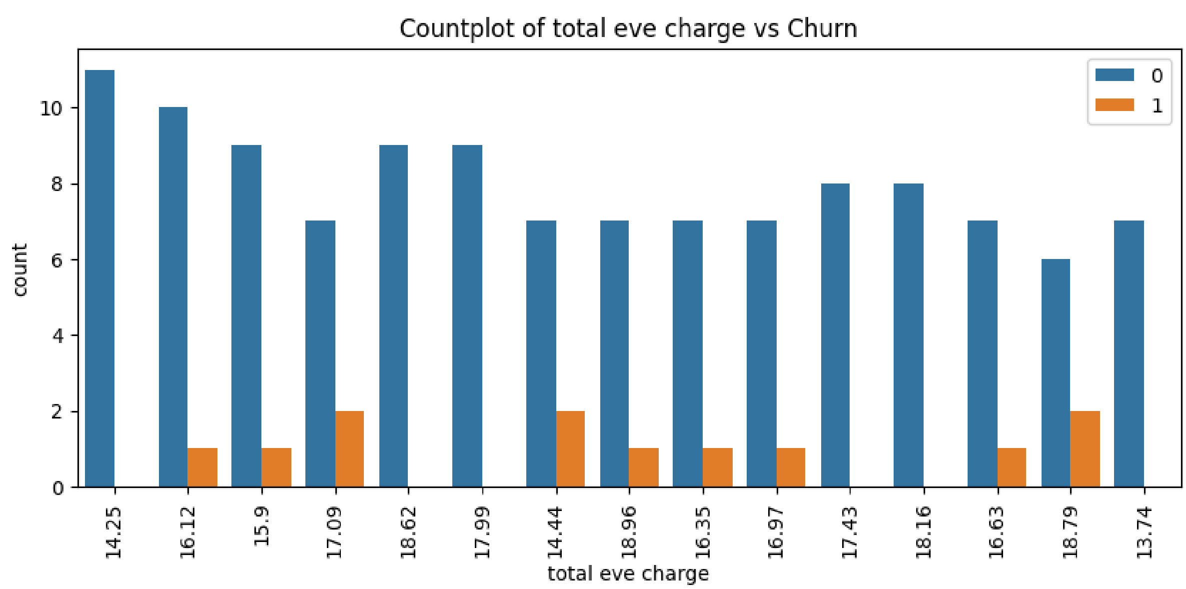

Countplot of total day minutes vs Churn
count
total day minutes
0
1
154.0
159.5
174.5
183.4
175.4
162.3
178.7
194.8
189.3
146.3
155.2
215.6
168.6
142.3
206.9

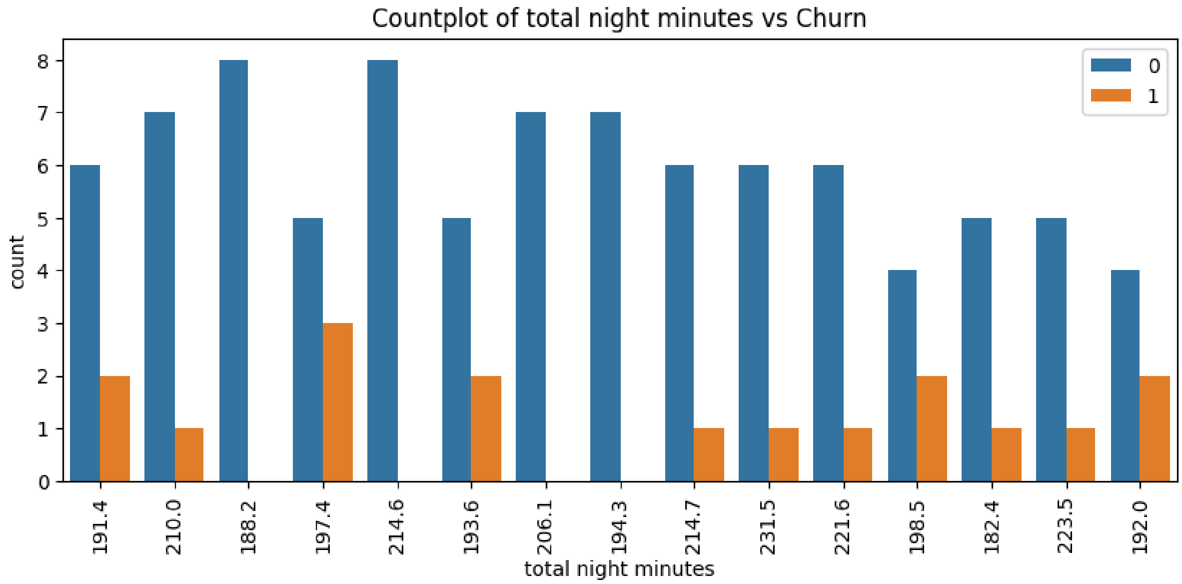

Countplot of total day calls vs Churn
count
total day calls
0
1
102
105
95
107
104
108
97
106
112
110
88
101
96
100
92

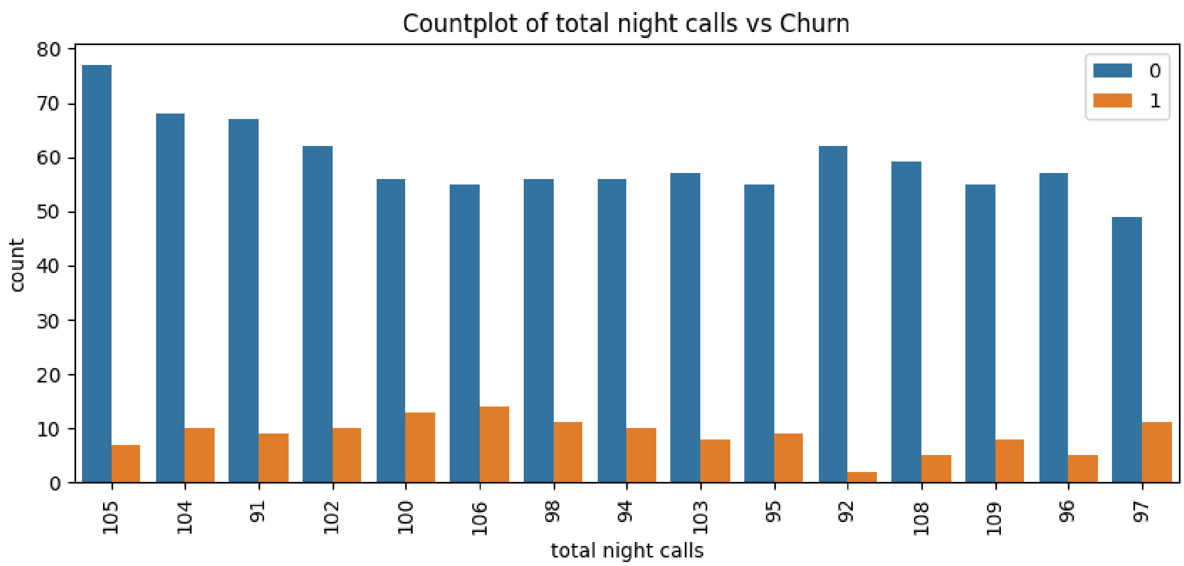

Countplot of total day charge vs Churn
count
total day charge
0
1
26.18
27.12
29.67
31.18
29.82
27.59
30.38
33.12
32.18
24.87
26.38
36.65
28.66
24.19
35.17

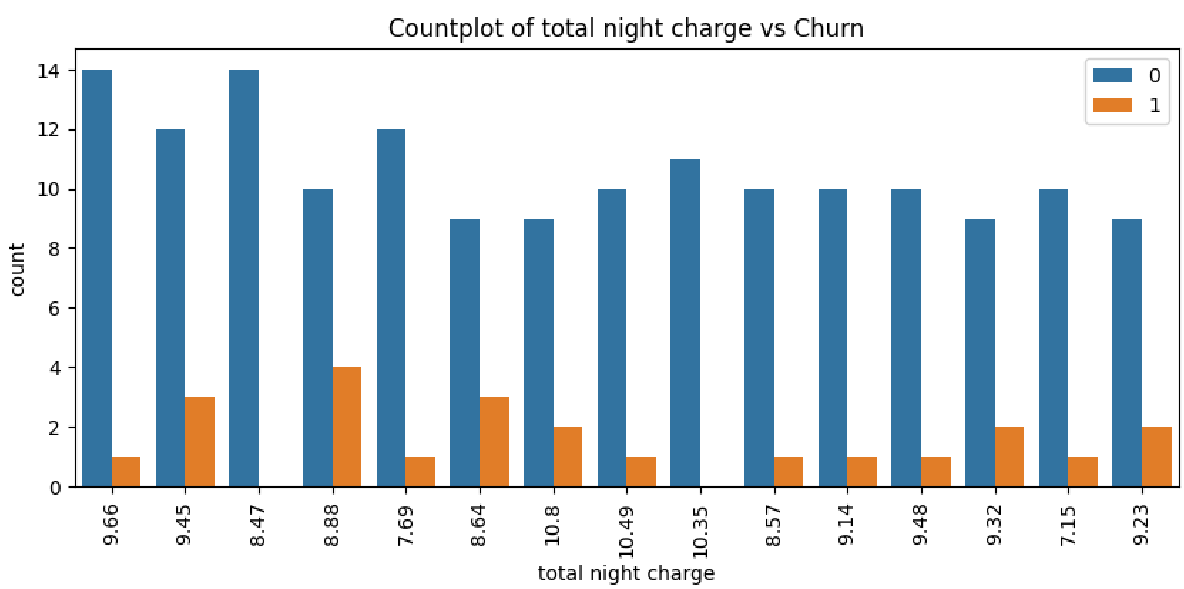

Countplot of total eve minutes vs Churn
count
total eve minutes
0
1
169.9
167.2
180.5
201.0
161.7
209.4
230.9
220.6
195.5
230.0
189.6
246.5
211.7
195.7
202.6

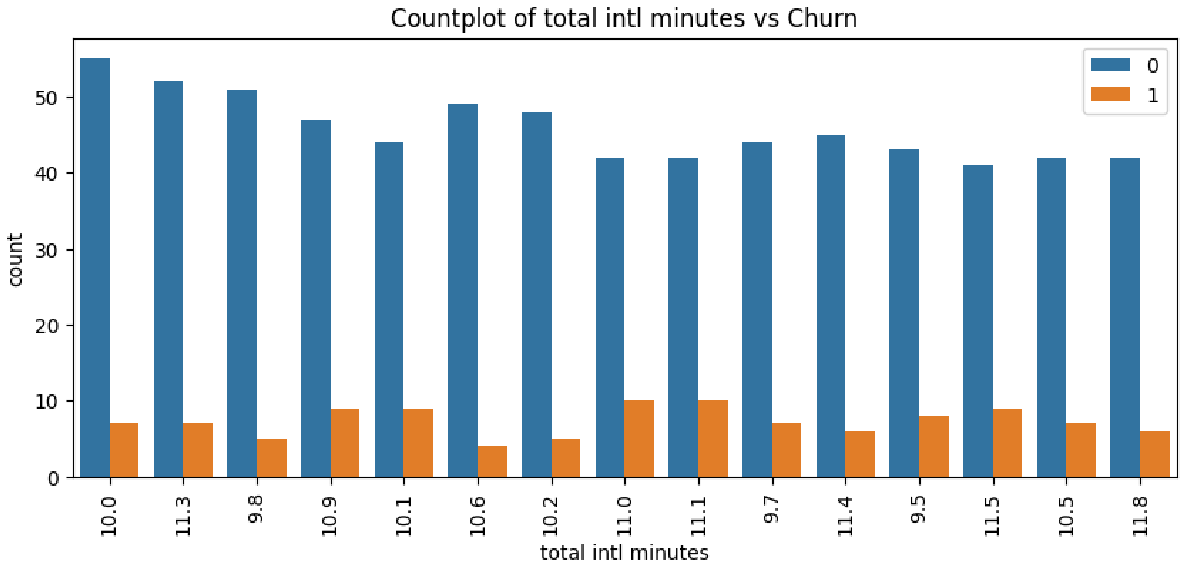

Countplot of total eve calls vs Churn
count
total eve calls
0
1
105
94
108
102
97
88
101
109
98
111
103
96
90
110
87

