Customer Churn Prediction Analysis Using Supervised Learning Approach

- Using Normalized Data
- RFE Feature Selection Technique
- Using SMOTE Technique to handle class imbalance
- Models: Logistic Regression, Random Forest and SVM Model
- Using ROC AUC Curve to evaluate the model's performance.

Define the Problem:

First we will define the objectives of this analysis and the questions you want to answer using the data and understand the context and purpose of the analysis.

- The analysis is to develop predictive model to forecast churn in telecommunication businesses

Importing Necessary Liabries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from sklearn.preprocessing import LabelEncoder
from sklearn.feature_selection import RFE
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectKBest, chi2
from sklearn import metrics
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, C
import matplotlib.pyplot as plt
from imblearn.over_sampling import SMOTE
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import roc_curve, roc_auc_score
```

Importing Dataset

In [2]:
```
data = pd.read_csv('Customer Churn Dataset.csv')
```

In [3]:
```
data.head()
```

Out[3]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Inte
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	
4	9237-HQITU	Female	0	No	No	2	Yes	No	

5 rows × 21 columns

Data Cleaning and Preprocessing

In this section we will;

- Handle missing values: Identify and deal with missing data by imputation or removal.
- Remove duplicates (if any): Eliminate duplicate records if present in the dataset (if any)
- Standardize data formats: Ensure consistency in data formats and units.
- Feature engineering: Create new features or transform existing ones to better represent the data and improve model performance.

In [4]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   object 
 1   gender            7043 non-null   object 
 2   SeniorCitizen     7043 non-null   int64  
 3   Partner           7043 non-null   object 
 4   Dependents        7043 non-null   object 
 5   tenure            7043 non-null   int64  
 6   PhoneService      7043 non-null   object 
 7   MultipleLines     7043 non-null   object 
 8   InternetService   7043 non-null   object 
 9   OnlineSecurity    7043 non-null   object 
 10  OnlineBackup      7043 non-null   object 
 11  DeviceProtection  7043 non-null   object 
 12  TechSupport       7043 non-null   object 
 13  StreamingTV       7043 non-null   object 
 14  StreamingMovies   7043 non-null   object 
 15  Contract          7043 non-null   object 
 16  PaperlessBilling  7043 non-null   object 
 17  PaymentMethod     7043 non-null   object 
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object 
 20  Churn             7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

In [5]:
```
data.size
```

Out[5]:
```
147903
```

In [6]:
```
data.nunique()
```

Out[6]:
```
customerID          7043
gender                 2
SeniorCitizen          2
Partner                2
Dependents             2
tenure                73
PhoneService           2
MultipleLines          3
InternetService        3
OnlineSecurity         3
OnlineBackup           3
DeviceProtection       3
TechSupport            3
StreamingTV            3
StreamingMovies        3
Contract               3
PaperlessBilling       2
PaymentMethod          4
MonthlyCharges      1585
TotalCharges        6531
Churn                  2
dtype: int64
```

In [7]:
```
data.dtypes
```

Out[7]:

```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

Handling Missing Data

In [8]:

```
data.isnull().sum()
```

Out[8]:

```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

We noticed that Total Charges is represented as a categorical variable instead of numeric, the code below converts it to numeric variable

In [9]:

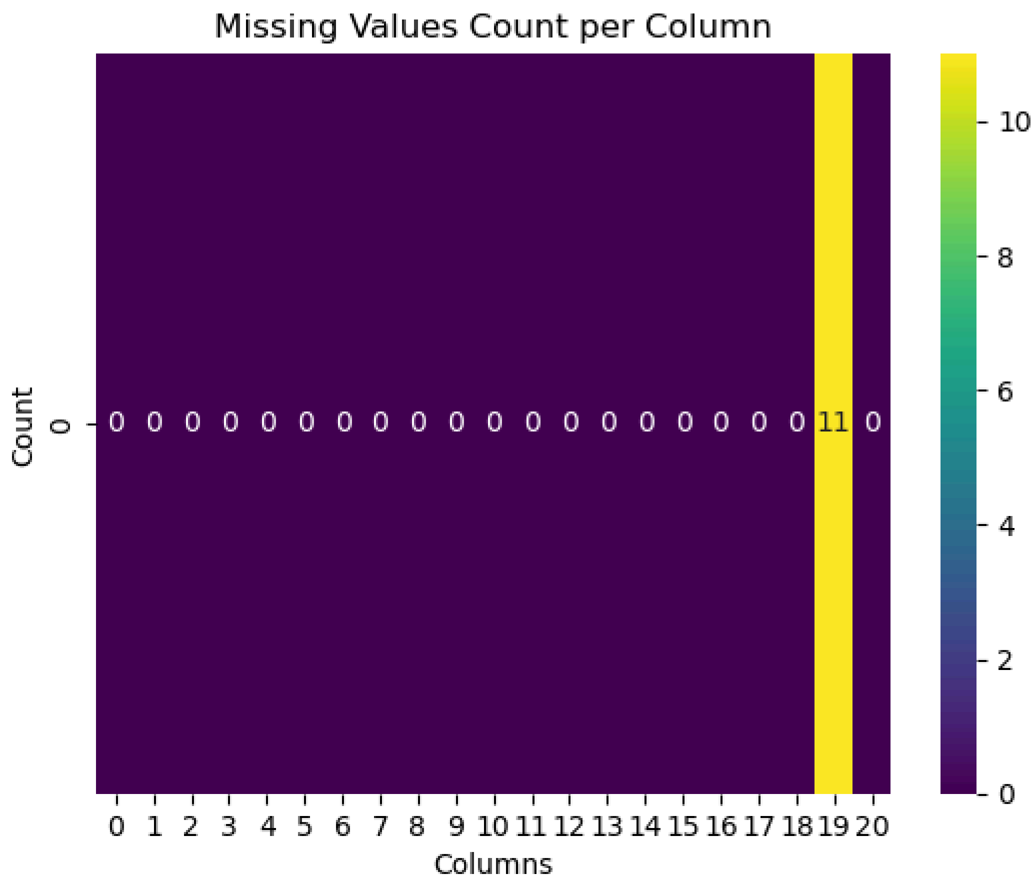
```
data.TotalCharges = pd.to_numeric(data.TotalCharges, errors='coerce')
```

In [10]:

```
data.isnull().sum()
```

Out[10]:
```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges       11
Churn               0
dtype: int64
```

In [11]:
```
# Calculate the count of missing values in each column and convert it to a 2D array
missing_values_count = data.isna().sum().values.reshape(1, -1)

# Create a heatmap to visualize missing values count
sns.heatmap(missing_values_count, annot=True, cmap='viridis')
plt.title('Missing Values Count per Column')
plt.xlabel('Columns')
plt.ylabel('Count')
plt.show()
```



Total Charges have 11 missing data. We will drop the enter columns

In [12]:
```
#Dropping the missing values in Total Charges column
data.dropna(subset=['TotalCharges'], inplace=True)
```

In [13]:
```
data.isna().sum()
```

Out[13]:
```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

In [14]:
```
data.drop(['customerID'], axis=1, inplace=True)
```

In [15]:
```
data.head()
```

Out[15]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService
0	Female	0	Yes	No	1	No	No phone service	DSL
1	Male	0	No	No	34	Yes	No	DSL
2	Male	0	No	No	2	Yes	No	DSL
3	Male	0	No	No	45	No	No phone service	DSL
4	Female	0	No	No	2	Yes	No	Fiber optic

Checking for Duplicates

In [16]:
```
duplicate_rows = data[data.duplicated()]

if len(duplicate_rows) == 0:
    print("No duplicate rows found.")
else:
    print("Duplicate Rows:")
    print(duplicate_rows)
```

```
Duplicate Rows:
      gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
964     Male              0      No         No       1          Yes
1338    Male              0      No         No       1          Yes
1491  Female              0      No         No       1          Yes
1739    Male              0      No         No       1          Yes
1932    Male              0      No         No       1          Yes
2713    Male              0      No         No       1          Yes
2892    Male              0      No         No       1          Yes
3301  Female              1      No         No       1          Yes
3754    Male              0      No         No       1          Yes
4098    Male              0      No         No       1          Yes
4476  Female              0      No         No       1          Yes
5506    Male              0      No         No       1          Yes
5736    Male              0      No         No       1          Yes
5759  Female              0      No         No       1          Yes
6267  Female              0      No         No       1          Yes
6499    Male              0      No         No       1          Yes
6518    Male              0      No         No       1          Yes
6609    Male              0      No         No       1          Yes
6706  Female              0      No         No       1          Yes
6764  Female              0      No         No       1          Yes
6774  Female              0      No         No       1          Yes
6924    Male              0      No         No       1          Yes

     MultipleLines InternetService       OnlineSecurity         OnlineBackup  \
964             No             DSL                   No                   No
1338            No              No  No internet service  No internet service
1491            No              No  No internet service  No internet service
1739            No     Fiber optic                   No                   No
1932            No              No  No internet service  No internet service
2713            No              No  No internet service  No internet service
2892            No              No  No internet service  No internet service
3301            No     Fiber optic                   No                   No
3754            No              No  No internet service  No internet service
4098            No              No  No internet service  No internet service
4476            No              No  No internet service  No internet service
5506            No              No  No internet service  No internet service
5736            No              No  No internet service  No internet service
5759            No     Fiber optic                   No                   No
6267            No     Fiber optic                   No                   No
6499            No              No  No internet service  No internet service
6518            No             DSL                   No                   No
6609            No              No  No internet service  No internet service
6706            No              No  No internet service  No internet service
6764            No     Fiber optic                   No                   No
6774            No              No  No internet service  No internet service
6924            No     Fiber optic                   No                   No

         DeviceProtection          TechSupport          StreamingTV  \
964                    No                   No                   No
1338  No internet service  No internet service  No internet service
1491  No internet service  No internet service  No internet service
1739                   No                   No                   No
1932  No internet service  No internet service  No internet service
2713  No internet service  No internet service  No internet service
2892  No internet service  No internet service  No internet service
3301                   No                   No                   No
3754  No internet service  No internet service  No internet service
4098  No internet service  No internet service  No internet service
```

```
4476  No internet service  No internet service  No internet service
5506  No internet service  No internet service  No internet service
5736  No internet service  No internet service  No internet service
5759                   No                   No                   No
6267                   No                   No                   No
6499  No internet service  No internet service  No internet service
6518                   No                   No                   No
6609  No internet service  No internet service  No internet service
6706  No internet service  No internet service  No internet service
6764                   No                   No                   No
6774  No internet service  No internet service  No internet service
6924                   No                   No                   No

          StreamingMovies        Contract PaperlessBilling     PaymentMethod  \
964                    No  Month-to-month              Yes      Mailed check
1338  No internet service  Month-to-month               No      Mailed check
1491  No internet service  Month-to-month               No      Mailed check
1739                   No  Month-to-month              Yes  Electronic check
1932  No internet service  Month-to-month               No      Mailed check
2713  No internet service  Month-to-month              Yes      Mailed check
2892  No internet service  Month-to-month               No      Mailed check
3301                   No  Month-to-month              Yes  Electronic check
3754  No internet service  Month-to-month               No      Mailed check
4098  No internet service  Month-to-month              Yes      Mailed check
4476  No internet service  Month-to-month               No      Mailed check
5506  No internet service  Month-to-month               No      Mailed check
5736  No internet service  Month-to-month               No      Mailed check
5759                   No  Month-to-month              Yes      Mailed check
6267                   No  Month-to-month              Yes  Electronic check
6499  No internet service  Month-to-month               No      Mailed check
6518                   No  Month-to-month               No  Electronic check
6609  No internet service  Month-to-month              Yes      Mailed check
6706  No internet service  Month-to-month               No      Mailed check
6764                   No  Month-to-month              Yes  Electronic check
6774  No internet service  Month-to-month               No      Mailed check
6924                   No  Month-to-month              Yes  Electronic check

      MonthlyCharges  TotalCharges Churn
964            45.70         45.70   Yes
1338           20.15         20.15   Yes
1491           19.55         19.55    No
1739           69.90         69.90   Yes
1932           20.20         20.20    No
2713           20.45         20.45    No
2892           20.45         20.45    No
3301           69.60         69.60   Yes
3754           20.05         20.05    No
4098           20.20         20.20   Yes
4476           20.90         20.90   Yes
5506           20.20         20.20    No
5736           20.05         20.05    No
5759           70.15         70.15   Yes
6267           70.10         70.10   Yes
6499           20.30         20.30    No
6518           45.30         45.30   Yes
6609           20.10         20.10   Yes
6706           19.90         19.90    No
6764           69.20         69.20   Yes
6774           19.65         19.65    No
6924           69.35         69.35   Yes
```

In [17]:
```
#Descriptive Analysis
data.describe(include = 'all')
```

Out[17]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Intern
count	7032	7032.000000	7032	7032	7032.000000	7032	7032	
unique	2	NaN	2	2	NaN	2	3	
top	Male	NaN	No	No	NaN	Yes	No	F
freq	3549	NaN	3639	4933	NaN	6352	3385	
mean	NaN	0.162400	NaN	NaN	32.421786	NaN	NaN	
std	NaN	0.368844	NaN	NaN	24.545260	NaN	NaN	
min	NaN	0.000000	NaN	NaN	1.000000	NaN	NaN	
25%	NaN	0.000000	NaN	NaN	9.000000	NaN	NaN	
50%	NaN	0.000000	NaN	NaN	29.000000	NaN	NaN	
75%	NaN	0.000000	NaN	NaN	55.000000	NaN	NaN	
max	NaN	1.000000	NaN	NaN	72.000000	NaN	NaN	

Now let's converts Senior Citizen column from numeric to categorical labels of ("No" and "Yes") and display the first few rows of the dataframe with the updated values in the "SeniorCitizen" column.

In [18]:
```
data.SeniorCitizen = data.SeniorCitizen.map({0: "No", 1: "Yes"})
data.head()
```

Out[18]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService
0	Female	No	Yes	No	1	No	No phone service	DSL
1	Male	No	No	No	34	Yes	No	DSL
2	Male	No	No	No	2	Yes	No	DSL
3	Male	No	No	No	45	No	No phone service	DSL
4	Female	No	No	No	2	Yes	No	Fiber optic

Exploratory Data Analysis (EDA):

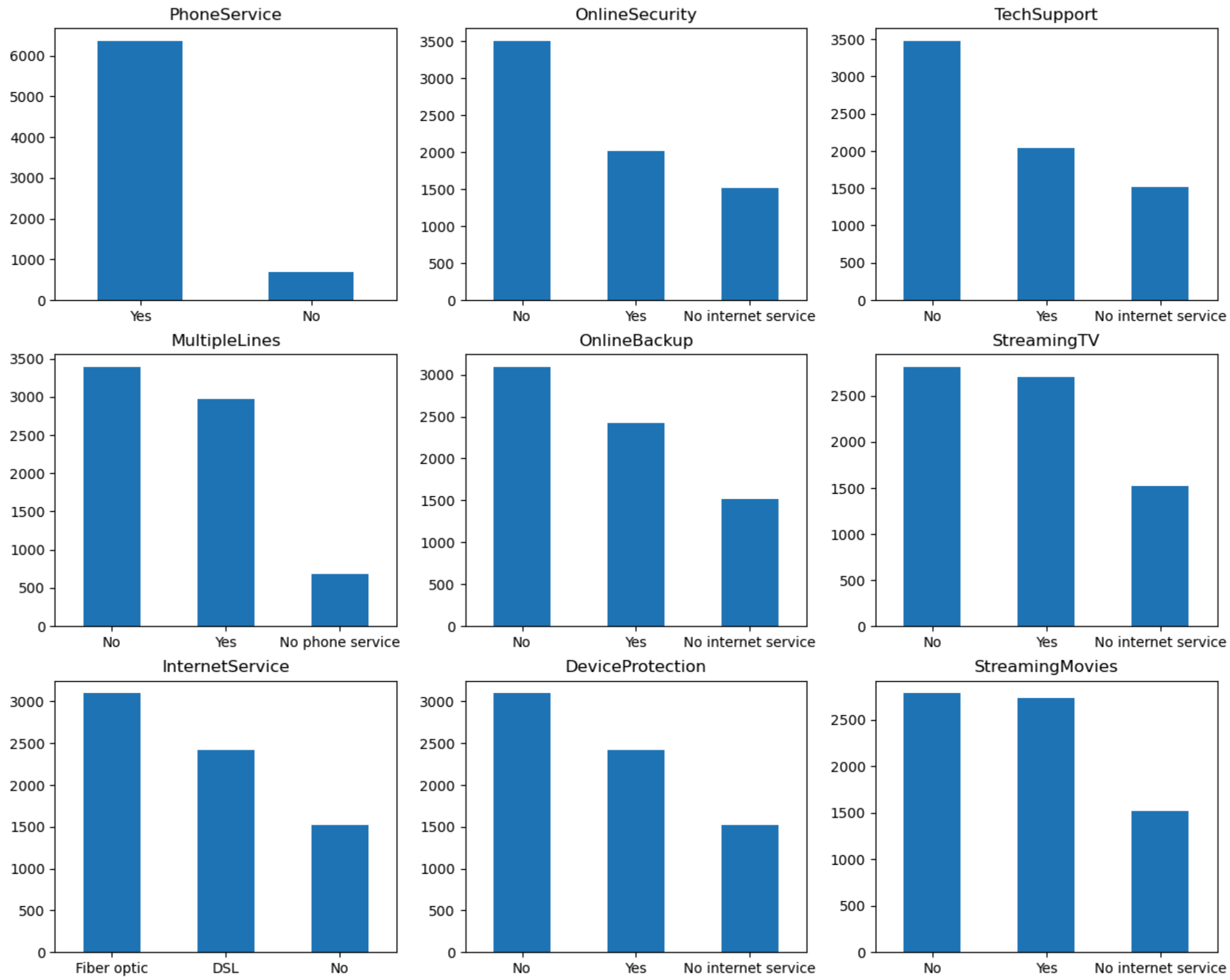
- Here we will summarize and visualize the data using statistical measures, charts, and graphs.

In [19]:
```python
data.dtypes
```

Out[19]:
```
gender               object
SeniorCitizen        object
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges        float64
Churn                object
dtype: object
```

Visualizing the Distribution of Services

In [20]:
```python
services = ['PhoneService','MultipleLines','InternetService','OnlineSecurity',
           'OnlineBackup','DeviceProtection','TechSupport','StreamingTV','StreamingMov

fig, axes = plt.subplots(nrows = 3,ncols = 3,figsize = (15,12))
for i, item in enumerate(services):
    if i < 3:
        ax = data[item].value_counts().plot(kind = 'bar',ax=axes[i,0],rot = 0)

    elif i >=3 and i < 6:
        ax = data[item].value_counts().plot(kind = 'bar',ax=axes[i-3,1],rot = 0)

    elif i < 9:
        ax = data[item].value_counts().plot(kind = 'bar',ax=axes[i-6,2],rot = 0)
    ax.set_title(item)
```



Using Groupby

In [21]:
```python
data.head()
```

Out[21]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService
0	Female	No	Yes	No	1	No	No phone service	DSL
1	Male	No	No	No	34	Yes	No	DSL
2	Male	No	No	No	2	Yes	No	DSL
3	Male	No	No	No	45	No	No phone service	DSL
4	Female	No	No	No	2	Yes	No	Fiber optic

Overall Percentage and Count of Customers that Churned

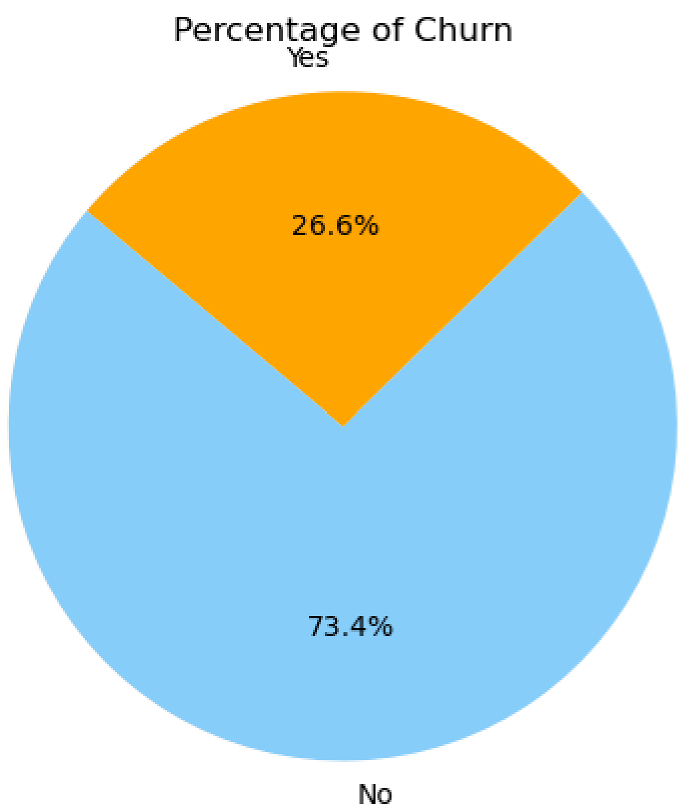
In [22]:
```
#data['Churn'].value_counts()/100
percentage_counts = data['Churn'].value_counts(normalize=True) * 100
print(percentage_counts)
```

```
No     73.421502
Yes    26.578498
Name: Churn, dtype: float64
```

In [23]:
```
 data['Churn'].value_counts()
```

Out[23]:
```
No     5163
Yes    1869
Name: Churn, dtype: int64
```

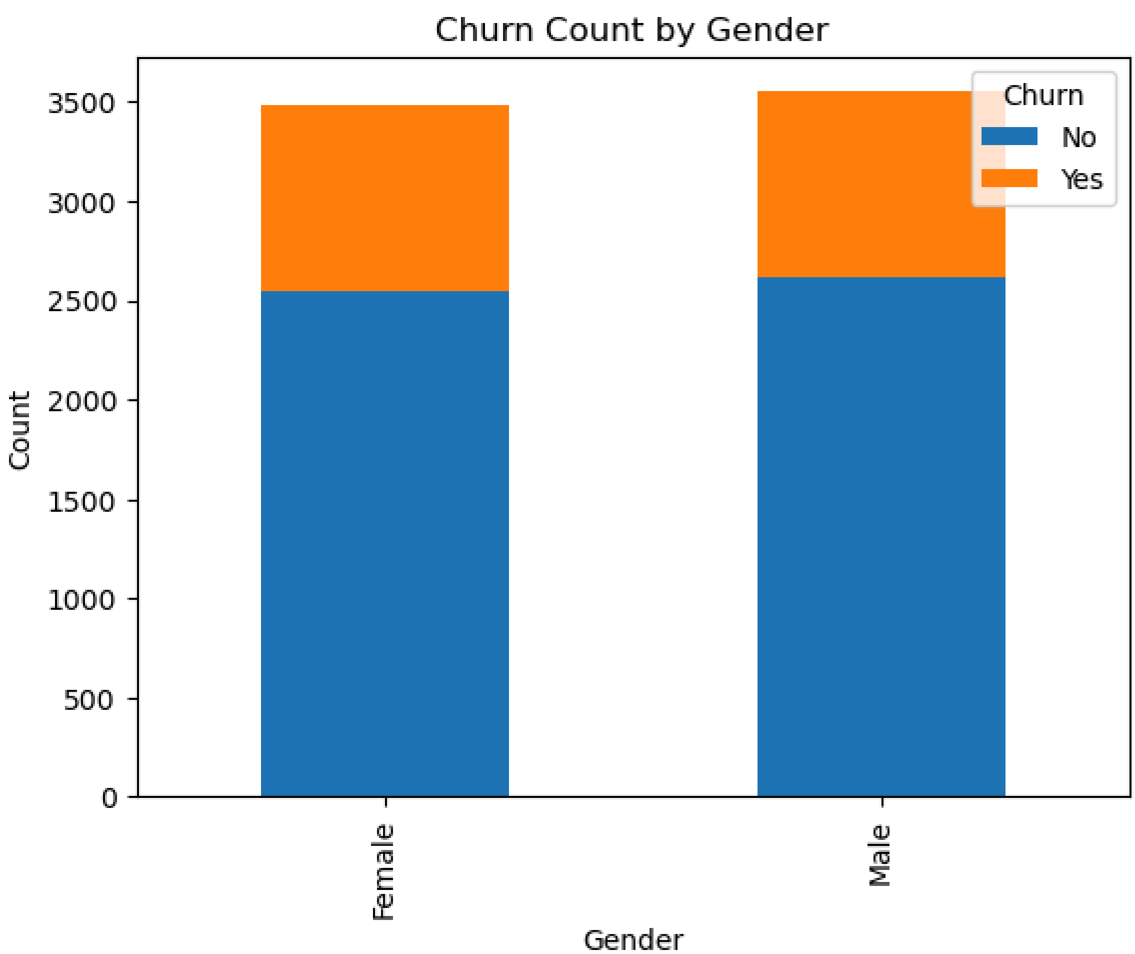
In [24]:
```
# Visualizing and Calculate percentage counts
percentage_counts = data['Churn'].value_counts(normalize=True) * 100

# Plotting
labels = percentage_counts.index
sizes = percentage_counts.values
colors = ['lightskyblue', 'orange']
plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%', startangle=140)
plt.title('Percentage of Churn')
plt.axis('equal')
plt.show()
```



We can see there is a significant class imbalance between customers that churned and customers that didn't churn. In the coming steps we will be using the SMOTE technique an oversampling method to address the class imbalance as this imbalance can affect the model's performance.

Churn by Gender

In [25]:
```
# Calculate the count of churned and non-churned customers by gender
churn_count = data.groupby(['gender', 'Churn']).size().unstack()

custom_palette = {"Male": "lightskyblue", "Female": "orange"}

# Plotting
churn_count.plot(kind='bar', stacked=True)
plt.xlabel('Gender')
plt.ylabel('Count')
plt.title('Churn Count by Gender')
plt.legend(title='Churn', loc='upper right')
plt.show()
```



Female and Male have almost the same number of churn and non-churn customers

Churn by Senior Citizen

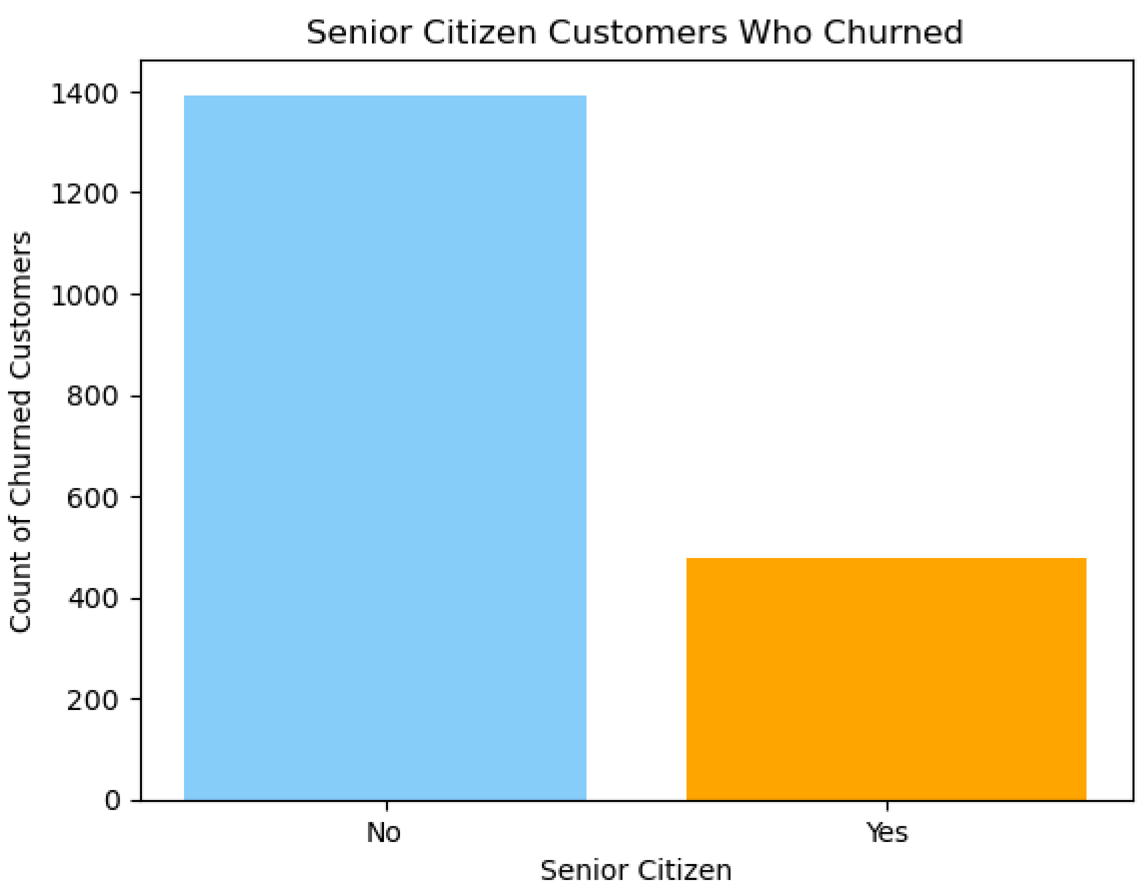
Customer that are Senior Citizen who Churned

In [26]:
```
churn_counts = data[data['Churn'] == 'Yes'].groupby('SeniorCitizen').size()
print(churn_counts)
```

```
SeniorCitizen
No     1393
Yes     476
dtype: int64
```

The above shows that there are 1393 customers who are not senior citizens have churned and also 476 customers who are senior citizens and have churned. In summary, this output tells you how many customers from each group have churned. It provides insight into the churn behavior based on the 'SeniorCitizen' status.

