Final Project Submission

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1. BUSINESS UNDERSTANDING

Problem Statement ¶

Syriatel Telecommunications company is a Syria Based tele-company that is facing a problem of losing customers, this action is known as churning.The company is conscerned by this and would like to know if the rate of churning would increase on the future.Not only does this project help them know that but also know how to better their relationship with their users to maintain a high rate of retention and even a high attraction of new clients.

Objectives

1. Find out why customers are churning.
2. Develop a model that will accurately predict future rate of churning.
3. Find a probable solution to reduce churning.

Success Metric

1. Develop a roburts prediciton model with a recall score of 0.7 - .80
2. Be able to identify features that significantly contribute to churning.
3. Provide possible solutions to the telecom company that will help reduce churning.

2. DATA UNDERSTANDING

Here's a summary of the columns:

- `state` : The state of the customer.
- `account length` : The length of the account in days or months.
- `area code` : The area code of the customer's phone number.
- `phone number` : The phone number of the customer.
- `international plan` : Whether the customer has an international plan or not.
- `voice mail plan` : Whether the customer has a voicemail plan or not.
- `number vmail messages` : The number of voicemail messages the customer has.
- `total day minutes` : Total minutes of day calls.
- `total day calls` : Total number of day calls.
- `total day charge` : Total charge for the day calls.
- `total eve minutes` : Total minutes of evening calls.
- `total eve calls` : Total number of evening calls.
- `total eve charge` : Total charge for the evening calls.
- `total night minutes` : Total minutes of night calls.
- `total night calls` : Total number of night calls.
- `total night charge` : Total charge for the night calls.
- `total intl minutes` : Total minutes of international calls.
- `total intl calls` : Total number of international calls.

- `total intl charge` : Total charge for the international calls.
- `customer service calls` : Number of times the customer called customer service.
- `churn` : Whether the customer churned or not (True/False).

In [1]:

```
# Importing necessary modules and packages

#for data analysis and manipulation
import pandas as pd
import numpy as np

#For plotting
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

# Set visualization style
sns.set_style("darkgrid")

# Display plots in the notebook
%matplotlib inline

#Modelling and supervised learning
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import accuracy_score, f1_score, recall_score, precision_score, roc_curve, roc_
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from sklearn.datasets import make_classification
from imblearn.over_sampling import SMOTE, SMOTENC

#Model tuning
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier


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

In [2]:

```
#Loading data
data = pd.read_csv("telecom.csv")
data.head()
```

Out[2]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...	total eve calls	total eve charge	total night minutes	total night calls
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16.78	244.7	91
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16.62	254.4	103
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10.30	162.6	104
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.26	196.9	89
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12.61	186.9	121

5 rows × 21 columns

In [3]:
```python
#General stats of the data
data.info()
```

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

From the above result we can see we have one Boolean column = churning, four object data type column = state, international plan, voice mail plan and phone number and the rest as interger types of data either int64 or float64

In [4]:
```python
data.describe()
```

Out[4]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	total ev charg
count	3333.000000	3333.000000	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	200.980348	100.114311	17.08354
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50.713844	19.922625	4.31066
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166.600000	87.000000	14.16000
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201.400000	100.000000	17.12000
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235.300000	114.000000	20.00000
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363.700000	170.000000	30.91000

3. DATA PREPARATION

3.1 Data preprocessing

In [5]:

```
# finding duplicates and missing values
duplicated = data.duplicated().sum()

missing_values = data.isna().sum()

#Display the total number of duplicate values and missing_values
print("Duplicated values are:", duplicated)
print("Missing values are:\n", missing_values)
```

```
Duplicated values are: 0
Missing values are:
 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 [6]:

```
# Converting string-based categorical values to integer-based categorical representations
intl_plan = {'yes': 1, 'no': 0}
vm_plan = {'yes': 1, 'no': 0}
churn_status = {True: 1, False: 0}

#Display the replacement of each column
data['international plan'].replace(intl_plan, inplace=True)
data['voice mail plan'].replace(vm_plan, inplace=True)
data['churn'].replace(churn_status, inplace=True)
```

In [7]:

```
data.sample(15)
```

Out[7]:

	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 calls	total eve charge	total night minutes	tot nig cal
1382	GA	125	415	380-6342	0	1	39	236.1	107	40.14	...	110	24.58	175.4	1(
619	KS	110	415	383-1657	1	0	0	293.3	79	49.86	...	90	16.02	266.9	(
119	ID	97	408	328-3266	0	0	0	239.8	125	40.77	...	111	18.26	143.3	٤
188	WY	164	510	373-4819	0	0	0	160.6	111	27.30	...	126	13.87	187.1	1'
1984	TN	112	415	339-6477	0	0	0	272.5	119	46.33	...	94	19.22	159.1	(
2453	HI	134	415	342-9394	0	1	38	214.4	93	36.45	...	57	17.99	165.0	˜
1623	ME	130	408	387-6031	0	0	0	176.3	140	29.97	...	104	17.09	161.9	1:
1134	TN	105	408	353-8849	0	0	0	206.2	84	35.05	...	138	21.79	117.1	(
3190	ID	103	415	346-5992	0	0	0	174.7	151	29.70	...	56	12.58	168.2	1(
210	LA	99	415	411-2284	0	0	0	241.1	72	40.99	...	98	13.23	188.2	1(
2190	NC	88	408	414-4037	0	1	27	93.4	106	15.88	...	92	21.42	189.0	1(
1264	TN	72	408	348-2009	0	0	0	147.0	79	24.99	...	103	13.80	162.9	٤
1105	NJ	135	510	401-8735	0	1	28	201.4	100	34.24	...	117	20.95	154.8	1:
732	IN	48	510	342-6696	0	0	0	300.4	94	51.07	...	103	11.32	197.4	(
3214	OK	149	510	365-9079	1	0	0	180.9	79	30.75	...	83	16.57	197.8	1(

15 rows × 21 columns

In [8]:

```
#totals for minutes, charges and calls

data['total_charges'] = round(data['total day charge'] + data['total eve charge'] + data['total nigh
data['total_calls'] = round(data['total day calls'] + data['total eve calls'] + data['total night ca
data['total_minutes'] = round(data['total day minutes'] + data['total eve minutes'] + data['total ni
```

In [9]:

```
print(data[['total_charges', 'total_calls','total_minutes']].sample(10))
```

```
      total_charges  total_calls  total_minutes
189            68.0          314          660.0
497            66.0          289          657.0
2319           78.0          317          715.0
2303           32.0          275          399.0
1471           61.0          291          619.0
643            74.0          307          734.0
1320           59.0          345          545.0
221            57.0          291          596.0
3112           49.0          262          492.0
3272           83.0          355          761.0
```

In [10]:

```
#Display 10 random entries to confirm changes
data.sample(10)
```

Out[10]:

	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 night calls	total night charge	total intl minutes	tot ir cal
1881	NE	76	415	334-6519	0	0	0	272.7	97	46.36	...	105	10.60	7.7	
895	MD	106	415	343-2350	0	0	0	165.3	118	28.10	...	93	8.42	8.5	
2244	KS	148	510	415-4051	0	0	0	239.3	84	40.68	...	104	10.47	10.9	
3207	DC	93	408	345-1994	0	1	22	306.2	123	52.05	...	107	10.81	11.7	
1471	OH	75	415	340-9803	0	0	0	150.6	99	25.60	...	104	7.14	8.1	
1503	WV	57	415	419-6418	1	1	17	236.5	94	40.21	...	117	10.65	12.2	
439	MI	81	415	408-3384	0	0	0	153.5	99	26.10	...	86	8.93	6.3	
2598	TN	196	415	340-8291	0	0	0	133.1	80	22.63	...	96	9.97	10.3	
1441	NC	172	408	331-5962	0	1	47	274.9	102	46.73	...	123	11.03	8.8	
1146	WA	161	415	378-8137	0	0	0	151.6	117	25.77	...	68	10.11	4.0	

10 rows × 24 columns

3.2 Create a copy of data

In [11]:
```python
import pandas as pd

# Assuming 'data' is your DataFrame
data_copy = data.copy()

# Specify the columns to drop
columns_to_drop = ['phone number','total day minutes', 'total eve minutes', 'total night minutes', '

# Use the drop method with the 'columns' parameter
data_copy = data_copy.drop(columns=columns_to_drop)

# Print a sample of the modified DataFrame
data_copy.sample(10)
```

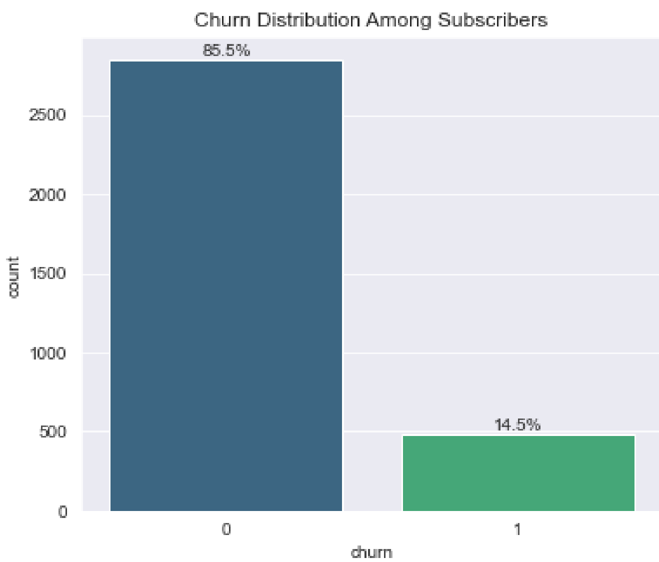
Out[11]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	customer service calls	churn	total_charges	total_calls	total_minutes
2028	SD	93	510	0	0	0	1	1	85.0	312	792.0
1435	IL	89	415	1	1	19	0	1	50.0	364	509.0
2863	ME	28	415	0	0	0	3	0	70.0	307	694.0
900	VA	72	510	1	1	29	0	0	47.0	299	504.0
2163	KS	119	415	0	0	0	1	0	74.0	307	717.0
569	NC	133	408	1	1	32	2	1	72.0	348	670.0
475	AR	74	510	0	0	0	3	0	53.0	242	594.0
171	NH	64	408	0	1	27	2	0	56.0	280	527.0
3161	NV	148	510	0	0	0	2	0	69.0	348	712.0
1342	AK	52	415	0	1	24	2	0	54.0	280	535.0

3.3 Univariate Analysis

In [12]:

```python
# Churn distribution among subscribers
#Setting size figure
plt.figure(figsize=(6, 5))
#Creating a countplot using seaborn
ax = sns.countplot(x='churn', data=data, palette='viridis')
#Calc the total number of data points
total = len(data['churn'])

#Adding percentage annotation for each bar
for p in ax.patches:
    percentage = '{:.1f}%'.format(100 * p.get_height() / total)
    x = p.get_x() + p.get_width() / 2
    y = p.get_height()
    ax.annotate(percentage, (x, y), ha='center', va='bottom')

#Set title for plot
plt.title("Churn Distribution Among Subscribers")
plt.show()
```



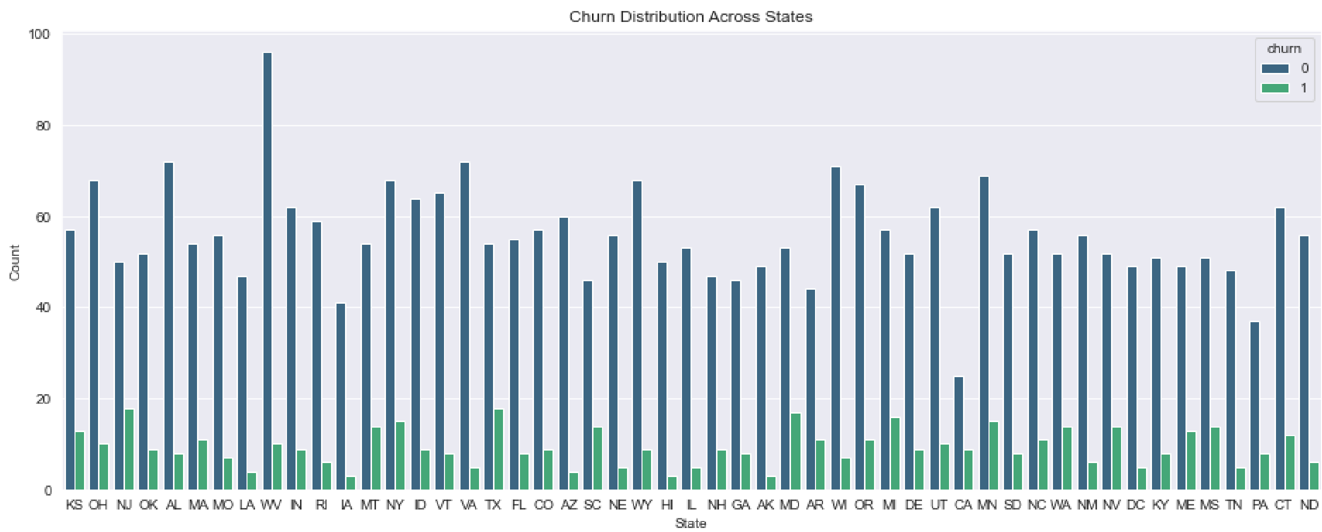
In [44]:

```python
# Pie chart of area code feature
area = data['area code'].value_counts()
transanction = area.index
quantity = area.values

# plot pie circle with plotly
figure = px.pie(data,
               values = quantity,
               names = transanction,
               hole = .5,
               title = 'Distribution of Area Code Feature')
figure.show()
```