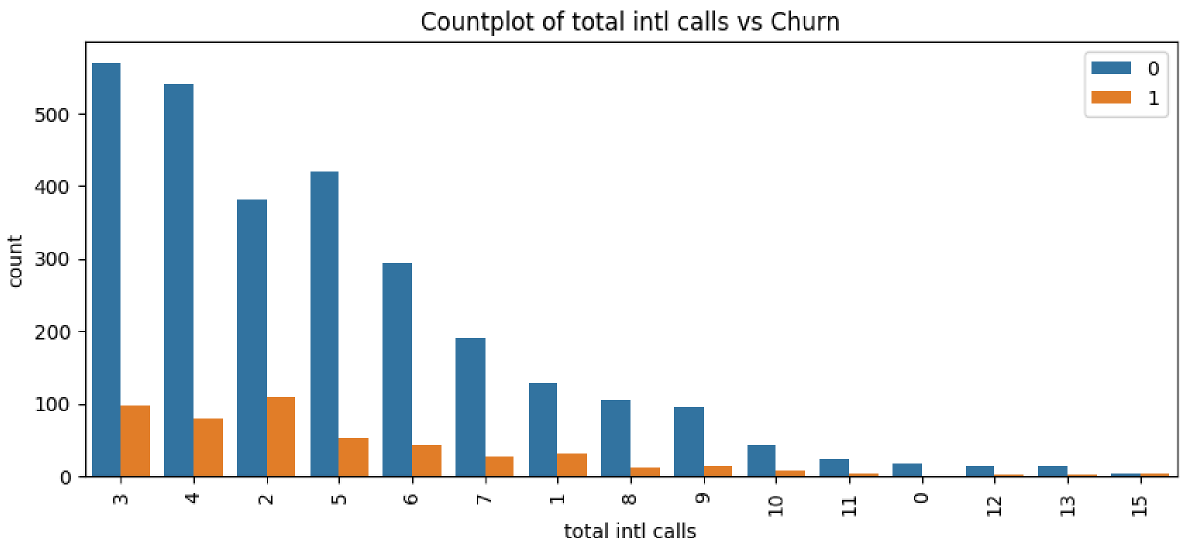

Countplot of total eve charge vs Churn
count
total eve charge
0
1
14.25
16.12
15.9
17.09
18.62
17.99
14.44
18.96
16.35
16.97
17.43
18.16
16.63
18.79
13.74

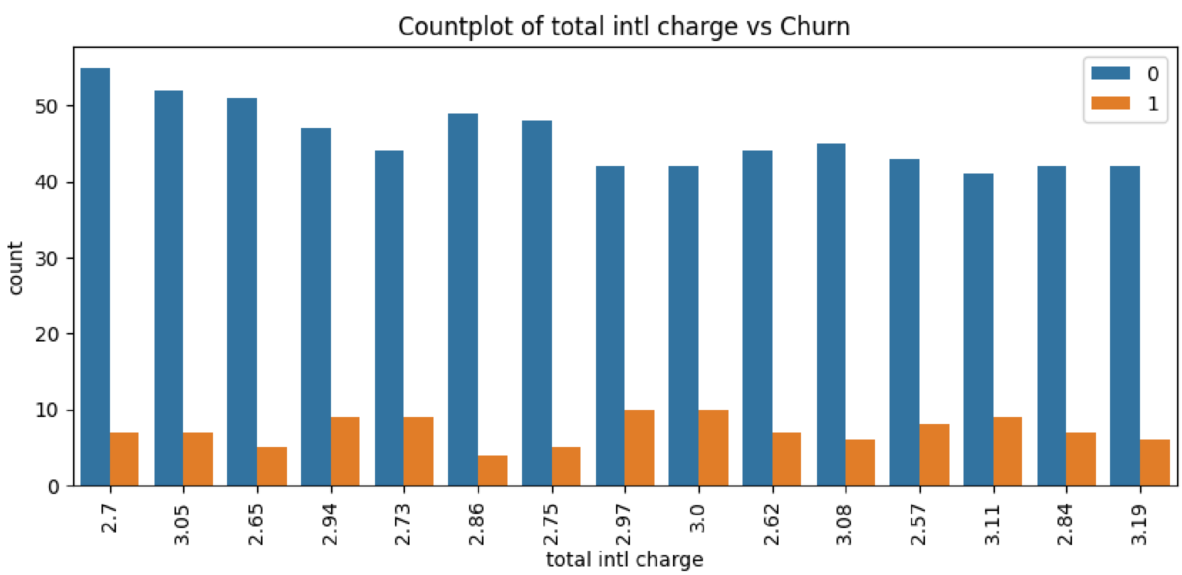

Countplot of total night minutes vs Churn
count
total night minutes
0
1
191.4
210.0
188.2
197.4
214.6
193.6
206.1
194.3
214.7
231.5
221.6
198.5
182.4
223.5
192.0

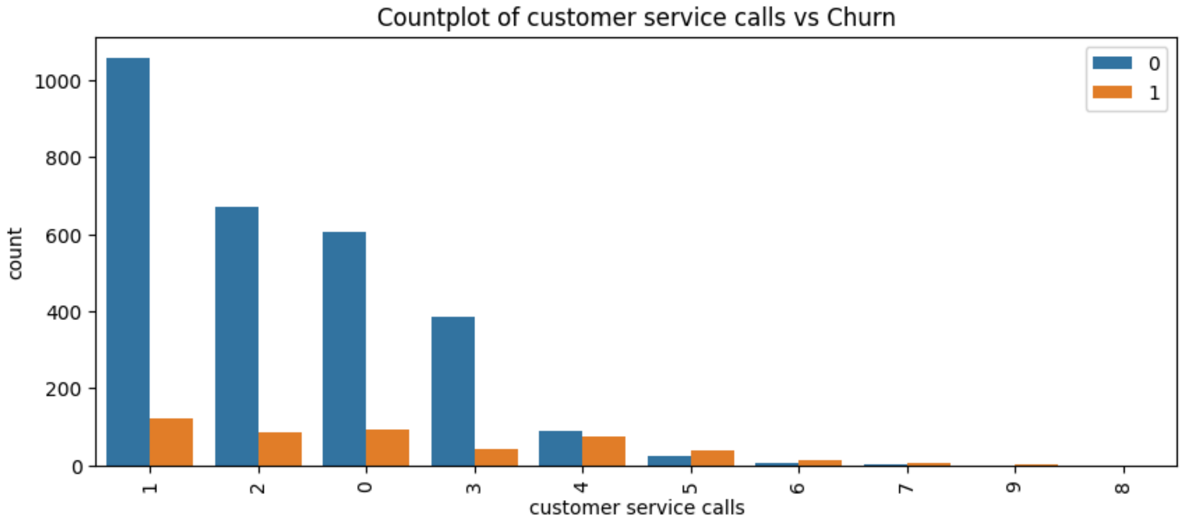

Countplot of total night calls vs Churn
count
total night calls
0
1
105
104
91
102
100
106
98
94
103
95
92
108
109
96
97


Countplot of total night charge vs Churn
count
total night charge
0
1
9.66
9.45
8.47
8.88
7.69
8.64
10.8
10.49
10.35
8.57
9.14
9.48
9.32
7.15
9.23


Countplot of total intl minutes vs Churn
count
total intl minutes
0
1
10.0
11.3
9.8
10.9
10.1
10.6
10.2
11.0
11.1
9.7
11.4
9.5
11.5
10.5
11.8

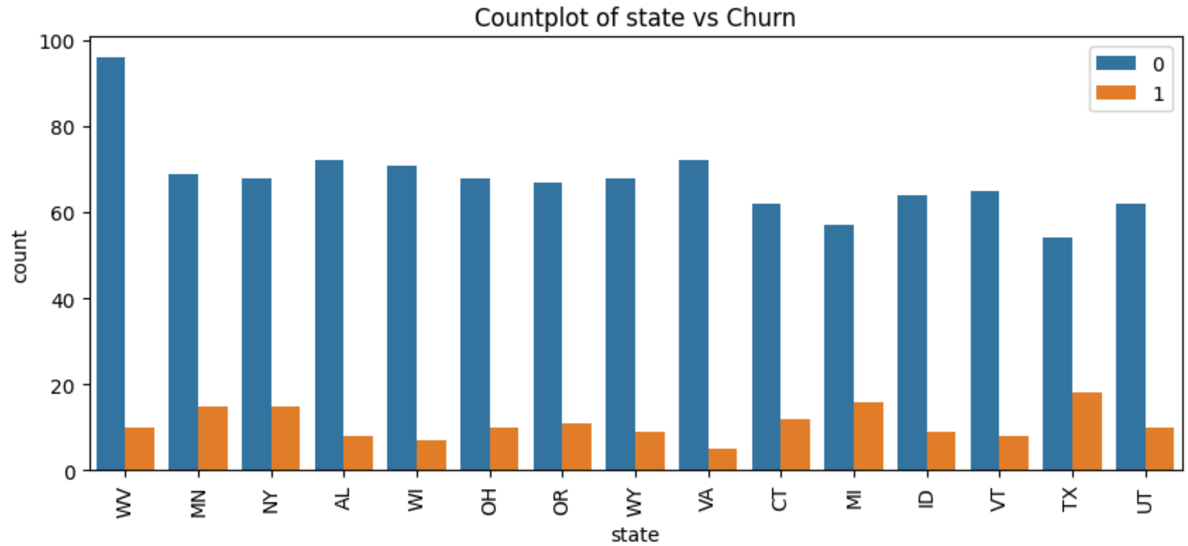

Countplot of total intl calls vs Churn
count
total intl calls
0
1

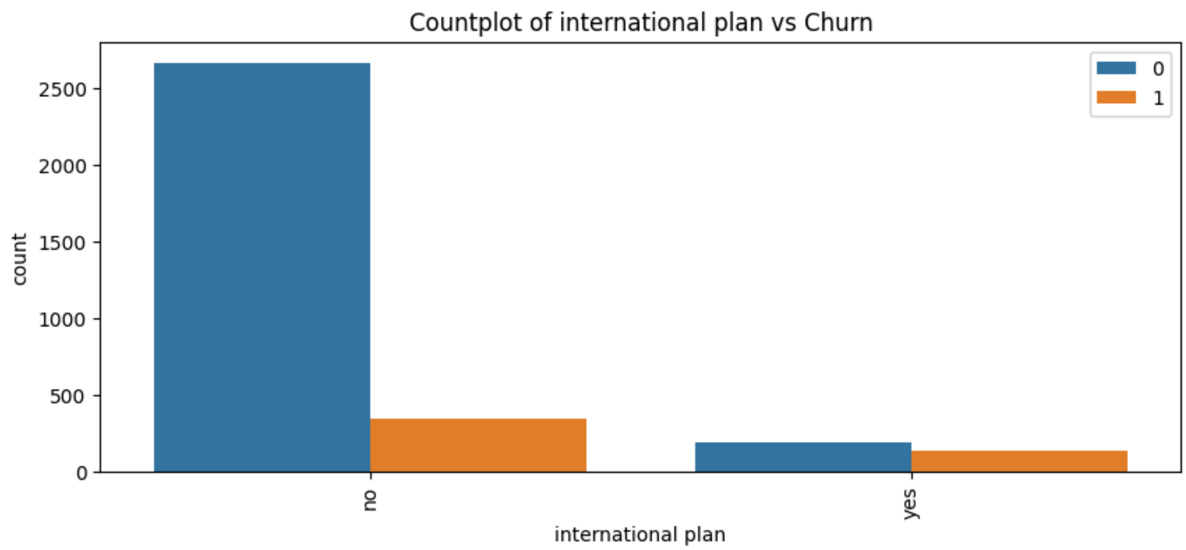

Countplot of total intl charge vs Churn
count
total intl charge
0
1
2.7
3.05
2.65
2.94
2.73
2.86
2.75
2.97
3.0
2.62
3.08
2.57
3.11
2.84
3.19