In [27]:
```
#Let's visualize it

# Define custom colors
colors = ['lightskyblue', 'orange']

# Plotting
plt.bar(churn_counts.index, churn_counts.values, color=colors)
plt.xlabel('Senior Citizen')
plt.ylabel('Count of Churned Customers')
plt.title('Senior Citizen Customers Who Churned')
plt.xticks(churn_counts.index, ['No', 'Yes'])  # Set the x-ticks labels
plt.show()
```



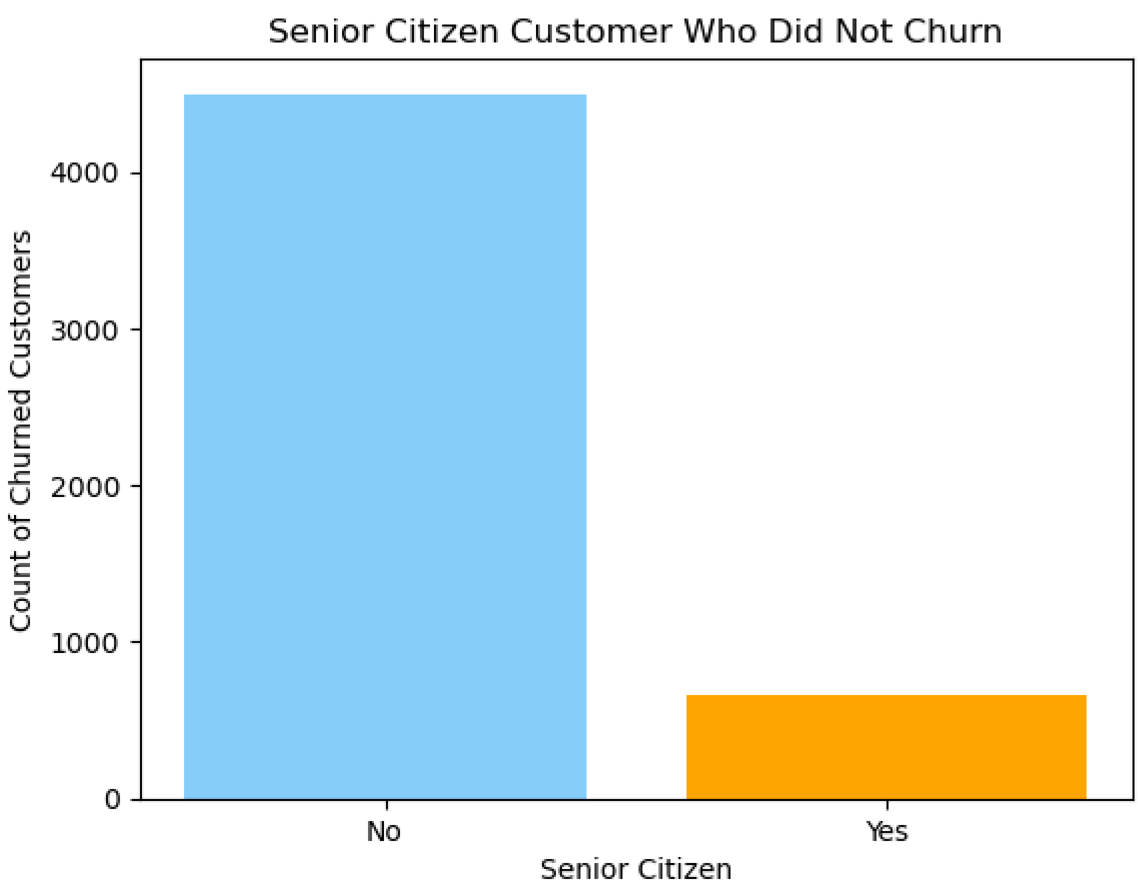
Customer that are Senior Citizen who did not Churn

In [28]:
```
churn_counts = data[data['Churn'] == 'No'].groupby('SeniorCitizen').size()
print(churn_counts)
```

```
SeniorCitizen
No     4497
Yes     666
dtype: int64
```

In [29]:
```
#Let's visualize it

# Define custom colors
colors = ['lightskyblue', 'orange']

# Plotting
plt.bar(churn_counts.index, churn_counts.values, color=colors)
plt.xlabel('Senior Citizen')
plt.ylabel('Count of Churned Customers')
plt.title('Senior Citizen Customer Who Did Not Churn')
plt.xticks
```

Out[29]:
```
<function matplotlib.pyplot.xticks(ticks=None, labels=None, **kwargs)>
```



Churn by Internet Service Customers

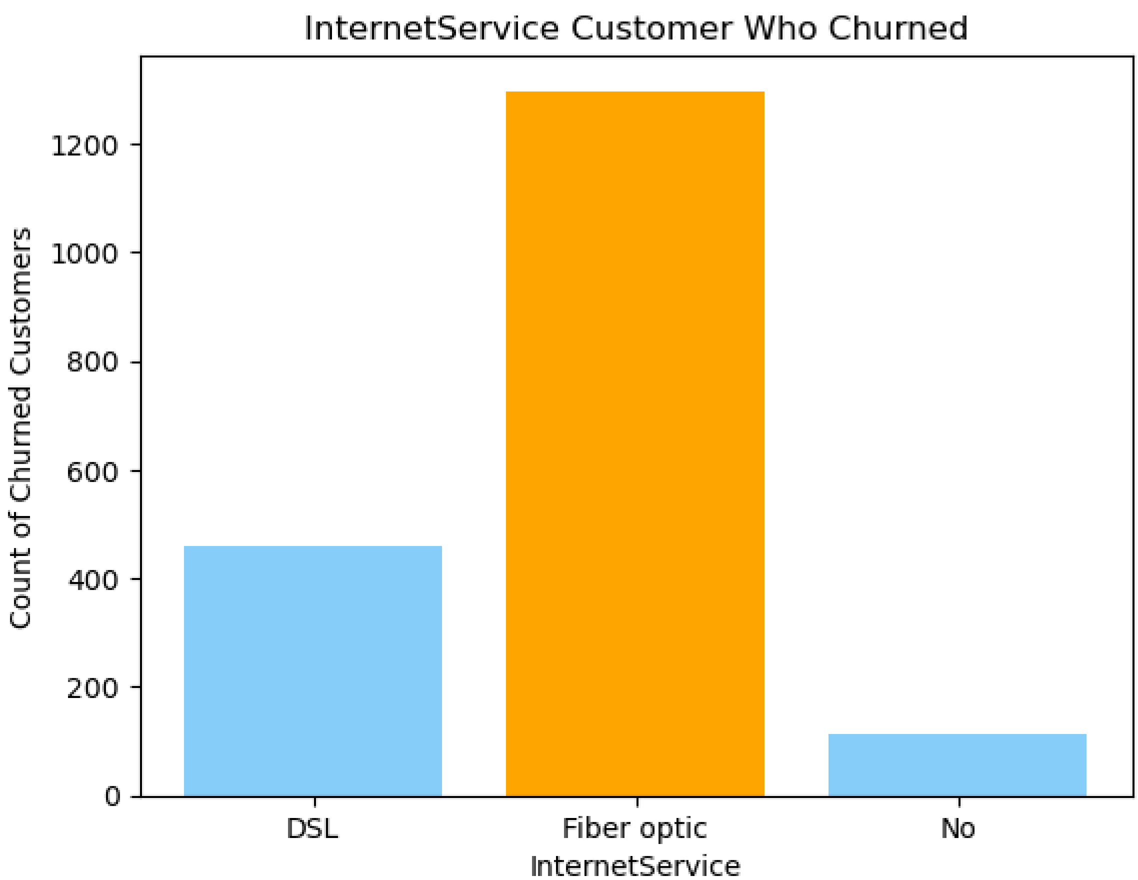
Internet Service Customers who Churned

In [30]:
```
churn_count = data[data['Churn'] == 'Yes'].groupby(['InternetService']).size()
print(churn_count)
```

```
InternetService
DSL              459
Fiber optic     1297
No               113
dtype: int64
```

In [31]:
```
#Let's visualize it

# Define custom colors
colors = ['lightskyblue', 'orange']

# Plotting
plt.bar(churn_count.index, churn_count.values, color=colors)
plt.xlabel('InternetService')
plt.ylabel('Count of Churned Customers')
plt.title('InternetService Customer Who Churned')
plt.xticks
```

Out[31]:
```
<function matplotlib.pyplot.xticks(ticks=None, labels=None, **kwargs)>
```



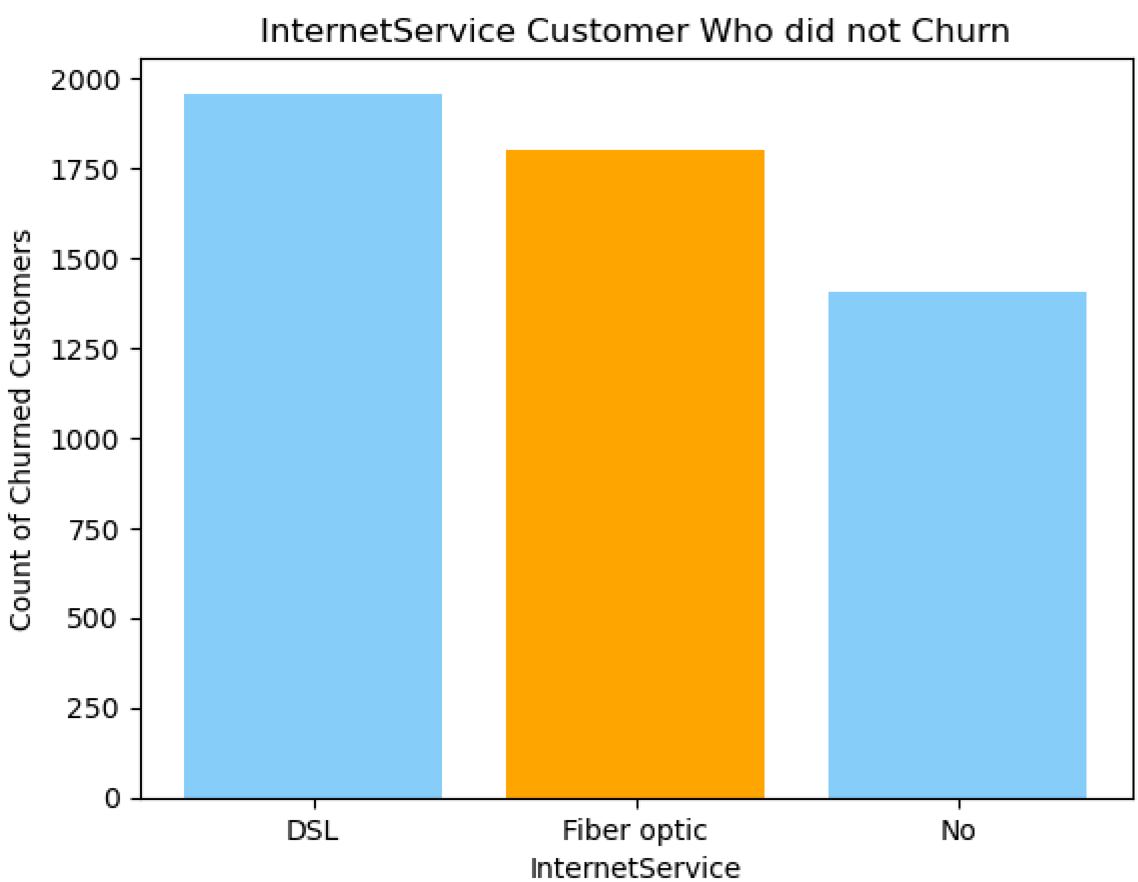
Internet Service Customers who did not Churned

In [32]:
```
churn_count = data[data['Churn'] == 'No'].groupby(['InternetService']).size()
print(churn_count)
```

```
InternetService
DSL             1957
Fiber optic     1799
No              1407
dtype: int64
```

In [33]:
```python
#Let's visualize it

# Define custom colors
colors = ['lightskyblue', 'orange']

# Plotting
plt.bar(churn_count.index, churn_count.values, color=colors)
plt.xlabel('InternetService')
plt.ylabel('Count of Churned Customers')
plt.title('InternetService Customer Who did not Churn')
plt.xticks
```

Out[33]:
```
<function matplotlib.pyplot.xticks(ticks=None, labels=None, **kwargs)>
```



Churn by MultipleLines

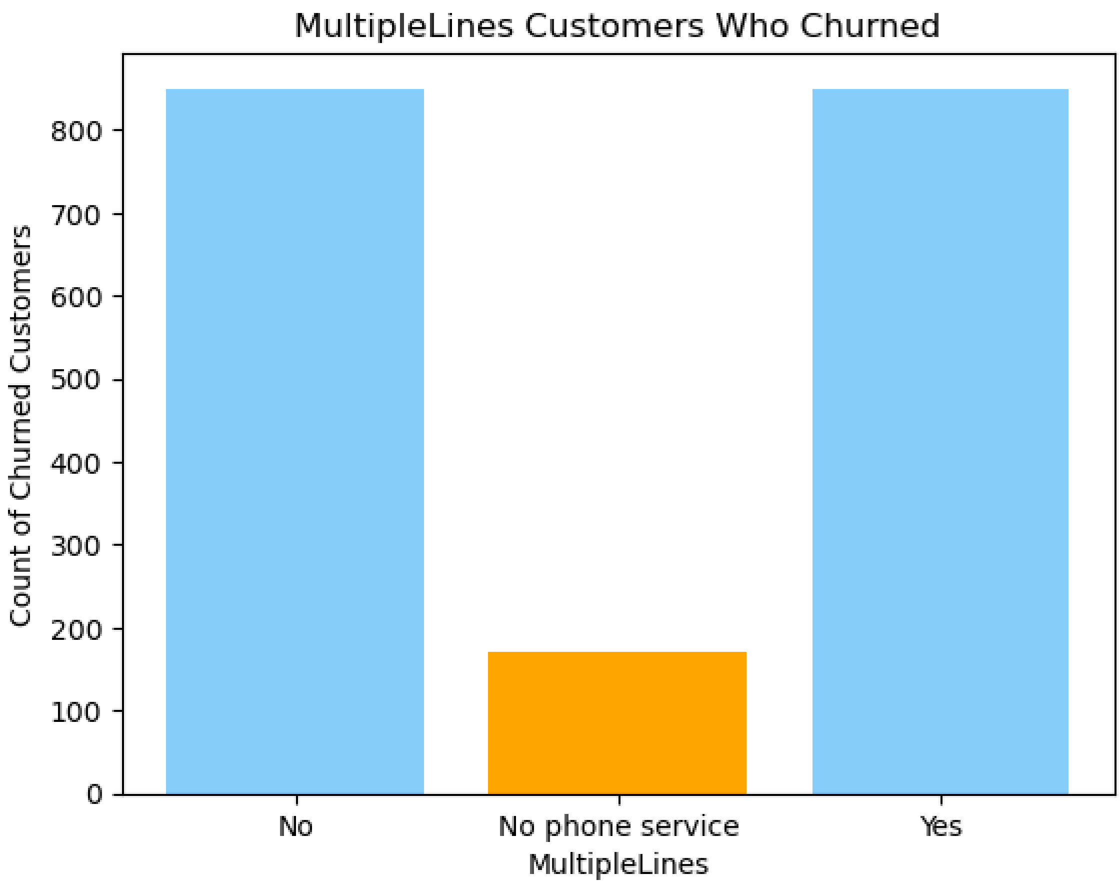
MultipleLines Customers who Churned

In [34]:
```python
churn_counts = data[data['Churn'] == 'Yes'].groupby(['MultipleLines']).size()
print(churn_counts)
```

```
MultipleLines
No                  849
No phone service    170
Yes                 850
dtype: int64
```

In [35]:
```
#Let's visualize it

# Define custom colors
colors = ['lightskyblue', 'orange']

# Plotting
plt.bar(churn_counts.index, churn_counts.values, color=colors)
plt.xlabel('MultipleLines')
plt.ylabel('Count of Churned Customers')
plt.title('MultipleLines Customers Who Churned')
plt.xticks
```

Out[35]:
```
<function matplotlib.pyplot.xticks(ticks=None, labels=None, **kwargs)>
```



MultipleLine Customers who did not Churn

In [36]:
```
churn_counts = data[data['Churn'] == 'No'].groupby(['MultipleLines']).size()
print(churn_counts)
```

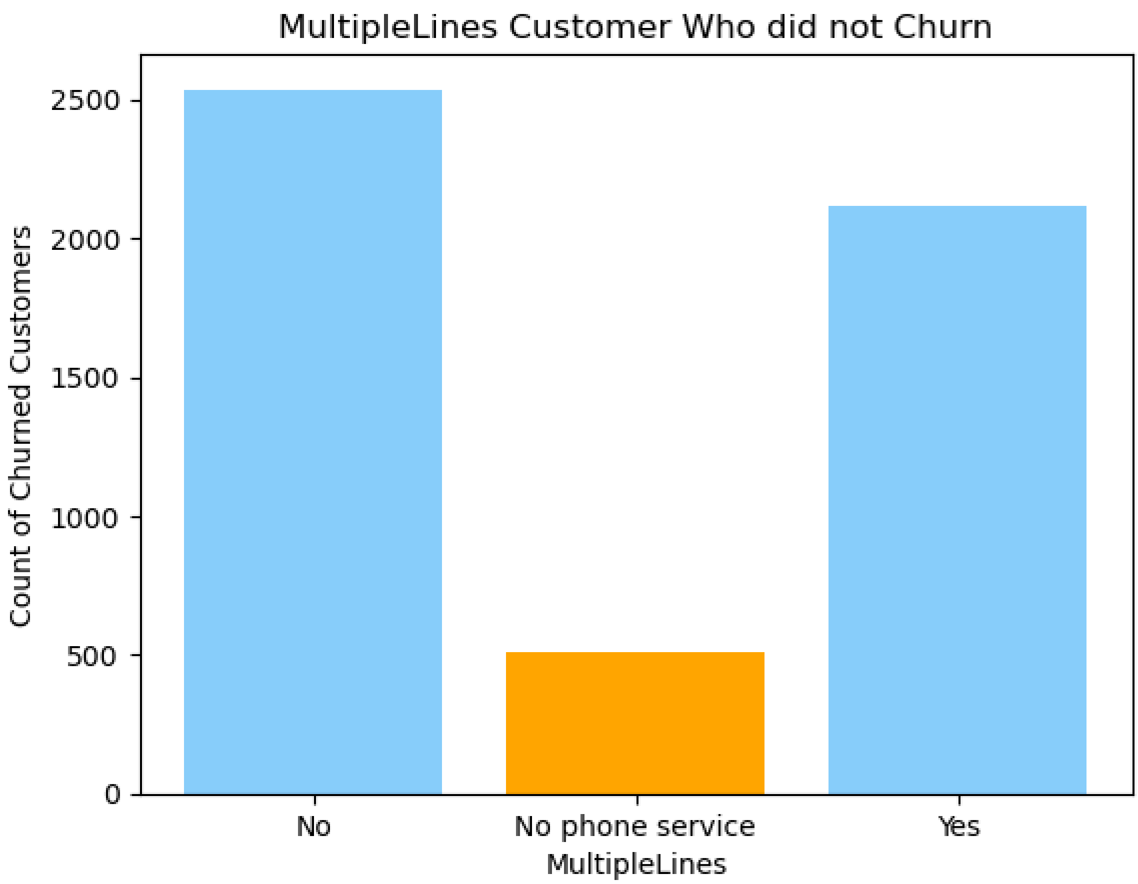
```
MultipleLines
No                  2536
No phone service     510
Yes                 2117
dtype: int64
```

In [37]:
```
#Let's visualize it

# Define custom colors
colors = ['lightskyblue', 'orange']
```

```
# Plotting
plt.bar(churn_counts.index, churn_counts.values, color=colors)
plt.xlabel('MultipleLines')
plt.ylabel('Count of Churned Customers')
plt.title('MultipleLines Customer Who did not Churn')
plt.xticks
```

Out[37]:

```
<function matplotlib.pyplot.xticks(ticks=None, labels=None, **kwargs)>
```



Churn by Contract Type

Contract Type by Customer who Churned

In [38]:

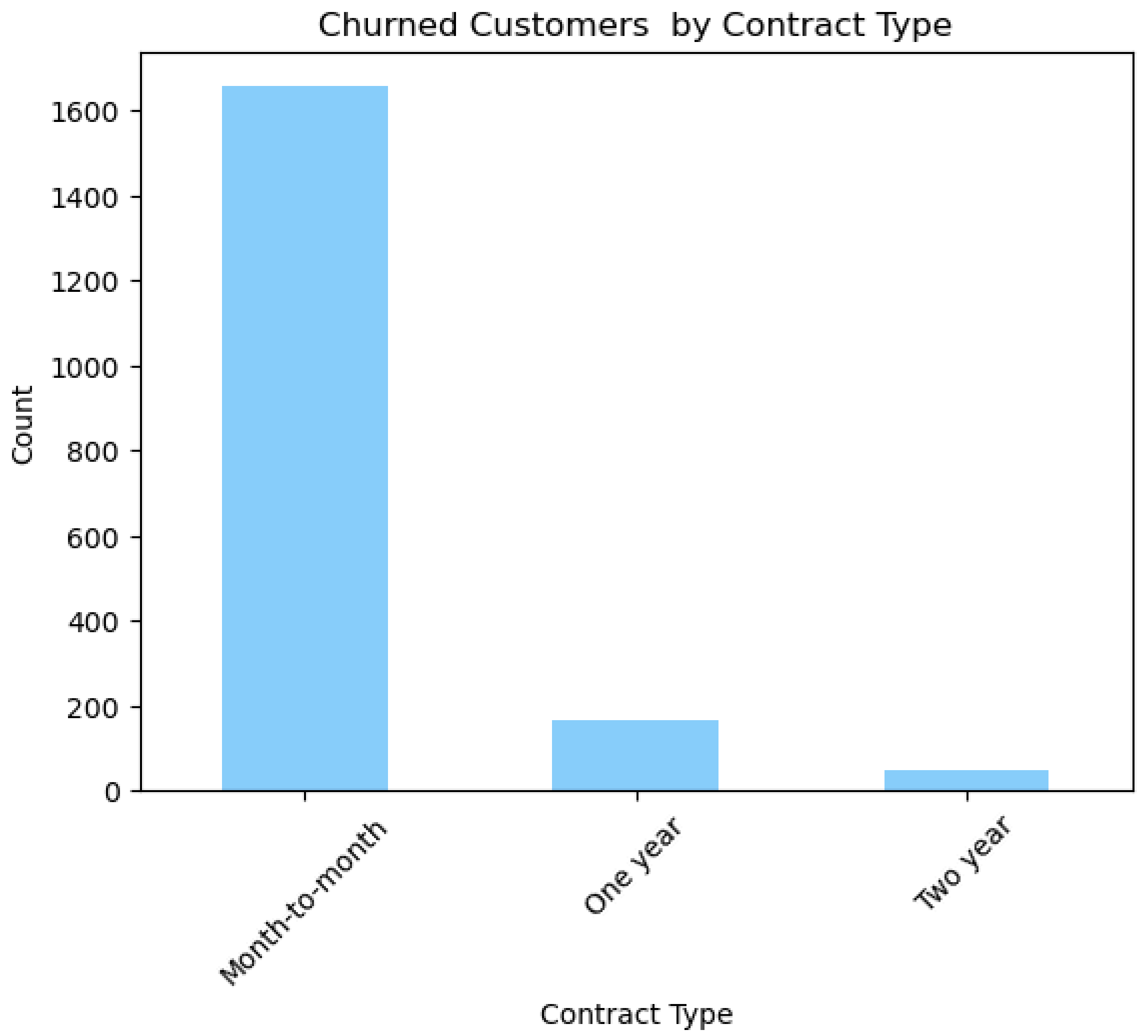
```
#Customers who Churned
churn_counts = data[data['Churn'] == 'Yes'].groupby(['Contract']).size()
print(churn_counts)
```

```
Contract
Month-to-month    1655
One year           166
Two year            48
dtype: int64
```

In [39]:

```
churn_counts = data[data['Churn'] == 'Yes'].groupby(['Contract']).size()

# Plotting
churn_counts.plot(kind='bar', color='lightskyblue')
plt.xlabel('Contract Type')
```

```
plt.ylabel('Count')
plt.title('Churned Customers  by Contract Type')
plt.xticks(rotation=45)
plt.show()
```

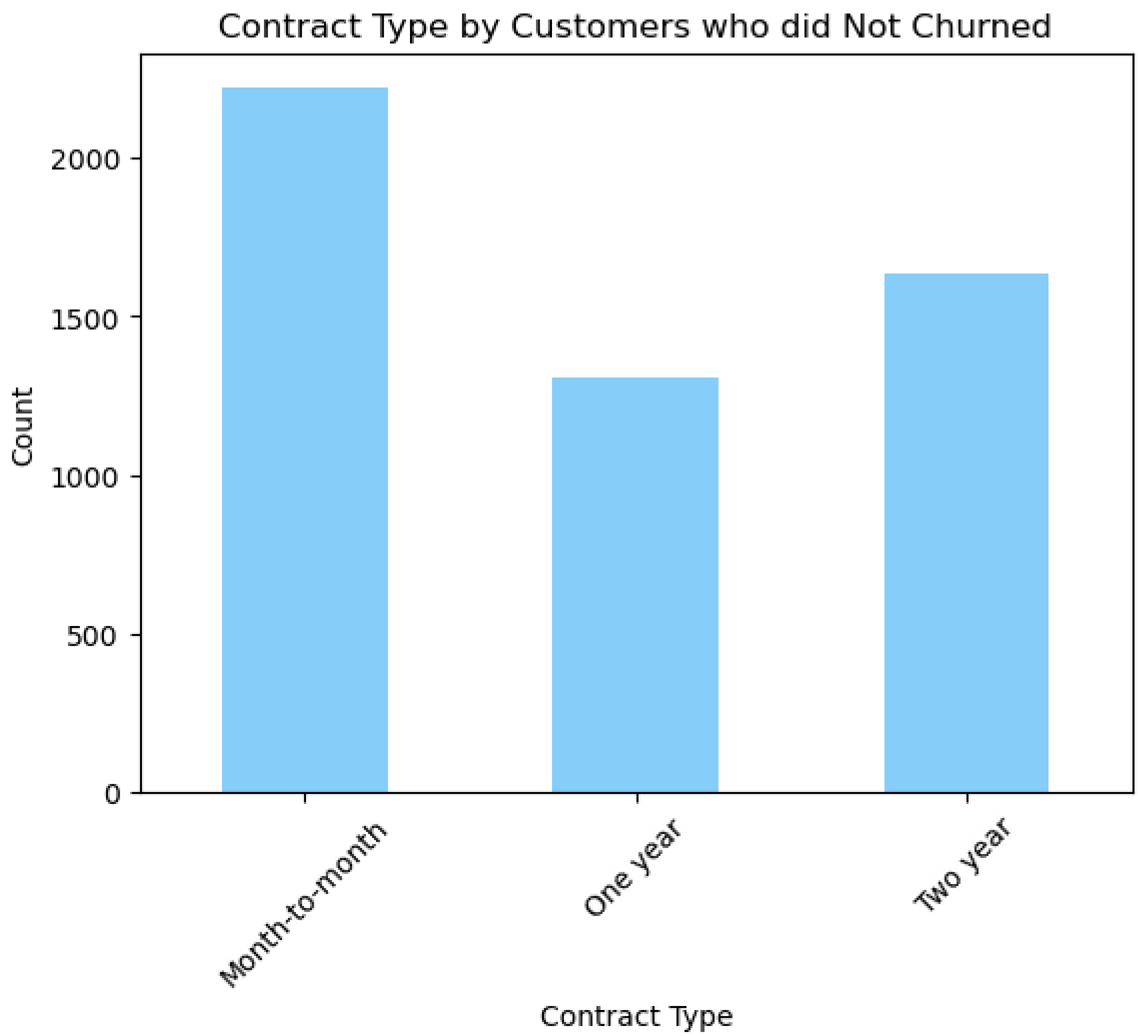


Contract Type by Customer who did not Churn

In [40]:
```
#Customers who did not Churn
churn_counts = data[data['Churn'] == 'No'].groupby(['Contract']).size()
print(churn_counts)
```

```
Contract
Month-to-month    2220
One year          1306
Two year          1637
dtype: int64
```

In [41]:
```
churn_counts = data[data['Churn'] == 'No'].groupby(['Contract']).size()

# Plotting
churn_counts.plot(kind='bar', color='lightskyblue')
plt.xlabel('Contract Type')
plt.ylabel('Count')
plt.title('Contract Type by Customers who did Not Churned')
plt.xticks(rotation=45)
plt.show()
```

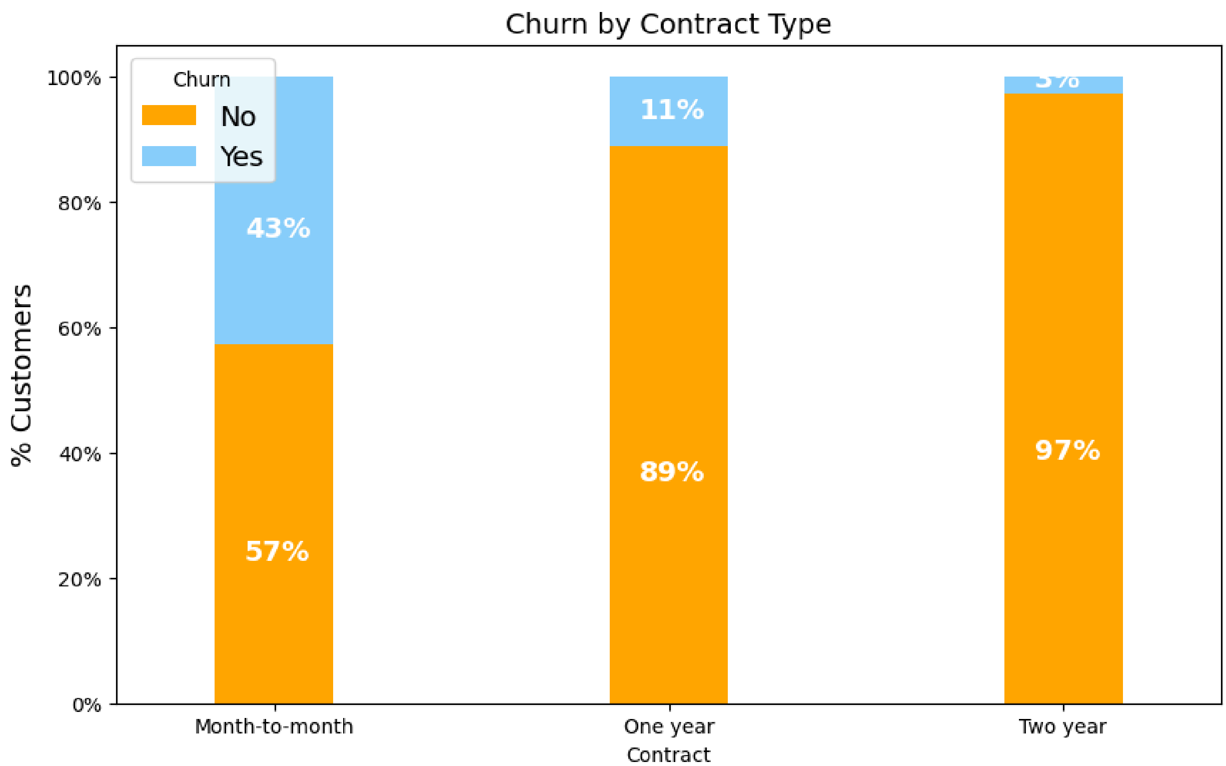


Summary of the Contract Type

In [42]:

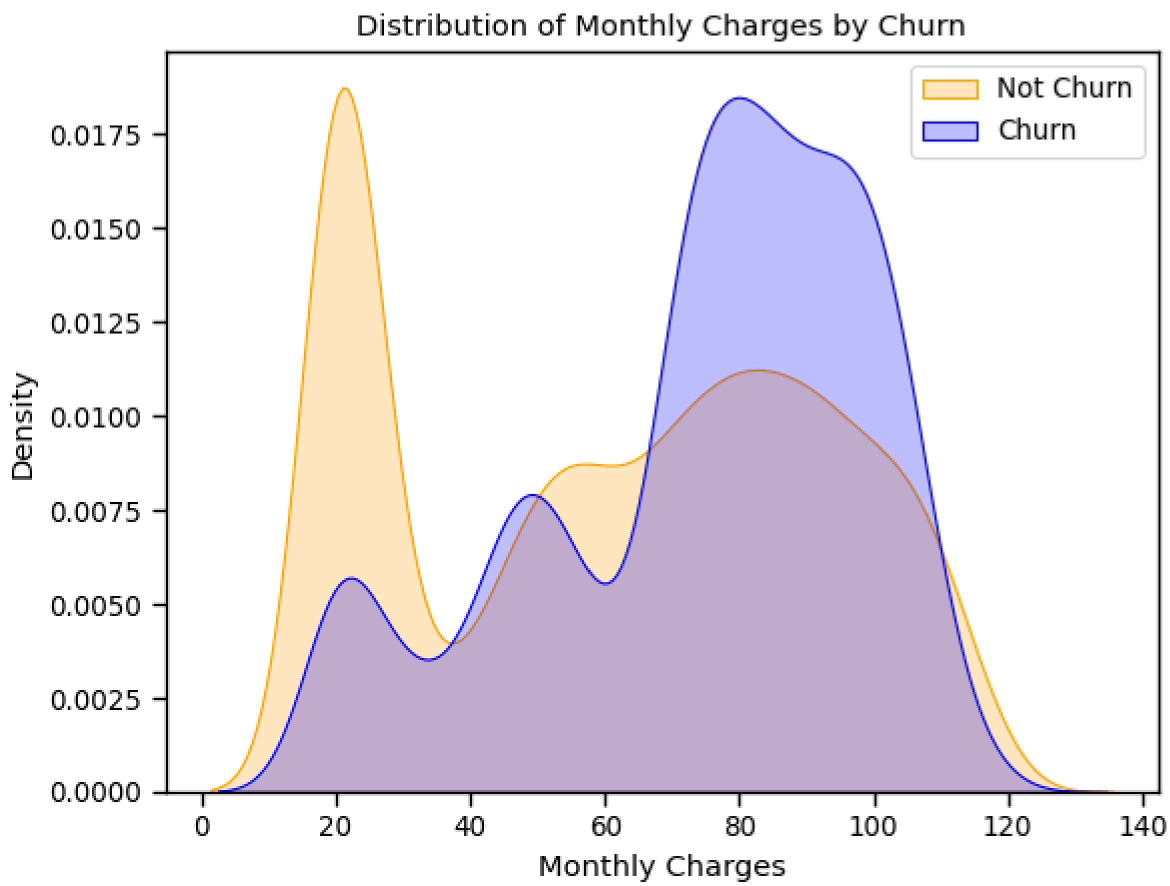
```
import matplotlib.pyplot as plt
import matplotlib.ticker as mtick

colors = ['orange', 'lightskyblue']
contract_churn = data.groupby(['Contract','Churn']).size().unstack()

ax = (contract_churn.T * 100.0 / contract_churn.T.sum()).T.plot(kind='bar',
                                                                width=0.3,
                                                                stacked=True,
                                                                rot=0,
                                                                figsize=(10,6),
                                                                color=colors)
ax.yaxis.set_major_formatter(mtick.PercentFormatter())
ax.legend(loc='best', prop={'size': 14}, title='Churn')
ax.set_ylabel('% Customers', size=14)
ax.set_title('Churn by Contract Type', size=14)

for p in ax.patches:
    width, height = p.get_width(), p.get_height()
    x, y = p.get_xy()
    ax.annotate('{:.0f}%'.format(height), (p.get_x() + 0.25 * width, p.get_y() + 0.4 *
                color='white',
                weight='bold',
```

```
                size=14)

plt.show()
```



Distribution of Monthly Charges by Churn

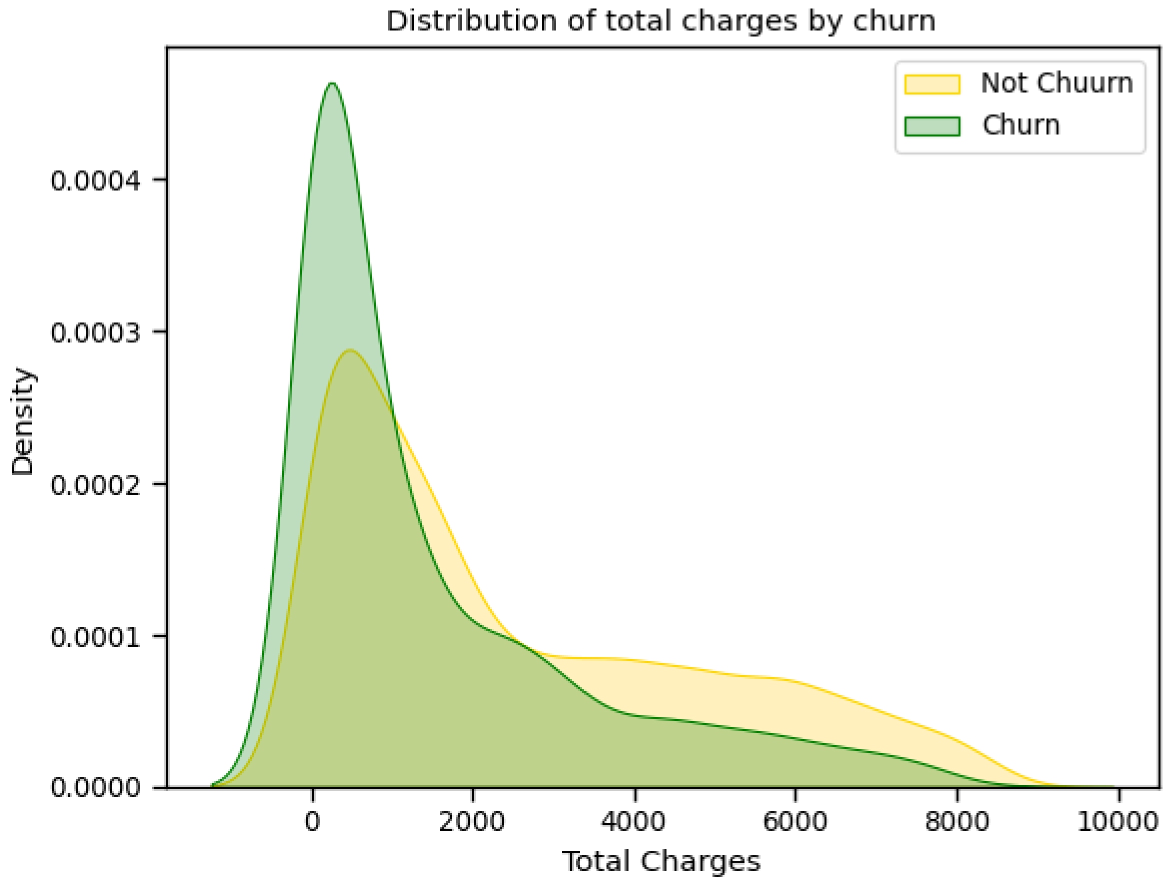
In [43]:
```
sns.set_context("paper",font_scale=1.1)
ax = sns.kdeplot(data.MonthlyCharges[(data["Churn"] == 'No') ],
                color="orange", shade = True);
ax = sns.kdeplot(data.MonthlyCharges[(data["Churn"] == 'Yes') ],
                ax =ax, color="Blue", shade= True);
ax.legend(["Not Churn","Churn"],loc='upper right');
ax.set_ylabel('Density');
ax.set_xlabel('Monthly Charges');
ax.set_title('Distribution of Monthly Charges by Churn');
```



Distribution of Total Charges by Churn

In [44]:

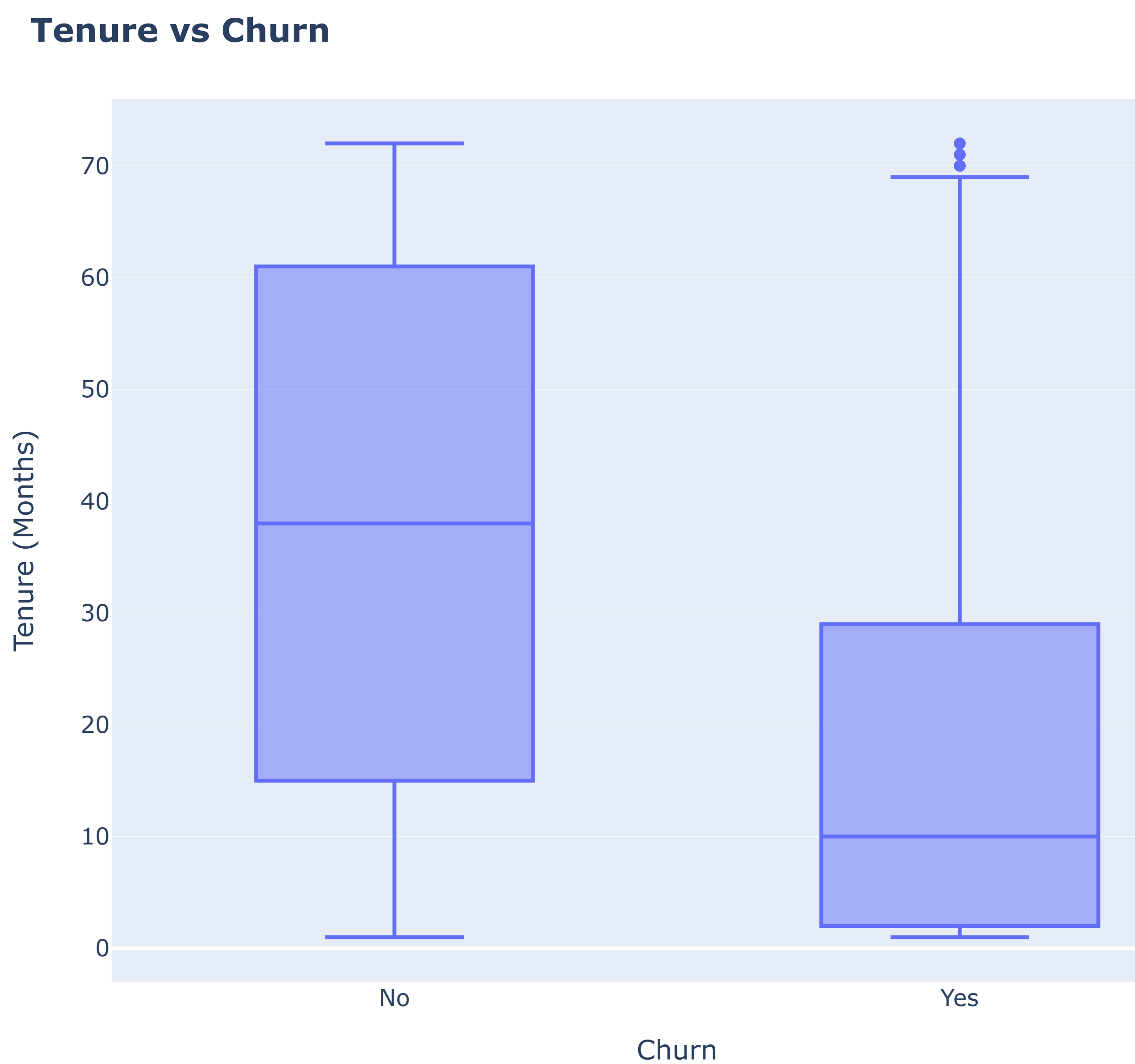
```
ax = sns.kdeplot(data.TotalCharges[(data["Churn"] == 'No') ],
                color="Gold", shade = True);
ax = sns.kdeplot(data.TotalCharges[(data["Churn"] == 'Yes') ],
                ax =ax, color="Green", shade= True);
ax.legend(["Not Chuurn","Churn"],loc='upper right');
ax.set_ylabel('Density');
ax.set_xlabel('Total Charges');
ax.set_title('Distribution of total charges by churn');
```



Tenure Vs Churn

In [45]:

```
# Create the box plot
fig = px.box(data, x='Churn', y='tenure')

# Update y-axis properties
fig.update_yaxes(title_text='Tenure (Months)', row=1, col=1)
# Update x-axis properties
fig.update_xaxes(title_text='Churn', row=1, col=1)

# Update size and title
fig.update_layout(autosize=True, width=750, height=600,
                  title_font=dict(size=25, family='Courier'),
                  title='<b>Tenure vs Churn</b>')

fig.show()
```



The above shows that majority of new customers are likely to churn than old customer

Data Pre-processing

Here we;

- Further explored the relationships between variables and identified patterns or trends.
- Performed feature engineering by creating new features/columns and transforming existing ones to better represent the data and improve model performance.
- Utilised encoding techniques like Label Encoder and One Hot Encoder.
- Performed Normalization using Min Max Scaler
- Performed Feature Selection for dimensionality reduction using “Recursive Feature Elimination (RFE)” to reduce complexity and improve model performance.

Let's start with MultipleLines that has 3 observations and transform the "No Phone Service" to No as it also presents customers with no MultipleLines.

In [46]:
```
data['MultipleLines'] = data['MultipleLines'].replace('No phone service', 'No')
data['MultipleLines'].value_counts()
```

Out[46]:
```
No     4065
Yes    2967
Name: MultipleLines, dtype: int64
```

We will do the same for Online Security, OnlineBackup, DeviceProtection, TechSupport, StreamingTV, and StreamingMovies

In [47]:
```
# Create a list for the columns to replace
columns_to_replace = ['OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSuppo

# Replace 'No internet service' in all specified columns with 'No'
data[columns_to_replace] = data[columns_to_replace].replace('No internet service', 'No

# Check value counts for all specified columns after replacement
value_counts_all = data[columns_to_replace].apply(pd.value_counts)

# Print the value counts for all specified columns
print(value_counts_all)
```

```
     OnlineSecurity  OnlineBackup  DeviceProtection  TechSupport  StreamingTV  \
No             5017          4607              4614         4992         4329
Yes            2015          2425              2418         2040         2703

     StreamingMovies
No              4301
Yes             2731
```

Label Encoding

Here we will perform Label Encoding to transform categorical columns with 2 observations to 0 and 1

And use One Hot Encoder for columns with more than 2 observations

In [48]:
```
data.head()
```

Out[48]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService
0	Female	No	Yes	No	1	No	No	DSL
1	Male	No	No	No	34	Yes	No	DSL
2	Male	No	No	No	2	Yes	No	DSL
3	Male	No	No	No	45	No	No	DSL
4	Female	No	No	No	2	Yes	No	Fiber optic

We will exclude Columns 'Internet Service, Contract, Payment Method, Monthly Charges and Total Charges' we will treat them after as 'Internet Service, Contract, and Payment Method' have more than 2 outputs and Monthly Charges and Total Charges are already in numeric form

In [49]:

```
# Get all column names
all_columns = data.columns

# Exclude the columns (Internet Service, Contract, Payment Method, Monthly Charges and
columns_to_exclude = ['InternetService', 'Contract', 'PaymentMethod', 'MonthlyCharges'

# Get the columns to encode by removing the excluded columns from all columns
columns_to_encode = [col for col in all_columns if col not in columns_to_exclude]

# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Encode each column
data[columns_to_encode] = data[columns_to_encode].apply(label_encoder.fit_transform)
```

In [50]:

```
data.dtypes
```

Out[50]:

```
gender               int32
SeniorCitizen        int32
Partner              int32
Dependents           int32
tenure               int64
PhoneService         int32
MultipleLines        int32
InternetService     object
OnlineSecurity       int32
OnlineBackup         int32
DeviceProtection     int32
TechSupport          int32
StreamingTV          int32
StreamingMovies      int32
Contract            object
PaperlessBilling     int32
PaymentMethod       object
MonthlyCharges       int64
TotalCharges         int64
Churn                int32
dtype: object
```

Using One Hot Encoder

Now let's convert Internet Service, Contract, and Payment Method to numeric using One Hot Encoder

In [51]:

```
# Perform one-hot encoding
data = pd.get_dummies(data, columns=['InternetService', 'Contract', 'PaymentMethod'])
```

In [52]:

```
#Let's view the data to ensure the columns have been coverted accordingly
data.head()
```

Out[52]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	OnlineSecurity
0	0	0	1	0	0	0	0	0
1	1	0	0	0	33	1	0	1
2	1	0	0	0	1	1	0	1
3	1	0	0	0	44	0	0	1
4	0	0	0	0	1	1	0	0

5 rows × 27 columns

In [53]:

```
data.dtypes
```

```
Out[53]: gender                                     int32
SeniorCitizen                              int32
Partner                                    int32
Dependents                                 int32
tenure                                     int64
PhoneService                               int32
MultipleLines                              int32
OnlineSecurity                             int32
OnlineBackup                               int32
DeviceProtection                           int32
TechSupport                                int32
StreamingTV                                int32
StreamingMovies                            int32
PaperlessBilling                           int32
MonthlyCharges                             int64
TotalCharges                               int64
Churn                                      int32
InternetService_DSL                        uint8
InternetService_Fiber optic                uint8
InternetService_No                         uint8
Contract_Month-to-month                    uint8
Contract_One year                          uint8
Contract_Two year                          uint8
PaymentMethod_Bank transfer (automatic)    uint8
PaymentMethod_Credit card (automatic)      uint8
PaymentMethod_Electronic check             uint8
PaymentMethod_Mailed check                 uint8
dtype: object
```

```
In [54]: data.head()
```

Out[54]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	OnlineSecurity
0	0	0	1	0	0	0	0	0
1	1	0	0	0	33	1	0	1
2	1	0	0	0	1	1	0	1
3	1	0	0	0	44	0	0	1
4	0	0	0	0	1	1	0	0

5 rows × 27 columns

```
In [55]: data.shape
```

```
Out[55]: (7032, 27)
```

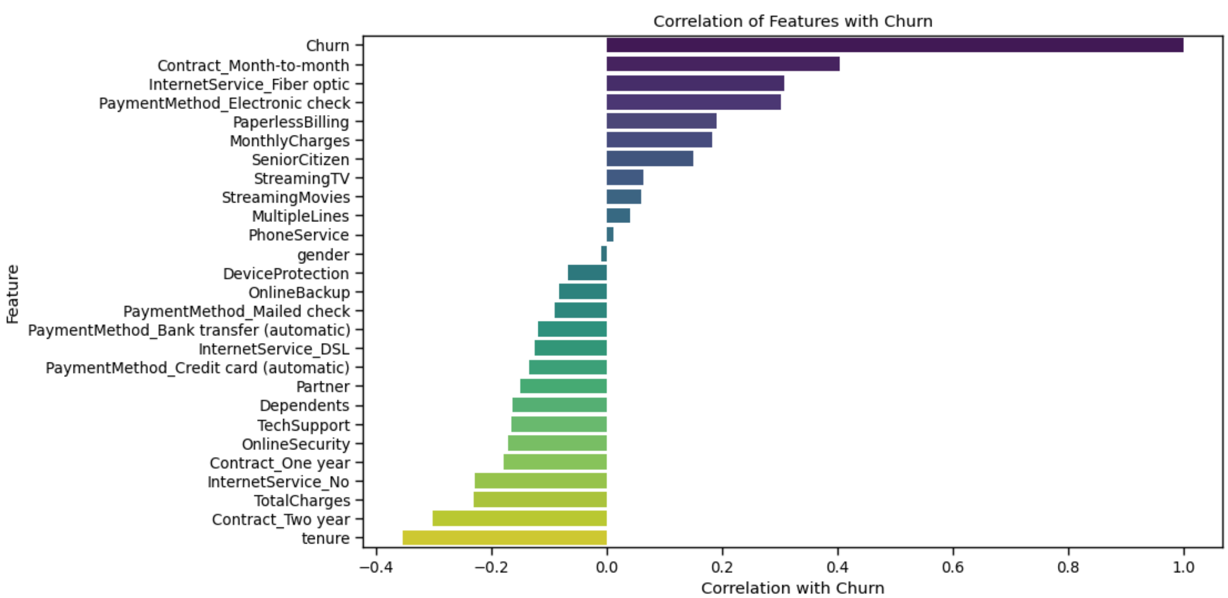
Correlation Analysis

```
In [56]: # Calculate correlations between all columns and the target variable "Churn"
correlation_with_churn = data.corr()['Churn'].sort_values(ascending=False)

# Print correlation values
print(correlation_with_churn)
```

```
Churn                                      1.000000
Contract_Month-to-month                    0.404565
InternetService_Fiber optic                0.307463
PaymentMethod_Electronic check             0.301455
PaperlessBilling                           0.191454
MonthlyCharges                             0.182989
SeniorCitizen                              0.150541
StreamingTV                                0.063254
StreamingMovies                            0.060860
MultipleLines                              0.040033
PhoneService                               0.011691
gender                                    -0.008545
DeviceProtection                          -0.066193
OnlineBackup                              -0.082307
PaymentMethod_Mailed check                -0.090773
PaymentMethod_Bank transfer (automatic)   -0.118136
InternetService_DSL                       -0.124141
PaymentMethod_Credit card (automatic)     -0.134687
Partner                                   -0.149982
Dependents                                -0.163128
TechSupport                               -0.164716
OnlineSecurity                            -0.171270
Contract_One year                         -0.178225
InternetService_No                        -0.227578
TotalCharges                              -0.230843
Contract_Two year                         -0.301552
tenure                                    -0.354049
Name: Churn, dtype: float64
```

In [57]:

```python
# Calculate correlations between all columns and the target variable "Churn"
correlation_with_churn = data.corr()['Churn'].sort_values(ascending=False)

# Plot the correlation values
plt.figure(figsize=(10, 6))
sns.barplot(x=correlation_with_churn.values, y=correlation_with_churn.index, palette='
plt.xlabel('Correlation with Churn')
plt.ylabel('Feature')
plt.title('Correlation of Features with Churn')
plt.show()
```



From the above we can see that there is no perfect correlation with the target variable

Feature Selection Using Recursive Feature Elimination Technique

Since we have 26 columns with no perfect correlation to the target variable we will be using a feature selection techniques to identify the most relevant variables for building the model. This would helps to improve the model performance, reduce overfitting, and enhance interpretability. For this we will be using 'Recursive Feature Elimination' (RFE) to help identify important features. It works by recursively removing features and builds the model on the remaining features until a specified number of features is reached.

Model Building and Evaluation.

- Choose appropriate statistical or machine learning models based on the problem and data characteristics.
- Split the data into training and testing sets for model evaluation.
- Train the models on the training data and evaluate their performance using appropriate metrics.
- Fine-tune model parameters and compare different models to select the best-performing one.
- Iterate and Refine Review the analysis process and results, and iterate as needed to refine the analysis or address new questions or insights.

Splitting the Data into Training and Testing

In [58]:
```
X = data.drop('Churn', axis = 1)

y = data['Churn']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=
```

Normalizing the Data Using MinMaxScaler

We will apply normalization technique on the dataset because the dataset columns are of different scale. Here we will using the Min Max Scaler to normalize the dataset.

In [59]:
```
# Initialize the MinMaxScaler
scaler = MinMaxScaler()
```

In [60]:
```
# Fit the scaler to your training data and transform it
X_train_normalized = scaler.fit_transform(X_train)
```

```python
# Transform the test data using the same scaler
X_test_normalized = scaler.transform(X_test)

# Now X_train_normalized and X_test_normalized contain the normalized data
```

Selecting the Model

Here we will be using 4 models

- Logistic Regression Model
- Random Forest Classifier
- Support Vector Machine Classifier

After which we will select the best fit model

Models

In [61]:
```python
#Initializing Models
logistic_regression = LogisticRegression()
random_forest = RandomForestClassifier()
svm_model = SVC(probability=True)
```

EXPERIMENT 1

Using All the Features without RFE

First let's build our model using all the features after which we will use the RFE on top 10 and 20

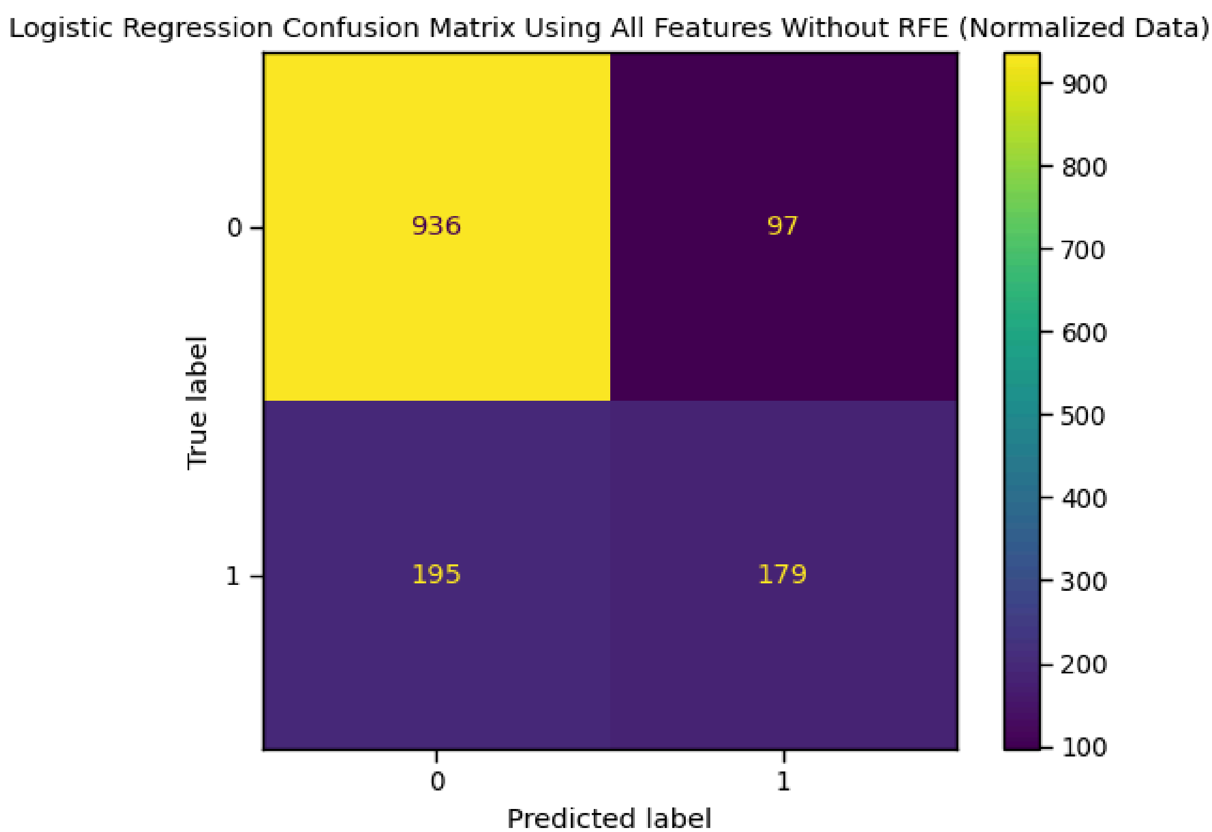
Logistic Regression Model

In [62]:
```python
# Train and evaluate Logistic Regression model on normalized data
logistic_regression.fit(X_train_normalized, y_train)
y_pred_lr_normalized = logistic_regression.predict(X_test_normalized)
accuracy_lr_normalized = accuracy_score(y_test, y_pred_lr_normalized)

print("Logistic Regression Accuracy (Normalized Data - Test Set):", accuracy_lr_normal

# Predict on the training set
y_pred_lr_normalized_train = logistic_regression.predict(X_train_normalized)

# Compute accuracy for the training set
accuracy_lr_normalized_train = accuracy_score(y_train, y_pred_lr_normalized_train)

# Print accuracy for the training set
print("Logistic Regression Accuracy (Normalized Data - Training Set):", accuracy_lr_nc

print("Logistic Regression Classification Report (Normalized Data):")
print(classification_report(y_test, y_pred_lr_normalized))
```

```
conf_matrix_lr_normalized = confusion_matrix(y_test, y_pred_lr_normalized)
print("Logistic Regression Confusion Matrix (Normalized Data):")
print(conf_matrix_lr_normalized)
```

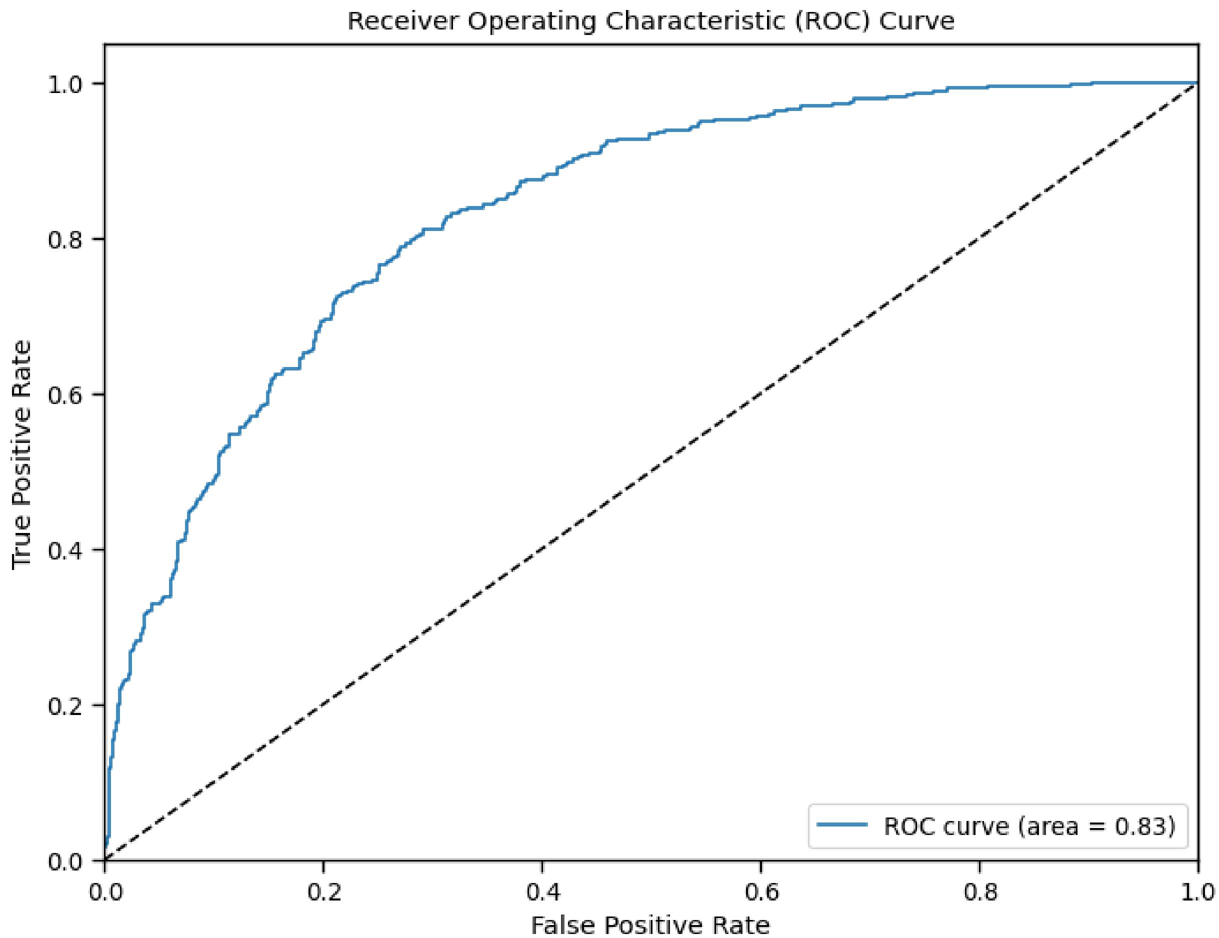
```
Logistic Regression Accuracy (Normalized Data - Test Set): 0.7924662402274343
Logistic Regression Accuracy (Normalized Data - Training Set): 0.8117333333333333
Logistic Regression Classification Report (Normalized Data):
              precision    recall  f1-score   support

           0       0.83      0.91      0.87      1033
           1       0.65      0.48      0.55       374

    accuracy                           0.79      1407
   macro avg       0.74      0.69      0.71      1407
weighted avg       0.78      0.79      0.78      1407

Logistic Regression Confusion Matrix (Normalized Data):
[[936  97]
 [195 179]]
```