3.4 Bivariate analysis

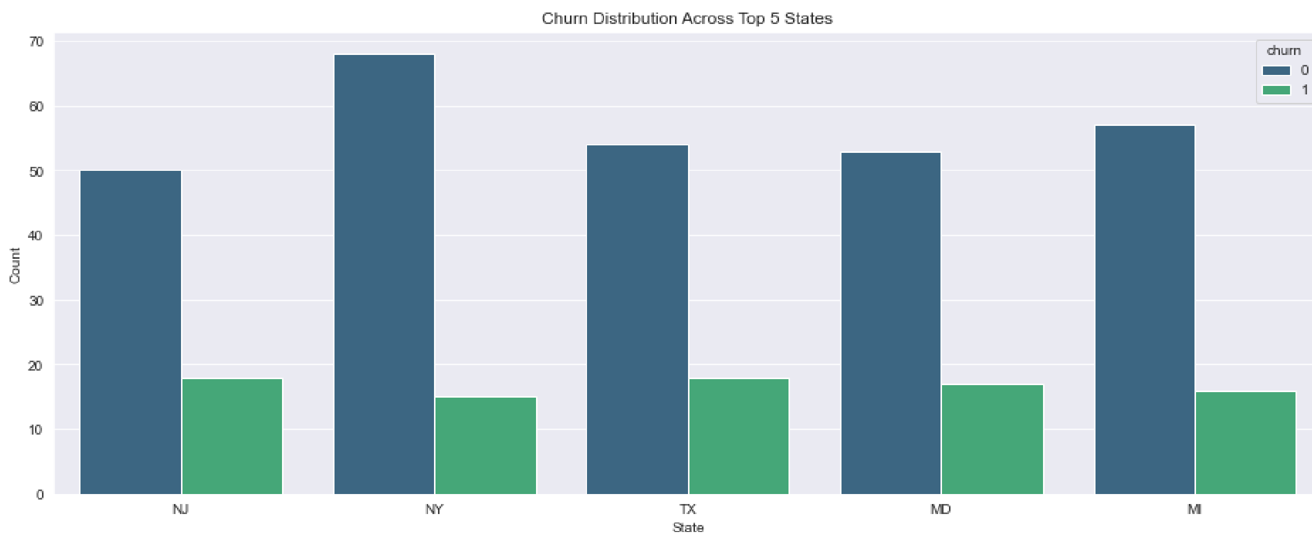
In [13]:

```
# Churn vs States

# Set figure size
plt.figure(figsize=(16, 6))

# Create a bar plot
sns.countplot(x='state', hue='churn', data=data_copy, palette='viridis')

# Add titles and labels
plt.title('Churn Distribution Across States')
plt.xlabel('State')
plt.ylabel('Count')

# Show the plot
plt.show()
```



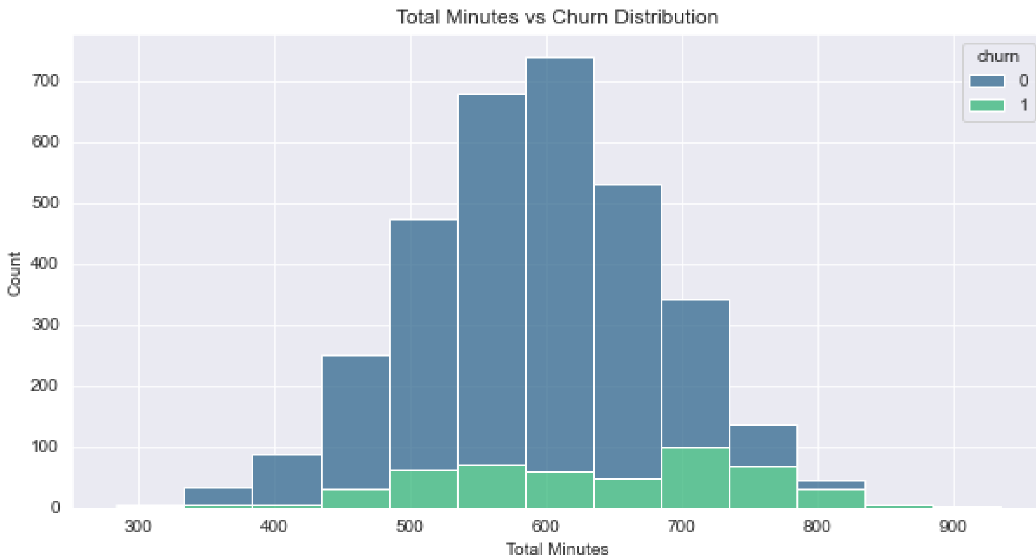
In [46]:

```python
# Calculate the total number of churns for each state
state_churn_counts = data.groupby('state')['churn'].sum()

# Find the top 5 states with the highest churn counts
top_5_states = state_churn_counts.sort_values(ascending=False).head(5).index

# Set figure size
plt.figure(figsize=(16, 6))

# Create a bar plot for the top 5 states
sns.countplot(x='state', hue='churn', data=data[data['state'].isin(top_5_states)], palette='viridis'

# Add titles and labels
plt.title('Churn Distribution Across Top 5 States')
plt.xlabel('State')
plt.ylabel('Count')

# Show the plot
plt.show()
```