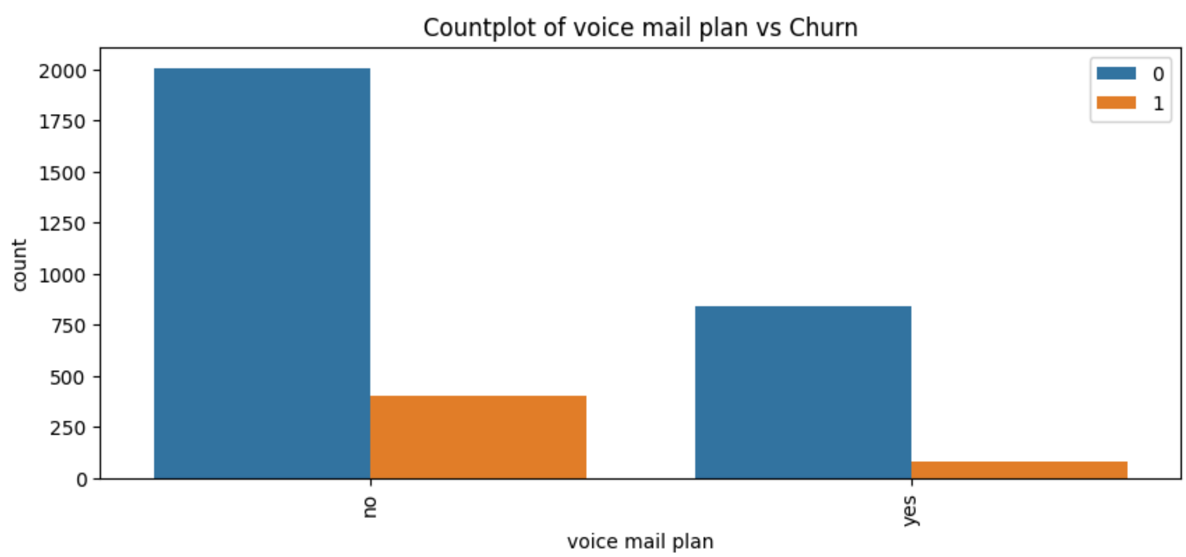

Countplot of customer service calls vs Churn
0
1
count
1000
800
600
400
200
0
1
2
0
3
4
5
6
7
9
8
customer service calls

Comparing Categorical Data to Churn

In [32]:
```
# Comparing categorical data to "churn"
for i in columns:
    plt.figure(figsize=(10, 4))
    sns.countplot(x=i, hue="churn", data=df, order=df[i].value_counts().iloc
[0:15].index)
    plt.xticks(rotation=90)
    plt.legend(loc="upper right")
    plt.title(f'Countplot of {i} vs Churn')
    plt.show()
```



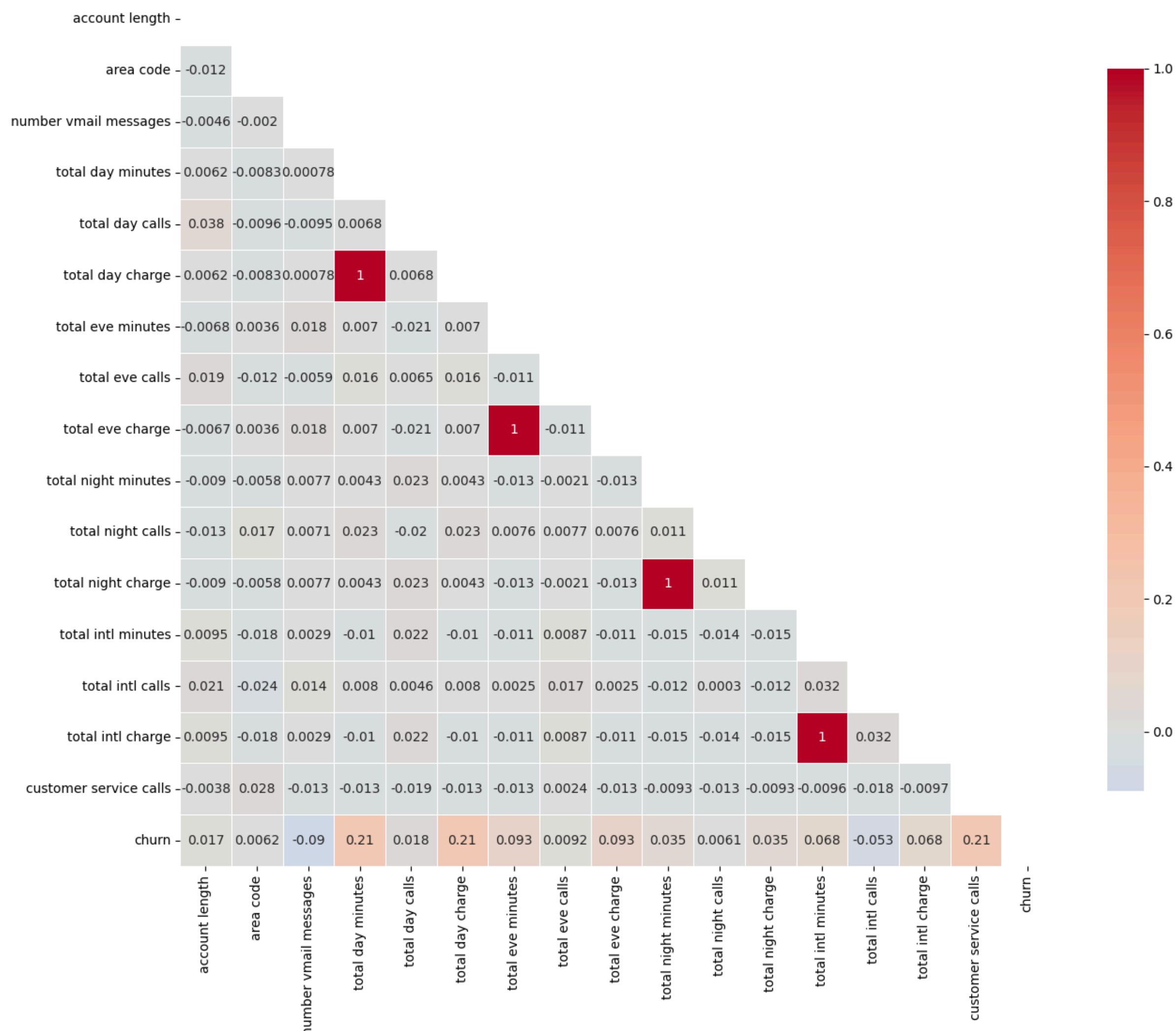




Multivariate Analysis

A heatmap was used to visualize the correlation matrix of the numerical features

In [33]:
```
# using heatmap to show collinearity
# Select only numeric columns for correlation calculation
numeric_df = df.select_dtypes(include=np.number)
corr = numeric_df.corr()

mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True

f, ax = plt.subplots(figsize=(15, 20))

sns.heatmap(corr, mask=mask, cmap='coolwarm', vmax=1, center=0,
            square=True, linewidths=.5, annot=True, cbar_kws={"shrink": .5});
```



From the heatmap, the following pairs of features are identified as having a correlation of 1 (perfect multicollinearity):

1. Total day minutes & Total day charge
2. Total eve minutes & Total eve charge
3. Total night minutes & Total night charge
4. Total intl minutes & Total intl charge

Perfect multicollinearity indicates that one feature can be perfectly predicted from the other. Therefore, one feature from each pair is redundant and can be dropped to simplify the model without losing information. Dropping these features reduces the risk of overfitting and improves model interpretability by minimizing redundancy.

Dropping Correlated Features

In [34]:
```
df_subset = df.drop(columns= ['total day minutes', 'total eve minutes', 'total night calls','total intl minutes','phone number' ], axis = 1)
df_subset
```

Out[34]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day calls	total day charge	total eve calls	total eve charge	total night minutes
0	KS	128	415	no	yes	25	110	45.07	99	16.78	244.7
1	OH	107	415	no	yes	26	123	27.47	103	16.62	254.4
2	NJ	137	415	no	no	0	114	41.38	110	10.30	162.6
3	OH	84	408	yes	no	0	71	50.90	88	5.26	196.9
4	OK	75	415	yes	no	0	113	28.34	122	12.61	186.9
...	...	...	...	...	...	...	...	...	...	...	...
3328	AZ	192	415	no	yes	36	77	26.55	126	18.32	279.1
3329	WV	68	415	no	no	0	57	39.29	55	13.04	191.3
3330	RI	28	510	no	no	0	109	30.74	58	24.55	191.9
3331	CT	184	510	yes	no	0	105	36.35	84	13.57	139.2
3332	TN	74	415	no	yes	25	113	39.85	82	22.60	241.4

3333 rows × 16 columns

Preprocessing

Feature engineering

In [35]:
```
# 1. Combined Usage Features: Create a single feature that combines the total
usage (day + evening)
df_subset['total_combined_usage'] = df_subset['total day calls'] + df_subset
['total eve calls']

# 2. Combined Charge Features: Create a single feature that combines all the c
harges (day + evening + international)
df_subset['total_combined_charge'] = df_subset['total day charge'] + df_subset
['total eve charge'] + df_subset['total intl charge']

# 3. Ratio of customer service calls to account length
df_subset['cust_serv_calls_ratio'] = df_subset['customer service calls'] / df_
subset['account length']

# 4. Binary Feature for high customer service interaction (over a threshold)
df_subset['high_cust_service_calls'] = df_subset['customer service calls'].app
ly(lambda x: 1 if x > 3 else 0)
```

In [36]:
```
# Dropping Unnecessary Features
# List of features to drop (those used in creating new features)
features_to_drop = [
    'total day calls', 'total eve calls',  # Combine into 'total_combined_usag
e'
    'total day charge', 'total eve charge', 'total intl charge',  # Combine in
to 'total_combined_charge'
    'customer service calls', 'account length'  # Used for ratio and binary fe
atures
]

# Drop the unnecessary features
df_subset = df_subset.drop(columns=features_to_drop)

# Display the remaining features in the DataFrame
df_subset.head()
```

Out[36]:

	state	area code	international plan	voice mail plan	number vmail messages	total night minutes	total night charge	total intl calls	churn	total_combined_us
0	KS	415	no	yes	25	244.7	11.01	3	0	
1	OH	415	no	yes	26	254.4	11.45	3	0	
2	NJ	415	no	no	0	162.6	7.32	5	0	
3	OH	408	yes	no	0	196.9	8.86	7	0	
4	OK	415	yes	no	0	186.9	8.41	3	0	

Encoding

Encoding Categorical Variables

Categorical variables were converted into numerical using one-hot encoding. The data is then split into predictor variables (X) and the target variable (y), and further split into training and testing sets to allow for model training and evaluation.

In [37]:
```
# one hot encoding categorical values
df_encoded = pd.get_dummies(df_subset)
df_encoded
```

Out[37]:

	area code	number vmail messages	total night minutes	total night charge	total intl calls	churn	total_combined_usage	total_combined_cha
0	415	25	244.7	11.01	3	0	209	64
1	415	26	254.4	11.45	3	0	226	47
2	415	0	162.6	7.32	5	0	224	54
3	408	0	196.9	8.86	7	0	159	57
4	415	0	186.9	8.41	3	0	235	43
...	...	...	...	...	...	...	...	
3328	415	36	279.1	12.56	6	0	203	47
3329	415	0	191.3	8.61	4	0	112	54
3330	510	0	191.9	8.64	6	0	167	59
3331	510	0	139.2	6.26	10	0	189	51
3332	415	25	241.4	10.86	4	0	195	66

3333 rows × 65 columns

Splitting Data

The data is then split into predictor variables (X) and the target variable (y), and further split into training and testing sets to allow for model training and evaluation.