In [63]:
```
# Plotting the Confusion Matrix for Logistic Regression Model with Normalized Data
cm_display_lr_normalized = ConfusionMatrixDisplay(confusion_matrix=conf_matrix_lr_norm
cm_display_lr_normalized.plot()
plt.title("Logistic Regression Confusion Matrix Using All Features Without RFE (Normal
plt.show()
```



In [64]:
```
# Plotting the ROC curve for Logistic Regression Model with Normalized Data
y_prob_lr_normalized = logistic_regression.predict_proba(X_test_normalized)[:, 1]
fpr_lr_normalized, tpr_lr_normalized, thresholds_lr_normalized = roc_curve(y_test, y_p
auc_lr_normalized = roc_auc_score(y_test, y_prob_lr_normalized)

plt.figure(figsize=(8, 6))
plt.plot(fpr_lr_normalized, tpr_lr_normalized, label='ROC curve (area = %0.2f)' % auc_
```

```python
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```



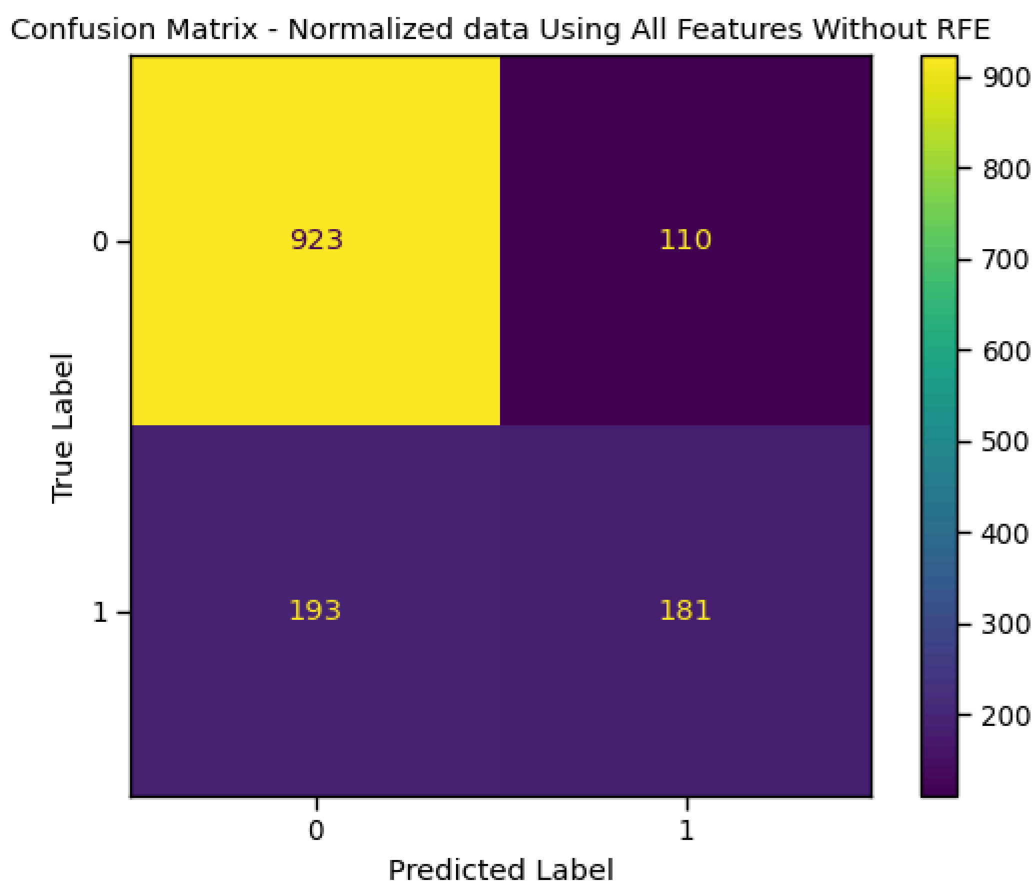
SVM Model

In [65]:
```python
# Train the SVM model on normalized data without RFE
svm_model.fit(X_train_normalized, y_train)

# Make predictions
y_pred = svm_model.predict(X_test_normalized)

# Make predictions
y_pred_train = svm_model.predict(X_train_normalized)

# Compute the accuracy of the train set
train_accuracy = accuracy_score(y_train, y_pred_train)
print("Accuracy on the train set:", train_accuracy)

# Evaluate the model
print("Scenario: Normalized data without RFE")
```

```
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Compute the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
```

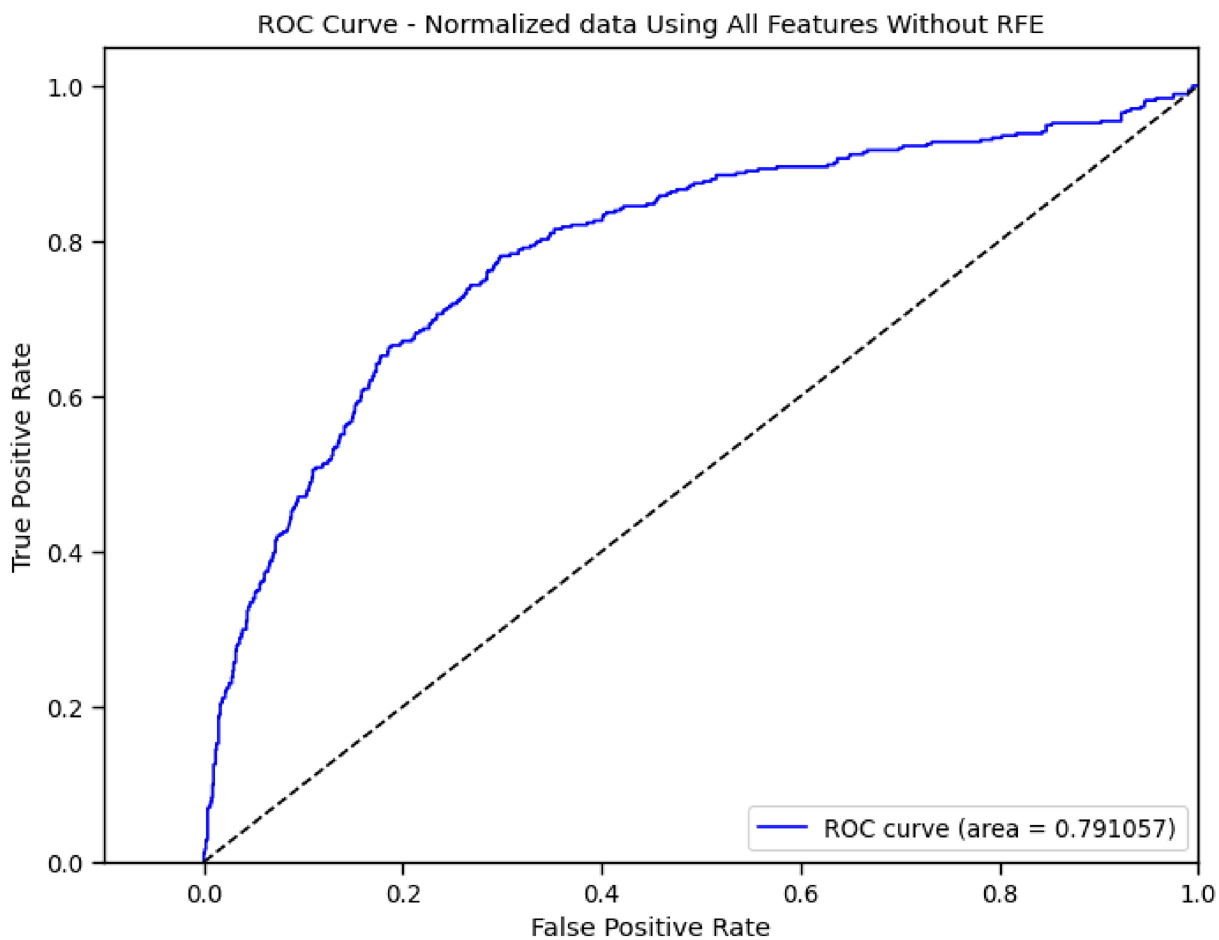
```
Accuracy on the train set: 0.8241777777777778
Scenario: Normalized data without RFE
Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.89      0.86      1033
           1       0.62      0.48      0.54       374

    accuracy                           0.78      1407
   macro avg       0.72      0.69      0.70      1407
weighted avg       0.77      0.78      0.78      1407

Confusion Matrix:
[[923 110]
 [193 181]]
```

In [66]:
```
# Plot the confusion matrix
cm_display = ConfusionMatrixDisplay(confusion_matrix=conf_matrix)
cm_display.plot()
plt.title("Confusion Matrix - Normalized data Using All Features Without RFE")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



In [67]:
```
# Compute the probability estimates for positive class
y_prob = svm_model.predict_proba(X_test_normalized)[:, 1]

# Compute fpr, tpr, and thresholds
fpr, tpr, thresholds = roc_curve(y_test, y_prob)

# Compute AUC
auc = roc_auc_score(y_test, y_prob)
print('AUC:', auc)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label='ROC curve (area = %f)' % auc)
plt.plot([0, 1], [0, 1], linestyle='--', color='black')
plt.xlim([-0.1, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc="lower right")
plt.title('ROC Curve - Normalized data Using All Features Without RFE')
plt.show()
```

```
AUC: 0.7910568874209898
```

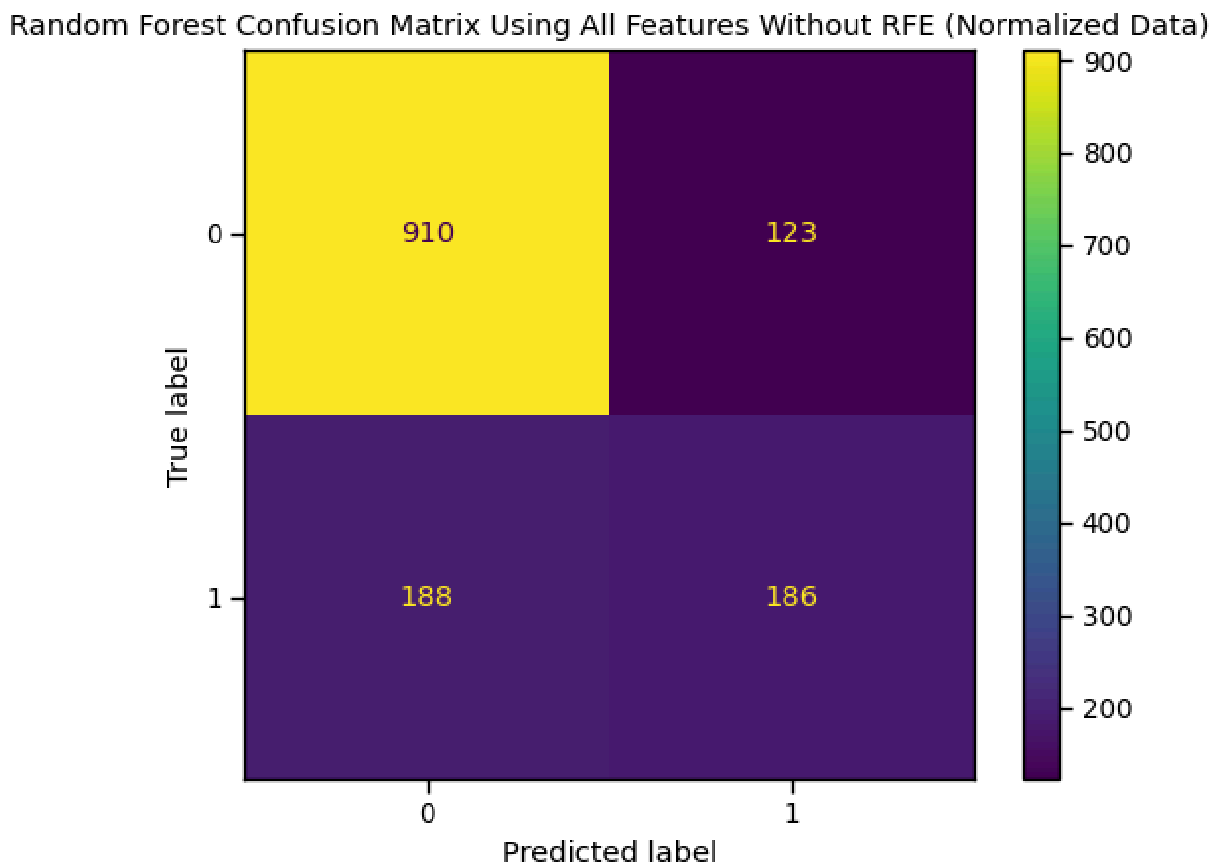


Random Forest Model

In [68]:
```
# Train and evaluate Random Forest model on normalized data
random_forest.fit(X_train_normalized, y_train)
y_pred_rf = random_forest.predict(X_test_normalized)


# Make predictions on the train set
y_pred_train_rf = random_forest.predict(X_train_normalized)

# Compute the accuracy of the train set for Random Forest model
train_accuracy_rf = accuracy_score(y_train, y_pred_train_rf)
print("Random Forest Accuracy on the train set (Normalized Data):", train_accuracy_rf)


# Compute confusion matrix for Random Forest model
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)

# Print accuracy, classification report, and confusion matrix
accuracy_rf = accuracy_score(y_test, y_pred_rf)
print("Random Forest Accuracy (Normalized Data - Test Set):", accuracy_rf)
print("Random Forest Classification Report (Normalized Data):")
print(classification_report(y_test, y_pred_rf))
print("Random Forest Confusion Matrix (Normalized Data):")
print(conf_matrix_rf)
```

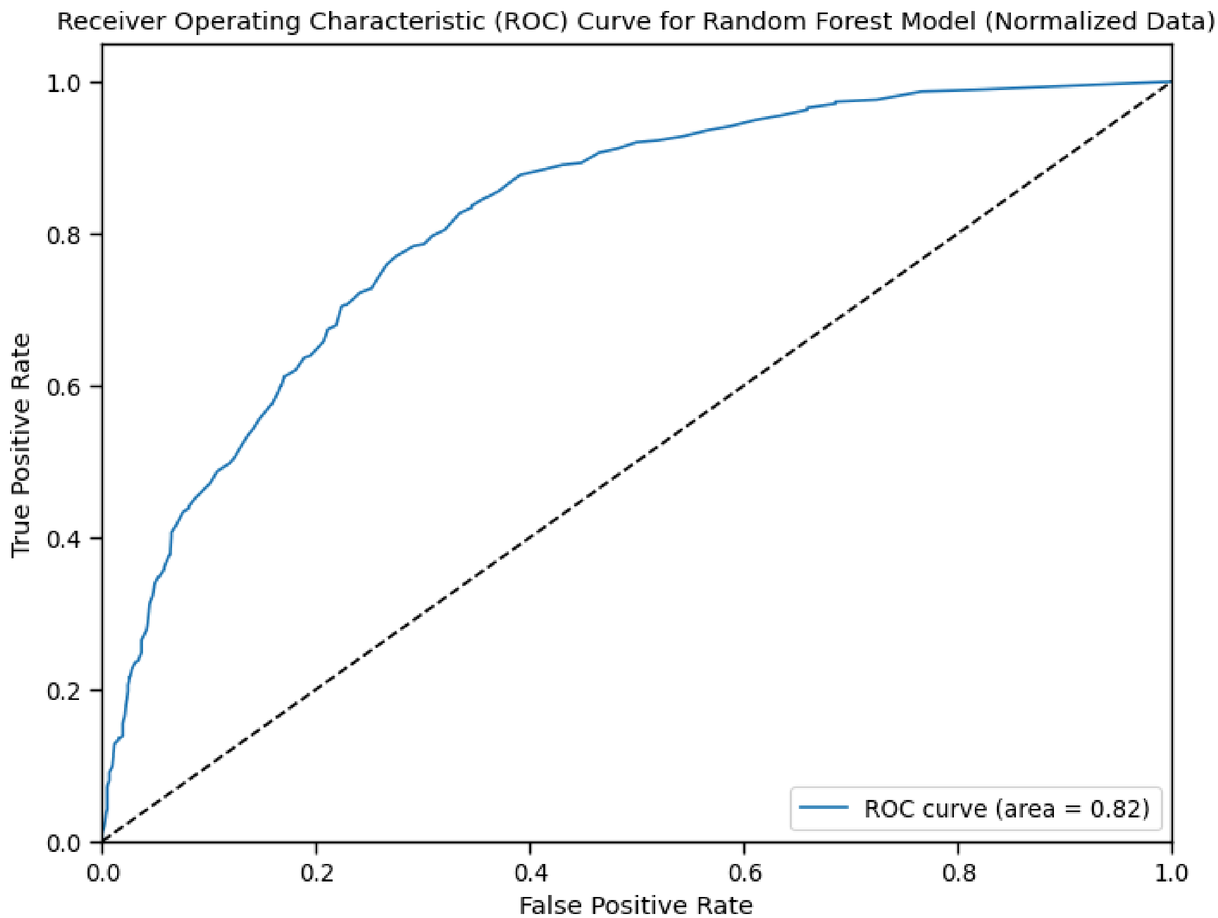
```
Random Forest Accuracy on the train set (Normalized Data): 0.9976888888888888
Random Forest Accuracy (Normalized Data - Test Set): 0.7789623312011372
Random Forest Classification Report (Normalized Data):
              precision    recall  f1-score   support

           0       0.83      0.88      0.85      1033
           1       0.60      0.50      0.54       374

    accuracy                           0.78      1407
   macro avg       0.72      0.69      0.70      1407
weighted avg       0.77      0.78      0.77      1407

Random Forest Confusion Matrix (Normalized Data):
[[910 123]
 [188 186]]
```

In [69]:
```
# Plotting the Confusion Matrix for Random Forest Model with Normalized Data
cm_display_rf = ConfusionMatrixDisplay(confusion_matrix=conf_matrix_rf, display_labels
cm_display_rf.plot()
plt.title("Random Forest Confusion Matrix Using All Features Without RFE (Normalized D
plt.show()
```



In [70]:

```
# Plotting the ROC curve for Random Forest Model with Normalized Data
y_prob_rf = random_forest.predict_proba(X_test_normalized)[:, 1]
fpr_rf, tpr_rf, thresholds_rf = roc_curve(y_test, y_prob_rf)
auc_rf = roc_auc_score(y_test, y_prob_rf)

plt.figure(figsize=(8, 6))
plt.plot(fpr_rf, tpr_rf, label='ROC curve (area = %0.2f)' % auc_rf)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve for Random Forest Model (Norm
plt.legend(loc="lower right")
plt.show()
```



EXPERIMENT 2

Using RFE on Logistic Regression, Random Forest and SVM to Select the Top 10 Features.

In [71]:
```
# Function to perform Recursive Feature Elimination (RFE)
def perform_rfe(model, X_train_normalized, y_train, n_features):
    rfe = RFE(model, n_features_to_select=n_features)
    rfe.fit(X_train_normalized, y_train)
    selected_features = rfe.support_
    return selected_features
```

In [72]:
```
# Initialize models
logistic_regression = LogisticRegression(max_iter=1000)
svm_model_linear = SVC(kernel='linear', probability=True)
random_forest = RandomForestClassifier()
```

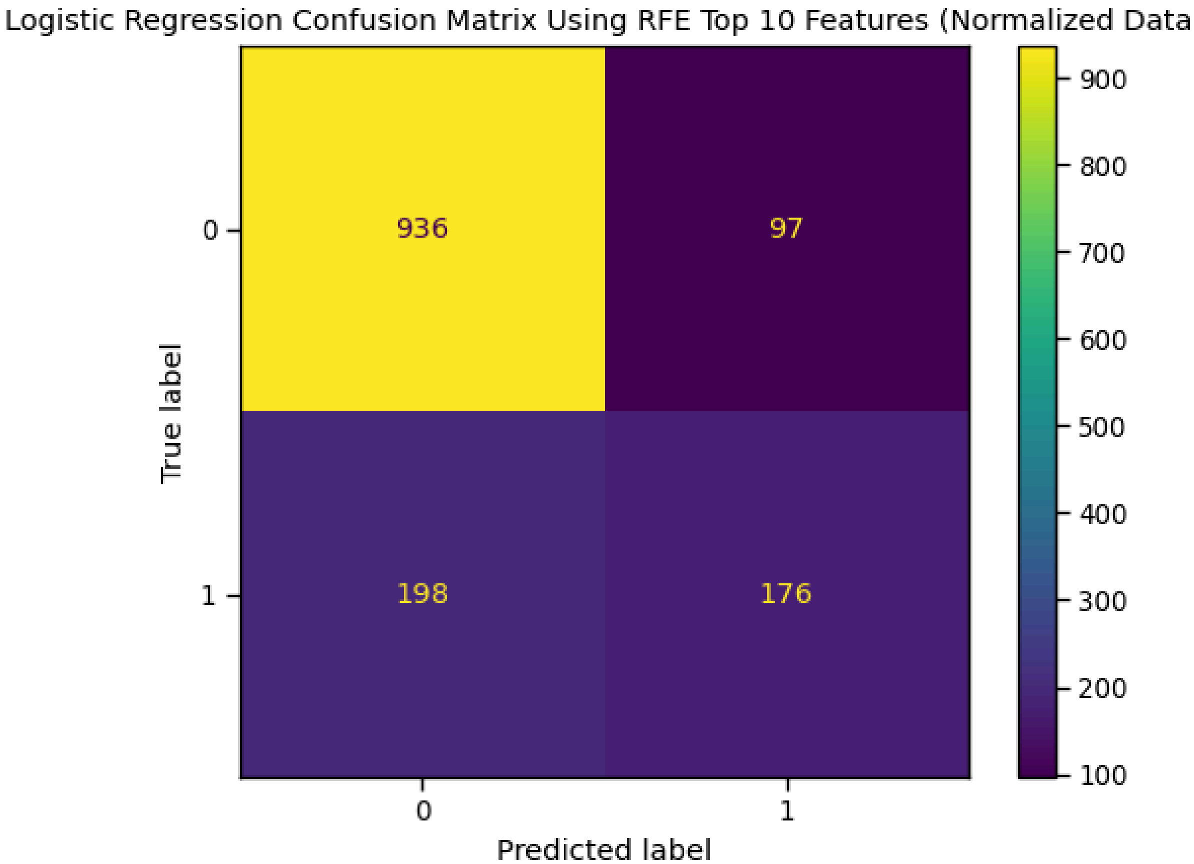
Logistic Regression Model

In [73]:
```
# Get Selected Features for each model using RFE with normalized data
logistic_regression_features = perform_rfe(logistic_regression, X_train_normalized, y_
```

In [74]:
```
# Train and evaluate Logistic Regression model with normalized data
logistic_regression.fit(X_train_normalized[:, logistic_regression_features], y_train)
y_pred_lr = logistic_regression.predict(X_test_normalized[:, logistic_regression_featu
accuracy_lr = accuracy_score(y_test, y_pred_lr)

# Make predictions on the train set
y_pred_train_lr = logistic_regression.predict(X_train_normalized[:, logistic_regressic

# Compute the accuracy of the train set for Logistic Regression model
train_accuracy_lr = accuracy_score(y_train, y_pred_train_lr)
print("Logistic Regression Accuracy on the train set:", train_accuracy_lr)

# compute the confusion matrix
conf_matrix_lr = confusion_matrix(y_test, y_pred_lr)

# Print accuracy and classification report
print("Logistic Regression Accuracy - Test Set:", accuracy_lr)
print("Logistic Regression Classification Report:")
print(classification_report(y_test, y_pred_lr))
```

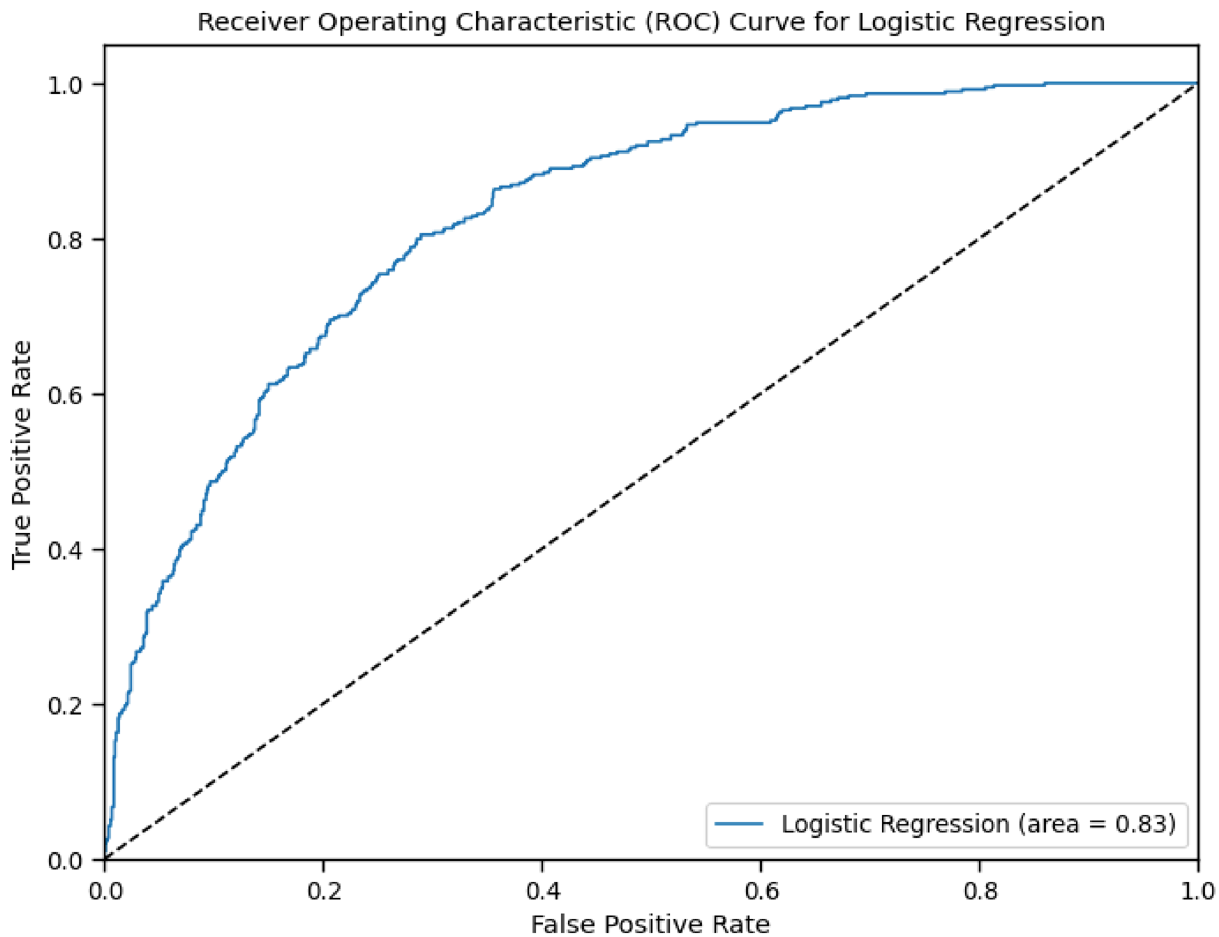
```
Logistic Regression Accuracy on the train set: 0.8030222222222222
Logistic Regression Accuracy - Test Set: 0.7903340440653873
Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.91      0.86      1033
           1       0.64      0.47      0.54       374

    accuracy                           0.79      1407
   macro avg       0.74      0.69      0.70      1407
weighted avg       0.78      0.79      0.78      1407
```

In [75]:
```
# Plot the Confusion Matrix for Logistic Regression Model with Normalized Data
cm_display_lr = ConfusionMatrixDisplay(confusion_matrix=conf_matrix_lr)
cm_display_lr.plot()
plt.title("Logistic Regression Confusion Matrix Using RFE Top 10 Features (Normalized
plt.show()
```



In [76]:

```
# Plot ROC AUC curve for Logistic Regression
y_prob_lr = logistic_regression.predict_proba(X_test_normalized[:, logistic_regressior
fpr_lr, tpr_lr, thresholds_lr = roc_curve(y_test, y_prob_lr)
auc_lr = roc_auc_score(y_test, y_prob_lr)
plt.figure(figsize=(8, 6))
plt.plot(fpr_lr, tpr_lr, label='Logistic Regression (area = %0.2f)' % auc_lr)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve for Logistic Regression')
plt.legend(loc="lower right")
plt.show()
```



In [77]:
```
# This function to prints the columns selected by RFE
#def print_selected_columns(selected_features):
    # Print the indices of the selected features

    #print("Indices of selected columns:")
    #for index, selected in enumerate(selected_features):
       # if selected:
        #    print(index)

# Assuming you have obtained the selected features from RFE
# For example, logistic_regression_features from your code snippet

# Print indices of selected columns
#print_selected_columns(logistic_regression_features)
```

Random Forest Model

In [78]:
```
# Get Selected Features for each model using RFE with normalized data
random_forest_features = perform_rfe(random_forest, X_train_normalized, y_train, n_fea
```

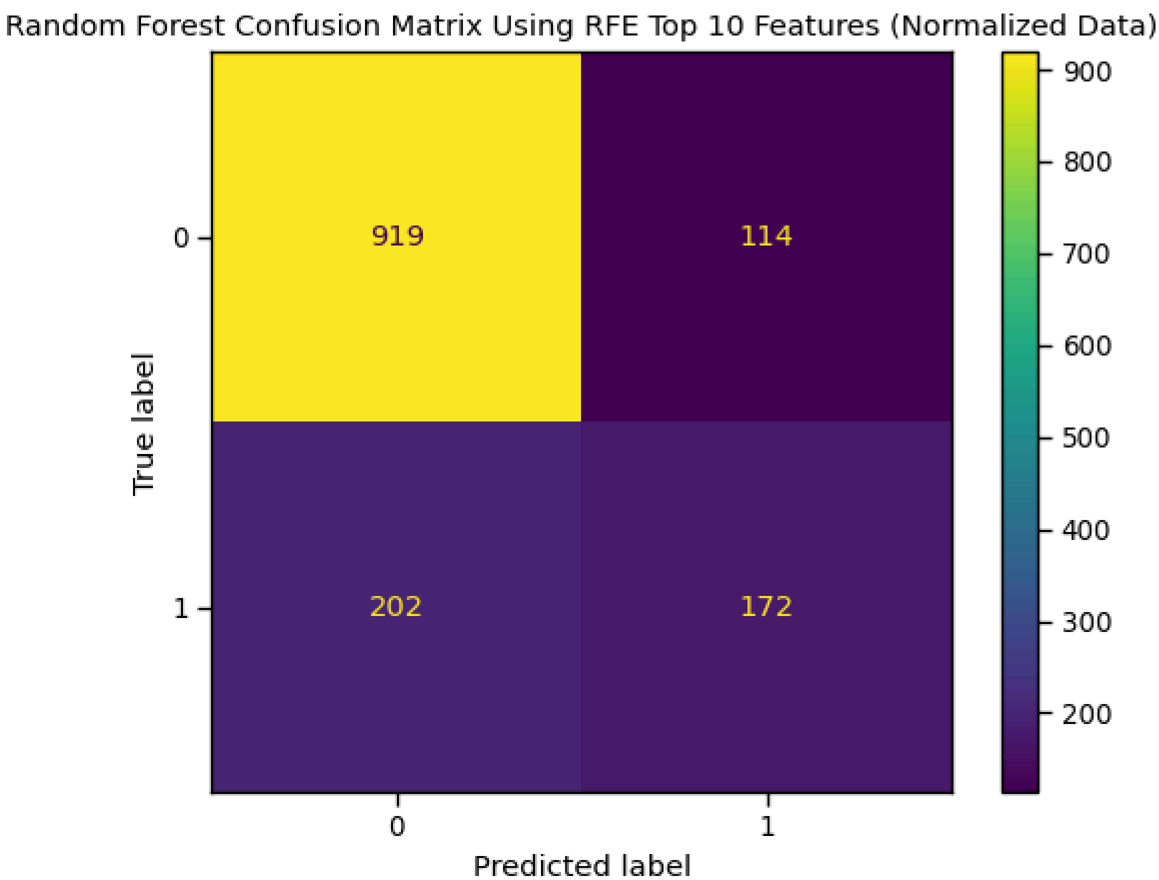
In [79]:
```
# Train and evaluate Random Forest model with normalized data
random_forest.fit(X_train_normalized[:, random_forest_features], y_train)
y_pred_rf = random_forest.predict(X_test_normalized[:, random_forest_features])
```

```
accuracy_rf = accuracy_score(y_test, y_pred_rf)

# Make predictions on the train set
y_pred_train_rf = random_forest.predict(X_train_normalized[:, random_forest_features])

# Compute the accuracy of the train set for Random Forest model
train_accuracy_rf = accuracy_score(y_train, y_pred_train_rf)
print("Random Forest Accuracy on the train set:", train_accuracy_rf)

# Compute the confusion matrix
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)

# Print accuracy and classification report
print("Random Forest Accuracy:", accuracy_rf)
print("Random Forest Classification Report:")
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Accuracy on the train set: 0.9971555555555556
Random Forest Accuracy: 0.775408670931059
Random Forest Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.89      0.85      1033
           1       0.60      0.46      0.52       374

    accuracy                           0.78      1407
   macro avg       0.71      0.67      0.69      1407
weighted avg       0.76      0.78      0.77      1407
```