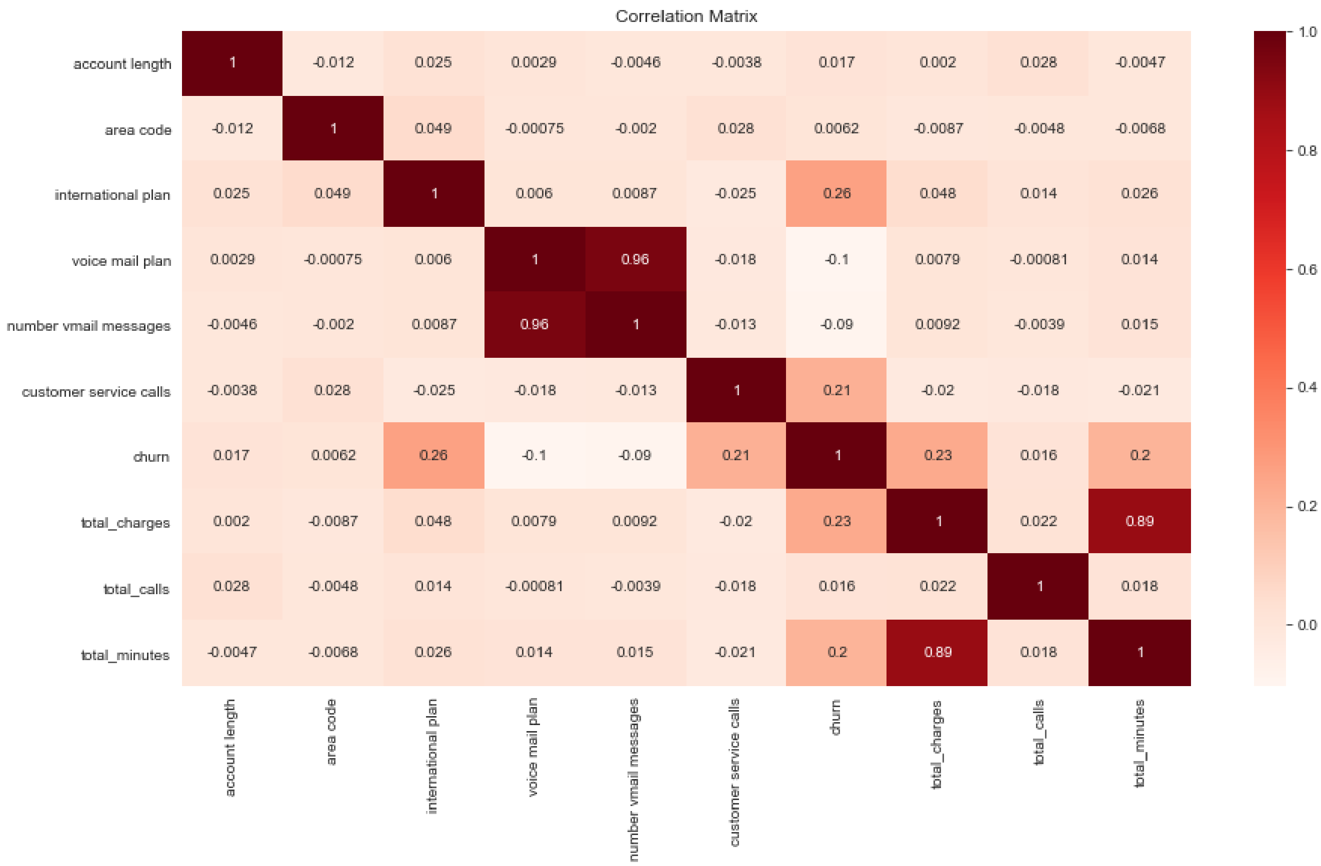


In [14]:

```
# Create a figure and axis
plt.figure(figsize=(10, 5))

# Plot the stacked bar plot
sns.histplot(data=data_copy, x='total_minutes', hue='churn', multiple='stack', binwidth=50, palette=

# Add labels and title
plt.xlabel('Total Minutes')
plt.ylabel('Count')
plt.title('Total Minutes vs Churn Distribution')

# Show the plot
plt.show()
```



In [15]:
```python
#Calculate the correlation matrix using the corr() method
correlation_matrix = data_copy.corr()

plt.figure(figsize=(15, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='Reds')
plt.title('Correlation Matrix')
plt.show()
```



Multicollinearity occurs when two or more features in the dataset are highly correlated with each other, which can cause issues during modeling such as instability, overfitting, or inaccurate coefficient estimates.

4. MODELLING

In [16]:
```python
#Onehote encoding for our categorcial features
data_copy = pd.get_dummies(data_copy, columns=['state', 'area code'], drop_first=True)
```

In [17]:

```python
#Display 10 samples
data_copy.sample(10)
```

Out[17]:

	account length	international plan	voice mail plan	number vmail messages	customer service calls	churn	total_charges	total_calls	total_minutes	state_AL	...	state
362	39	0	1	36	1	0	57.0	370	608.0	0	...	
2611	135	0	0	0	0	0	54.0	282	529.0	0	...	
3068	78	0	1	21	2	0	54.0	257	517.0	0	...	
2934	24	0	0	0	2	1	50.0	226	527.0	0	...	
2198	127	0	0	0	0	0	65.0	348	548.0	0	...	
2214	90	0	0	0	1	0	64.0	355	625.0	0	...	
82	55	0	1	25	3	0	51.0	310	488.0	0	...	
3046	110	0	0	0	1	0	34.0	251	402.0	0	...	
2587	105	0	0	0	3	0	66.0	362	641.0	0	...	
3094	91	0	0	0	1	0	48.0	251	493.0	0	...	

10 rows × 61 columns

In [18]:

```python
#Scale the transform the data to avoid any interference from outliers
scaler = MinMaxScaler()

#iterate over the numerical columns in the data_copy set a scale of -1 to 1
def scaling(columns):
    return scaler.fit_transform(data_copy[columns].values.reshape(-1,1))
for i in data_copy.select_dtypes(include=[np.number]).columns:
    data_copy[i] = scaling(i)
# Display 10 samples
data_copy.sample(10)
```

Out[18]:

	account length	international plan	voice mail plan	number vmail messages	customer service calls	churn	total_charges	total_calls	total_minutes	state_AL	...	stat
2742	0.595041	0.0	1.0	0.607843	0.222222	0.0	0.630137	0.604444	0.668885	0.0	...	
281	0.330579	0.0	0.0	0.000000	0.222222	0.0	0.547945	0.386667	0.547421	0.0	...	
1508	0.380165	0.0	0.0	0.000000	0.333333	0.0	0.534247	0.426667	0.668885	0.0	...	
2658	0.413223	0.0	0.0	0.000000	0.000000	0.0	0.616438	0.551111	0.465890	0.0	...	
2112	0.615702	0.0	0.0	0.000000	0.444444	1.0	0.397260	0.364444	0.391015	0.0	...	
2323	0.123967	0.0	0.0	0.000000	0.111111	0.0	0.465753	0.293333	0.490849	0.0	...	
2739	0.413223	0.0	1.0	0.176471	0.000000	0.0	0.424658	0.533333	0.392679	0.0	...	
2636	0.425620	0.0	0.0	0.000000	0.222222	0.0	0.452055	0.262222	0.462562	0.0	...	
1460	0.326446	0.0	0.0	0.000000	0.333333	0.0	0.479452	0.600000	0.435940	0.0	...	
115	0.144628	1.0	1.0	0.823529	0.000000	1.0	0.602740	0.675556	0.542429	0.0	...	

10 rows × 61 columns

4.1 train test split

In [19]:

```python
#Defining X(independent variables) and y(target variable)
X = data_copy.drop("churn", axis=1)
y = data_copy["churn"]
```

In [20]:
```python
#train test split
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.25, random_state=42)
```

4.2 SMOTE/SMOTENC technique

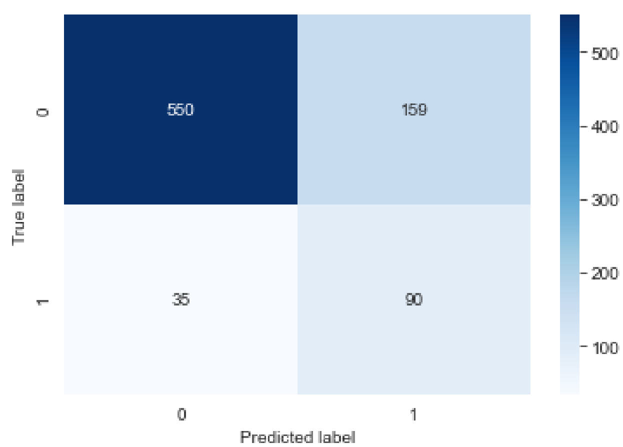
In [21]:
```python
#SMOTE to fix the class imbalancemnt found during the decison tree classification

#instantiate SMOTENC

smote = SMOTENC(categorical_features = [1,2],random_state = 123)
resampled_X_train, resampled_y_train = smote.fit_resample(X_train,y_train)
```

4.3 Logistic Regression

In [22]:
```python
#logistic regression
logreg =LogisticRegression(random_state=42)
```

In [23]:
```python
#fit the model
logreg.fit(resampled_X_train, resampled_y_train)
#predict on the labels
y_pred_log = logreg.predict(X_test)
```

In [24]:
```python
def plot_confusion_matrix(y_true, y_pred, classes):
    #plots confusion matrix

    cm = confusion_matrix(y_true, y_pred)
    plt.figure()
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=classes, yticklabels=classes)
    plt.xlabel('Predicted label')
    plt.ylabel('True label')
    plt.show()

plot_confusion_matrix(y_test, y_pred_log, [0,1])
```