In [38]:
```
# Spliting data into predictor and target Variables
y = df_encoded.churn
X = df_encoded.drop(['churn'], axis=1)
```

In [39]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
m_state=42)
```

Scaling the Data

Standardization is applied to scale the features so that they have a mean of 0 and a standard deviation of 1.

In [40]:
```
# Scaling the data

scaler = StandardScaler()

# Fit the scaler on the training data
X_train_scaled = pd.DataFrame(scaler.fit_transform(X_train), columns=X_train.c
olumns)

# Transform the test data using the same scaler
X_test_scaled = pd.DataFrame(scaler.transform(X_test), columns=X_test.columns)


X_test_scaled.head()
```

Out[40]:

	area code	number vmail messages	total night minutes	total night charge	total intl calls	total_combined_usage	total_combined_cl
0	1.735840	-0.584936	-0.219520	-0.220859	-0.593980	-0.053505	0.7
1	-0.517168	-0.584936	-0.239243	-0.238391	0.634849	1.438671	-0.9
2	-0.517168	-0.584936	-0.659356	-0.659155	-1.413199	-2.504937	-3.4
3	-0.683179	-0.584936	-0.874343	-0.873920	-1.003589	-1.083817	0.5
4	-0.683179	-0.584936	0.535893	0.537392	1.044458	-0.906177	-0.3

Handling Class Imbalance with SMOTE

Synthetic Minority Over-sampling Technique is applied to address class imbalance by generating synthetic samples for the minority class, ensuring that the model is not biased towards the majority class.

In [41]:
```
# Using SMOTE to deal with class imbalance

# Previous original class distribution
print(y_train.value_counts())

# Fit SMOTE to training data
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)

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

```
churn
0    2284
1     382
Name: count, dtype: int64


churn
0    2284
1    2284
Name: count, dtype: int64
```

Modeling

In [42]:
```
# Creating a function to calculate evaluation metrics

def evaluate_model_performance(y_train_resampled, y_hat_train, y_test, y_hat_t
est):
    # Calculate metrics
    metrics = {
        'Metric': ['Precision', 'Recall', 'Accuracy', 'F1-Score'],
        'Training': [
            precision_score(y_train_resampled, y_hat_train),
            recall_score(y_train_resampled, y_hat_train),
            accuracy_score(y_train_resampled, y_hat_train),
            f1_score(y_train_resampled, y_hat_train)
        ],
        'Testing': [
            precision_score(y_test, y_hat_test),
            recall_score(y_test, y_hat_test),
            accuracy_score(y_test, y_hat_test),
            f1_score(y_test, y_hat_test)
        ]
    }

    # Create a DataFrame to store the results
    metrics_df = pd.DataFrame(metrics)

    # Display the DataFrame
    display(metrics_df)
    return metrics_df
```

In [43]:
```
# Creating a function to plot a confusion matrix
def plot_confusion_matrix(y_test, y_hat_test, figsize=(10, 4), cmap='coolwar
m'):
    """
    Plots a heatmap of the confusion matrix.

    Parameters:
    y_test (array-like): True labels of the test set.
    y_hat_test (array-like): Predicted labels of the test set.
    figsize (tuple): Size of the figure for the plot.
    cmap (str): Colormap to use for the heatmap.

    Returns:
    None
    """
    # Create the confusion matrix
    cm = confusion_matrix(y_test, y_hat_test)

    # Plotting the heatmap
    plt.figure(figsize=figsize)
    sns.heatmap(cm, annot=True, cmap=cmap, fmt='d')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title('Confusion Matrix')
    plt.show()
```

In [44]:
```
# Creating a function to plot ROC and AUC
def plot_roc_curve(lr, X_test, y_test, figsize=(20, 8)):
    """
    Plots the ROC curve and prints the AUC score.

    Parameters:
    lr (model): The trained logistic regression model.
    X_test (array-like): The test dataset features.
    y_test (array-like): The true labels of the test dataset.
    figsize (tuple): Size of the figure for the plot.

    Returns:
    None
    """
    # Calculate the predicted probabilities
    y_pred_prob = lr.predict_proba(X_test)[:, 1]

    # Calculate the ROC curve
    fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)

    # Calculate the area under the ROC curve
    auc = roc_auc_score(y_test, y_pred_prob)

    # Plot the ROC curve
    plt.figure(figsize=figsize)
    plt.plot(fpr, tpr, color='darkorange', label=f'ROC curve (AUC = {auc:.2
f})')
    plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.yticks([i/20.0 for i in range(21)])
    plt.xticks([i/20.0 for i in range(21)])
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.title("ROC Curve")
    plt.legend(loc="lower right")
    plt.show()

    # Print the AUC score
    print('The AUC score is:', auc)
```

Model 1: Logistic Regression

A Logistic Regression model was trained on the resampled data and predictions are made for both the training and testing datasets.

In [45]:
```
# create an instance
lr = LogisticRegression()

# fit the model
lr.fit(X_train_resampled, y_train_resampled)

# predict the model
y_hat_train = lr.predict(X_train_resampled)
y_hat_test=lr.predict(X_test)
```

Evaluation Metrics for Logistic Regression

In [46]:
```
metrics_df = evaluate_model_performance(y_train_resampled, y_hat_train, y_tes
t, y_hat_test)
```

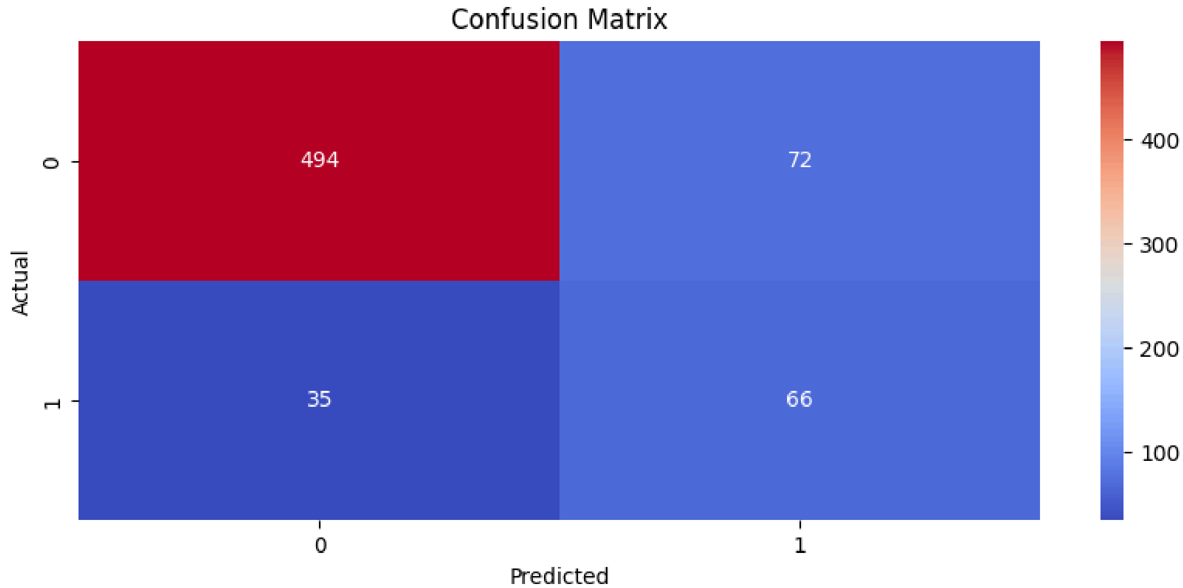
	Metric	Training	Testing
0	Precision	0.853076	0.478261
1	Recall	0.813485	0.653465
2	Accuracy	0.836690	0.839580
3	F1-Score	0.832810	0.552301

The model shows signs of overfitting, as evidenced by the significant drop in precision and F1-score when moving from training to testing data.

The relatively consistent recall and accuracy suggest that the model is able to correctly identify a fair number of positive cases and has a similar overall performance between training and testing sets.

Confusion Matrix and ROC Curve for Logistic Regression

In [47]:
```
plot_confusion_matrix(y_test, y_hat_test)
```

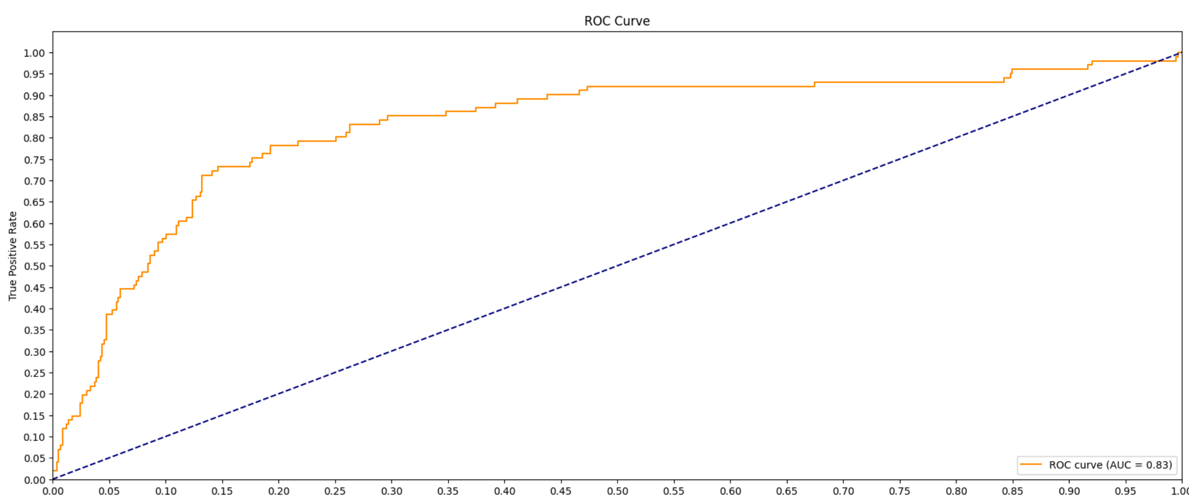


Interpretation:

- True Positives (TP): The model correctly predicted the positive class (74).
- True Negatvies (TN): The model correctly predicted the negative class (507).

- False Positives (FP): The model incorrectly predicted the positive class when it was actually negative (59).
- False Negatives (FN): The model incorrectly predicted the negative class when it was actually positive (27).

In [48]:
```
plot_roc_curve(lr, X_test, y_test)
```




```
The AUC score is: 0.8292866389112411
```

The AUC score is: 0.853864185005073

The ROC curve is above the diagonal line, indicating that the model performs better than random guessing. The AUC score of 0.85 indicates that the model has a good ability to distinguish between the positive and negative classes.