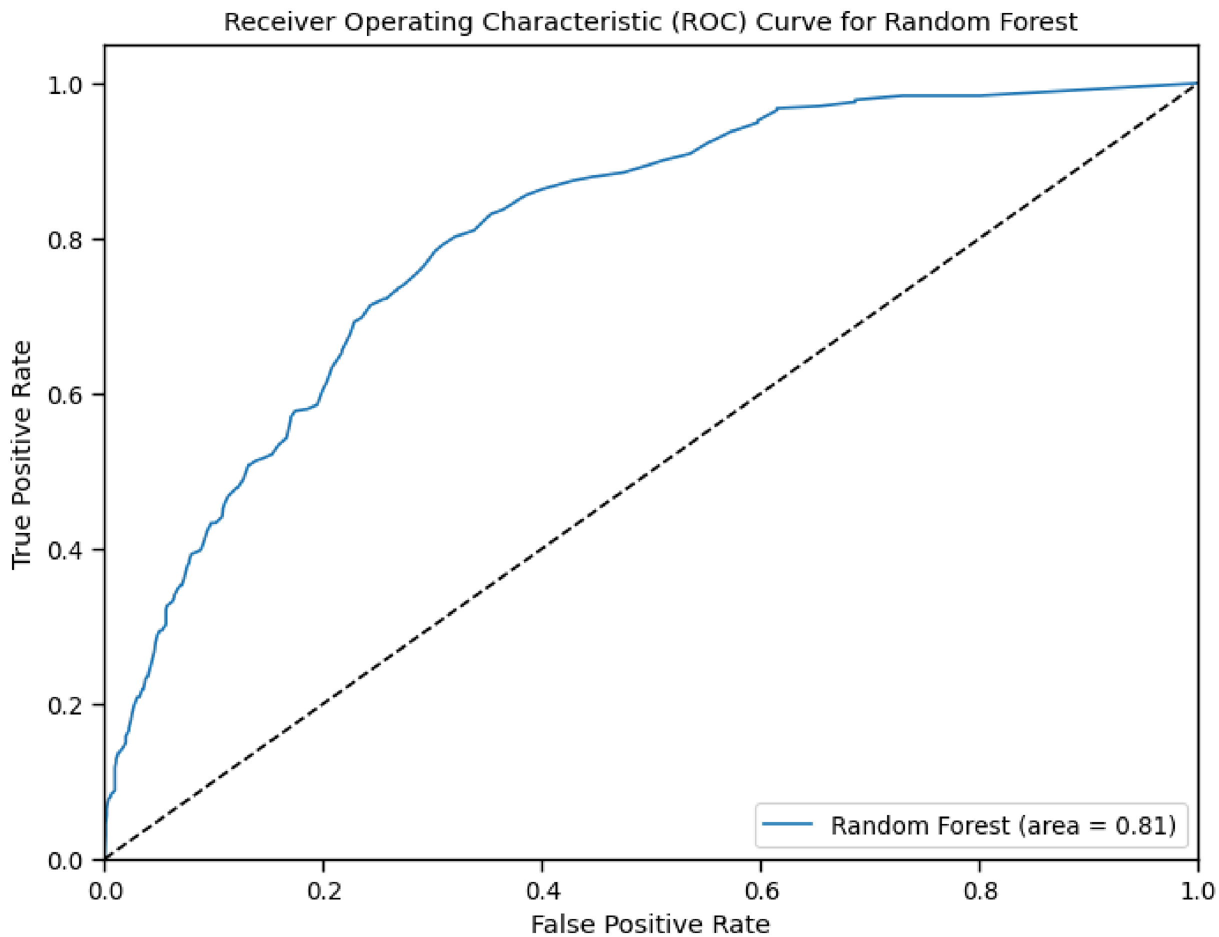
In [80]:

```
# Plot the Confusion Matrix for Random Forest Model with Normalized Data
cm_display_rf = ConfusionMatrixDisplay(confusion_matrix=conf_matrix_rf)
cm_display_rf.plot()
plt.title("Random Forest Confusion Matrix Using RFE Top 10 Features (Normalized Data)"
plt.show()
```



In [81]:

```
# Plot ROC AUC curve for Random Forest
y_prob_rf = random_forest.predict_proba(X_test_normalized[:, random_forest_features])[
fpr_rf, tpr_rf, thresholds_rf = roc_curve(y_test, y_prob_rf)
auc_rf = roc_auc_score(y_test, y_prob_rf)
plt.figure(figsize=(8, 6))
plt.plot(fpr_rf, tpr_rf, label='Random Forest (area = %0.2f)' % auc_rf)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve for Random Forest')
plt.legend(loc="lower right")
plt.show()
```



SVM Model

In [82]:
```
# Initialize RFE for feature selection with SVM model
rfe = RFE(estimator=svm_model_linear, n_features_to_select=10)

# Fit RFE on normalized data
rfe.fit(X_train_normalized, y_train)

# Get the selected features
selected_features_svm = rfe.support_

# Select top 10 features from training and test data
X_train_top10_svm = X_train_normalized[:, selected_features_svm]
X_test_top10_svm = X_test_normalized[:, selected_features_svm]
```

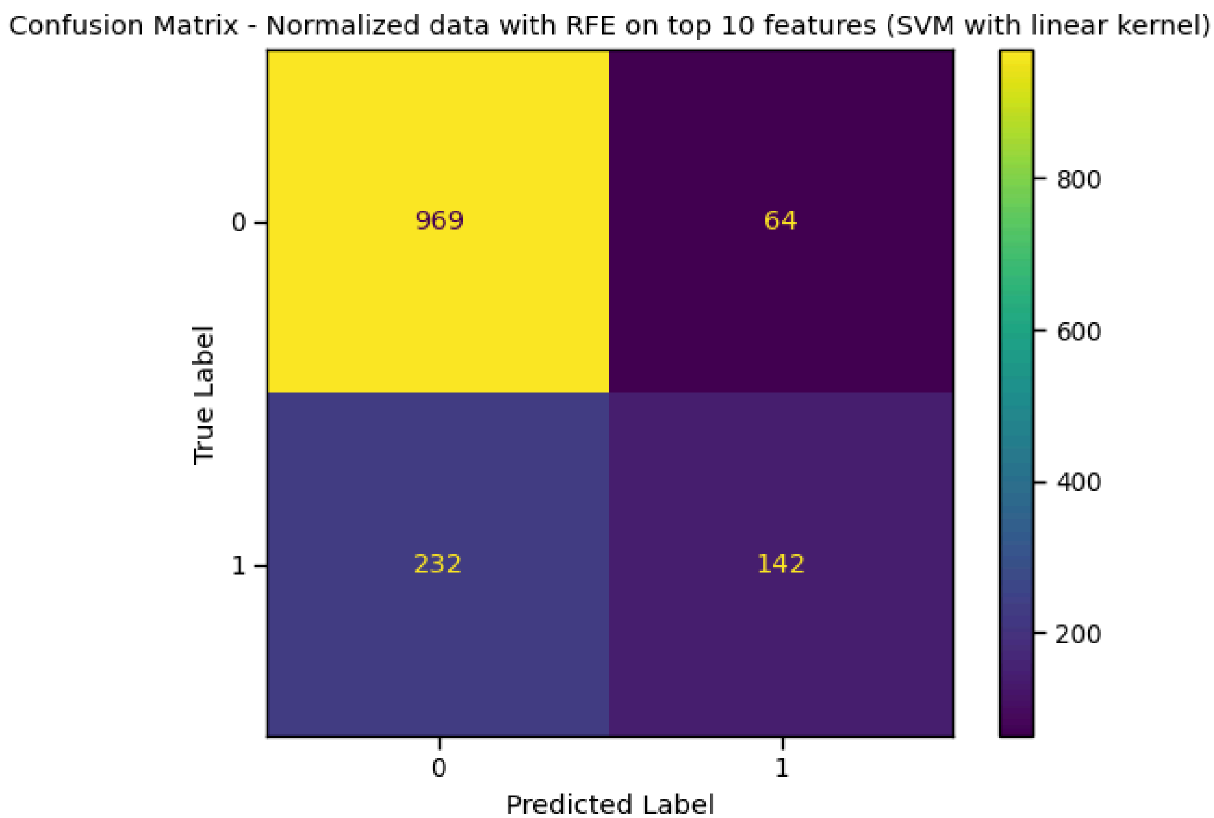
In [83]:
```
# Train the SVM model on top 10 features
svm_model_linear.fit(X_train_top10_svm, y_train)

# Make predictions on the test set
y_pred_svm = svm_model_linear.predict(X_test_top10_svm)

# Make predictions on the train set
y_pred_train_svm = svm_model_linear.predict(X_train_top10_svm)

# Compute the accuracy of the train set for SVM model
train_accuracy_svm = accuracy_score(y_train, y_pred_train_svm)
```

```python
print("SVM Accuracy on the train set with top 10 features:", train_accuracy_svm)

# Evaluate the model
print("Scenario: Normalized data with RFE on top 10 features (SVM with linear kernel)"
print("Classification Report:")
print(classification_report(y_test, y_pred_svm))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_svm))
```

```
SVM Accuracy on the train set with top 10 features: 0.8
Scenario: Normalized data with RFE on top 10 features (SVM with linear kernel)
Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.94      0.87      1033
           1       0.69      0.38      0.49       374

    accuracy                           0.79      1407
   macro avg       0.75      0.66      0.68      1407
weighted avg       0.78      0.79      0.77      1407

Confusion Matrix:
[[969  64]
 [232 142]]
```

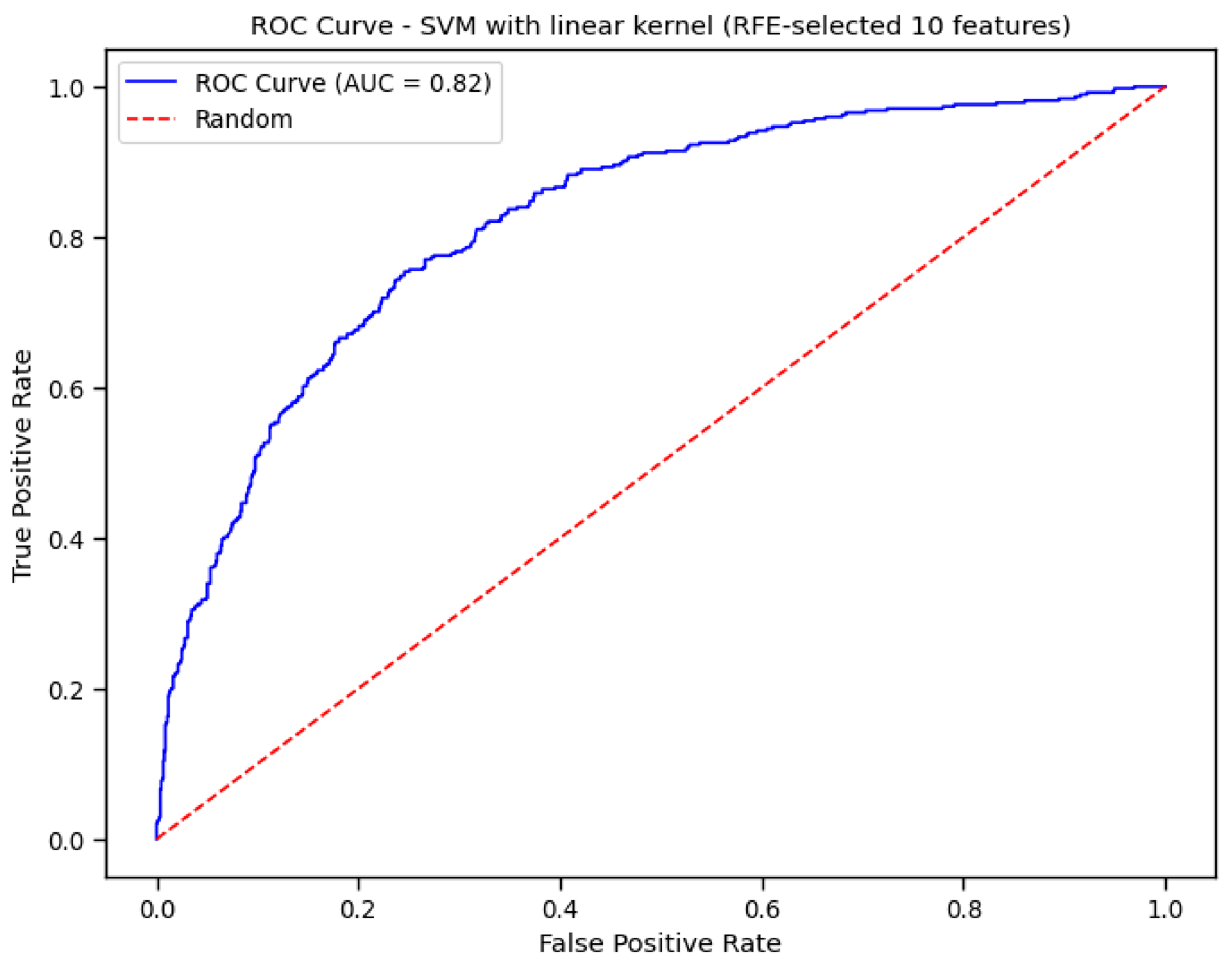
In [84]:

```python
# Plot the Confusion Matrix for SVM Model with Linear Kernel and RFE-selected features
cm_display_svm = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix(y_test, y_pr
cm_display_svm.plot()
plt.title("Confusion Matrix - Normalized data with RFE on top 10 features (SVM with li
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



In [85]:
```
# Compute the probability estimates for positive class
y_prob_svm = svm_model_linear.predict_proba(X_test_top10_svm)[:, 1]

# Compute fpr, tpr, and thresholds
fpr_svm, tpr_svm, thresholds_svm = roc_curve(y_test, y_prob_svm)

# Compute ROC AUC score
roc_auc_svm = roc_auc_score(y_test, y_prob_svm)
print('ROC AUC (SVM with linear kernel):', roc_auc_svm)

# Plot ROC AUC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr_svm, tpr_svm, color='blue', label='ROC Curve (AUC = {:.2f})'.format(roc_a
plt.plot([0, 1], [0, 1], color='red', linestyle='--', label='Random')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - SVM with linear kernel (RFE-selected 10 features)')
plt.legend()
plt.show()
```

```
ROC AUC (SVM with linear kernel): 0.8217097804535878
```



EXPERIMENT 3

PERFORMING RFE ON TOP TWENTY (20) FEATURES

Logistic Regression, SVM Model and Random Forest Using 20 Top features

Models

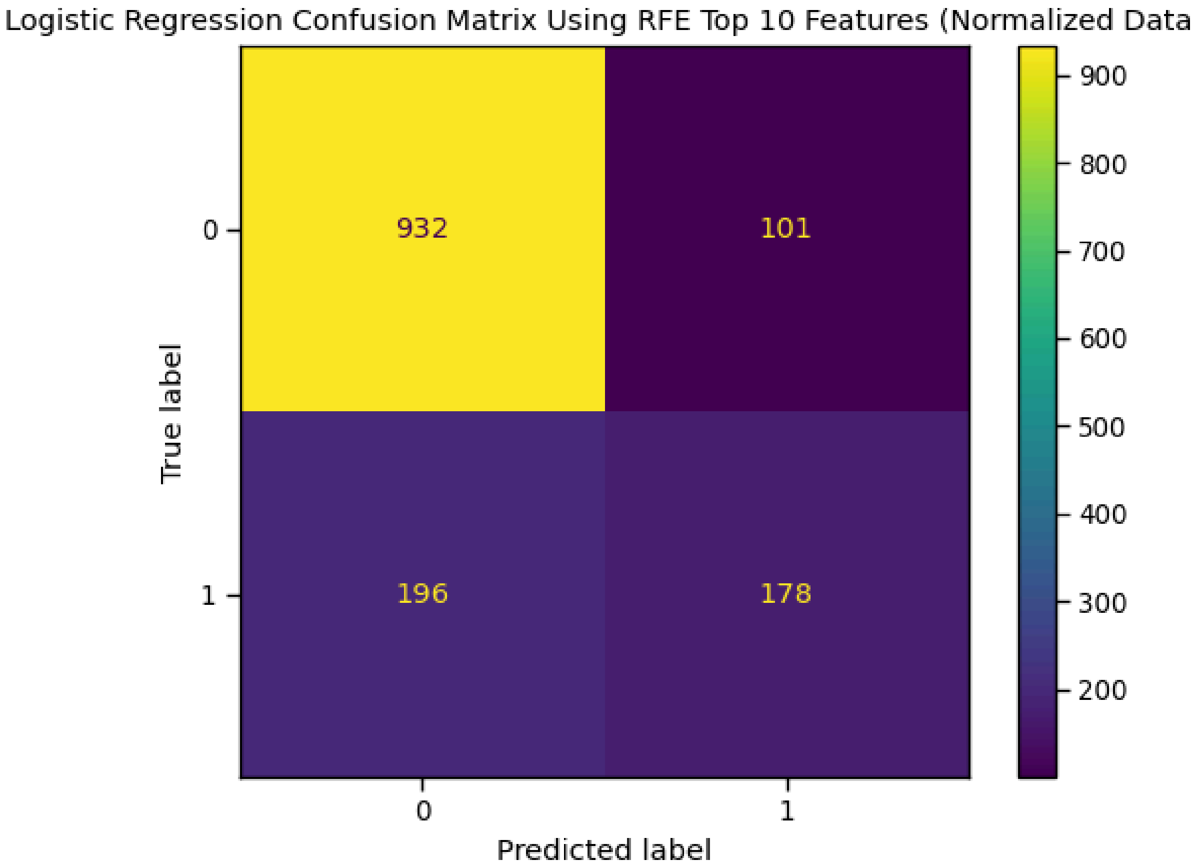
Logistics Regression Model

In [86]:
```
# Get Selected Features for each model using RFE with normalized data
logistic_regression_features = perform_rfe(logistic_regression, X_train_normalized, y_
```

In [87]:
```
# Train and evaluate Logistic Regression model with normalized data
logistic_regression.fit(X_train_normalized[:, logistic_regression_features], y_train)
y_pred_lr = logistic_regression.predict(X_test_normalized[:, logistic_regression_featu
accuracy_lr = accuracy_score(y_test, y_pred_lr)

# Make predictions on the train set
y_pred_train_lr = logistic_regression.predict(X_train_normalized[:, logistic_regressic

# Compute the accuracy of the train set for Logistic Regression model
train_accuracy_lr = accuracy_score(y_train, y_pred_train_lr)
print("Logistic Regression Accuracy on the train set:", train_accuracy_lr)

# Compute the confusion matrix
conf_matrix_lr = confusion_matrix(y_test, y_pred_lr)

# Print accuracy and classification report
print("Logistic Regression Accuracy:", accuracy_lr)
print("Logistic Regression Classification Report:")
print(classification_report(y_test, y_pred_lr))
```

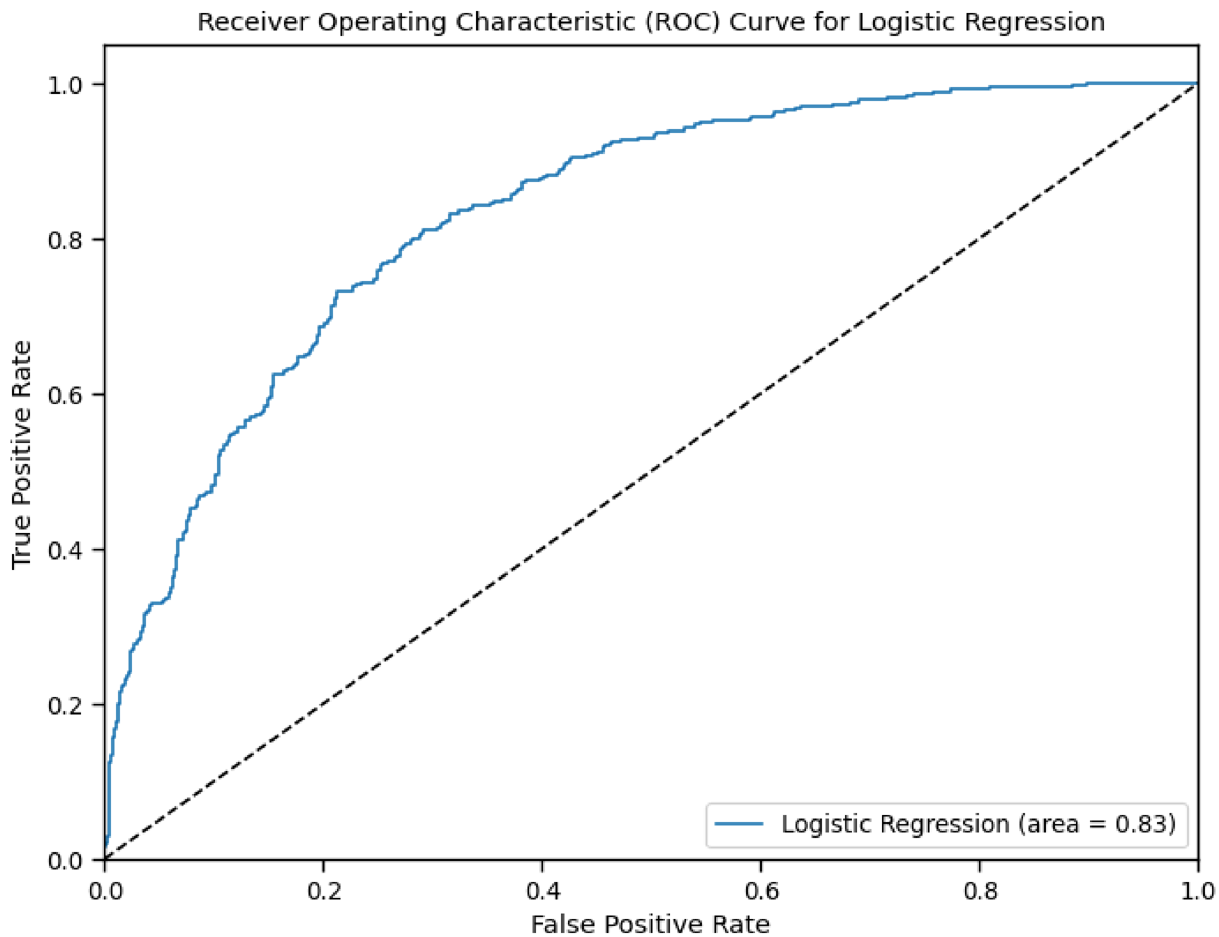
```
Logistic Regression Accuracy on the train set: 0.8094222222222223
Logistic Regression Accuracy: 0.7889125799573561
Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.90      0.86      1033
           1       0.64      0.48      0.55       374

    accuracy                           0.79      1407
   macro avg       0.73      0.69      0.70      1407
weighted avg       0.78      0.79      0.78      1407
```

In [88]:
```
# Plot the Confusion Matrix for Logistic Regression Model with Normalized Data
cm_display_lr = ConfusionMatrixDisplay(confusion_matrix=conf_matrix_lr)
cm_display_lr.plot()
plt.title("Logistic Regression Confusion Matrix Using RFE Top 10 Features (Normalized
plt.show()
```



In [89]:

```
# Plot ROC AUC curve for Logistic Regression
y_prob_lr = logistic_regression.predict_proba(X_test_normalized[:, logistic_regressior
fpr_lr, tpr_lr, thresholds_lr = roc_curve(y_test, y_prob_lr)
auc_lr = roc_auc_score(y_test, y_prob_lr)
plt.figure(figsize=(8, 6))
plt.plot(fpr_lr, tpr_lr, label='Logistic Regression (area = %0.2f)' % auc_lr)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve for Logistic Regression')
plt.legend(loc="lower right")
plt.show()
```



Random Forest Model

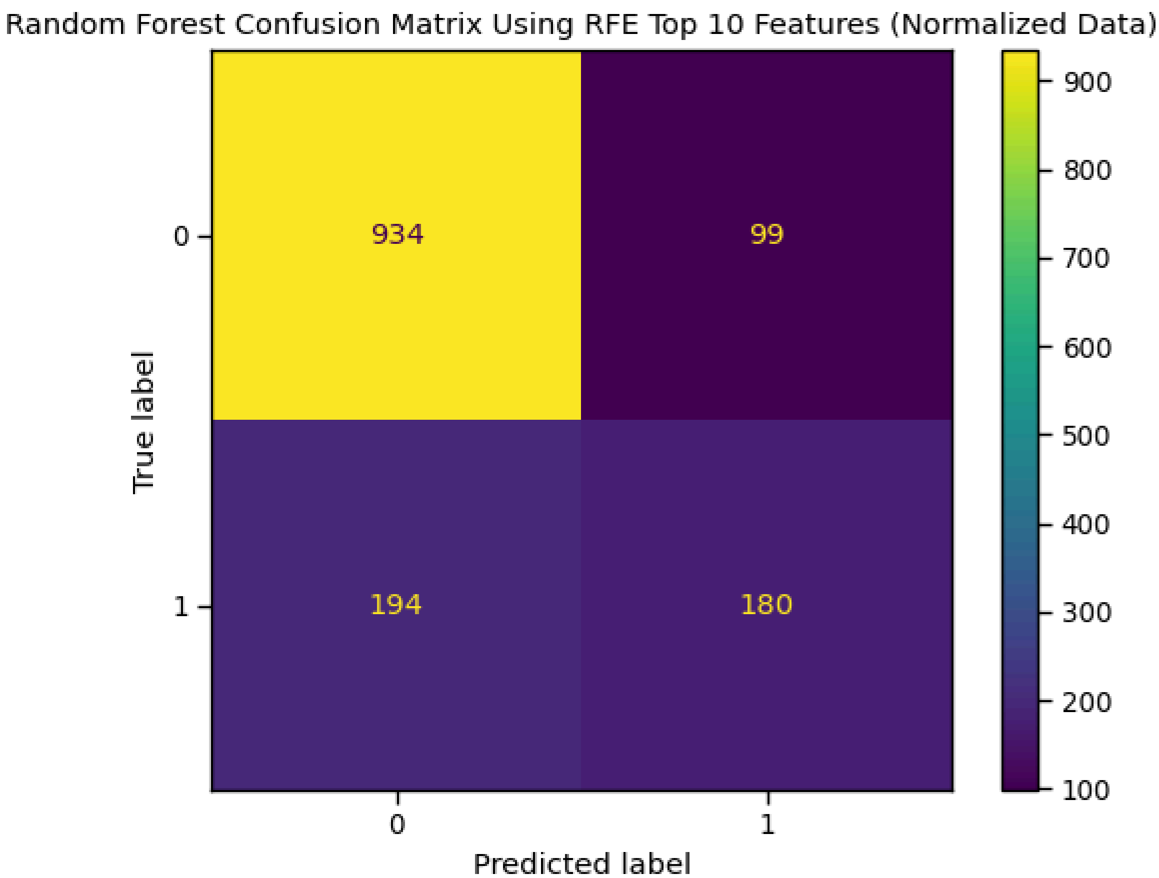
In [90]:
```
# Get Selected Features for each model using RFE with normalized data
random_forest_features = perform_rfe(random_forest, X_train_normalized, y_train, n_fea
```

In [91]:
```
# Train and evaluate Random Forest model with normalized data
random_forest.fit(X_train_normalized[:, random_forest_features], y_train)
y_pred_rf = random_forest.predict(X_test_normalized[:, random_forest_features])
accuracy_rf = accuracy_score(y_test, y_pred_rf)

# Make predictions on the train set
y_pred_train_rf = random_forest.predict(X_train_normalized[:, random_forest_features])

# Compute the accuracy of the train set for Random Forest model
train_accuracy_rf = accuracy_score(y_train, y_pred_train_rf)
print("Random Forest Accuracy on the train set:", train_accuracy_rf)