In [25]:
```python
print(classification_report(y_test,y_pred_log))
```

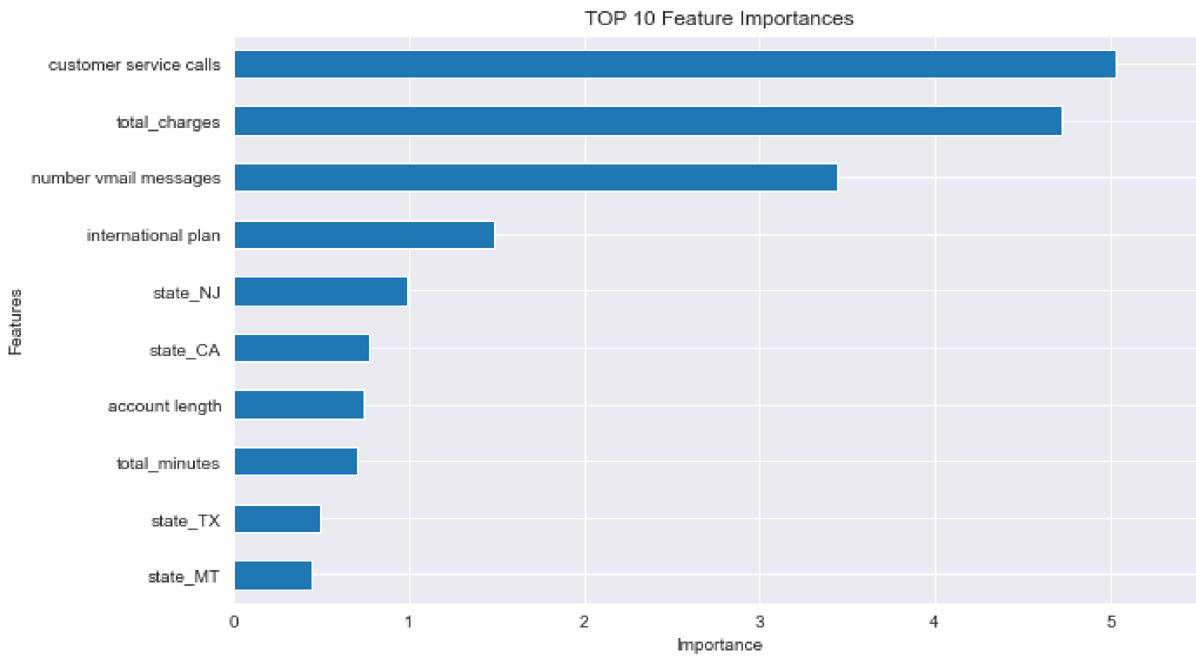
```
              precision    recall  f1-score   support

         0.0       0.94      0.78      0.85       709
         1.0       0.36      0.72      0.48       125

    accuracy                           0.77       834
   macro avg       0.65      0.75      0.67       834
weighted avg       0.85      0.77      0.79       834
```

The classification report of the logistic regression model in summary:

- The recall score was .78(78%),means it was only able to identify 78% 'No Churn' correctly and .72(72%) for 'Churn instances
- Had an accuracy of 77% which is not enough so hence we try another type of model!

In [26]:

```python
#Feature Importance in the Logistics Regression

importance_logreg = logreg.coef_[0]
Feature_names = resampled_X_train.columns
Feature_importances = pd.Series(importance_logreg,index=Feature_names)
Feature_importances = Feature_importances.sort_values(ascending=False)
plt.figure(figsize=(10,6))
top_features = Feature_importances[:10] #selecting the top 10
top_features.sort_values().plot(kind='barh')
plt.xlabel('Importance')
plt.ylabel('Features')
plt.title('TOP 10 Feature Importances')
plt.xlim(0, max(top_features)*1.1) #setting nthe xlim to the max importance vakue
plt.show()
```

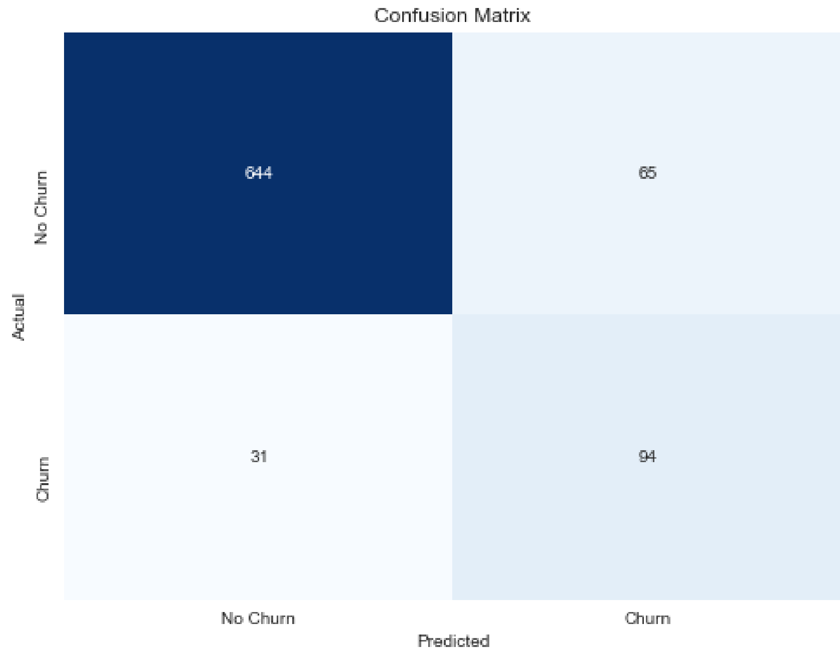


4.3 Decision Tree Classification

In [27]:

```
#Decision Tree

#create the decision tree
clf = DecisionTreeClassifier(random_state=42)

#Train the classifier on the training data
clf.fit(resampled_X_train, resampled_y_train)

#Make predicitons on the testing data
y_pred = clf.predict(X_test)

#Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy:{accuracy:.2f}")

#Dsiplay the classification report and confusion matrix
print('\nClassfication Report:')
print(classification_report(y_test, y_pred))

print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred))

# Calculate the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Create a DataFrame from the confusion matrix for better visualization
conf_matrix_df = pd.DataFrame(cm, index=['No Churn', 'Churn'],columns=['No Churn', 'Churn'])

# Plot the heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix_df, annot=True, fmt="d", cmap="Blues", cbar=False)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
Accuracy:0.88

Classfication Report:
              precision    recall  f1-score   support

         0.0       0.95      0.91      0.93       709
         1.0       0.59      0.75      0.66       125

    accuracy                           0.88       834
   macro avg       0.77      0.83      0.80       834
weighted avg       0.90      0.88      0.89       834


Confusion Matrix:
[[644  65]
 [ 31  94]]
```

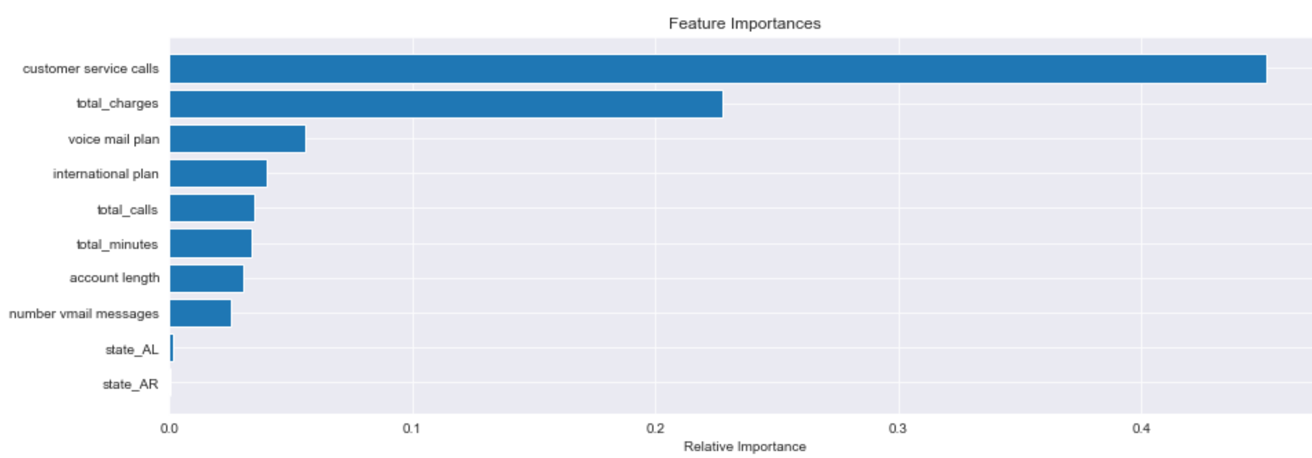


Classification report of Decision Tree in summary:

- The model performs well in predicting 'No Churn' instances, with high precision and recall.
- For 'Churn' predictions, precision is lower, indicating a higher rate of false positives, but recall is still reasonable.
- The model has an overall accuracy of 88%, suggesting good overall performance.

In [28]:

```
#Feature Importance in the Decision Tree

column_names = list(resampled_X_train.columns)
importances = clf.feature_importances_[0:10]
indices = np.argsort(importances)

plt.figure(figsize=(15,5))
plt.title('Feature Importances')
plt.barh(range(len(indices)),importances[indices], align= 'center')
plt.yticks(range(len(indices)), [column_names[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



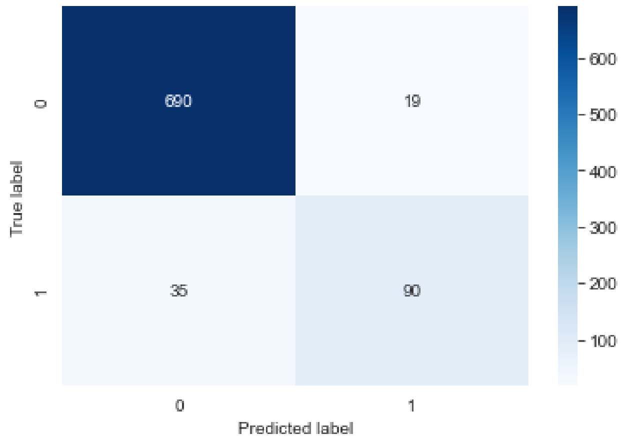
4.4 Random Tree Classifier

In [29]:
```
#Random forest classifier
#Instantiate the classifier
rf = RandomForestClassifier(random_state=42)
#Fit on the training data
rf.fit(resampled_X_train,resampled_y_train)
```

Out[29]:
```
RandomForestClassifier(random_state=42)
```

In [30]:
```
#predict on the test data
y_pred_rf = rf.predict(X_test)
```

In [31]:
```
#rf confusion matrix

plot_confusion_matrix(y_test, y_pred_rf,[0,1])
```



In [32]:
```
print(classification_report(y_test, y_pred_rf))
```

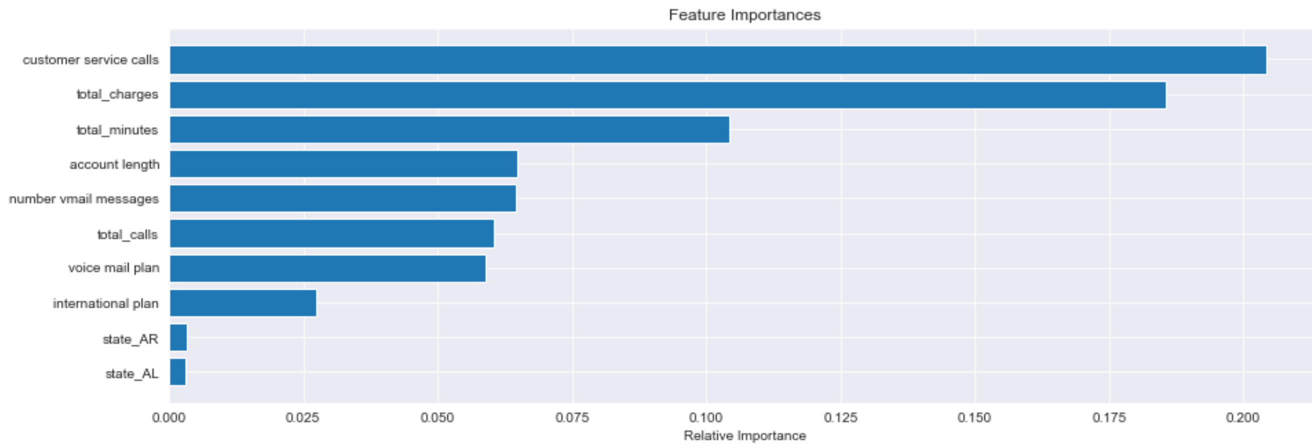
```
              precision    recall  f1-score   support

         0.0       0.95      0.97      0.96       709
         1.0       0.83      0.72      0.77       125

    accuracy                           0.94       834
   macro avg       0.89      0.85      0.87       834
weighted avg       0.93      0.94      0.93       834
```

Classification report of Random Tree Classsifier in summary:

- The model performs well, with high precision for both classes.
- 'No Churn' instances are well-identified with high recall (97%), and precision is also high (95%).
- For 'Churn' predictions, recall is 72%, indicating that the model identified 72% of the actual 'Churn' instances. Precision for - - - 'Churn' is also high at 83%.
- The overall accuracy is 94%, suggesting good overall performance.

In [33]:

```
column_names = list(resampled_X_train.columns)
importances = rf.feature_importances_[0:10]
indices = np.argsort(importances)

plt.figure(figsize=(15,5))
plt.title('Feature Importances')
plt.barh(range(len(indices)),importances[indices], align= 'center')
plt.yticks(range(len(indices)), [column_names[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



5. EVALUATION

In this section I will be able to evaluate models on the recall score and ROC_AUC, which in turn I;ll be able to know which model was the best and later tuning it for better perfomance.

5.1 Recall Score

This is a measure of how many positive instances the model correctly indetifies. The higher the recall score the better the model.

In [34]:

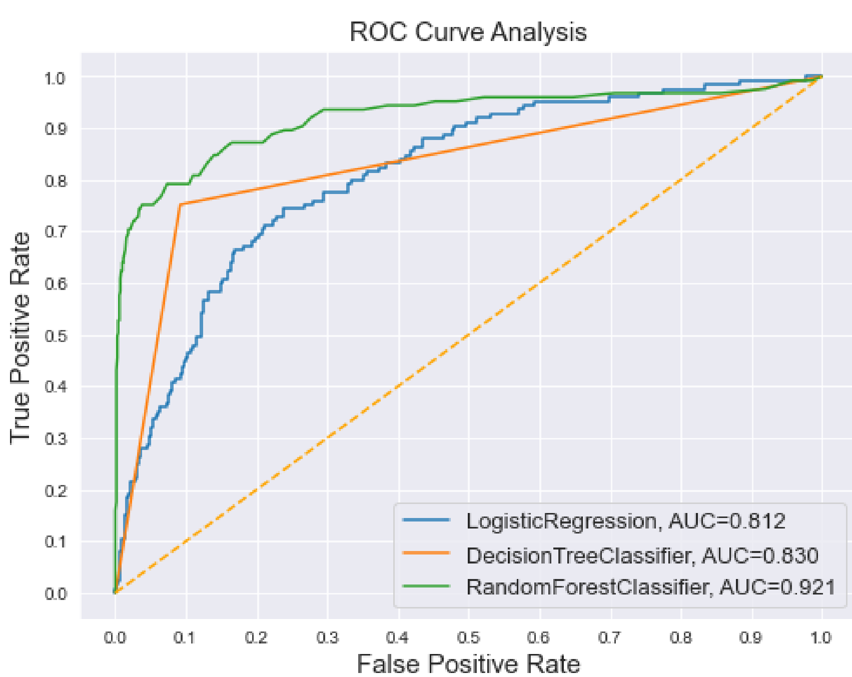
```python
np.random.seed(42)

classifiers = [LogisticRegression(),
               DecisionTreeClassifier(),
               RandomForestClassifier()]

# Define a result table as a DataFrame
result_table = pd.DataFrame(columns=['classifiers', 'recall'])

# Train the models and record the results
for cls in classifiers:
    model = cls.fit(resampled_X_train, resampled_y_train)
    y_pred = model.predict(X_test)

    recall = recall_score(y_test, y_pred)

    result_table = result_table.append({'classifiers': cls.__class__.__name__,
                                        'recall': recall}, ignore_index=True)

# Set name of the classifiers as index labels
result_table.set_index('classifiers', inplace=True)

result_table
```

Out[34]:

	recall
classifiers	
LogisticRegression	0.720
DecisionTreeClassifier	0.752
RandomForestClassifier	0.720

In [35]:

```
np.random.seed(42)
classifiers = [LogisticRegression(),
               DecisionTreeClassifier(),
               RandomForestClassifier()]

# Define a result table as a DataFrame
result_table = pd.DataFrame(columns=['classifiers', 'fpr','tpr','auc'])

# Train the models and record the results
for cls in classifiers:
    model = cls.fit(resampled_X_train, resampled_y_train)
    yproba = model.predict_proba(X_test)[::,1]

    fpr, tpr, _ = roc_curve(y_test,  yproba)
    auc = roc_auc_score(y_test, yproba)

    result_table = result_table.append({'classifiers':cls.__class__.__name__,
                                        'fpr':fpr,
                                        'tpr':tpr,
                                        'auc':auc}, ignore_index=True)

# Set name of the classifiers as index labels
result_table.set_index('classifiers', inplace=True)

fig = plt.figure(figsize=(8,6))

for i in result_table.index:
    plt.plot(result_table.loc[i]['fpr'],
             result_table.loc[i]['tpr'],
             label="{}, AUC={:.3f}".format(i, result_table.loc[i]['auc']))

plt.plot([0,1], [0,1], color='orange', linestyle='--')

plt.xticks(np.arange(0.0, 1.1, step=0.1))
plt.xlabel("False Positive Rate", fontsize=15)

plt.yticks(np.arange(0.0, 1.1, step=0.1))
plt.ylabel("True Positive Rate", fontsize=15)

plt.title('ROC Curve Analysis', fontsize=15)
plt.legend(prop={'size':13}, loc='lower right')

plt.show()
```



- The ROC curve shows that the RandomForestClassifier has the best performance among our three models with a score of 0.921 and LogisticRgression with the lowest performance with a score of 0.812.

- The ROC curve essential show us the trade-off between the (TPR) true positive rate and (FPR) false positive rate for our binary classifiers.
- TPR = those positive instances correctly classified as such
- FPR = those negatives instances incorrectly classifies as positives

5.2 Model Tuning

As seen from out evaluation section the RandomForestClassification hadd the best performance among the three.To improve the perfomance of the model we have to carry out model tuning by use of GridSearch.

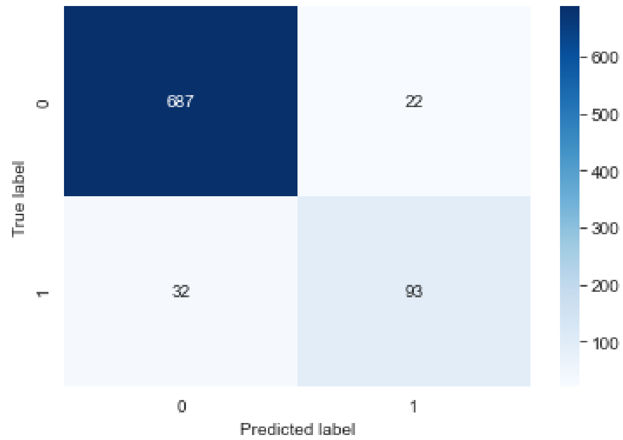
In [36]:
```
#Tuning RandomForestClassification

#Define the grid
param_grid = {
    "n_estimators": [50, 100],
    "max_depth": [15, 20, 35],
    "min_samples_split":[5, 10, 15],
    "min_samples_leaf":[2, 4, 10],
    "criterion":['entropy','gini']
}

#Create a RandomForestClassifier instance
rf_classifier = RandomForestClassifier(random_state=42)
grid_search = GridSearchCV(estimator=rf_classifier, param_grid=param_grid, scoring="recall", cv=5, n
grid_search.fit(resampled_X_train, resampled_y_train)
best_params = grid_search.best_params_
best_rf_classifier = grid_search.best_estimator_
#Evaluate
y_pred_grid = best_rf_classifier.predict(X_test)
#Display the best parameters
print("Best Parameters:", best_params)

#Display the classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred_grid))
```

```
Best Parameters: {'criterion': 'entropy', 'max_depth': 35, 'min_samples_leaf': 2, 'min_samples_spli
t': 15, 'n_estimators': 100}

Classification Report:
              precision    recall  f1-score   support

         0.0       0.96      0.97      0.96       709
         1.0       0.81      0.74      0.78       125

    accuracy                           0.94       834
   macro avg       0.88      0.86      0.87       834
weighted avg       0.93      0.94      0.93       834
```

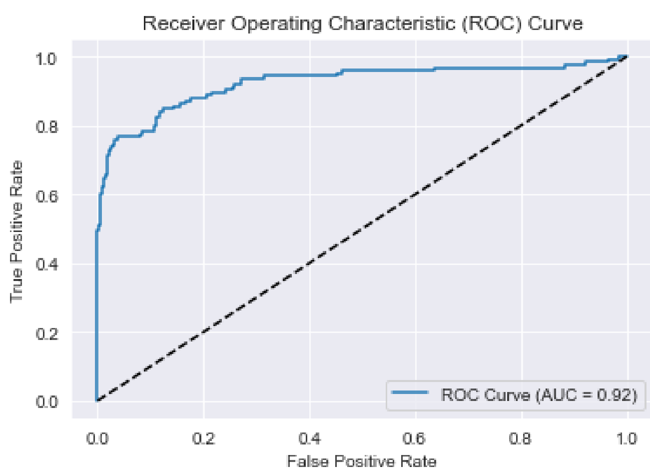
classification_report of RandomForestClassifier after tuning:

- The model performs well, with high precision for both classes.
- 'No Churn' instances are well-identified with high recall (97%), and precision is also high (95%).
- For 'Churn' predictions, recall is 72%, indicating that the model identified 72% of the actual 'Churn' instances. This as close as to the 0.8 recall score we needed to make our model effective.
- The model iwth a recall score can be called Pretty Good model.
- Precision for 'Churn' is also high at 83%.
- The overall accuracy is 94%, suggesting good overall performance.

In [37]:
```python
#Confusion matrix
plot_confusion_matrix(y_test, y_pred_grid,[0,1])
```



In [38]:
```python
# Get the predicted probabilities for the positive class
y_prob_grid = best_rf_classifier.predict_proba(X_test)[:, 1]

# Compute the false positive rate, true positive rate, and thresholds
fpr, tpr, thresholds = roc_curve(y_test, y_prob_grid)

# Compute the AUC score
auc_score = roc_auc_score(y_test, y_prob_grid)

# Plot the ROC curve
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(auc_score))
plt.plot([0, 1], [0, 1], 'k--')  # Diagonal line for random classifier
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```



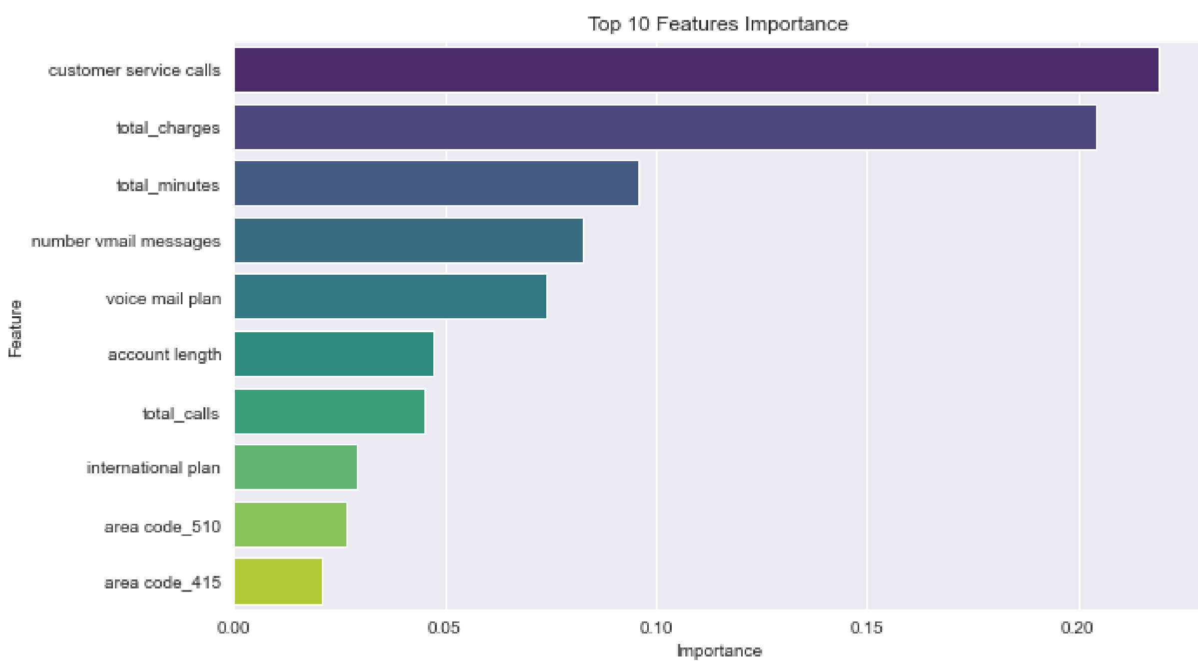
For 'Churn' predictions, recall is 74% indicating that the model identified 74% of the actual 'Churn' instances. This as close as to the 0.8 recall score we needed to make our model effective.

- The model with this recall score can be called Pretty Good model.

In [50]:

```python
# Assuming you have a tuned RandomForestClassifier stored in `tuned_rf_classifier`

# Get feature importances
feature_importances = best_rf_classifier.feature_importances_

# Create a DataFrame with feature names and their importances
feature_importance_df = pd.DataFrame({'Feature': X_train.columns, 'Importance': feature_importances}

# Sort the DataFrame by importance in descending order
top_features = feature_importance_df.sort_values(by='Importance', ascending=False).head(10)

# Print or visualize the top 10 features
print(top_features)

import matplotlib.pyplot as plt
import seaborn as sns

# Set figure size
plt.figure(figsize=(10, 6))

# Create a bar plot of the top 10 features
sns.barplot(x='Importance', y='Feature', data=top_features, palette='viridis')

# Add titles and labels
plt.title('Top 10 Features Importance')
plt.xlabel('Importance')
plt.ylabel('Feature')

# Show the plot
plt.show()
```

```
                   Feature  Importance
4   customer service calls    0.218844
5            total_charges    0.204155
7            total_minutes    0.095880
3     number vmail messages    0.082754
2          voice mail plan    0.074110
0           account length    0.047124
6              total_calls    0.045037
1       international plan    0.029042
59           area code_510    0.026658
58           area code_415    0.021068
```



6. CONCLUSION

- As our recall score for our model was .74 as good as it is a predictive model, more time is neede for further engineering to help improve this score.

6.1 Reccomendations

For SyriaTel to improve on customer retention they need to deploy the machine learning model to get realtime predicitions. Realtime continuous monitoring ensure the model is always learning and improving with time. With use of feature importance on can leverage it to provide insight on how to target service improvements and personalize retention efforts.

A few ways into which SyriaTel can reduce Churning rate is by:

- Focusing on retention programss in area code 415 and 510 as these have the highest churning rate.
- Improve on quality customer service call:
- By having responsive customer support.Provide quick and effective customer support. Resolve issues promptly and ensure that customers feel heard and valued.
- Encourage and act upon customer feedback. Use surveys, reviews, and feedback forms to understand customer satisfaction and areas for improvement.
- Competitive Pricing on plans : Regularly review and adjust pricing strategies on different plans to remain competitive in the market. Consider offering flexible pricing plans that cater to different customer needs.

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