Model 2: Decision Trees

In [49]:
```
Dt = DecisionTreeClassifier(random_state = 42)
# fit the model
Dt.fit(X_train_resampled, y_train_resampled)

# predict
y_hat_train = Dt.predict(X_train_resampled)
y_hat_test= Dt.predict(X_test)
```

Evaluation Metrics for Decision Tress

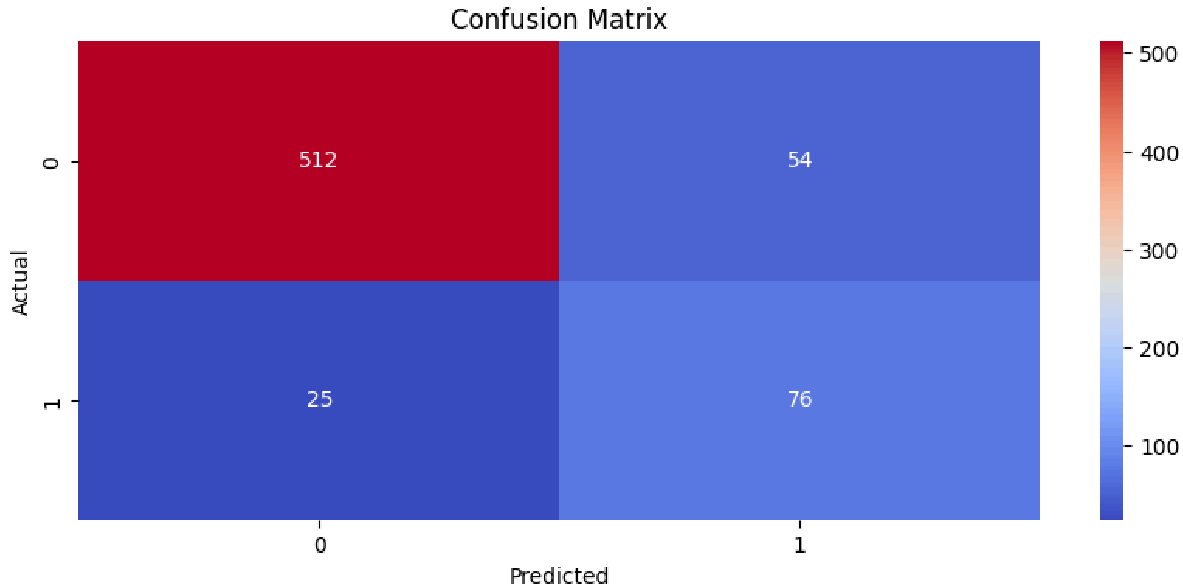
In [50]:
```
# Testing the perfomance of the model using different metrics
metrics_df = evaluate_model_performance(y_train_resampled, y_hat_train, y_tes
t, y_hat_test)
```

	Metric	Training	Testing
0	Precision	1.0	0.584615
1	Recall	1.0	0.752475
2	Accuracy	1.0	0.881559
3	F1-Score	1.0	0.658009

The model shows signs of overfitting, as evidenced by the significant drop in precision and F1-score when moving from training to testing data.

Confusion Matrix and ROC Curve for Decision Trees

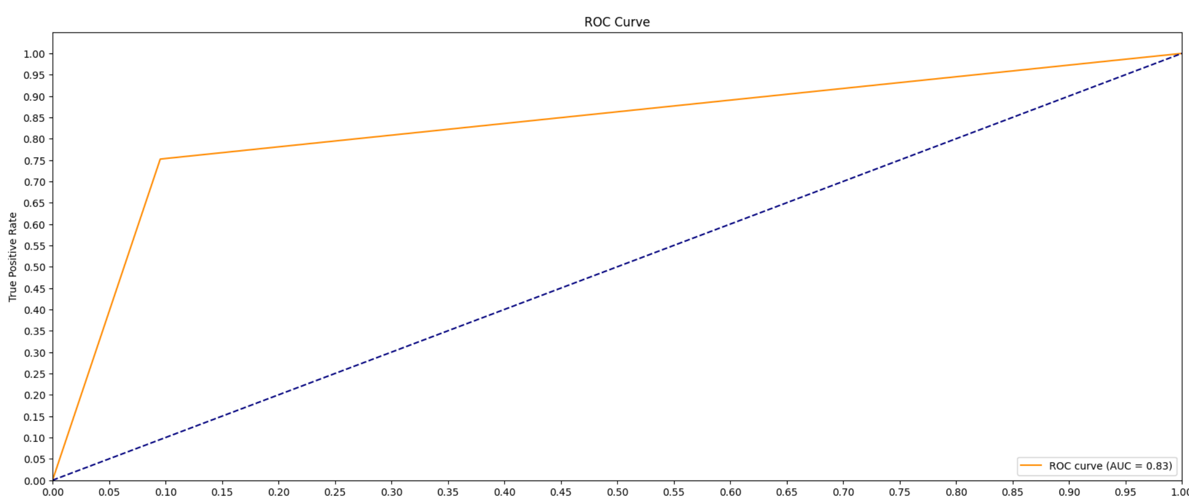
In [51]:
```
plot_confusion_matrix(y_test, y_hat_test)
```



Interpretation:

- True Positives (TP): 84 cases were correctly predicted as positive.
- True Negatives (TN): 495 cases were correctly predicted as negative.
- False Positives (FP): 71 cases were incorrectly predicted as positive when they were actually negative.
- False Negatives (FN): 17 cases were incorrectly predicted as negative when they were actually positive.

In [52]:
```
plot_roc_curve(Dt, X_test, y_test)
```




```
The AUC score is: 0.8285344435503621
```

- The ROC curve is above the diagonal line, indicating that the model performs better than random guessing.
- The AUC score of 0.85 indicates that the model has a good ability to distinguish between the positive and negative classes.

Model 3: Random Forest

In [53]:
```
# Create an instance of the Random Forest model
rf = RandomForestClassifier(random_state=42, n_estimators=100)

# Fit the model on the resampled training data
rf.fit(X_train_resampled, y_train_resampled)

# Predict on both the training and testing datasets
y_hat_train_rf = rf.predict(X_train_resampled)
y_hat_test_rf = rf.predict(X_test)
```

Evaluation Metrics for Random Forest

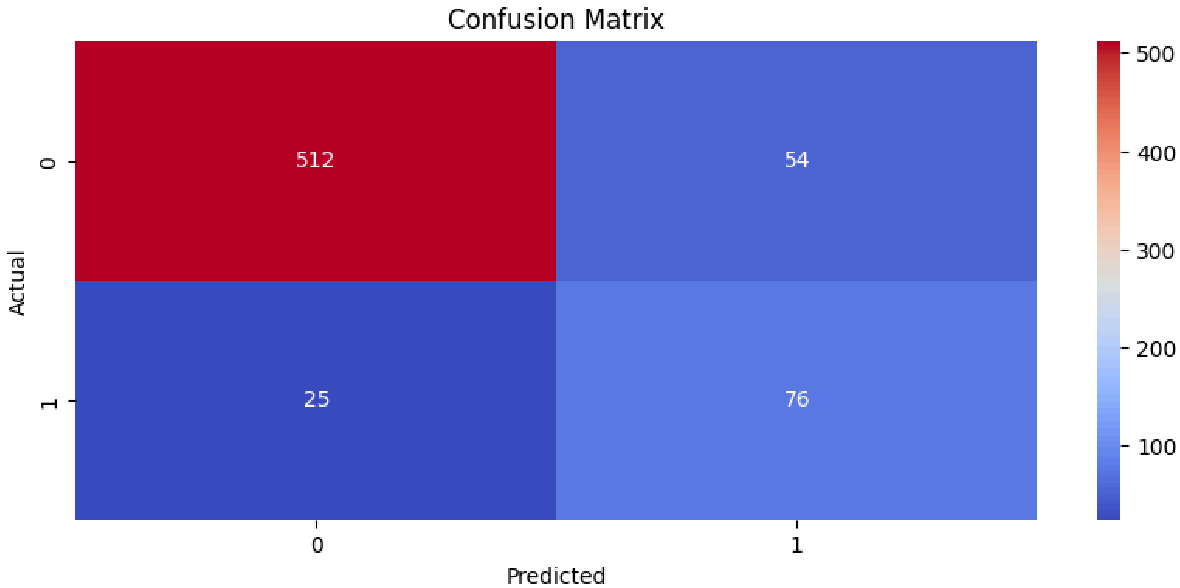
In [54]:
```
# Testing the perfomance of the model using different metrics
metrics_df = evaluate_model_performance(y_train_resampled, y_hat_train, y_tes
t, y_hat_test)
```

	Metric	Training	Testing
0	Precision	1.0	0.584615
1	Recall	1.0	0.752475
2	Accuracy	1.0	0.881559
3	F1-Score	1.0	0.658009

The model shows signs of overfitting, as evidenced by the significant drop in precision and F1-score when moving from training to testing data.

Confusion Matrix and ROC Curve for Random Forest

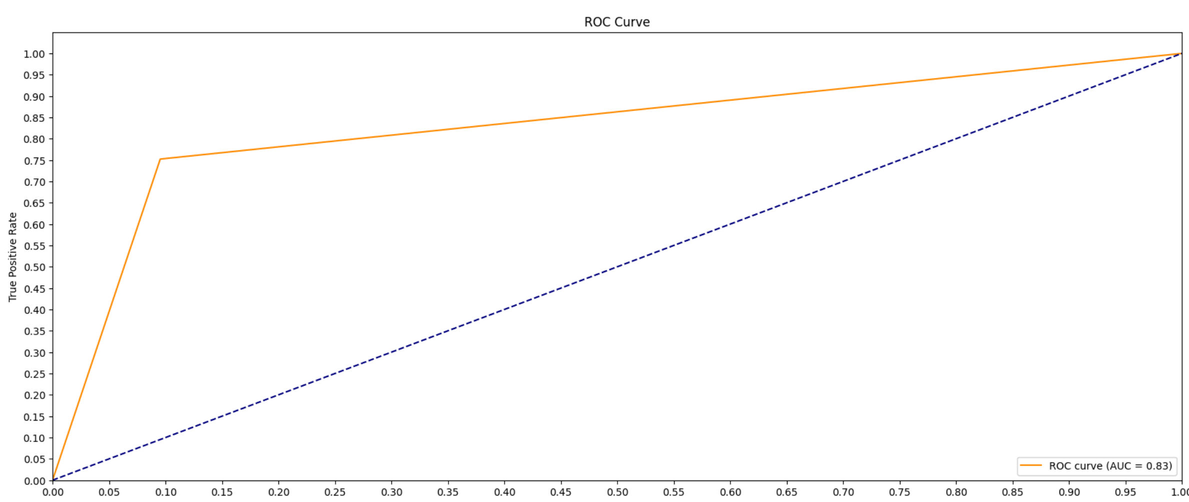
In [55]:
```
plot_confusion_matrix(y_test, y_hat_test)
```



Interpretation:

- True Positives (TP): The model correctly predicted the positive class (84).
- True Negatives (TN): The model correctly predicted the negative class (495).
- False Positives (FP): The model incorrectly predicted the positive class when it was actually negative (71).
- False Negatives (FN): The model incorrectly predicted the negative class when it was actually positive (17).

In [56]:
```
plot_roc_curve(Dt, X_test, y_test)
```




```
The AUC score is: 0.8285344435503621
```

- The ROC curve is above the diagonal line, indicating that the model performs better than random guessing.
- The AUC score of 0.85 indicates that the model has a good ability to distinguish between the positive and negative classes

Model Tuning

The models were improved using hyperparameter tuning. Hyperparameter tuning involves finding the best combination of parameters for the model, which can enhance its performance on the validation set and subsequently improve generalization to unseen data.