# Compute the confusion matrix
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)

# Print accuracy and classification report
print("Random Forest Accuracy:", accuracy_rf)
```

```
print("Random Forest Classification Report:")
print(classification_report(y_test, y_pred_rf))
```

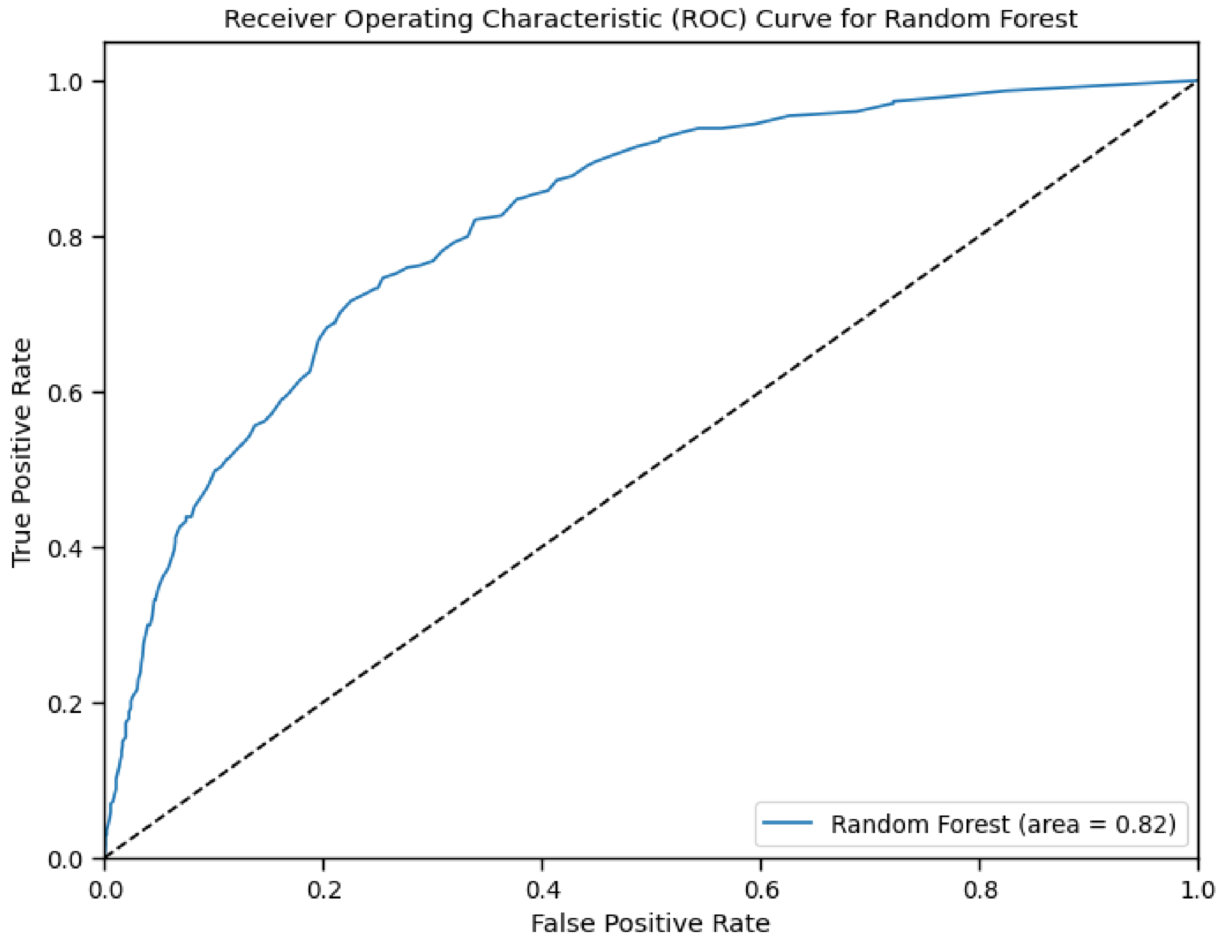
```
Random Forest Accuracy on the train set: 0.9976888888888888
Random Forest Accuracy: 0.7917555081734187
Random Forest Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.90      0.86      1033
           1       0.65      0.48      0.55       374

    accuracy                           0.79      1407
   macro avg       0.74      0.69      0.71      1407
weighted avg       0.78      0.79      0.78      1407
```

In [92]:
```
# Plot the Confusion Matrix for Random Forest Model with Normalized Data
cm_display_rf = ConfusionMatrixDisplay(confusion_matrix=conf_matrix_rf)
cm_display_rf.plot()
plt.title("Random Forest Confusion Matrix Using RFE Top 10 Features (Normalized Data)"
plt.show()
```



In [93]:
```
# Plot ROC AUC curve for Random Forest
y_prob_rf = random_forest.predict_proba(X_test_normalized[:, random_forest_features])[
fpr_rf, tpr_rf, thresholds_rf = roc_curve(y_test, y_prob_rf)
auc_rf = roc_auc_score(y_test, y_prob_rf)
plt.figure(figsize=(8, 6))
plt.plot(fpr_rf, tpr_rf, label='Random Forest (area = %0.2f)' % auc_rf)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
```

```
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve for Random Forest')
plt.legend(loc="lower right")
plt.show()
```



SVM Model

In [94]:
```
# Initialize RFE for feature selection with SVM model
rfe = RFE(estimator=svm_model_linear, n_features_to_select=20)
```

In [95]:
```
# Fit RFE on normalized data
rfe.fit(X_train_normalized, y_train)

# Get the selected features
selected_features_svm = rfe.support_

# Select top 20 features from training and test data
X_train_top20_svm = X_train_normalized[:, selected_features_svm]
X_test_top20_svm = X_test_normalized[:, selected_features_svm]
```

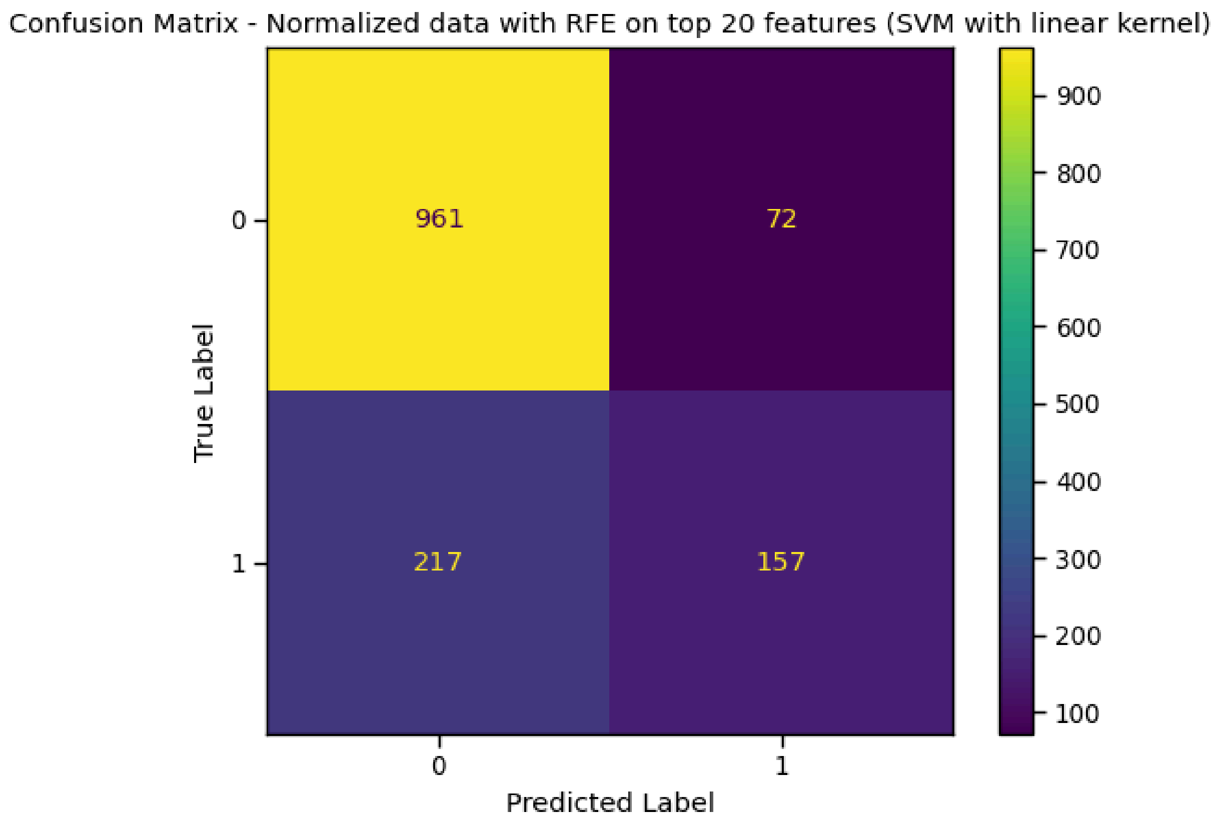
In [96]:
```
# Train the SVM model on top 20 features
svm_model_linear.fit(X_train_top20_svm, y_train)

# Make predictions on the test set
```

```python
y_pred_svm = svm_model_linear.predict(X_test_top20_svm)

# Make predictions on the train set
y_pred_train_svm = svm_model_linear.predict(X_train_top20_svm)

# Compute the accuracy of the train set for SVM model
train_accuracy_svm = accuracy_score(y_train, y_pred_train_svm)
print("SVM Accuracy on the train set with top 20 features:", train_accuracy_svm)

# Evaluate the model
print("Scenario: Normalized data with RFE on top 20 features (SVM with linear kernel)"
print("Classification Report:")
print(classification_report(y_test, y_pred_svm))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_svm))
```

```
SVM Accuracy on the train set with top 20 features: 0.8062222222222222
Scenario: Normalized data with RFE on top 20 features (SVM with linear kernel)
Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.93      0.87      1033
           1       0.69      0.42      0.52       374

    accuracy                           0.79      1407
   macro avg       0.75      0.68      0.70      1407
weighted avg       0.78      0.79      0.78      1407

Confusion Matrix:
[[961  72]
 [217 157]]
```

In [97]:

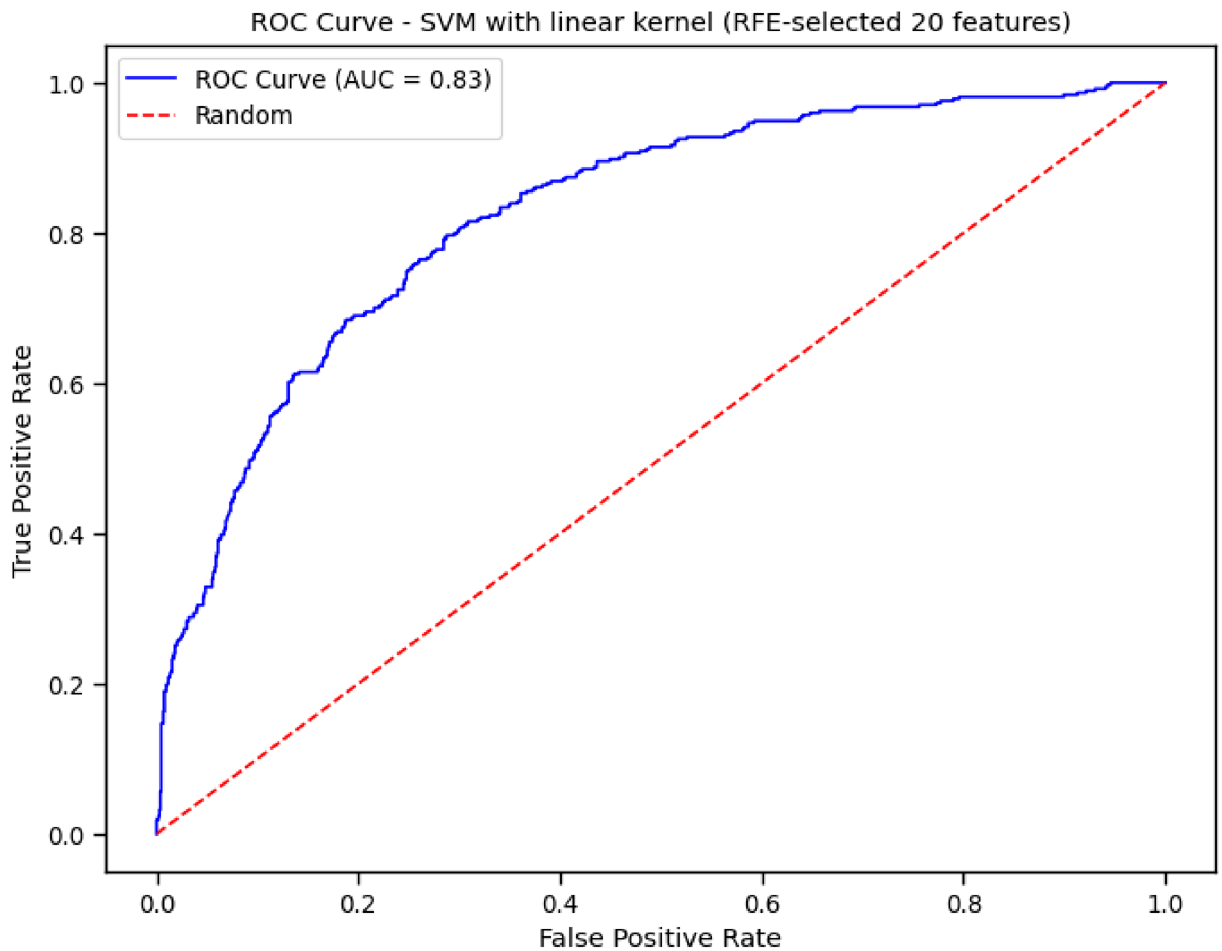
```python
# Plot the Confusion Matrix for SVM Model with Linear Kernel and RFE-selected features
cm_display_svm = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix(y_test, y_pr
cm_display_svm.plot()
plt.title("Confusion Matrix - Normalized data with RFE on top 20 features (SVM with li
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



In [98]:

```
# Compute the probability estimates for positive class
y_prob_svm = svm_model_linear.predict_proba(X_test_top20_svm)[:, 1]

# Compute fpr, tpr, and thresholds
fpr_svm, tpr_svm, thresholds_svm = roc_curve(y_test, y_prob_svm)

# Compute ROC AUC score
roc_auc_svm = roc_auc_score(y_test, y_prob_svm)
print('ROC AUC (SVM with linear kernel):', roc_auc_svm)

# Plot ROC AUC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr_svm, tpr_svm, color='blue', label='ROC Curve (AUC = {:.2f})'.format(roc_a
plt.plot([0, 1], [0, 1], color='red', linestyle='--', label='Random')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - SVM with linear kernel (RFE-selected 20 features)')
plt.legend()
plt.show()
```

```
ROC AUC (SVM with linear kernel): 0.8258175398998815
```



EXPERIMENT 4

Using SMOTE Technique with RFE TOP 10 Features

Earlier we discovered that there is a class imbalance in the target variable we will be using the SMOTHE technique to address this class imabalance and compare results with other models done.

In [99]:
```
# Apply SMOTE to handle class imbalance
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train_normalized, y_train)
```

Logistic Regression Model

In [100…
```
# Get Selected Features for each model using RFE with normalized data
logistic_regression_features = perform_rfe(logistic_regression, X_train_smote, y_trair
```

In [101…
```
# Train and evaluate Logistic Regression model with normalized data
logistic_regression.fit(X_train_smote[:, logistic_regression_features], y_train_smote)
y_pred_lr = logistic_regression.predict(X_test_normalized[:, logistic_regression_featu
```

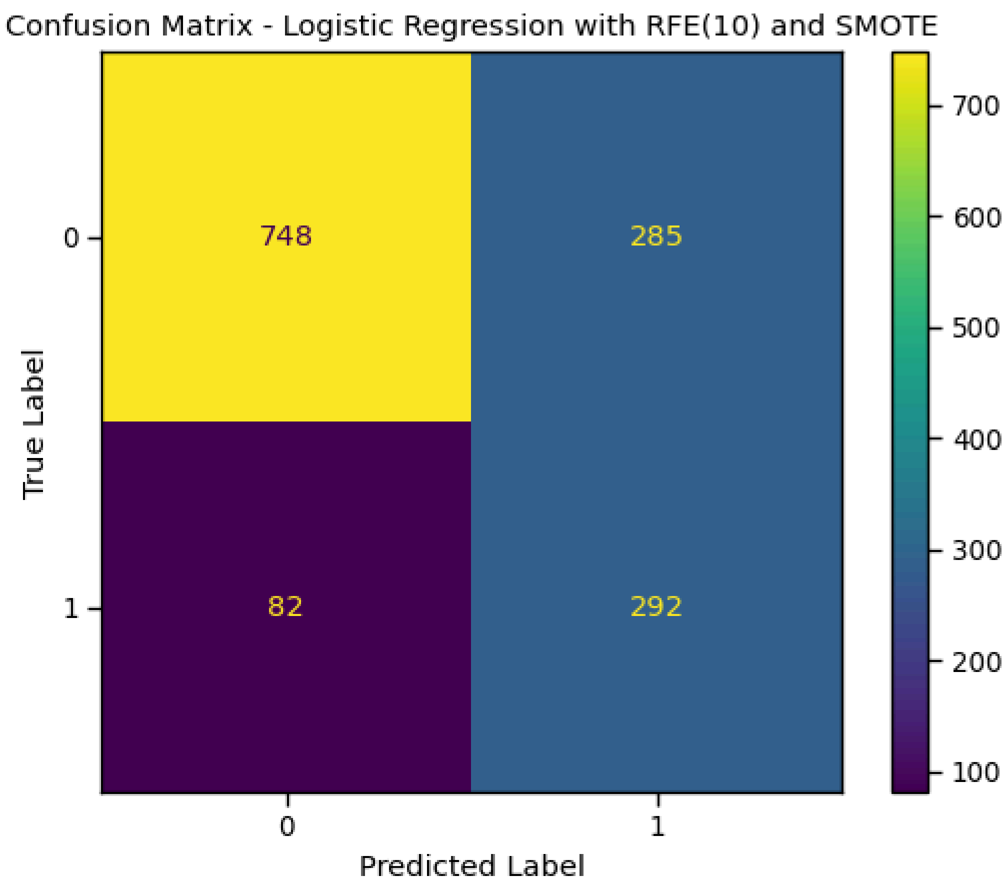
```
accuracy_lr = accuracy_score(y_test, y_pred_lr)
conf_matrix_lr = confusion_matrix(y_test, y_pred_lr)

# Make predictions on the train set
y_pred_train_lr = logistic_regression.predict(X_train_smote[:, logistic_regression_fea

# Compute the accuracy of the train set for Logistic Regression model
train_accuracy_lr = accuracy_score(y_train_smote, y_pred_train_lr)
print("Logistic Regression Accuracy on the train set:", train_accuracy_lr)

# Print accuracy and classification report
print("Logistic Regression Accuracy:", accuracy_lr)
print(classification_report(y_test, y_pred_lr))
```

```
Logistic Regression Accuracy on the train set: 0.765859564164649
Logistic Regression Accuracy: 0.7391613361762616
              precision    recall  f1-score   support

           0       0.90      0.72      0.80      1033
           1       0.51      0.78      0.61       374

    accuracy                           0.74      1407
   macro avg       0.70      0.75      0.71      1407
weighted avg       0.80      0.74      0.75      1407
```

In [102…

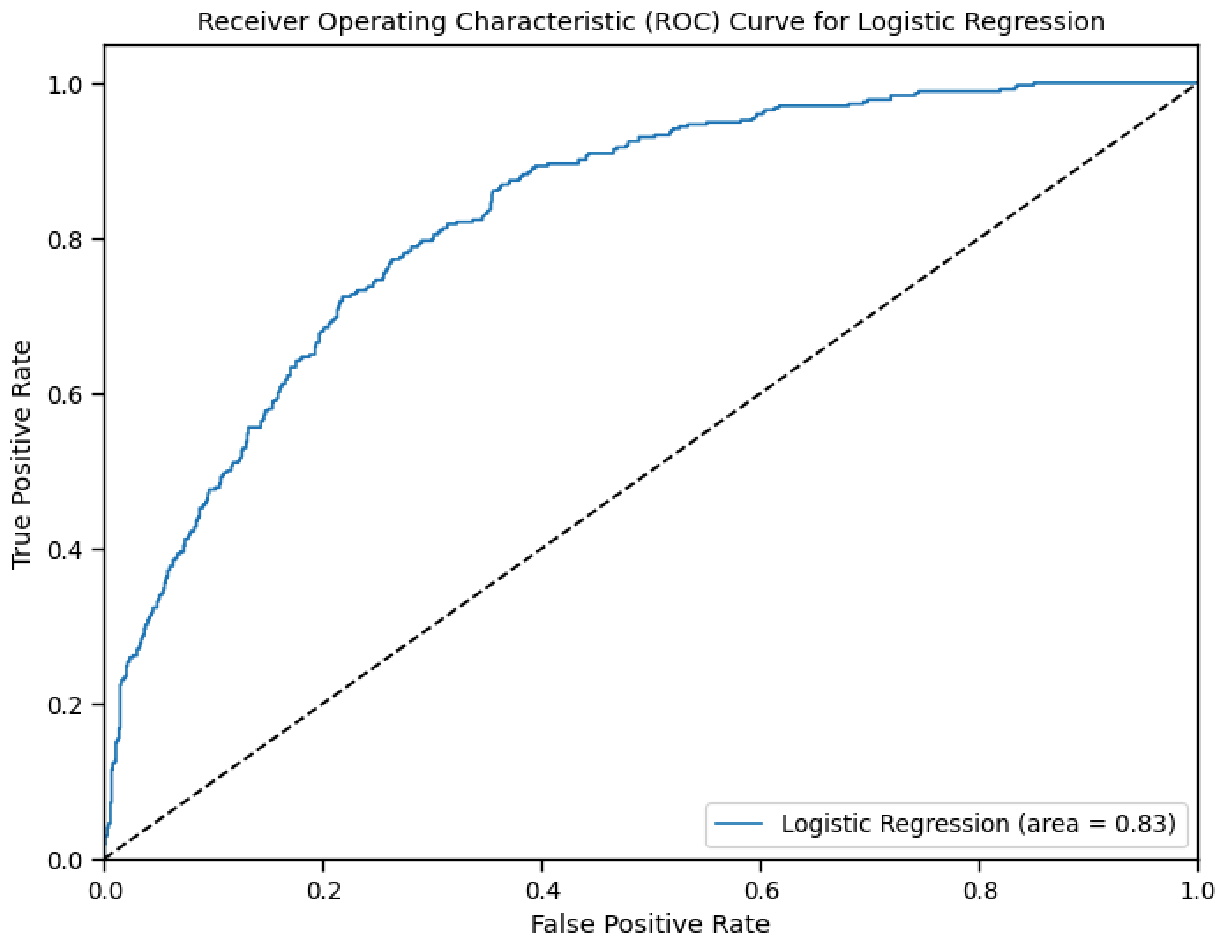
```
# Plot the confusion matrix
plt.figure()
cm_display_lr = ConfusionMatrixDisplay(confusion_matrix=conf_matrix_lr)
cm_display_lr.plot()
plt.title("Confusion Matrix - Logistic Regression with RFE(10) and SMOTE")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

```
<Figure size 640x480 with 0 Axes>
```



In [103…

```
# Get predicted probabilities for positive class
y_prob_lr = logistic_regression.predict_proba(X_test_normalized[:, logistic_regressior

# Compute false positive rate, true positive rate, and thresholds
fpr_lr, tpr_lr, thresholds_lr = roc_curve(y_test, y_prob_lr)

# Compute Area Under the Receiver Operating Characteristic Curve (ROC AUC)
auc_lr = roc_auc_score(y_test, y_prob_lr)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr_lr, tpr_lr, label='Logistic Regression (area = %0.2f)' % auc_lr)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve for Logistic Regression')
plt.legend(loc="lower right")
plt.show()
```



Random Forest Model

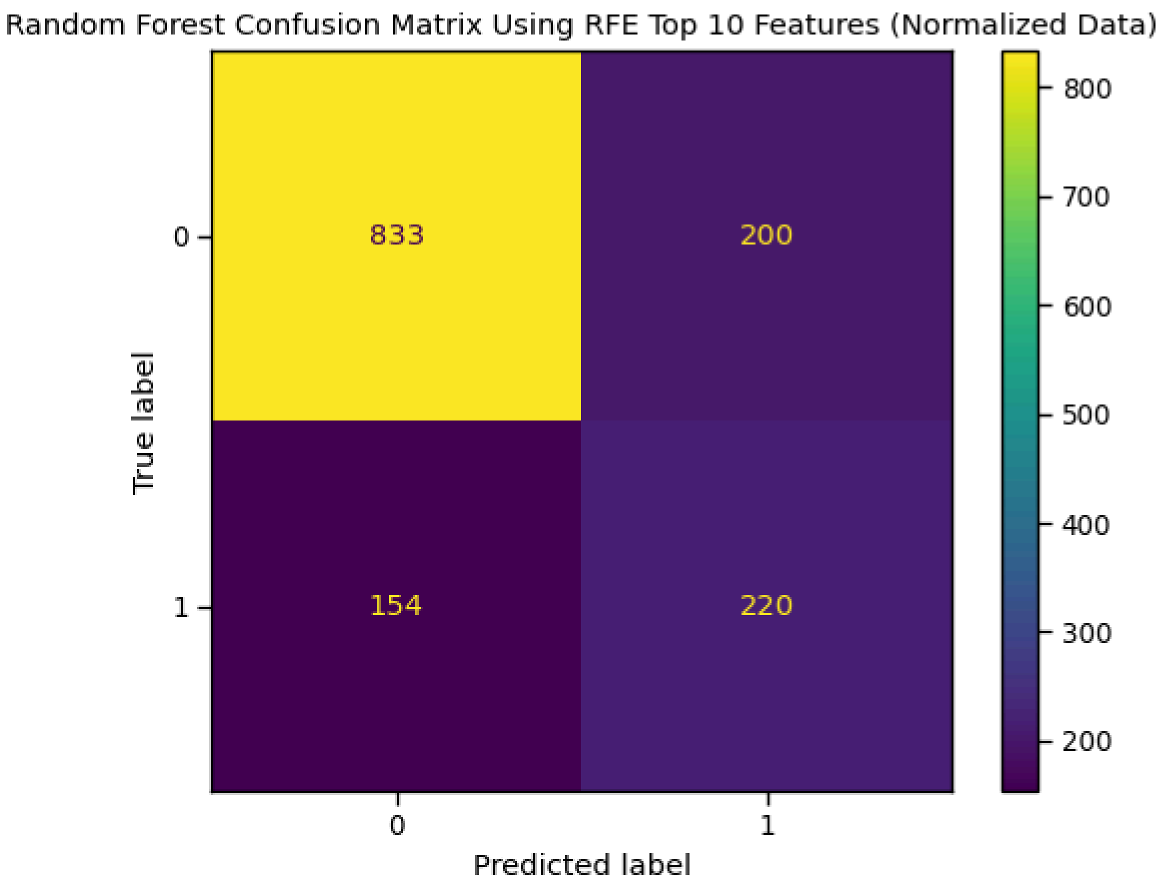
In [104…
```
# Get Selected Features for Random Forest using RFE with normalized data
random_forest_features = perform_rfe(random_forest, X_train_smote, y_train_smote, n_fe
```

In [105…
```
# Train Random Forest model with SMOTE data
random_forest.fit(X_train_smote[:, random_forest_features], y_train_smote)
y_pred_rf = random_forest.predict(X_test_normalized[:, random_forest_features])

# Evaluate Random Forest model
accuracy_rf = accuracy_score(y_test, y_pred_rf)
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)

# Make predictions on the train set
y_pred_train_rf = random_forest.predict(X_train_smote[:, random_forest_features])

# Compute the accuracy of the train set for Random Forest model
train_accuracy_rf = accuracy_score(y_train_smote, y_pred_train_rf)
print("Random Forest Accuracy on the train set with SMOTE data:", train_accuracy_rf)

print("Random Forest Accuracy:", accuracy_rf)
print("Random Forest Classification Report:")
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Accuracy on the train set with SMOTE data: 0.997457627118644
Random Forest Accuracy: 0.7484008528784648
Random Forest Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.81      0.82      1033
           1       0.52      0.59      0.55       374

    accuracy                           0.75      1407
   macro avg       0.68      0.70      0.69      1407
weighted avg       0.76      0.75      0.75      1407
```

In [106…

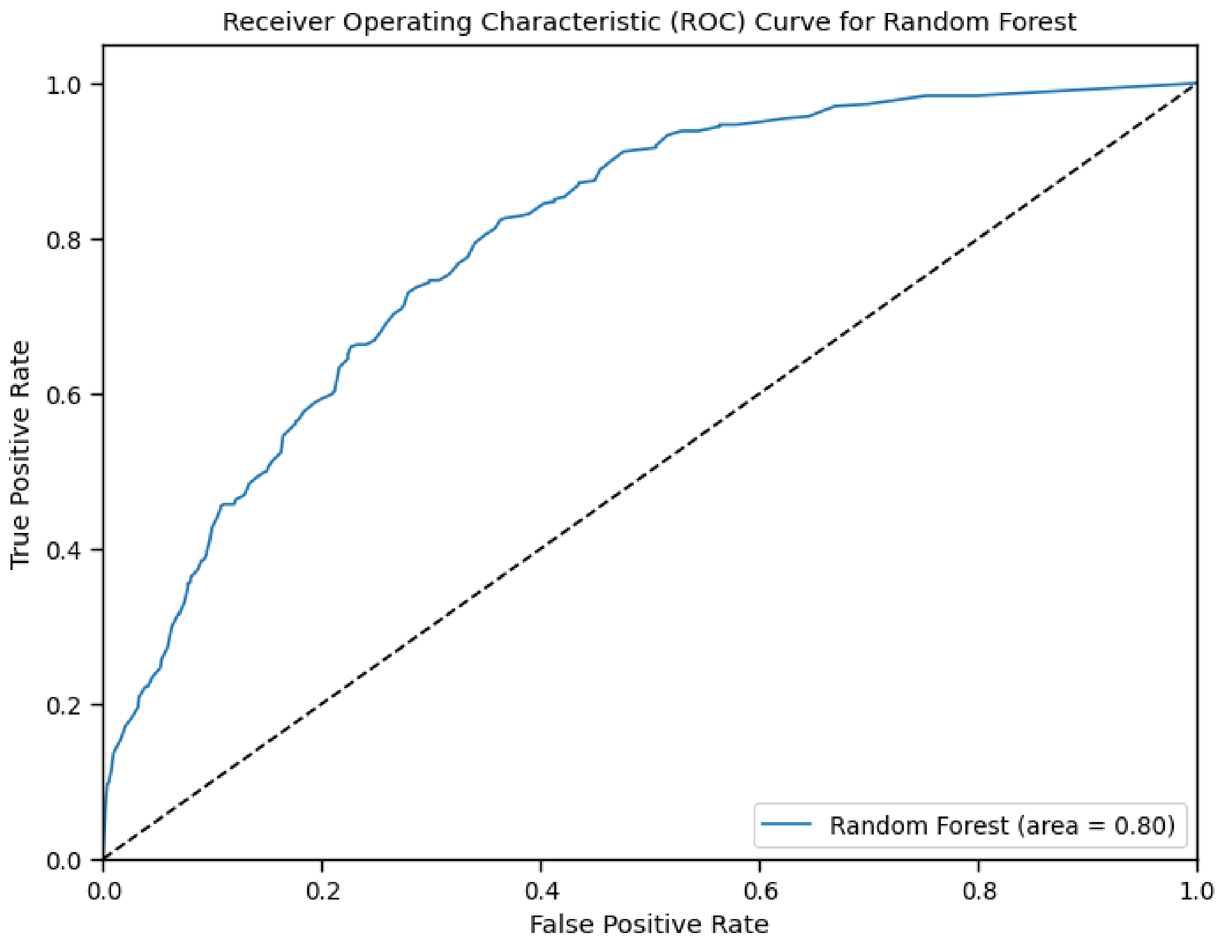
```python
# Plot the Confusion Matrix for Random Forest Model
cm_display_rf = ConfusionMatrixDisplay(confusion_matrix=conf_matrix_rf, display_labels
cm_display_rf.plot()
plt.title("Random Forest Confusion Matrix Using RFE Top 10 Features (Normalized Data)"
plt.show()
```



In [107…

```python
# Plot the ROC curve for Random Forest Model
y_prob_rf = random_forest.predict_proba(X_test_normalized[:, random_forest_features])[
fpr_rf, tpr_rf, thresholds_rf = roc_curve(y_test, y_prob_rf)
auc_rf = roc_auc_score(y_test, y_prob_rf)

plt.figure(figsize=(8, 6))
plt.plot(fpr_rf, tpr_rf, label='Random Forest (area = %0.2f)' % auc_rf)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
```

```python
plt.title('Receiver Operating Characteristic (ROC) Curve for Random Forest')
plt.legend(loc="lower right")
plt.show()
```



SVM Model

In [108…

```python
# Initialize RFE for feature selection with SVM model
rfe = RFE(estimator=svm_model_linear, n_features_to_select=10)

# Fit RFE on balanced data
rfe.fit(X_train_smote, y_train_smote)

# Get the selected features
selected_features_svm = rfe.support_
```

In [109…

```python
# Select top 10 features from training and test data
X_train_top10_svm = X_train_smote[:, selected_features_svm]
X_test_top10_svm = X_test_normalized[:, selected_features_svm]
```

In [110…

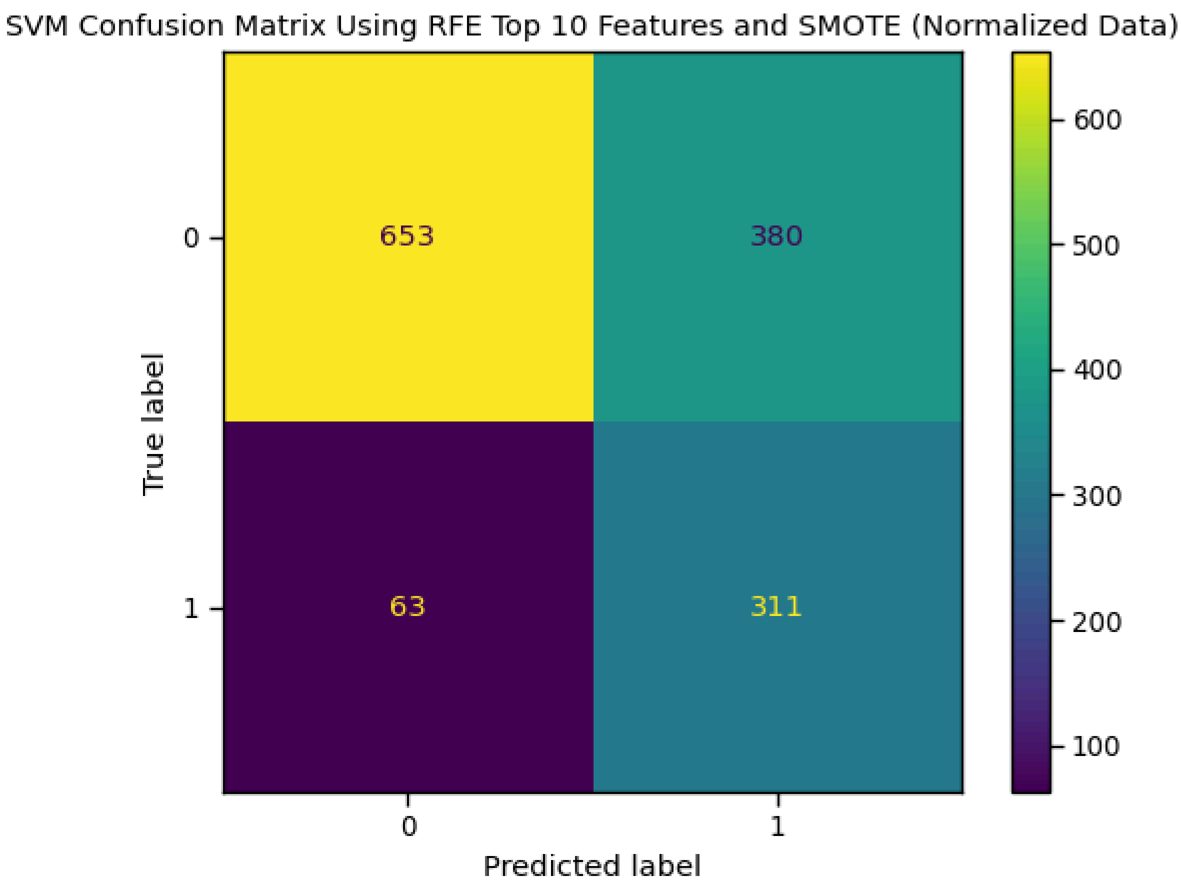
```python
# Train the SVM model on top 10 features
svm_model_linear.fit(X_train_top10_svm, y_train_smote)

# Make predictions
y_pred_svm = svm_model_linear.predict(X_test_top10_svm)
```

```python
# Make predictions on the train set
y_pred_train_svm = svm_model_linear.predict(X_train_top10_svm)

# Compute the accuracy of the train set for SVM model
train_accuracy_svm = accuracy_score(y_train_smote, y_pred_train_svm)
print("SVM Accuracy on the train set with top 10 features and SMOTE data:", train_accu


# Evaluate the model
print("Scenario: SVM with RFE and SMOTE for dealing with class imbalance")
print("Classification Report:")
print(classification_report(y_test, y_pred_svm))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_svm))
```

```
SVM Accuracy on the train set with top 10 features and SMOTE data: 0.7456416464891041
Scenario: SVM with RFE and SMOTE for dealing with class imbalance
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.63      0.75      1033
           1       0.45      0.83      0.58       374

    accuracy                           0.69      1407
   macro avg       0.68      0.73      0.67      1407
weighted avg       0.79      0.69      0.70      1407

Confusion Matrix:
[[653 380]
 [ 63 311]]
```

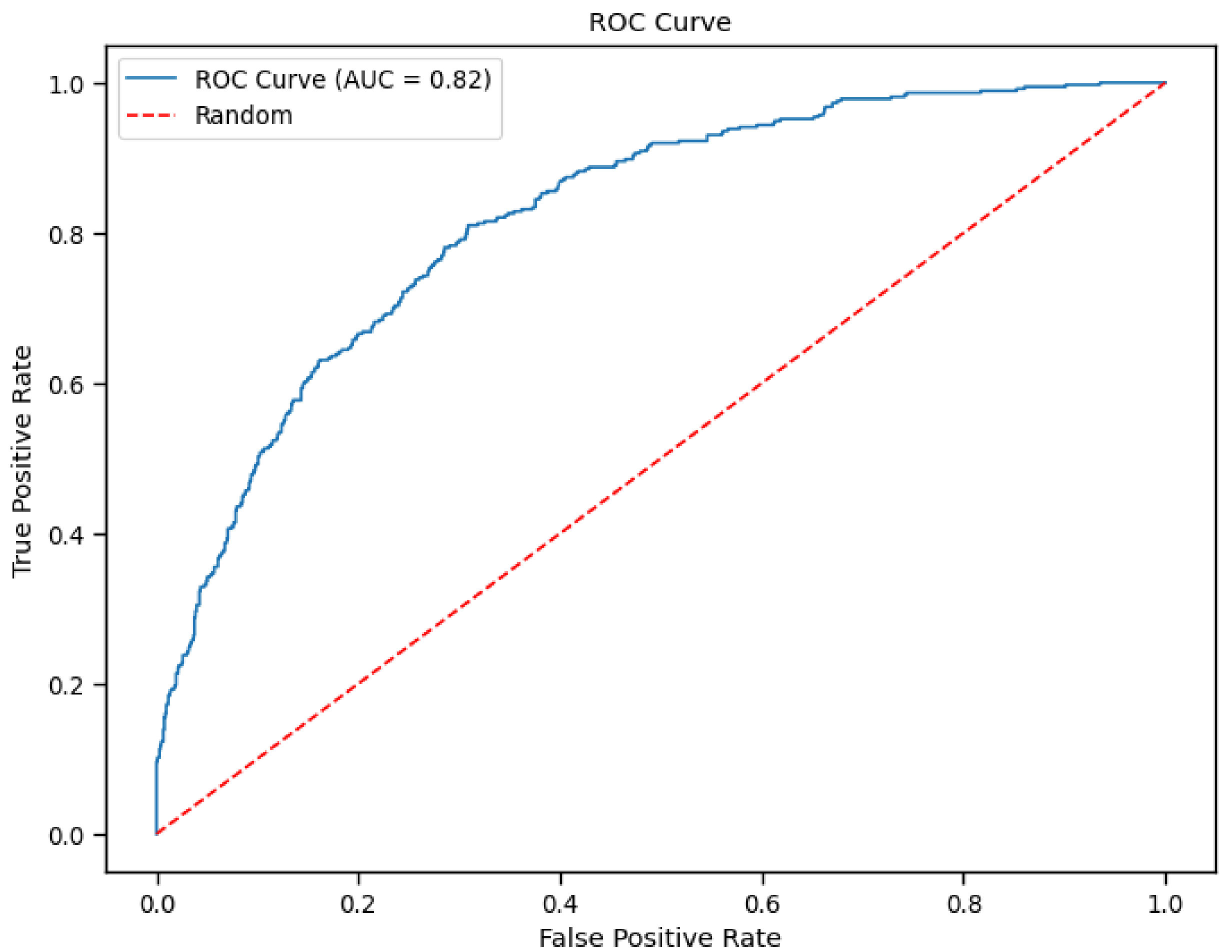
In [111…

```python
# Plot the confusion matrix for SVM
cm_display_svm = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix(y_test, y_pr
cm_display_svm.plot()
plt.title("SVM Confusion Matrix Using RFE Top 10 Features and SMOTE (Normalized Data)"
plt.show()
```



In [112…

```
# Get the predicted probabilities for the positive class
y_prob_svm = svm_model_linear.predict_proba(X_test_top10_svm)[:, 1]

# Compute fpr, tpr, and thresholds
fpr, tpr, thresholds = roc_curve(y_test, y_prob_svm)

# Compute AUC score
auc = roc_auc_score(y_test, y_prob_svm)

# Plot ROC AUC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label="ROC Curve (AUC = {:.2f})".format(auc))
plt.plot([0, 1], [0, 1], linestyle="--", color="r", label="Random")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.grid(False)  # Remove gridlines
plt.show()
```



EXPERIMENT 5

Using SMOTE Technique with RFE TOP 20 Features

In [113...

```
# Apply SMOTE to handle class imbalance
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train_normalized, y_train)
```

Logistic Regression Model

In [114...

```
# Get Selected Features for each model using RFE with normalized data
logistic_regression_features = perform_rfe(logistic_regression, X_train_smote, y_trair
```

In [115...

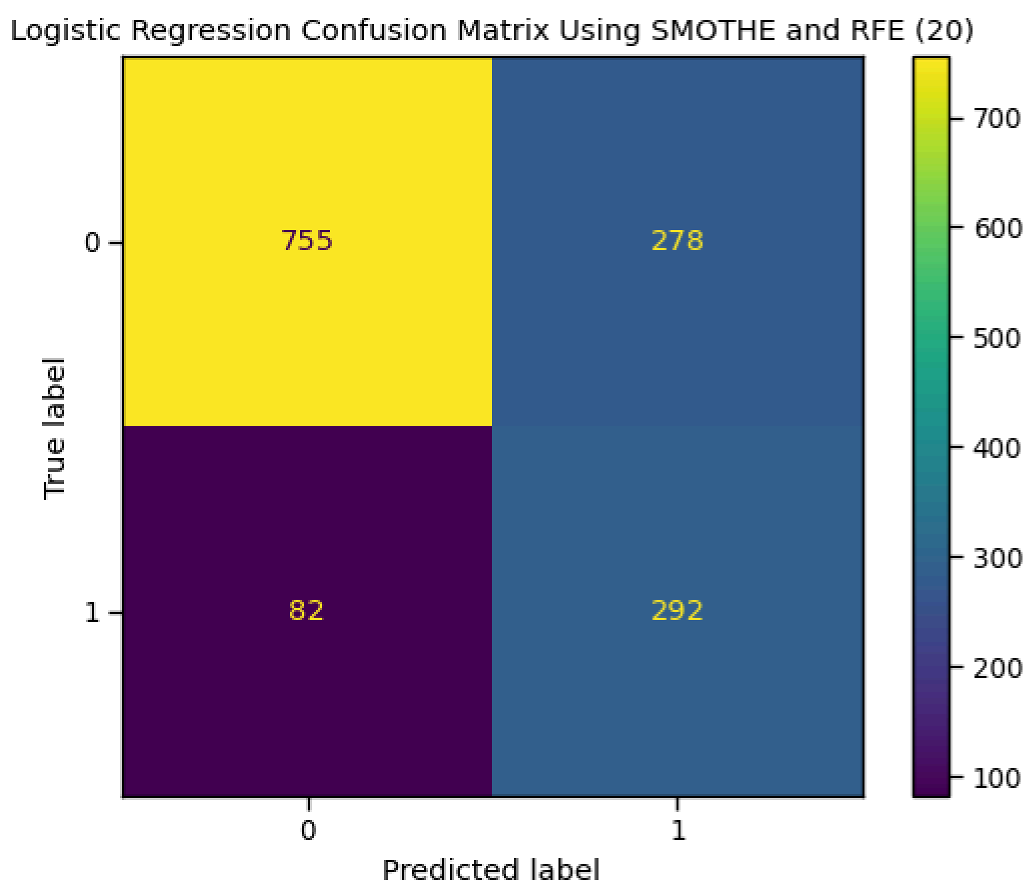
```
# Train and evaluate Logistic Regression model with normalized data
logistic_regression.fit(X_train_smote[:, logistic_regression_features], y_train_smote)
y_pred_lr = logistic_regression.predict(X_test_normalized[:, logistic_regression_featu
accuracy_lr = accuracy_score(y_test, y_pred_lr)
conf_matrix_lr = confusion_matrix(y_test, y_pred_lr)

# Make predictions on the train set
```

```
y_pred_train_lr = logistic_regression.predict(X_train_smote[:, logistic_regression_fea

# Compute the accuracy of the train set for Logistic Regression model
train_accuracy_lr = accuracy_score(y_train_smote, y_pred_train_lr)
print("Logistic Regression Accuracy on the train set with SMOTE data:", train_accuracy

# Print accuracy and classification report
print("Logistic Regression Accuracy:", accuracy_lr)
print(classification_report(y_test, y_pred_lr))
```

```
Logistic Regression Accuracy on the train set with SMOTE data: 0.7723970944309927
Logistic Regression Accuracy: 0.744136460554371
              precision    recall  f1-score   support

           0       0.90      0.73      0.81      1033
           1       0.51      0.78      0.62       374

    accuracy                           0.74      1407
   macro avg       0.71      0.76      0.71      1407
weighted avg       0.80      0.74      0.76      1407
```

In [116…

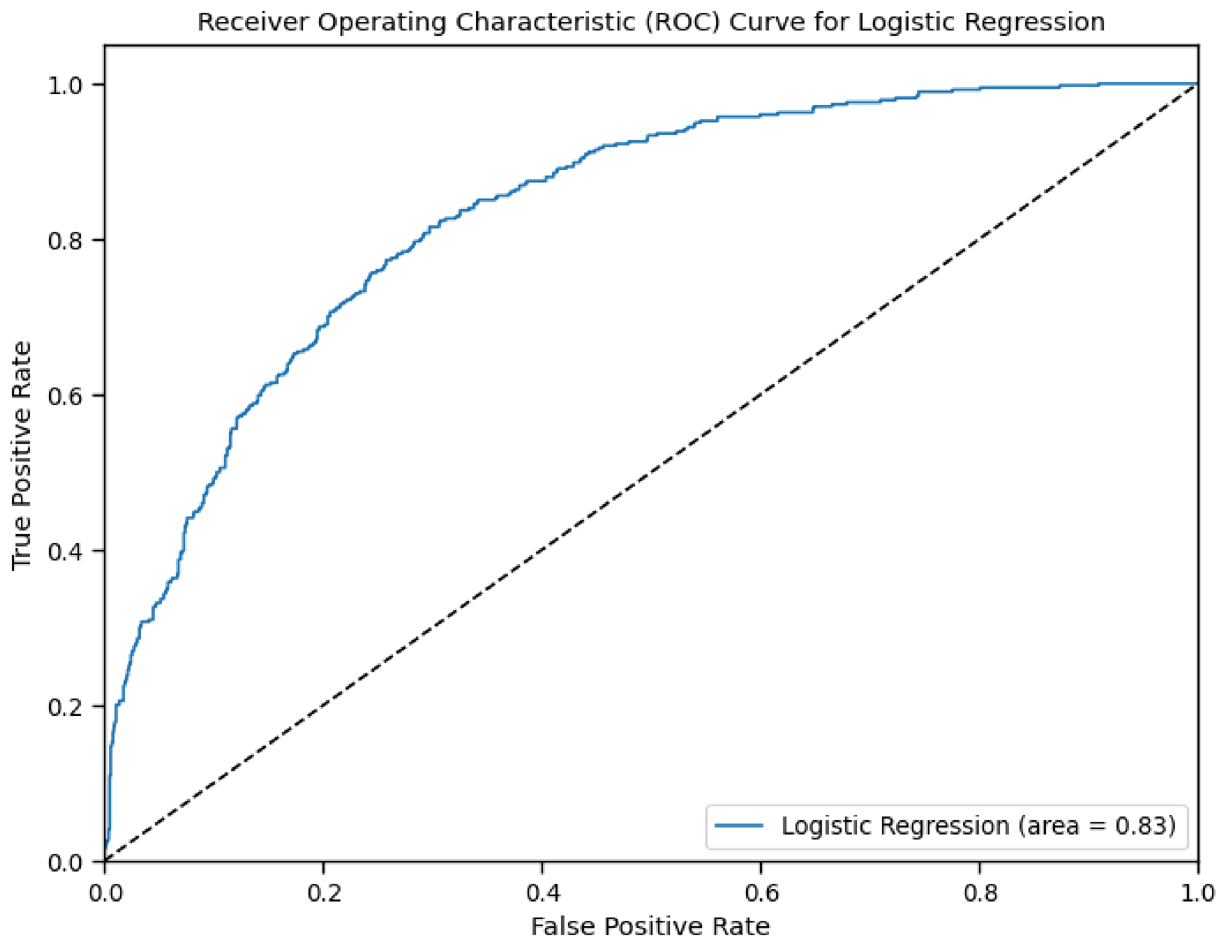
```
# Plotting the Confusion Matrix for Logistic Regression with RFE and Smothe
cm_display_lr = ConfusionMatrixDisplay(conf_matrix_lr).plot()
plt.title("Logistic Regression Confusion Matrix Using SMOTHE and RFE (20)")
plt.show()
```



In [117…

```
# Get predicted probabilities for positive class
y_prob_lr = logistic_regression.predict_proba(X_test_normalized[:, logistic_regressior

# Compute false positive rate, true positive rate, and thresholds
```

```python
fpr_lr, tpr_lr, thresholds_lr = roc_curve(y_test, y_prob_lr)

# Compute Area Under the Receiver Operating Characteristic Curve (ROC AUC)
auc_lr = roc_auc_score(y_test, y_prob_lr)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr_lr, tpr_lr, label='Logistic Regression (area = %0.2f)' % auc_lr)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve for Logistic Regression')
plt.legend(loc="lower right")
plt.show()
```



Random Forest Model

In [118…

```python
# Get Selected Features for Random Forest using RFE with normalized data
random_forest_features = perform_rfe(random_forest, X_train_smote, y_train_smote, n_fe
```

In [119…

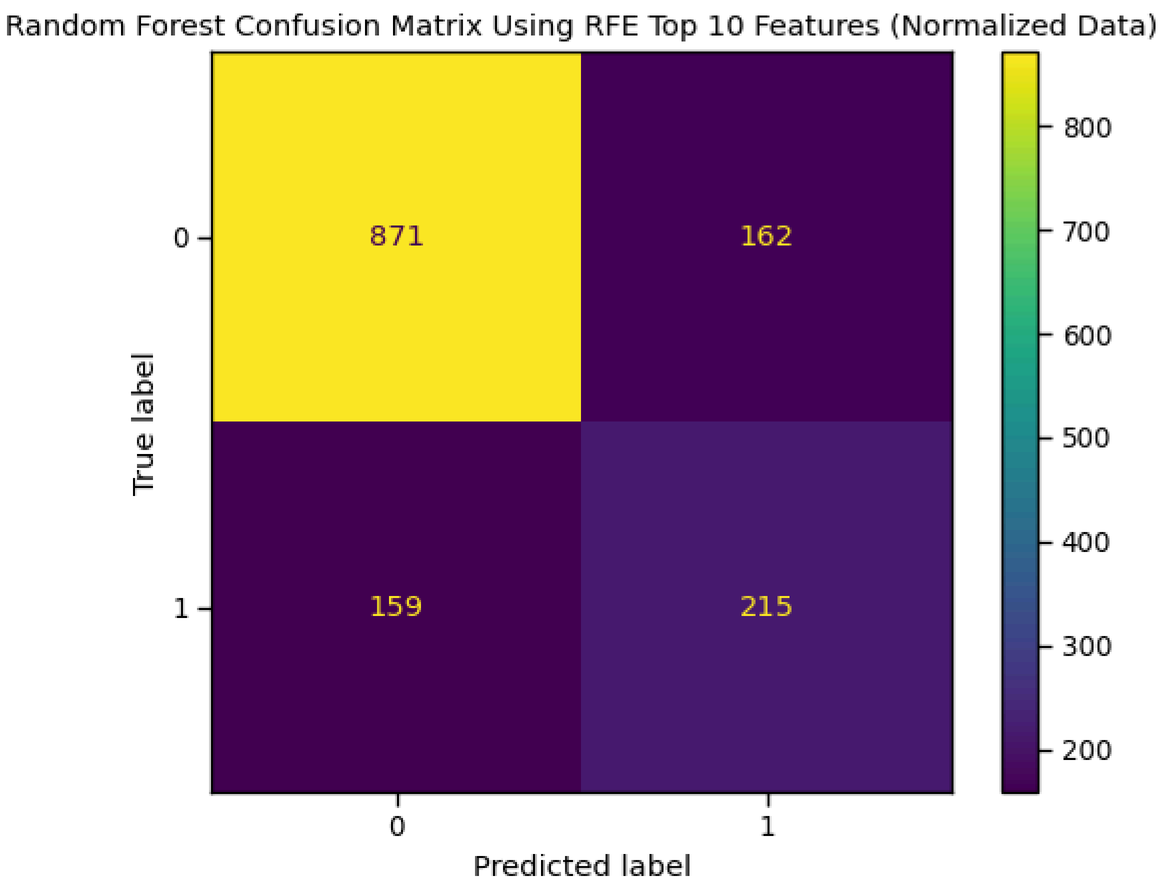
```python
# Train Random Forest model with SMOTE data
random_forest.fit(X_train_smote[:, random_forest_features], y_train_smote)
y_pred_rf = random_forest.predict(X_test_normalized[:, random_forest_features])
```

```
# Make predictions on the train set
y_pred_train_rf = random_forest.predict(X_train_smote[:, random_forest_features])

# Compute the accuracy of the train set for Random Forest model
train_accuracy_rf = accuracy_score(y_train_smote, y_pred_train_rf)
print("Random Forest Accuracy on the train set with SMOTE data:", train_accuracy_rf)

# Evaluate Random Forest model
accuracy_rf = accuracy_score(y_test, y_pred_rf)
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)

print("Random Forest Accuracy:", accuracy_rf)
print("Random Forest Classification Report:")
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Accuracy on the train set with SMOTE data: 0.9984261501210654
Random Forest Accuracy: 0.7718550106609808
Random Forest Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.84      0.84      1033
           1       0.57      0.57      0.57       374

    accuracy                           0.77      1407
   macro avg       0.71      0.71      0.71      1407
weighted avg       0.77      0.77      0.77      1407
```

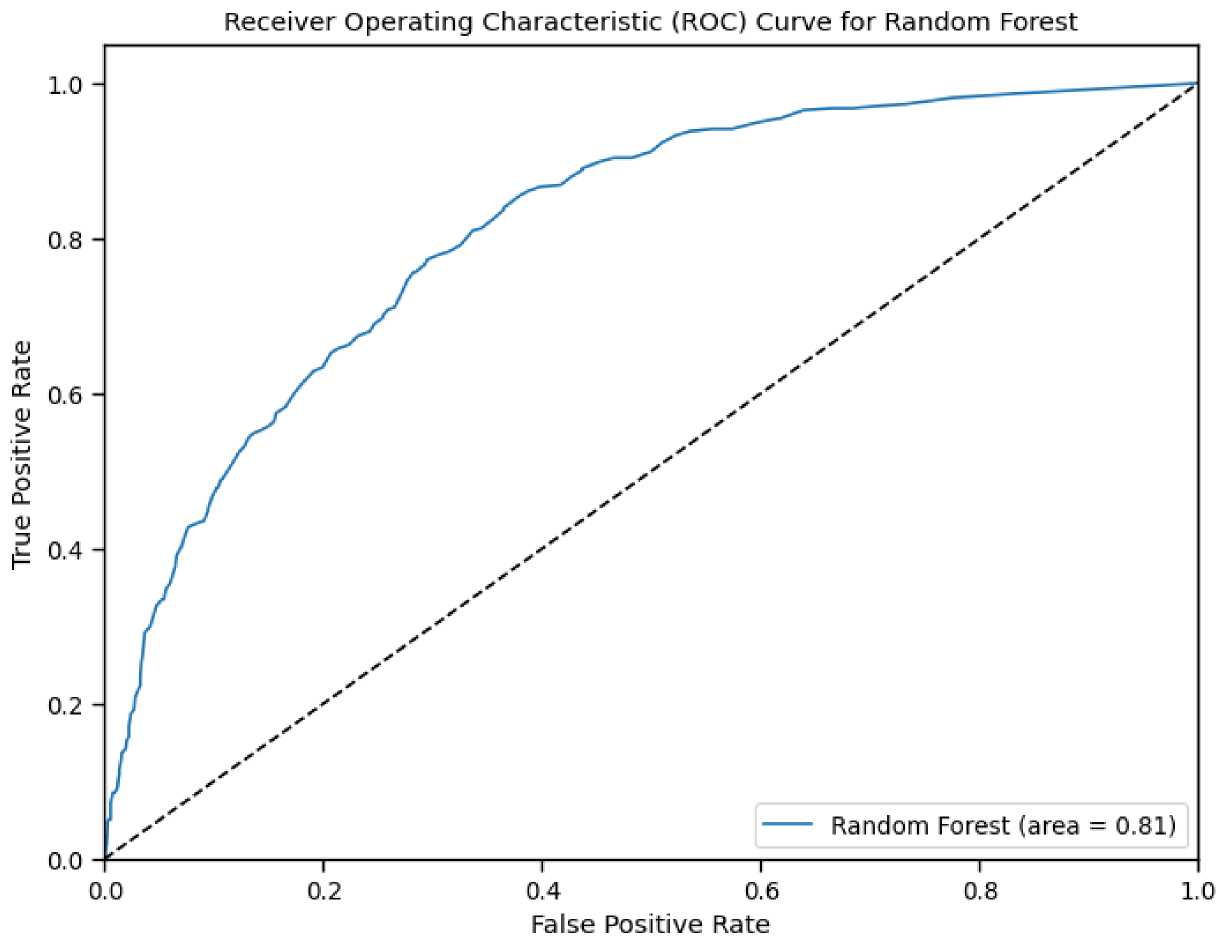
In [120…

```
# Plot the Confusion Matrix for Random Forest Model
cm_display_rf = ConfusionMatrixDisplay(confusion_matrix=conf_matrix_rf, display_labels
cm_display_rf.plot()
plt.title("Random Forest Confusion Matrix Using RFE Top 10 Features (Normalized Data)"
plt.show()
```



In [121…

```
# Plot the ROC curve for Random Forest Model
y_prob_rf = random_forest.predict_proba(X_test_normalized[:, random_forest_features])[
fpr_rf, tpr_rf, thresholds_rf = roc_curve(y_test, y_prob_rf)
auc_rf = roc_auc_score(y_test, y_prob_rf)

plt.figure(figsize=(8, 6))
plt.plot(fpr_rf, tpr_rf, label='Random Forest (area = %0.2f)' % auc_rf)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve for Random Forest')
plt.legend(loc="lower right")
plt.show()
```



SVM Model

In [122…

```
# Initialize RFE for feature selection with SVM model
rfe = RFE(estimator=svm_model_linear, n_features_to_select=20)

# Fit RFE on normalized data
rfe.fit(X_train_smote, y_train_smote)

# Get the selected features
selected_features_svm = rfe.support_
```

In [123…

```
# Select top 20 features from training and test data
X_train_top20_svm = X_train_smote[:, selected_features_svm]
X_test_top20_svm = X_test_normalized[:, selected_features_svm]
```

In [124…

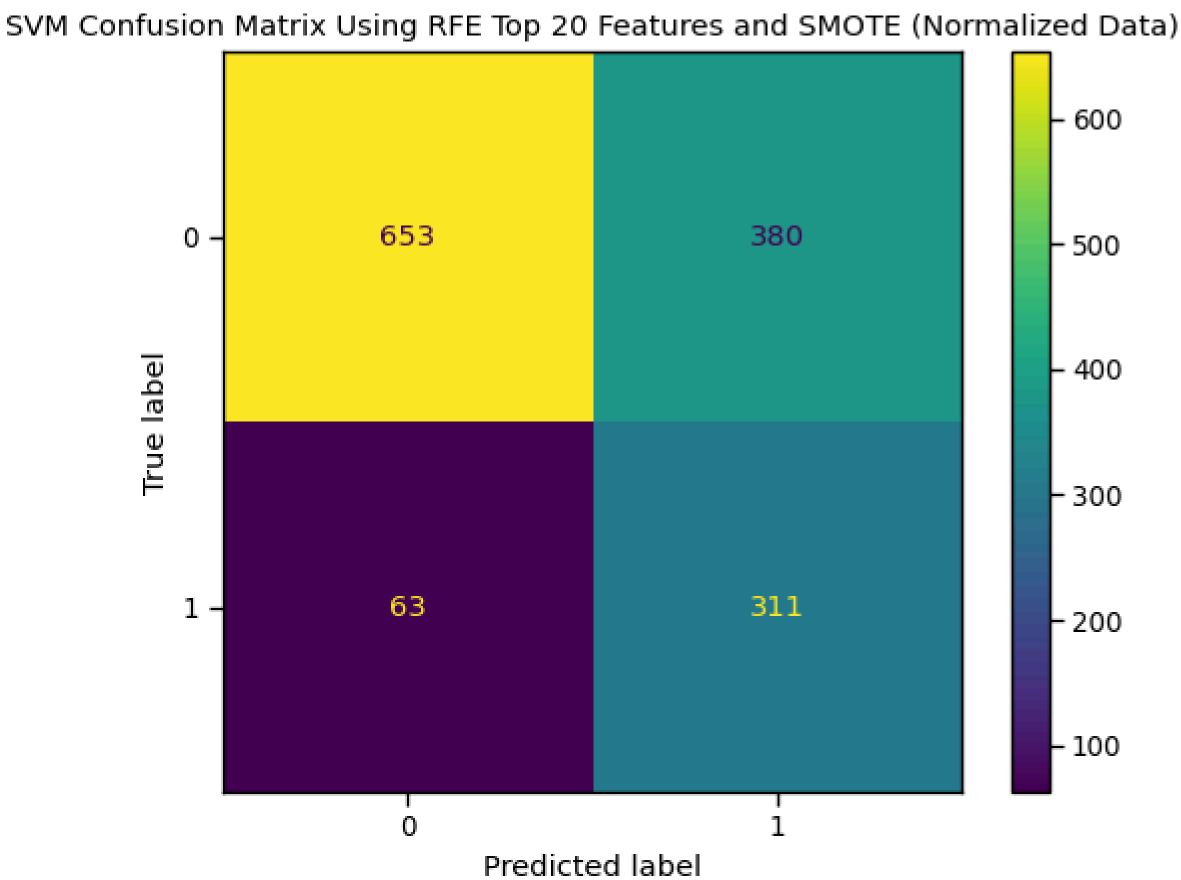
```
# Train the SVM model on top 20 features
svm_model_linear.fit(X_train_top20_svm, y_train_smote)

# Make predictions
y_pred_svm = svm_model_linear.predict(X_test_top20_svm)

# Make predictions on the train set
y_pred_train_svm = svm_model_linear.predict(X_train_top20_svm)
```

```
# Compute the accuracy of the train set for SVM model
train_accuracy_svm = accuracy_score(y_train_smote, y_pred_train_svm)
print("SVM Accuracy on the train set with top 20 features and SMOTE data:", train_accu

# Evaluate the model
print("SVM with RFE and SMOTE")
print("Classification Report:")
print(classification_report(y_test, y_pred_svm))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_svm))
```

```
SVM Accuracy on the train set with top 20 features and SMOTE data: 0.7452784503631962
SVM with RFE and SMOTE
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.63      0.75      1033
           1       0.45      0.83      0.58       374

    accuracy                           0.69      1407
   macro avg       0.68      0.73      0.67      1407
weighted avg       0.79      0.69      0.70      1407

Confusion Matrix:
[[653 380]
 [ 63 311]]
```

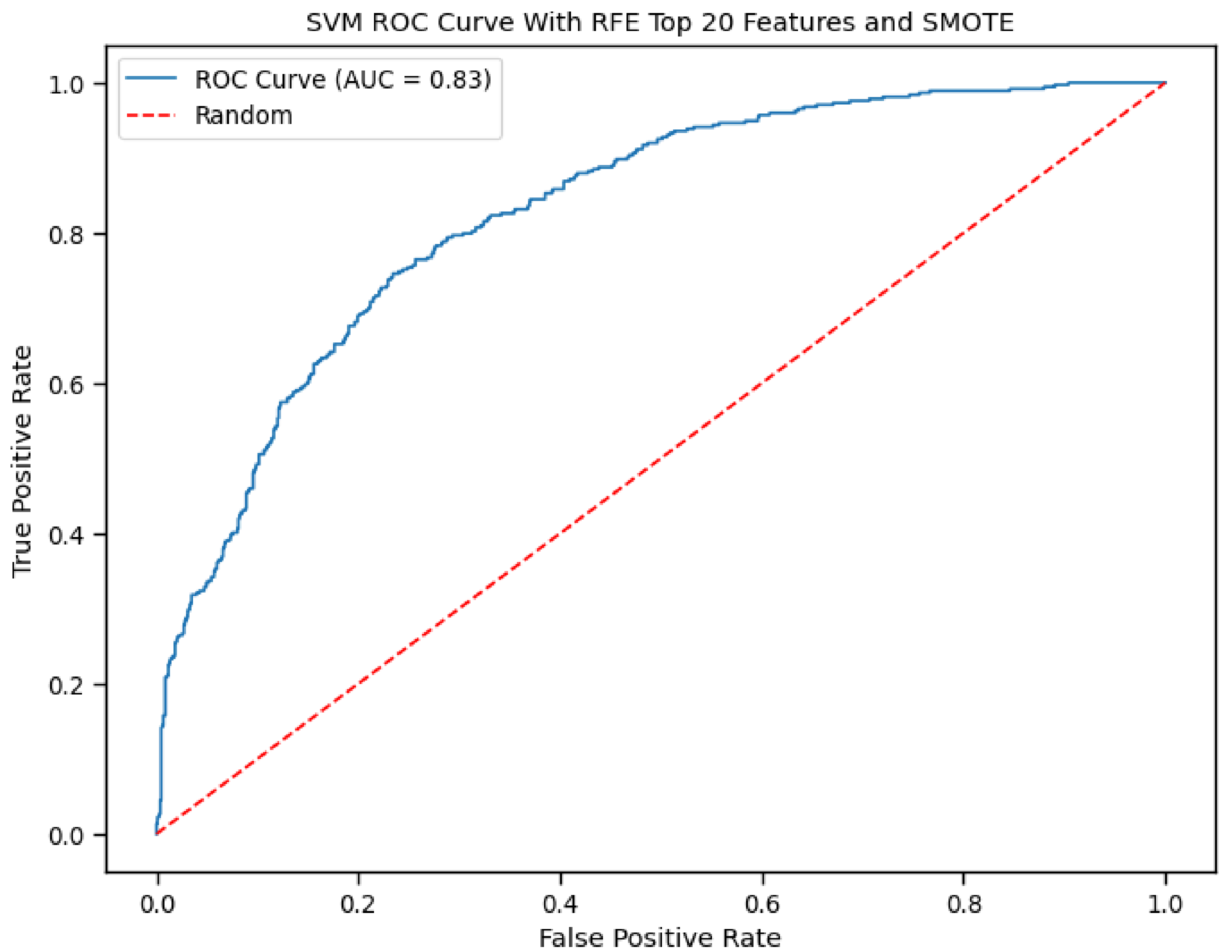
In [125…

```
# Plot the confusion matrix for SVM
cm_display_svm = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix(y_test, y_pr
cm_display_svm.plot()
plt.title("SVM Confusion Matrix Using RFE Top 20 Features and SMOTE (Normalized Data)"
plt.show()
```



In [126…

```
# Get the predicted probabilities for the positive class
y_prob_svm = svm_model_linear.predict_proba(X_test_top20_svm)[:, 1]

# Compute fpr, tpr, and thresholds
fpr, tpr, thresholds = roc_curve(y_test, y_prob_svm)

# Compute AUC score
auc = roc_auc_score(y_test, y_prob_svm)

# Plot ROC AUC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label="ROC Curve (AUC = {:.2f})".format(auc))
plt.plot([0, 1], [0, 1], linestyle="--", color="r", label="Random")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("SVM ROC Curve With RFE Top 20 Features and SMOTE")
plt.legend()
plt.grid(False)  # Remove gridlines
plt.show()
```



EXPERIMENT 6

Using SMOTE Technique On All Features

In [127…

```
# Apply SMOTE to handle class imbalance
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train_normalized, y_train)
```

Logistic Regression Model

In [128…

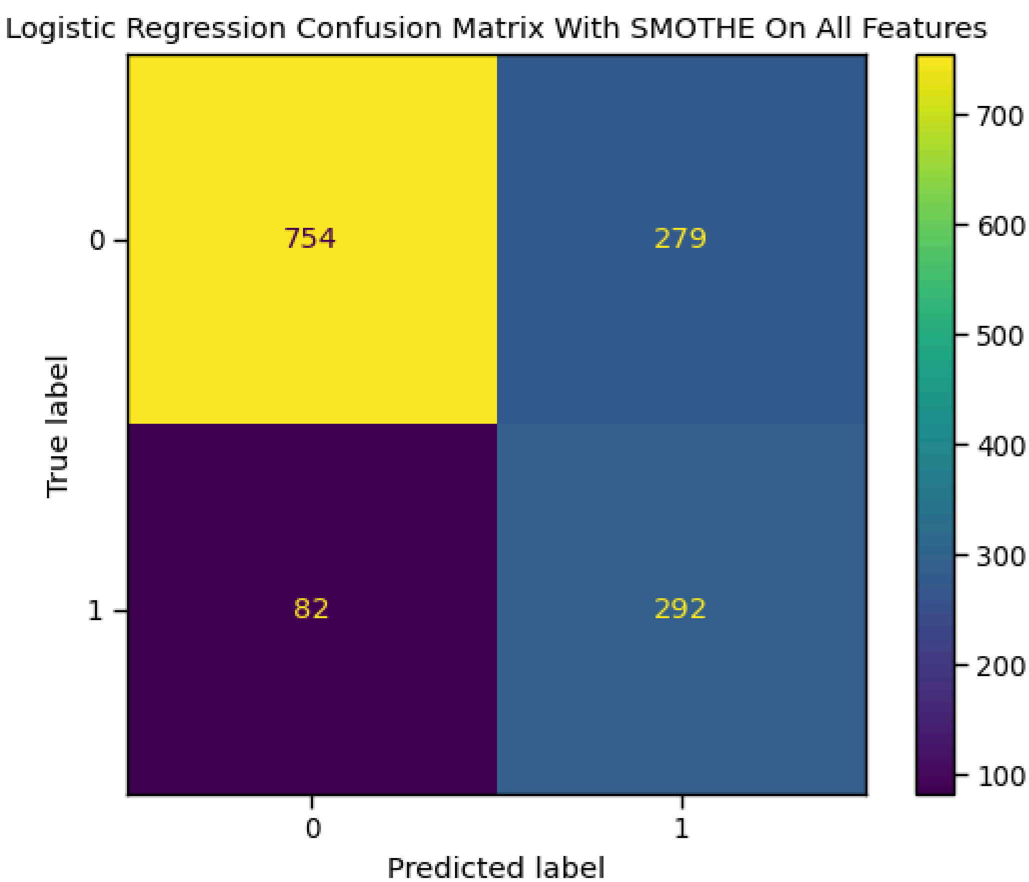
```
# Train and evaluate Logistic Regression model with SMOTE data
logistic_regression.fit(X_train_smote, y_train_smote)
y_pred_lr = logistic_regression.predict(X_test_normalized)
accuracy_lr = accuracy_score(y_test, y_pred_lr)
conf_matrix_lr = confusion_matrix(y_test, y_pred_lr)

# Make predictions on the train set
y_pred_train_lr = logistic_regression.predict(X_train_smote)

# Compute the accuracy of the train set for Logistic Regression model
train_accuracy_lr = accuracy_score(y_train_smote, y_pred_train_lr)
print("Logistic Regression Accuracy on the train set with SMOTE data:", train_accuracy
```

```
# Print accuracy and classification report
print("Logistic Regression Accuracy:", accuracy_lr)
print("Logistic Regression Classification Report:")
print(classification_report(y_test, y_pred_lr))
```

```
Logistic Regression Accuracy on the train set with SMOTE data: 0.7730024213075061
Logistic Regression Accuracy: 0.7434257285003554
Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.73      0.81      1033
           1       0.51      0.78      0.62       374

    accuracy                           0.74      1407
   macro avg       0.71      0.76      0.71      1407
weighted avg       0.80      0.74      0.76      1407
```

In [129…

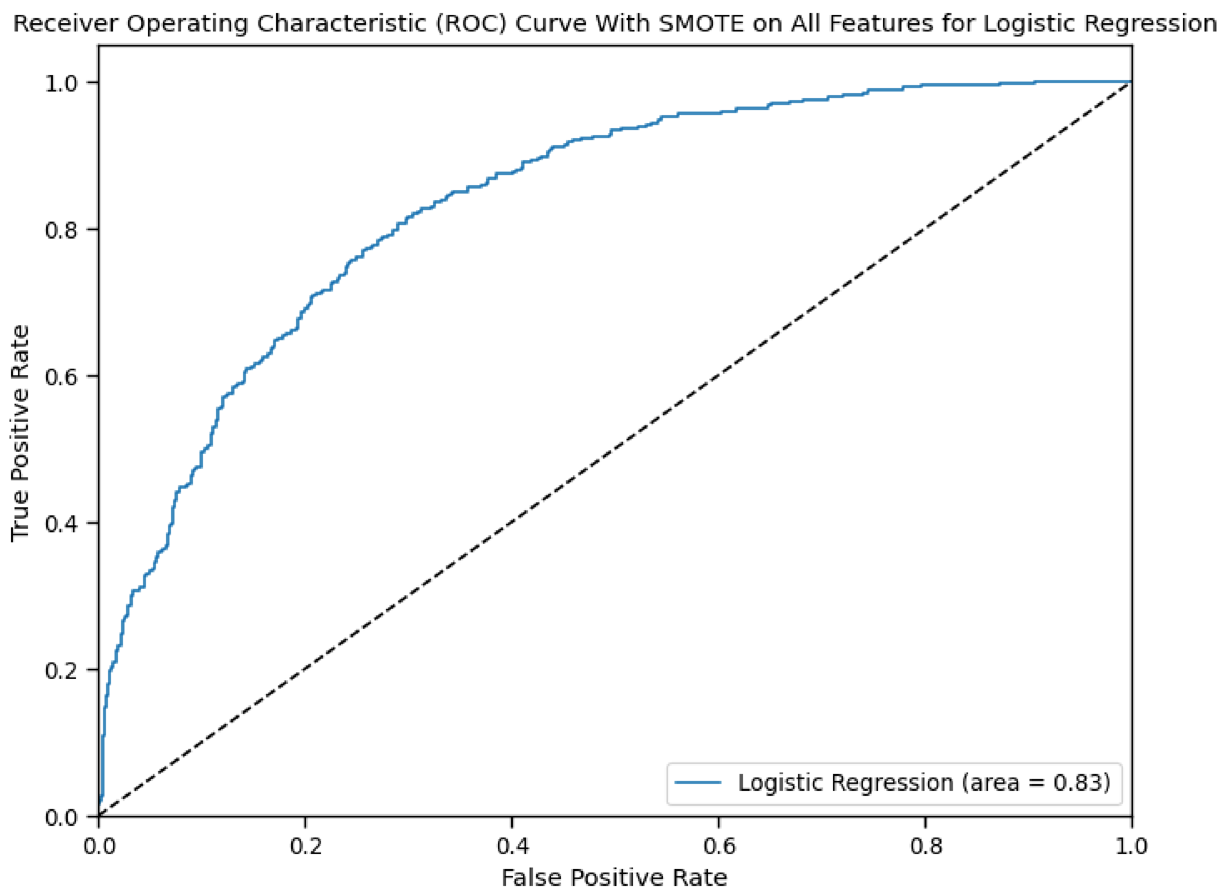
```
# Plot Confusion Matrix
cm_display_lr = ConfusionMatrixDisplay(conf_matrix_lr).plot()
plt.title("Logistic Regression Confusion Matrix With SMOTHE On All Features")
plt.show()
```



In [130…

```
# Calculate predicted probabilities
y_prob_lr = logistic_regression.predict_proba(X_test_normalized)[:, 1]

# Calculate ROC curve
fpr_lr, tpr_lr, thresholds_lr = roc_curve(y_test, y_prob_lr)

# Calculate AUC score
```

```
auc_lr = roc_auc_score(y_test, y_prob_lr)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr_lr, tpr_lr, label='Logistic Regression (area = %0.2f)' % auc_lr)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve With SMOTE on All Features fo
plt.legend(loc="lower right")
plt.show()
```



Random Forest Model

In [131...
```
# Apply SMOTE to handle class imbalance
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train_normalized, y_train)
```

In [132...
```
# Build and train Random Forest model
random_forest = RandomForestClassifier(random_state=42)
random_forest.fit(X_train_smote, y_train_smote)
# Predict on test set
y_pred_rf = random_forest.predict(X_test_normalized)

# Make predictions on the train set
```

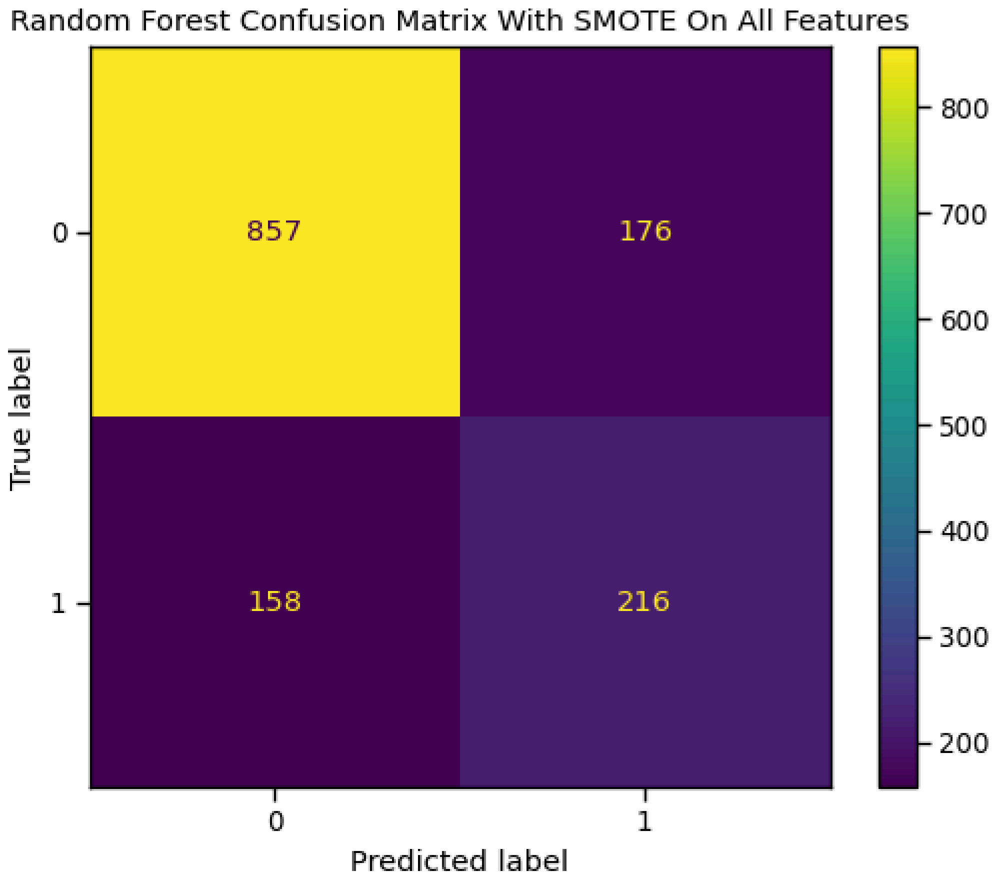
```python
y_pred_train_rf = random_forest.predict(X_train_smote)

# Compute the accuracy of the train set for Random Forest model
train_accuracy_rf = accuracy_score(y_train_smote, y_pred_train_rf)
print("Random Forest Accuracy on the train set with SMOTE data:", train_accuracy_rf)

# Evaluate the model
accuracy_rf = accuracy_score(y_test, y_pred_rf)
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)
print("Random Forest Accuracy:", accuracy_rf)
print("Random Forest Confusion Matrix:")
print(conf_matrix_rf)
print("Random Forest Classification Report:")
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Accuracy on the train set with SMOTE data: 0.9984261501210654
Random Forest Accuracy: 0.7626154939587776
Random Forest Confusion Matrix:
[[857 176]
 [158 216]]
Random Forest Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.83      0.84      1033
           1       0.55      0.58      0.56       374

    accuracy                           0.76      1407
   macro avg       0.70      0.70      0.70      1407
weighted avg       0.77      0.76      0.76      1407
```

In [133…

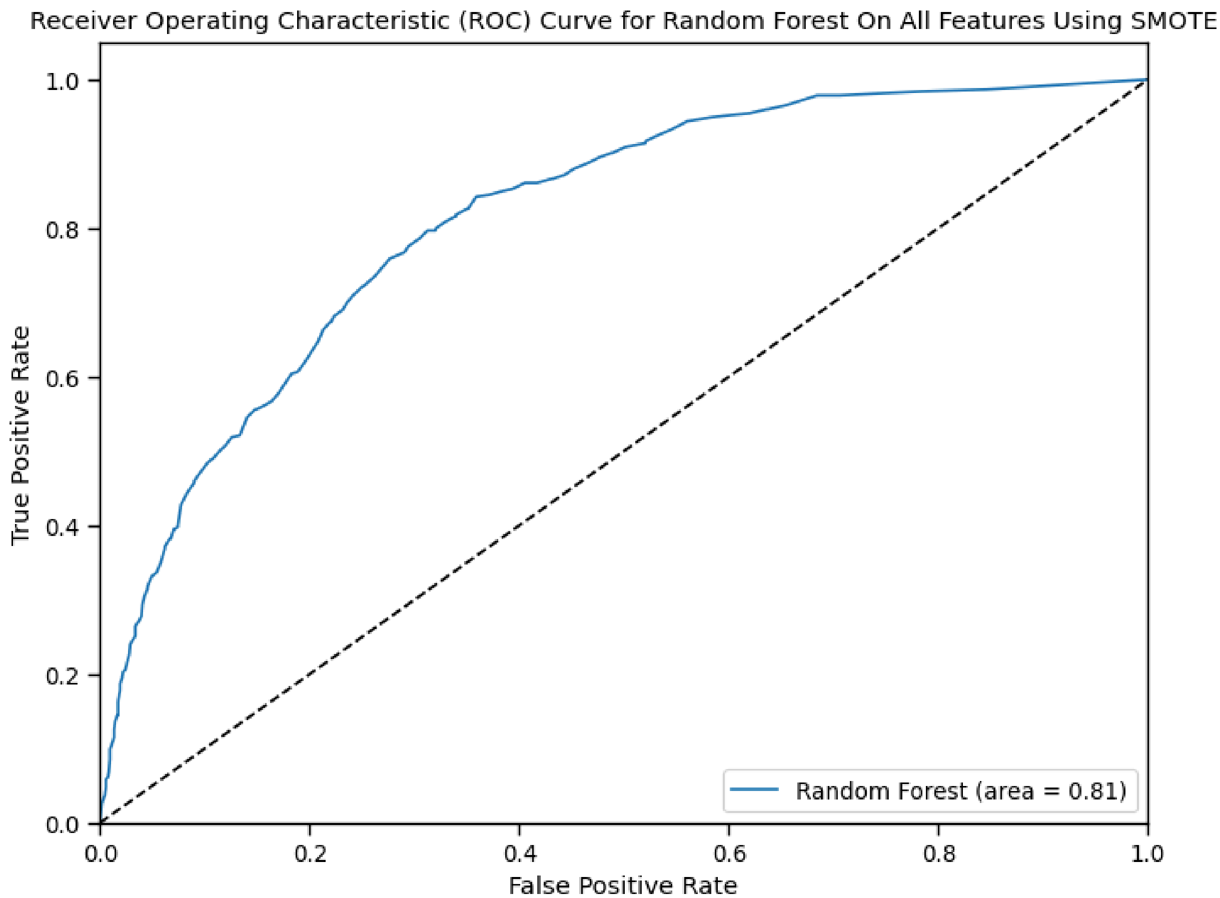
```python
# Plot Confusion Matrix
plt.figure(figsize=(8, 6))
cm_display_rf = ConfusionMatrixDisplay(confusion_matrix=conf_matrix_rf)
cm_display_rf.plot()
plt.title("Random Forest Confusion Matrix With SMOTE On All Features")
plt.show()
```

```
<Figure size 800x600 with 0 Axes>
```



In [134…

```
# Calculate AUC ROC for Random Forest
y_prob_rf = random_forest.predict_proba(X_test_normalized)[:, 1]
fpr_rf, tpr_rf, thresholds_rf = roc_curve(y_test, y_prob_rf)
auc_rf = roc_auc_score(y_test, y_prob_rf)

# Plot ROC curve for Random Forest
plt.figure(figsize=(8, 6))
plt.plot(fpr_rf, tpr_rf, label='Random Forest (area = %0.2f)' % auc_rf)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve for Random Forest On All Feat
plt.legend(loc="lower right")
plt.show()
```



SVM Model

In [135…

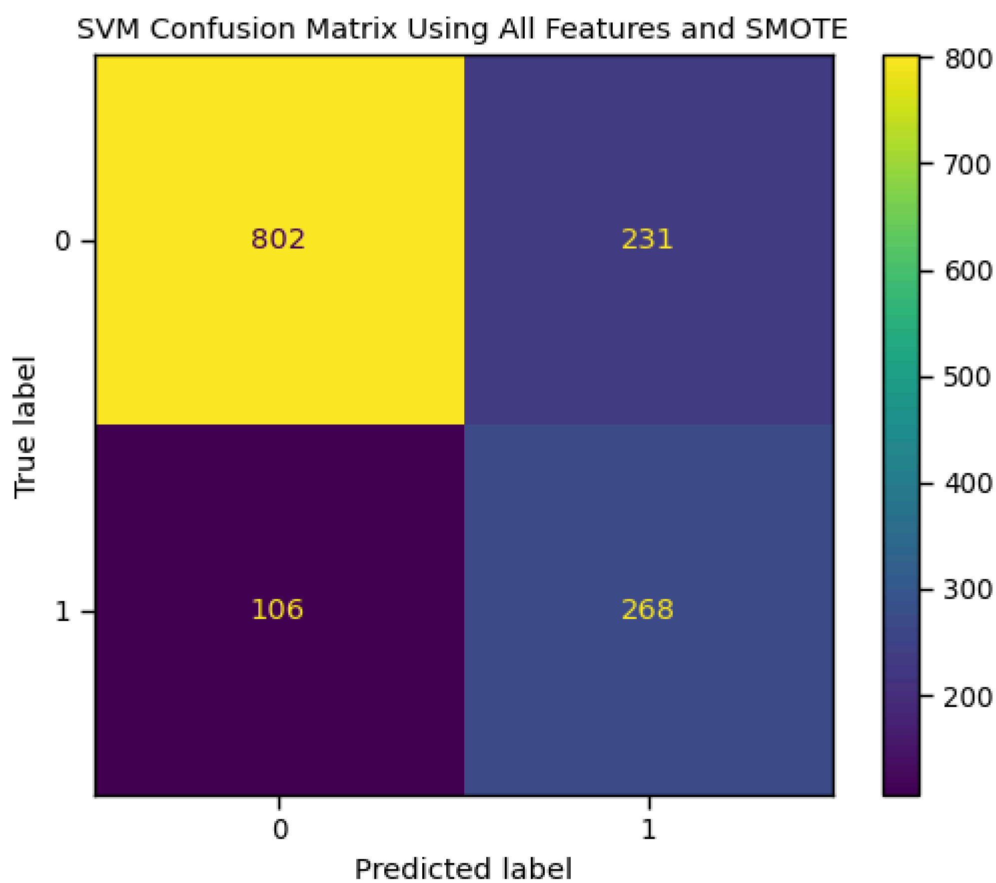
```
# Train the SVM model on all features
svm_model.fit(X_train_smote, y_train_smote)

# Make predictions
y_pred_svm = svm_model.predict(X_test_normalized)

# Make predictions on the train set
y_pred_train_svm = svm_model.predict(X_train_smote)

# Compute the accuracy of the train set for SVM model
train_accuracy_svm = accuracy_score(y_train_smote, y_pred_train_svm)
print("SVM Accuracy on the train set with SMOTE data:", train_accuracy_svm)

# Evaluate the model
print("SVM with SMOTE")
print("Classification Report:")
print(classification_report(y_test, y_pred_svm))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_svm))
```

```
SVM Accuracy on the train set with SMOTE data: 0.8504842615012107
SVM with SMOTE
Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.78      0.83      1033
           1       0.54      0.72      0.61       374

    accuracy                           0.76      1407
   macro avg       0.71      0.75      0.72      1407
weighted avg       0.79      0.76      0.77      1407

Confusion Matrix:
[[802 231]
 [106 268]]
```

In [136…

```
# Plot the confusion matrix
plt.figure()
cm_display_svm = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix(y_test, y_pr
cm_display_svm.plot()
plt.title("SVM Confusion Matrix Using All Features and SMOTE")
plt.show()
```

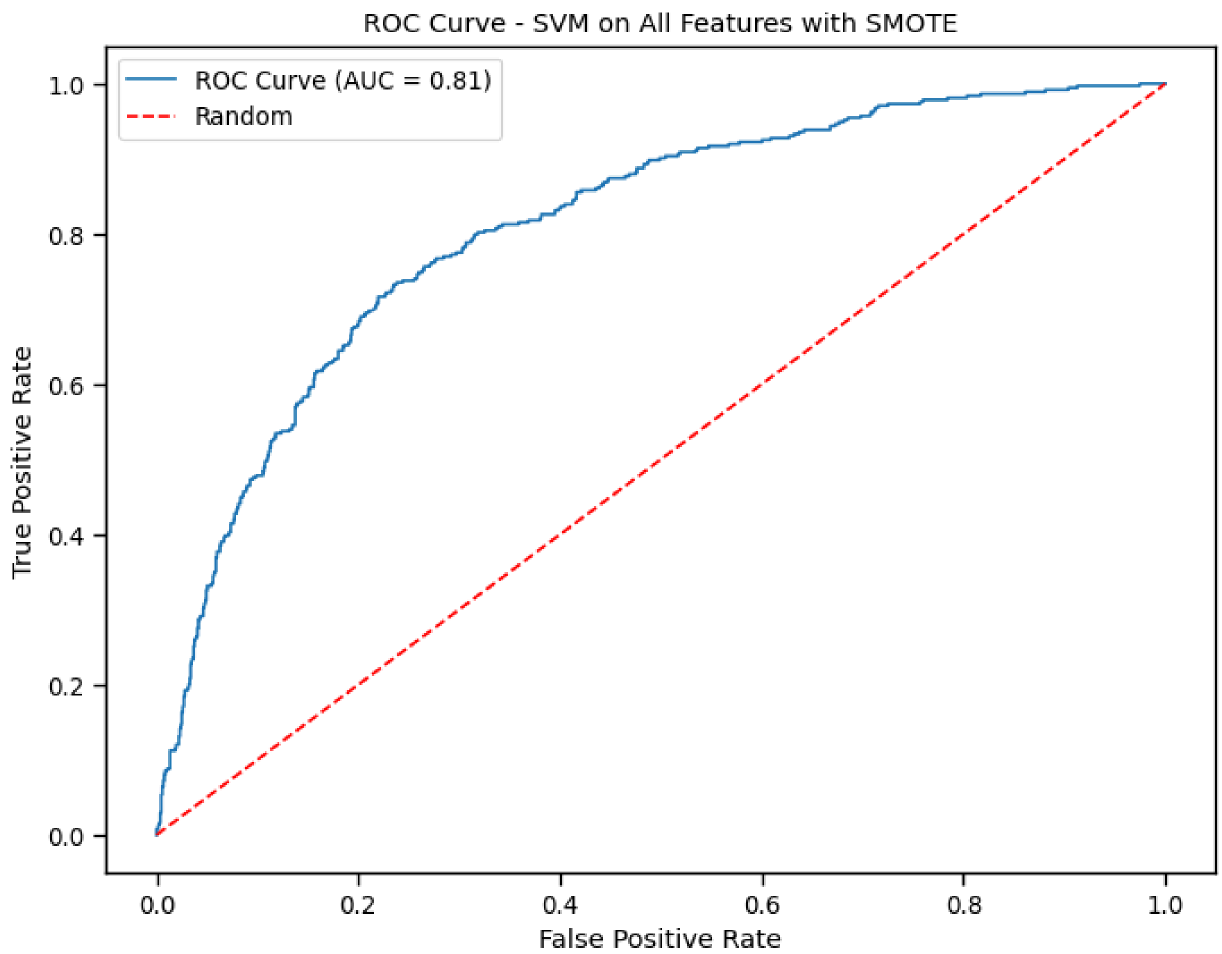
```
<Figure size 640x480 with 0 Axes>
```



In [137…

```
# Get the predicted probabilities for the positive class
y_prob_svm = svm_model.predict_proba(X_test_normalized)[:, 1]

# Compute fpr, tpr, and thresholds
fpr, tpr, thresholds = roc_curve(y_test, y_prob_svm)

# Compute AUC score
```

```python
auc = roc_auc_score(y_test, y_prob_svm)

# Plot ROC AUC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label="ROC Curve (AUC = {:.2f})".format(auc))
plt.plot([0, 1], [0, 1], linestyle="--", color="r", label="Random")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve - SVM on All Features with SMOTE")
plt.legend()
plt.show()
```



In the next step we will;

- Interpret the model outputs and draw conclusions based on the analysis.
- Communicate findings to stakeholders through reports, visualizations and presentations.
- Deployment of Models
- Outline actionable insights derived from the analysis into decision-making processes.