1. Hyperparameter Tuning for Logistic Regression

In [60]:
```
# Define the hyperparameters grid
param_grid = {
    'C': [0.01, 0.1, 1, 10, 100],
    'penalty': ['l1', 'l2', 'elasticnet'],
    'solver': ['liblinear', 'saga']
}

# Set up the grid search
grid_search_lr = GridSearchCV(lr, param_grid, cv=5, scoring='accuracy')

# Fit the grid search to the data
grid_search_lr.fit(X_train_resampled, y_train_resampled)

# Print the best parameters and best score
print("Best parameters for Logistic Regression:", grid_search_lr.best_params_)
print("Best accuracy for Logistic Regression:", grid_search_lr.best_score_)
```

```
Best parameters for Logistic Regression: {'C': 100, 'penalty': 'l1', 'solve
r': 'liblinear'}
Best accuracy for Logistic Regression: 0.8960483269860824
```

In [61]:
```
# Logistic Regression with best parameters
best_lr = grid_search_lr.best_estimator_
best_lr.fit(X_train_resampled, y_train_resampled)

# predict the model
y_hat_train = best_lr.predict(X_train_resampled)
y_hat_test= best_lr.predict(X_test)
```

Evaluation Metrics for Tuned Logistic Regression

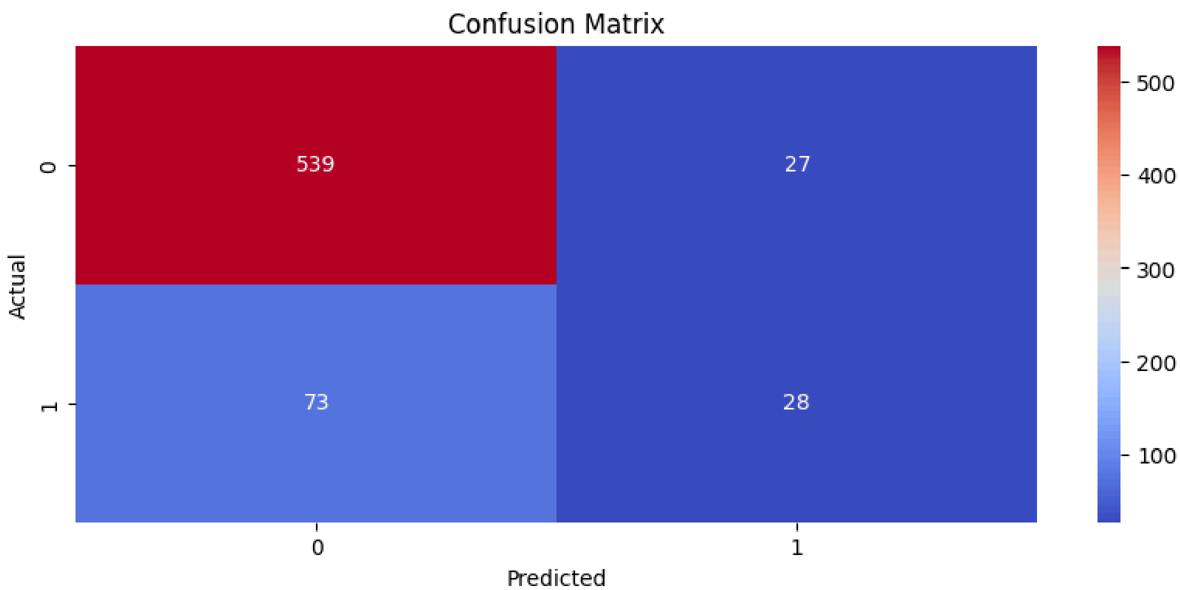
In [62]:
```
metrics_df = evaluate_model_performance(y_train_resampled, y_hat_train, y_tes
t, y_hat_test)
```

	Metric	Training	Testing
0	Precision	0.956605	0.509091
1	Recall	0.878284	0.277228
2	Accuracy	0.919221	0.850075
3	F1-Score	0.915773	0.358974

The significant difference in performance between the training and testing sets indicates that the model is overfitting.

Confusion Matrix and ROC Curve for Tuned Logistic Regression

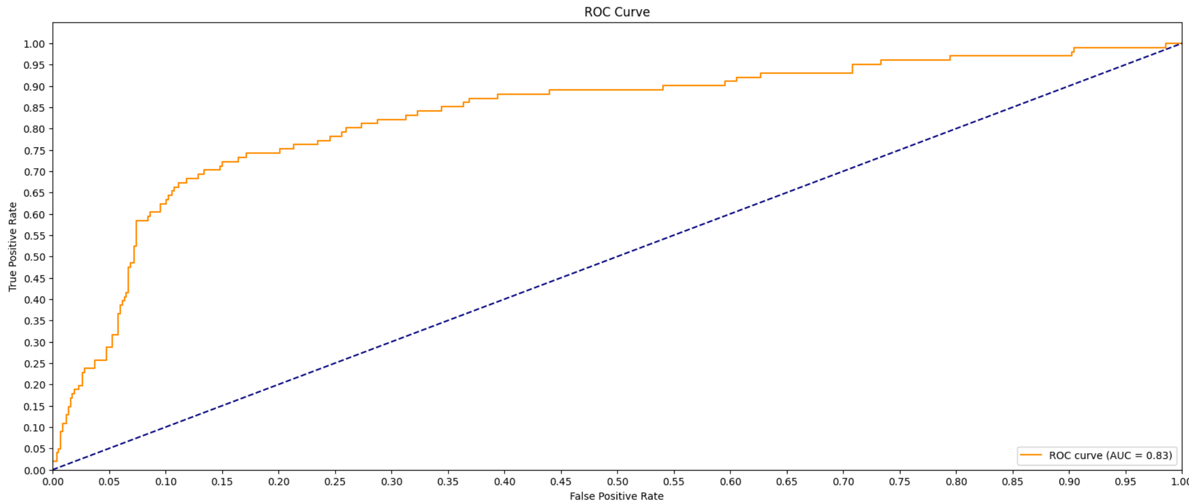
In [63]:
```
plot_confusion_matrix(y_test, y_hat_test)
```



Interpretation:

- True Positives (TP): The model correctly predicted the positive class (27).
- True Negatives (TN): The model correctly predicted the negative class (539).
- False Positives (FP): The model incorrectly predicted the positive class when it was actually negative (27).
- False Negatives (FN): The model incorrectly predicted the negative class when it was actually positive (74).

In [64]:
```
plot_roc_curve(best_lr, X_test, y_test)
```




```
The AUC score is: 0.8313682958401848
```

- The ROC curve is above the diagonal line, indicating that the model performs better than random guessing.
- The AUC score of 0.83 indicates that the model has a good ability to distinguish between the positive and negative classes.

2. Hyperparameter Tuning for Decision Tree

In [65]:
```
# Define the hyperparameters grid
param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [3, 5, 10, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt', 'log2', None]
}

# Set up the grid search
grid_search_Dt = GridSearchCV(Dt, param_grid, cv=5, scoring='accuracy')

# Fit the grid search to the data
grid_search_Dt.fit(X_train_resampled, y_train_resampled)

# Print the best parameters and best score
print("Best parameters for Decision Tree:", grid_search_Dt.best_params_)
print("Best accuracy for Decision Tree:", grid_search_Dt.best_score_)
```

```
Best parameters for Decision Tree: {'criterion': 'gini', 'max_depth': None,
'max_features': None, 'min_samples_leaf': 1, 'min_samples_split': 2}
Best accuracy for Decision Tree: 0.9146260794121384
```

In [66]:
```
best_Dt = grid_search_Dt.best_estimator_
best_Dt.fit(X_train_resampled, y_train_resampled)

y_hat_train = best_Dt.predict(X_train_resampled)
y_hat_test= best_Dt.predict(X_test)
```

Evaluation Metrics for Tuned Decision Tree

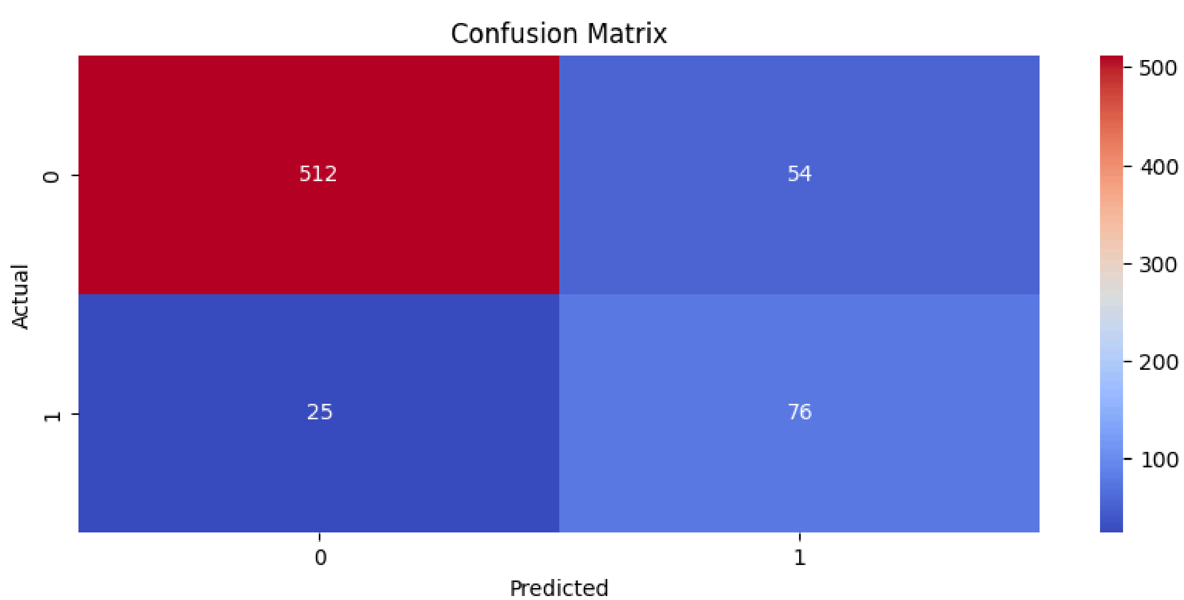
In [67]:
```
metrics_df = evaluate_model_performance(y_train_resampled, y_hat_train, y_tes
t, y_hat_test)
```

	Metric	Training	Testing
0	Precision	1.0	0.584615
1	Recall	1.0	0.752475
2	Accuracy	1.0	0.881559
3	F1-Score	1.0	0.658009

Compared to the tuned logistic model, this one shows better generalization, especially in terms of recall and accuracy on the testing set. However, the significant drop in precision and F1-score from training to testing still suggests some level of overfitting

Confusion Matrix and ROC Curve for Tuned Decision Tree

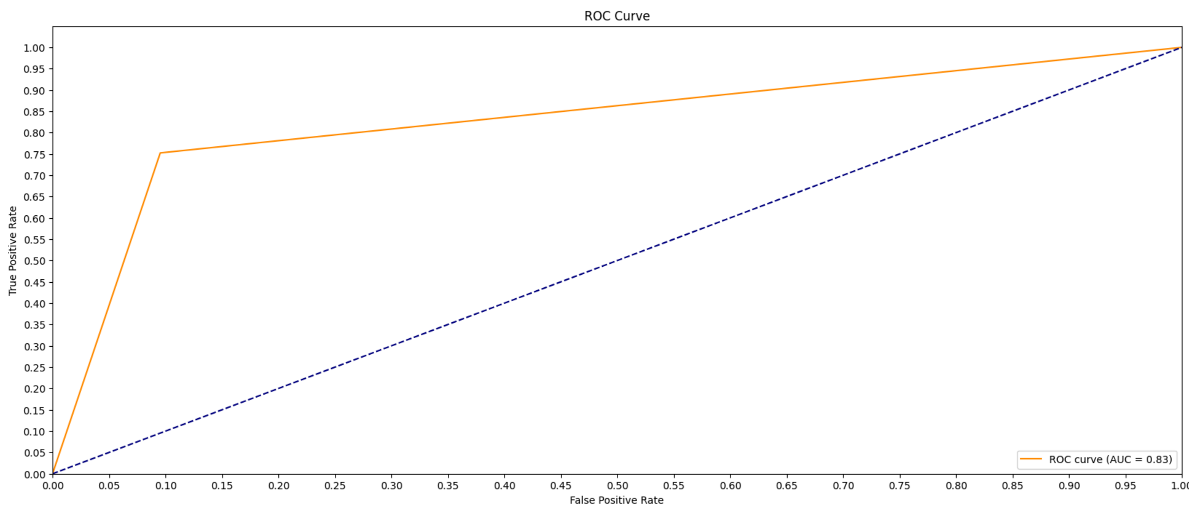
In [68]:
```
plot_confusion_matrix(y_test, y_hat_test)
```



Interpretation:

- True Positives (TP): The model correctly predicted the positive class (78).
- True Negatives (TN): The model correctly predicted the negative class (525).
- False Positives (FP): The model incorrectly predicted the positive class when it was actually negative (41).
- False Negatives (FN): The model incorrectly predicted the negative class when it was actually positive (23).

In [73]:
```
plot_roc_curve(best_Dt, X_test, y_test)
```




```
The AUC score is: 0.8285344435503621
```

- The ROC curve is above the diagonal line, indicating that the model performs better than random guessing.
- The AUC score of 0.87 indicates that the model has a good ability to distinguish between the positive and negative classes.

3. Hyperparameter Tuning for Random Forest

In [79]:
```
# Define the hyperparameters grid for Random Forest
param_grid_rf = {
    'n_estimators': [50, 100, 200],  # Number of trees in the forest
    'criterion': ['gini', 'entropy'],  # Function to measure the quality of a
split
    'max_depth': [None, 10, 20, 30],  # Maximum depth of the tree
    'min_samples_split': [2, 5, 10],  # Minimum number of samples required to
split a node
    'min_samples_leaf': [1, 2, 4],  # Minimum number of samples required to be
at a leaf node
    'max_features': ['auto', 'sqrt', 'log2']  # Number of features to consider
for the best split
}

# Create the Random Forest model
rf = RandomForestClassifier(random_state=42)

# Set up the grid search
grid_search_rf = GridSearchCV(rf, param_grid_rf, cv=5, scoring='accuracy')

# Fit the grid search to the data
grid_search_rf.fit(X_train_resampled, y_train_resampled)

# Print the best parameters and best score
print("Best parameters for Random Forest:", grid_search_rf.best_params_)
print("Best accuracy for Random Forest:", grid_search_rf.best_score_)
```

```
Best parameters for Random Forest: {'criterion': 'gini', 'max_depth': None,
'max_features': 'log2', 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_est
imators': 200}
Best accuracy for Random Forest: 0.9588468055632117
```

In [80]:
```
# Best model after hyperparameter tuning
best_rf = grid_search_rf.best_estimator_

# Fit the model on the resampled training data
best_rf.fit(X_train_resampled, y_train_resampled)

# Predict on both the training and testing datasets
y_hat_train_rf = best_rf.predict(X_train_resampled)
y_hat_test_rf = best_rf.predict(X_test)
```

Evaluation Metrics for Tuned Random Forest

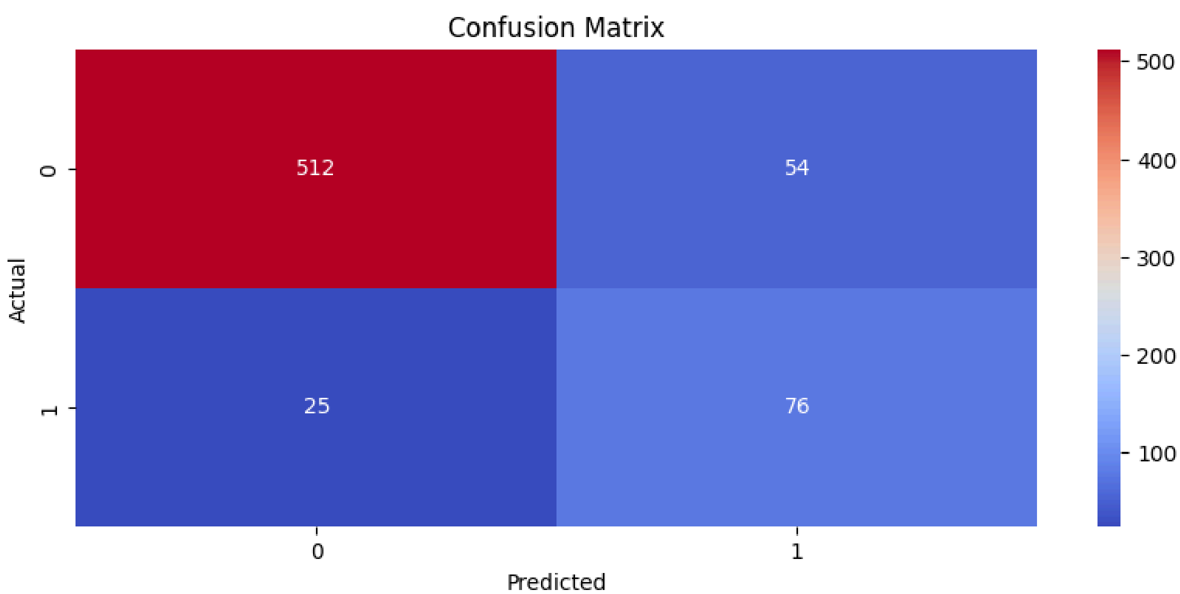
In [81]:
```
# Evaluate the model performance
metrics_df_rf = evaluate_model_performance(y_train_resampled, y_hat_train_rf,
y_test, y_hat_test_rf)
```

	Metric	Training	Testing
0	Precision	1.0	0.775281
1	Recall	1.0	0.683168
2	Accuracy	1.0	0.922039
3	F1-Score	1.0	0.726316

The model demonstrates severe overfitting, as indicated by the perfect scores across all metrics on the training data and the significant drops on the testing data. This suggests that the model has memorized the training data rather than learning patterns that generalize to new data.

Confusion Matrix and ROC Curve for Tuned Random Forest

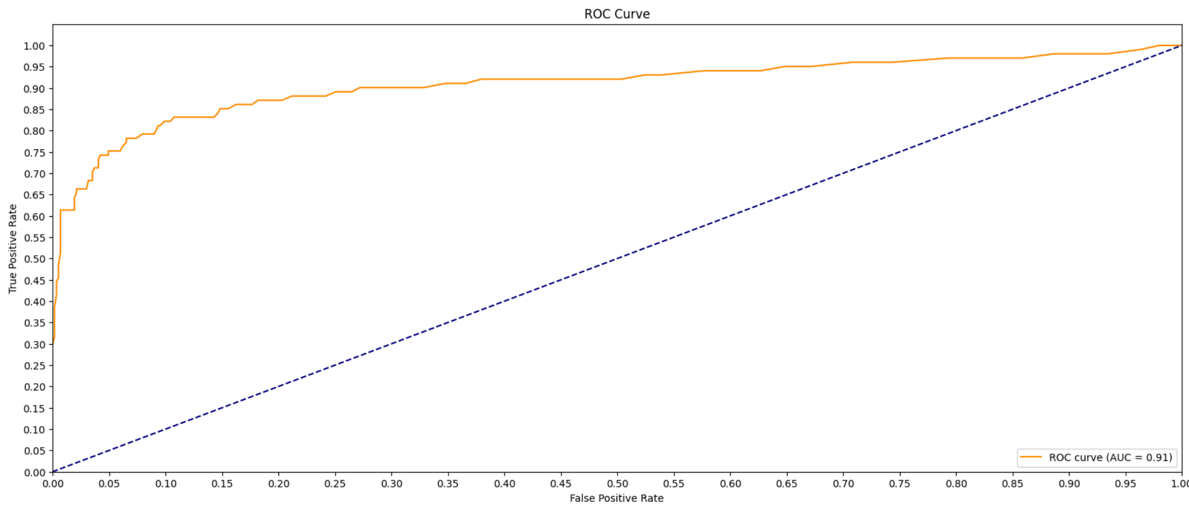
In [82]:
```
plot_confusion_matrix(y_test, y_hat_test)
```



nterpretation:

- True Positives (TP): The model correctly predicted the positive class (78).
- True Negatives (TN): The model correctly predicted the negative class (525).
- False Positives (FP): The model incorrectly predicted the positive class when it was actually negative (41).
- False Negatives (FN): The model incorrectly predicted the negative class when it was actually positive (23).

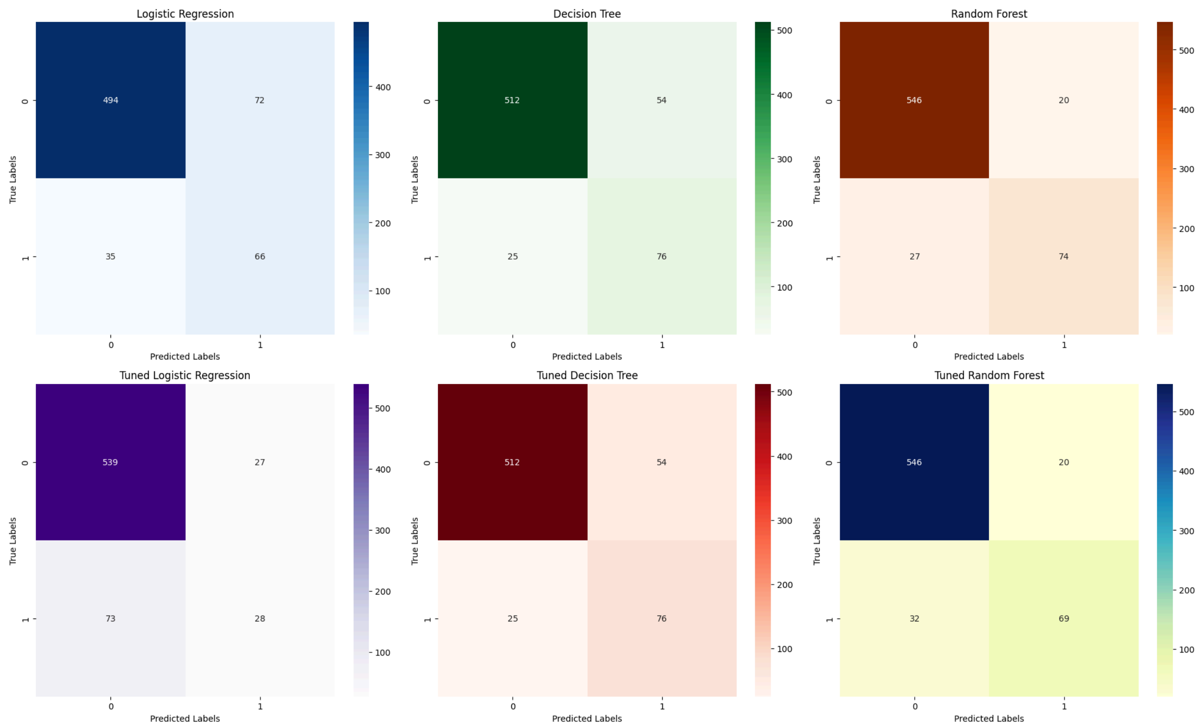
In [83]:
```
plot_roc_curve(best_rf, X_test, y_test)
```



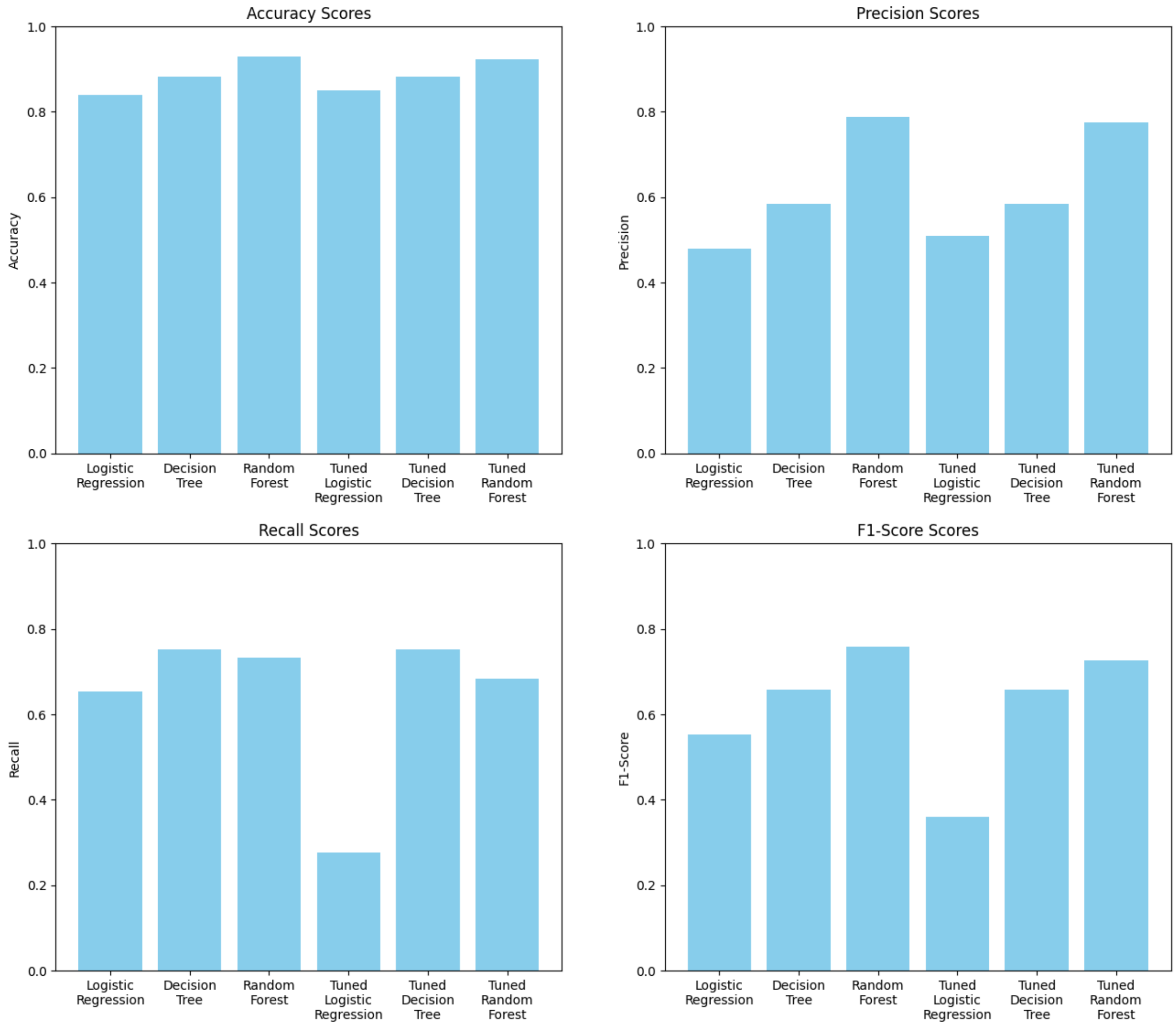

```
The AUC score is: 0.9082846447188888
```

Model Evaluation and Selection

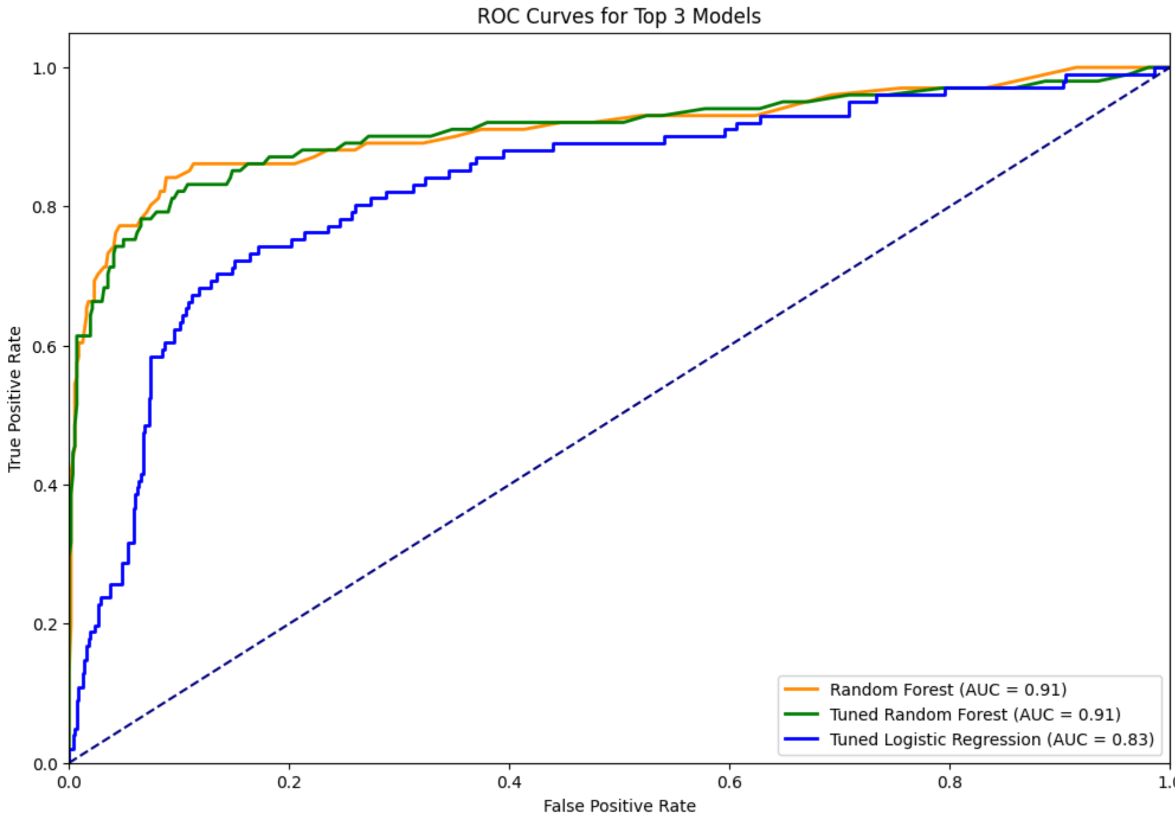
In [95]:
```
models = [lr, Dt, rf, best_lr, best_Dt, best_rf]
model_names = ['Logistic Regression', 'Decision Tree', 'Random Forest', 'Tuned Logistic Regression', 'Tuned Decision Tree', 'Tuned Random Forest']

#Fit the base RandomForestClassifier model (rf)
rf.fit(X_train_resampled, y_train_resampled) # Add this line to fit the rf model

plot_confusion_matrices(models, X_test, y_test, model_names)
```



In [96]:
```
plot_evaluation_metrics(models, X_test, y_test, model_names)
```



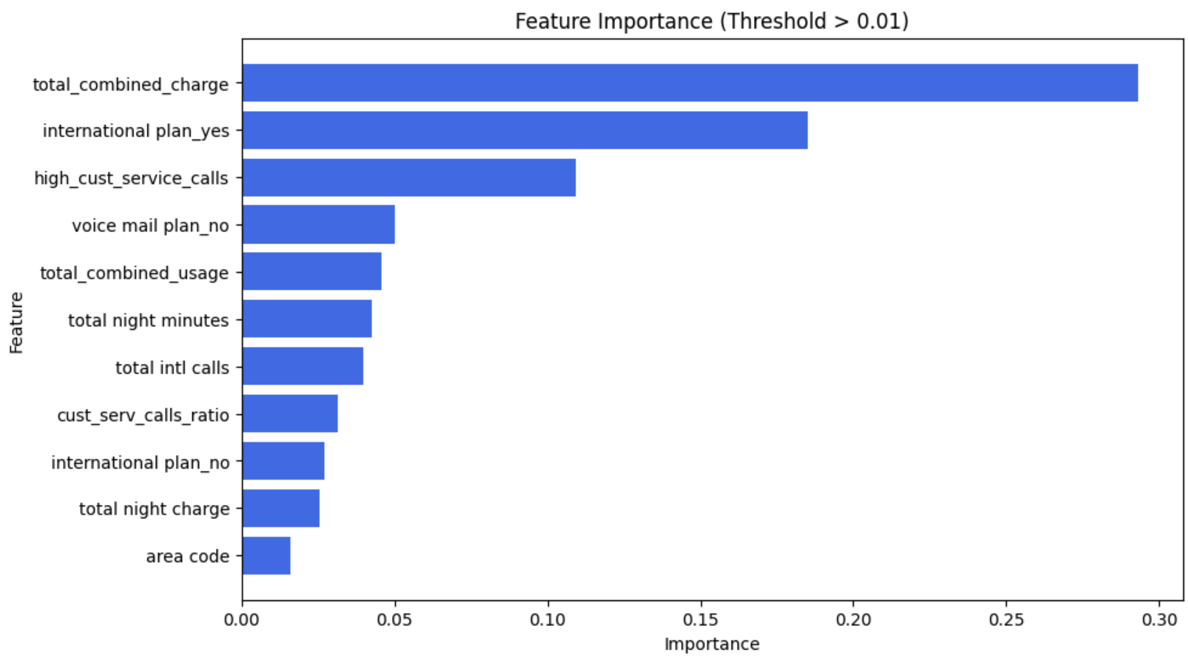
In [97]:
```
plot_roc_curves(models, X_test, y_test, model_names)
```



The tuned decision tree model offers a good balance between precision, recall, accuracy, and F1-score on the testing set, indicating that it generalizes better to new data compared to the other two models. While the tuned random forest model also performs well, the significant overfitting and slightly lower generalization performance makes it less desirable. The tuned logistic regression model is not recommended due to its poor recall and F1-score on the testing data.

Feature Importance

In [98]:
```
# Get the feature importance
importances = best_Dt.feature_importances_

# Create a DataFrame
feature_importance_df = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': importances
})

# Set a threshold for feature importance
threshold = 0.01

# Filter the DataFrame to include only features above the threshold
important_features_df = feature_importance_df[feature_importance_df['Importanc
e'] > threshold]

# Sort the DataFrame by importance
important_features_df = important_features_df.sort_values(by='Importance', asc
ending=False)

# Plot the feature importance
plt.figure(figsize=(10, 6))
plt.barh(important_features_df['Feature'], important_features_df['Importanc
e'], color='royalblue')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title(f'Feature Importance (Threshold > {threshold})')
plt.gca().invert_yaxis()  # To display the most important feature at the top
plt.show()
```



Important Features :

Total Combined Charge:

This feature has the highest importance by a significant margin. The total amount charged to the customer across various plans (day, evening, international) is the most critical factor in predicting whether a customer will churn. This suggests that customers who incur higher charges are more likely to consider leaving SyriaTel, possibly due to dissatisfaction with the cost of services.

International Plan (No):

The second most important feature is whether the customer does not have an international plan. Customers who do not subscribe to an international plan are more likely to churn. This could indicate that such customers might not find the existing plans valuable or that they might be looking for more comprehensive offerings, including international services.

High Customer Service Calls:

This feature also ranks high in importance. Customers who make a large number of calls to customer service are more likely to churn. This suggests that frequent interactions with customer service, possibly due to unresolved issues or dissatisfaction, are strong indicators of potential churn.

Total Combined Usage:

This feature also contributes significantly to the model. The total usage of services (day and evening calls) is another important predictor. Customers with high usage may churn if they feel they are not getting value for their money, or conversely, low usage could indicate that customers might not be fully engaged with the service.

Conclusion

Cost-Related Factors: The biggest drivers of churn are cost-related, especially total charges. This highlights the importance of pricing and perceived value in SyriaTel's customer retention efforts.

Service Dissatisfaction: Frequent customer service interactions, particularly high call volumes, suggest that unresolved issues or poor service experiences increase churn risk. Improving customer support could help retain more customers.

Plan Offerings: The availability of specific plans, such as international plans, significantly impacts churn. This suggests a need to reassess how these plans are marketed and whether they provide sufficient value to customers.

Recommendation

- Focus retention efforts on customers with high total charges, as they are at the greatest risk of churn. Consider offering discounts, personalized plans, or loyalty rewards to increase perceived value.
- Improve Customer Service: Reduce churn by improving the customer service experience, ensuring that issues are resolved efficiently and that customers feel their concerns are being addressed.
- Given the importance of the international plan features, SyriaTel should consider re-evaluating these offerings to ensure they meet customer needs and are priced competitively.

In [ ]: