FINAL PROJECT SUBMISSION

Michael Achoki

1. BUSINESS UNDERSTANDING

Problem Statement

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

Objectives

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

Success Metric

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

2. DATA UNDERSTANDING

Here's a summary of the columns:

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

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

```
# Importing necessary modules and packages

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

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

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

# Display plots in the notebook
%matplotlib inline

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

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


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

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

```
  state  account length  area code phone number international plan  \
0    KS             128        415     382-4657                 no   
1    OH             107        415     371-7191                 no   
2    NJ             137        415     358-1921                 no   
3    OH              84        408     375-9999                yes   
4    OK              75        415     330-6626                yes   

  voice mail plan  number vmail messages  total day minutes  total day
calls  \
0             yes                     25              265.1
110   
1             yes                     26              161.6
123   
2              no                      0              243.4
114   
3              no                      0              299.4
71   
4              no                      0              166.7
113   

   total day charge  ...  total eve calls  total eve charge  \
0             45.07  ...               99             16.78   
1             27.47  ...              103             16.62   
2             41.38  ...              110             10.30   
3             50.90  ...               88              5.26   
4             28.34  ...              122             12.61   

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01   
1                254.4                103               11.45   
2                162.6                104                7.32   
3                196.9                 89                8.86   
4                186.9                121                8.41   

   total intl minutes  total intl calls  total intl charge  \
0                10.0                 3               2.70   
1                13.7                 3               3.70   
2                12.2                 5               3.29   
3                 6.6                 7               1.78   
4                10.1                 3               2.73   

   customer service calls  churn  
0                       1  False  
1                       1  False  
2                       0  False  
3                       2  False  
```

```
4                      3  False

[5 rows x 21 columns]
```

```
#General stats of the data
data.info()
```

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

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

```
data.describe()
```

```
       account length    area code  number vmail messages  total day
minutes  \
count     3333.000000  3333.000000            3333.000000
3333.000000
mean       101.064806   437.182418               8.099010
179.775098
std         39.822106    42.371290              13.688365
54.467389
```

```
min          1.000000   408.000000              0.000000
0.000000
25%         74.000000   408.000000              0.000000
143.700000
50%        101.000000   415.000000              0.000000
179.400000
75%        127.000000   510.000000             20.000000
216.400000
max        243.000000   510.000000             51.000000
350.800000

       total day calls  total day charge  total eve minutes  total eve
calls  \
count      3333.000000       3333.000000        3333.000000
3333.000000
mean        100.435644         30.562307         200.980348
100.114311
std          20.069084          9.259435          50.713844
19.922625
min           0.000000          0.000000           0.000000
0.000000
25%          87.000000         24.430000         166.600000
87.000000
50%         101.000000         30.500000         201.400000
100.000000
75%         114.000000         36.790000         235.300000
114.000000
max         165.000000         59.640000         363.700000
170.000000

       total eve charge  total night minutes  total night calls  \
count       3333.000000          3333.000000        3333.000000
mean          17.083540           200.872037         100.107711
std            4.310668            50.573847          19.568609
min            0.000000            23.200000          33.000000
25%           14.160000           167.000000          87.000000
50%           17.120000           201.200000         100.000000
75%           20.000000           235.300000         113.000000
max           30.910000           395.000000         175.000000

       total night charge  total intl minutes  total intl calls  \
count         3333.000000         3333.000000       3333.000000
mean             9.039325           10.237294          4.479448
std              2.275873            2.791840          2.461214
min              1.040000            0.000000          0.000000
25%              7.520000            8.500000          3.000000
50%              9.050000           10.300000          4.000000
75%             10.590000           12.100000          6.000000
max             17.770000           20.000000         20.000000
```

```
       total intl charge  customer service calls
count        3333.000000             3333.000000
mean            2.764581                1.562856
std             0.753773                1.315491
min             0.000000                0.000000
25%             2.300000                1.000000
50%             2.780000                1.000000
75%             3.270000                2.000000
max             5.400000                9.000000
```

3. DATA PREPARATION

3.1 Data preprocessing

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

missing_values = data.isna().sum()

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

```
Duplicated values are: 0
Missing values are:
 state                     0
account length            0
area code                 0
phone number              0
international plan        0
voice mail plan           0
number vmail messages     0
total day minutes         0
total day calls           0
total day charge          0
total eve minutes         0
total eve calls           0
total eve charge          0
total night minutes       0
total night calls         0
total night charge        0
total intl minutes        0
total intl calls          0
total intl charge         0
customer service calls    0
churn                     0
dtype: int64
```

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

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


data.sample(15)
```

	state	account length	area code	phone number	international plan
1382	GA	125	415	380-6342	0
619	KS	110	415	383-1657	1
119	ID	97	408	328-3266	0
188	WY	164	510	373-4819	0
1984	TN	112	415	339-6477	0
2453	HI	134	415	342-9394	0
1623	ME	130	408	387-6031	0
1134	TN	105	408	353-8849	0
3190	ID	103	415	346-5992	0
210	LA	99	415	411-2284	0
2190	NC	88	408	414-4037	0
1264	TN	72	408	348-2009	0
1105	NJ	135	510	401-8735	0
732	IN	48	510	342-6696	0
3214	OK	149	510	365-9079	1

	voice mail plan	number vmail messages	total day minutes
1382	1	39	236.1
619	0	0	293.3
119	0	0	239.8

```
188                   0                       0              160.6
1984                  0                       0              272.5
2453                  1                      38              214.4
1623                  0                       0              176.3
1134                  0                       0              206.2
3190                  0                       0              174.7
210                   0                       0              241.1
2190                  1                      27               93.4
1264                  0                       0              147.0
1105                  1                      28              201.4
732                   0                       0              300.4
3214                  0                       0              180.9

      total day calls  total day charge  ...  total eve calls  \
1382              107             40.14  ...              110
619                79             49.86  ...               90
119               125             40.77  ...              111
188               111             27.30  ...              126
1984              119             46.33  ...               94
2453               93             36.45  ...               57
1623              140             29.97  ...              104
1134               84             35.05  ...              138
3190              151             29.70  ...               56
210                72             40.99  ...               98
2190              106             15.88  ...               92
1264               79             24.99  ...              103
1105              100             34.24  ...              117
732                94             51.07  ...              103
3214               79             30.75  ...               83

      total eve charge  total night minutes  total night calls  \
1382             24.58                175.4                107
619              16.02                266.9                 91
119              18.26                143.3                 81
188              13.87                187.1                112
1984             19.22                159.1                 94
2453             17.99                165.0                 79
1623             17.09                161.9                123
1134             21.79                117.1                 91
3190             12.58                168.2                109
210              13.23                188.2                109
2190             21.42                189.0                104
1264             13.80                162.9                 80
1105             20.95                154.8                131
732              11.32                197.4                 94
3214             16.57                197.8                109

      total night charge  total intl minutes  total intl calls  \
1382                7.89                 9.1                 4
619                12.01                14.5                 4
```

```
119                    6.45                 8.7                   5
188                    8.42                 9.0                   3
1984                   7.16                16.4                   5
2453                   7.43                10.0                   8
1623                   7.29                11.3                   5
1134                   5.27                 9.0                   3
3190                   7.57                15.8                   3
210                    8.47                11.6                  10
2190                   8.50                10.9                   1
1264                   7.33                10.5                   4
1105                   6.97                12.9                   4
732                    8.88                 7.2                   5
3214                   8.90                 8.8                   9

      total intl charge  customer service calls  churn
1382                2.46                       2      0
619                 3.92                       0      1
119                 2.35                       2      0
188                 2.43                       1      0
1984                4.43                       3      1
2453                2.70                       1      0
1623                3.05                       1      0
1134                2.43                       1      0
3190                4.27                       6      1
210                 3.13                       1      0
2190                2.94                       1      0
1264                2.84                       1      0
1105                3.48                       2      1
732                 1.94                       2      0
3214                2.38                       3      0

[15 rows x 21 columns]

#totals for minutes, charges and calls

data['total_charges'] = round(data['total day charge'] + data['total
eve charge'] + data['total night charge'] + data['total intl charge'])
data['total_calls'] = round(data['total day calls'] + data['total eve
calls'] + data['total night calls'] + data['total intl calls'])
data['total_minutes'] = round(data['total day minutes'] + data['total
eve minutes'] + data['total night minutes'] + data['total intl
minutes'])

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

      total_charges  total_calls  total_minutes
189            68.0          314          660.0
497            66.0          289          657.0
2319           78.0          317          715.0
```

```
2303          32.0          275          399.0
1471          61.0          291          619.0
643           74.0          307          734.0
1320          59.0          345          545.0
221           57.0          291          596.0
3112          49.0          262          492.0
3272          83.0          355          761.0
```

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

```
     state  account length  area code phone number  international plan  \
1881    NE              76        415     334-6519                   0

895     MD             106        415     343-2350                   0

2244    KS             148        510     415-4051                   0

3207    DC              93        408     345-1994                   0

1471    OH              75        415     340-9803                   0

1503    WV              57        415     419-6418                   1

439     MI              81        415     408-3384                   0

2598    TN             196        415     340-8291                   0

1441    NC             172        408     331-5962                   0

1146    WA             161        415     378-8137                   0


      voice mail plan  number vmail messages  total day minutes  \
1881                0                      0              272.7
895                 0                      0              165.3
2244                0                      0              239.3
3207                1                     22              306.2
1471                0                      0              150.6
1503                1                     17              236.5
439                 0                      0              153.5
2598                0                      0              133.1
1441                1                     47              274.9
1146                0                      0              151.6

      total day calls  total day charge  ...  total night calls  \
1881               97             46.36  ...                105
895               118             28.10  ...                 93
2244               84             40.68  ...                104
3207              123             52.05  ...                107
```

```
1471                99             25.60  ...                104
1503                94             40.21  ...                117
439                 99             26.10  ...                 86
2598                80             22.63  ...                 96
1441               102             46.73  ...                123
1146               117             25.77  ...                 68

      total night charge  total intl minutes  total intl calls  \
1881               10.60                 7.7                 2
895                 8.42                 8.5                 3
2244               10.47                10.9                 3
3207               10.81                11.7                 2
1471                7.14                 8.1                 5
1503               10.65                12.2                 3
439                 8.93                 6.3                 2
2598                9.97                10.3                 8
1441               11.03                 8.8                 2
1146               10.11                 4.0                 5

      total intl charge  customer service calls  churn  total_charges  
\
1881               2.08                       0      1           79.0

895                2.30                       2      0           57.0

2244               2.94                       1      0           71.0

3207               3.16                       0      0           82.0

1471               2.19                       0      0           61.0

1503               3.29                       2      0           68.0

439                1.70                       2      0           54.0

2598               2.78                       1      0           53.0

1441               2.38                       1      0           76.0

1146               1.08                       1      0           56.0


      total_calls  total_minutes
1881          299          752.0
895           315          571.0
2244          276          678.0
3207          315          748.0
1471          291          619.0
1503          308          648.0
439           289          556.0
```

```
2598          304          572.0
1441          345          715.0
1146          277          600.0

[10 rows x 24 columns]
```

3.2 Create a copy of data

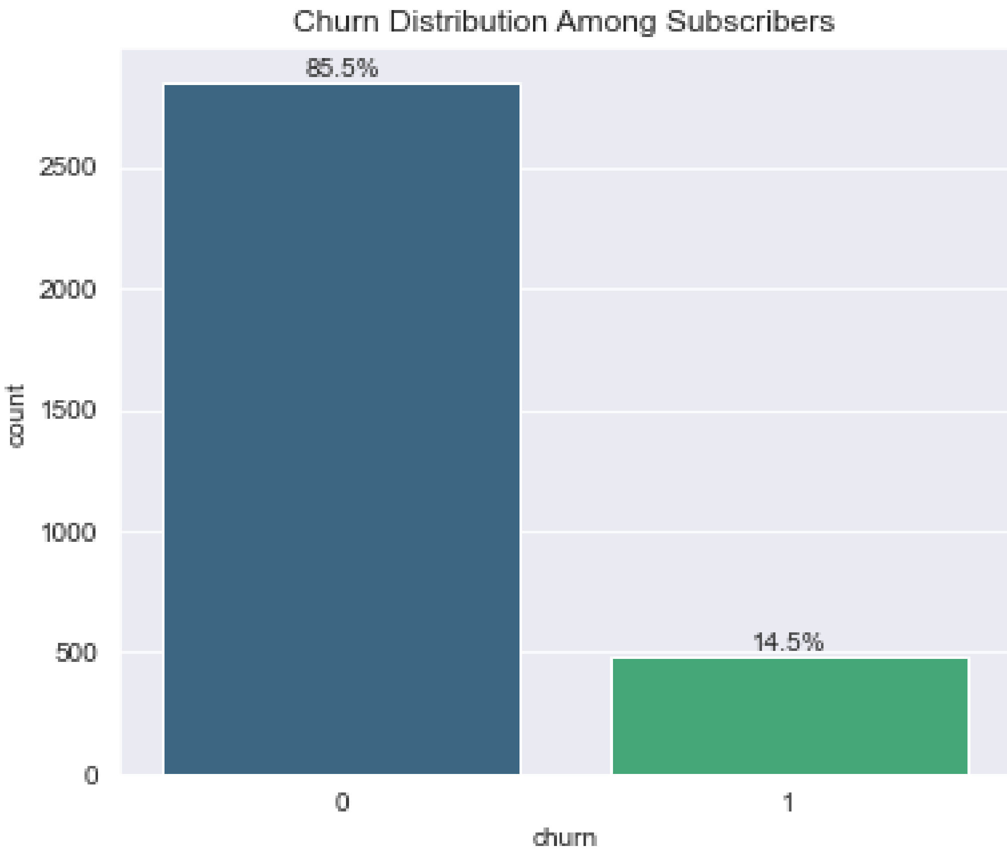
```
import pandas as pd

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

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

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

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

     state  account length  area code  international plan  voice mail
plan  \
2028    SD              93        510                   0
0
1435    IL              89        415                   1
1
2863    ME              28        415                   0
0
900     VA              72        510                   1
1
2163    KS             119        415                   0
0
569     NC             133        408                   1
1
475     AR              74        510                   0
0
171     NH              64        408                   0
1
3161    NV             148        510                   0
0
1342    AK              52        415                   0
1

      number vmail messages  customer service calls  churn
```

```
total_charges  \
2028                       0                        1      1
85.0
1435                      19                        0      1
50.0
2863                       0                        3      0
70.0
900                       29                        0      0
47.0
2163                       0                        1      0
74.0
569                       32                        2      1
72.0
475                        0                        3      0
53.0
171                       27                        2      0
56.0
3161                       0                        2      0
69.0
1342                      24                        2      0
54.0

      total_calls  total_minutes
2028          312          792.0
1435          364          509.0
2863          307          694.0
900           299          504.0
2163          307          717.0
569           348          670.0
475           242          594.0
171           280          527.0
3161          348          712.0
1342          280          535.0
```

3.3 Univariate Analysis

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

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

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




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

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


{"config":{"plotlyServerURL":"https://plot.ly"},"data":[{"domain":{"x":[0,1],"y":[0,1]},"hole":0.5,"hovertemplate":"label=%{label}
value=%{value}<extra></extra>","labels":[415,510,408],"legendgroup":"","name":"","showlegend":true,"type":"pie","values":[1655,840,838]}],"layout":{"legend":

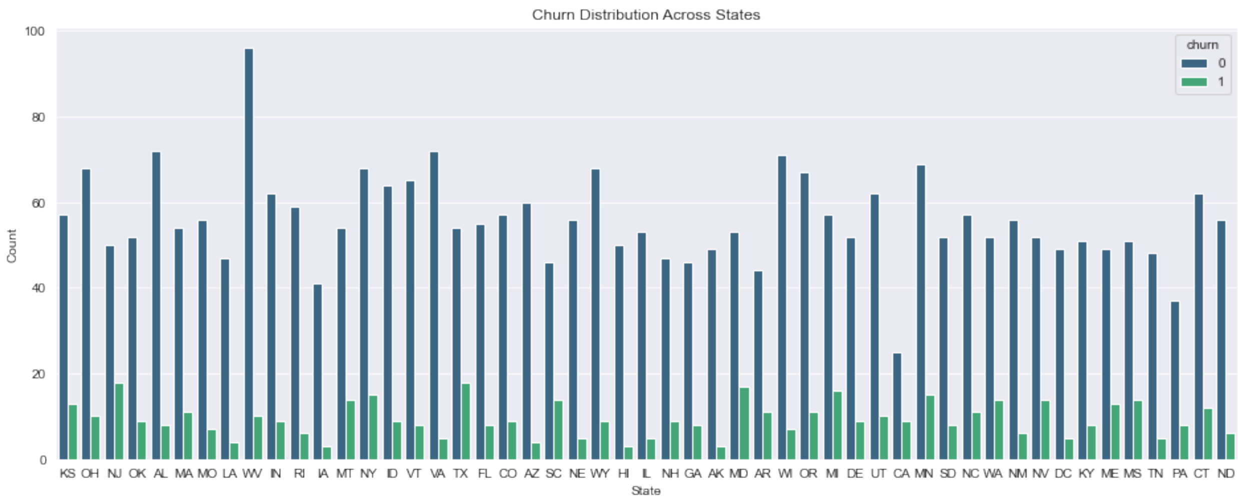
```
{"tracegroupgap":0},"template":{"data":{"bar":[{"error_x":
{"color":"#2a3f5f"},"error_y":{"color":"#2a3f5f"},"marker":{"line":
{"color":"#E5ECF6","width":0.5}},"type":"bar"}],"barpolar":[{"marker":
{"line":{"color":"#E5ECF6","width":0.5}},"type":"barpolar"}],"carpet":
[{"aaxis":
{"endlinecolor":"#2a3f5f","gridcolor":"white","linecolor":"white","min
orgridcolor":"white","startlinecolor":"#2a3f5f"},"baxis":
{"endlinecolor":"#2a3f5f","gridcolor":"white","linecolor":"white","min
orgridcolor":"white","startlinecolor":"#2a3f5f"},"type":"carpet"}],"ch
oropleth":[{"colorbar":
{"outlinewidth":0,"ticks":""},"type":"choropleth"}],"contour":
[{"colorbar":{"outlinewidth":0,"ticks":""},"colorscale":
[[0,"#0d0887"],[0.1111111111111111,"#46039f"],
[0.2222222222222222,"#7201a8"],[0.3333333333333333,"#9c179e"],
[0.4444444444444444,"#bd3786"],[0.5555555555555556,"#d8576b"],
[0.6666666666666666,"#ed7953"],[0.7777777777777778,"#fb9f3a"],
[0.8888888888888888,"#fdca26"],
[1,"#f0f921"]],"type":"contour"}],"contourcarpet":[{"colorbar":
{"outlinewidth":0,"ticks":""},"type":"contourcarpet"}],"heatmap":
[{"colorbar":{"outlinewidth":0,"ticks":""},"colorscale":
[[0,"#0d0887"],[0.1111111111111111,"#46039f"],
[0.2222222222222222,"#7201a8"],[0.3333333333333333,"#9c179e"],
[0.4444444444444444,"#bd3786"],[0.5555555555555556,"#d8576b"],
[0.6666666666666666,"#ed7953"],[0.7777777777777778,"#fb9f3a"],
[0.8888888888888888,"#fdca26"],
[1,"#f0f921"]],"type":"heatmap"}],"heatmapgl":[{"colorbar":
{"outlinewidth":0,"ticks":""},"colorscale":[[0,"#0d0887"],
[0.1111111111111111,"#46039f"],[0.2222222222222222,"#7201a8"],
[0.3333333333333333,"#9c179e"],[0.4444444444444444,"#bd3786"],
[0.5555555555555556,"#d8576b"],[0.6666666666666666,"#ed7953"],
[0.7777777777777778,"#fb9f3a"],[0.8888888888888888,"#fdca26"],
[1,"#f0f921"]],"type":"heatmapgl"}],"histogram":[{"marker":
{"colorbar":
{"outlinewidth":0,"ticks":""}},"type":"histogram"}],"histogram2d":
[{"colorbar":{"outlinewidth":0,"ticks":""},"colorscale":
[[0,"#0d0887"],[0.1111111111111111,"#46039f"],
[0.2222222222222222,"#7201a8"],[0.3333333333333333,"#9c179e"],
[0.4444444444444444,"#bd3786"],[0.5555555555555556,"#d8576b"],
[0.6666666666666666,"#ed7953"],[0.7777777777777778,"#fb9f3a"],
[0.8888888888888888,"#fdca26"],
[1,"#f0f921"]],"type":"histogram2d"}],"histogram2dcontour":
[{"colorbar":{"outlinewidth":0,"ticks":""},"colorscale":
[[0,"#0d0887"],[0.1111111111111111,"#46039f"],
[0.2222222222222222,"#7201a8"],[0.3333333333333333,"#9c179e"],
[0.4444444444444444,"#bd3786"],[0.5555555555555556,"#d8576b"],
[0.6666666666666666,"#ed7953"],[0.7777777777777778,"#fb9f3a"],
[0.8888888888888888,"#fdca26"],
[1,"#f0f921"]],"type":"histogram2dcontour"}],"mesh3d":[{"colorbar":
{"outlinewidth":0,"ticks":""},"type":"mesh3d"}],"parcoords":[{"line":
```

```
{"colorbar":{"outlinewidth":0,"ticks":""}},"type":"parcoords"}],"pie":
[{"automargin":true,"type":"pie"}],"scatter":[{"marker":{"colorbar":
{"outlinewidth":0,"ticks":""}},"type":"scatter"}],"scatter3d":
[{"line":{"colorbar":{"outlinewidth":0,"ticks":""}},"marker":
{"colorbar":
{"outlinewidth":0,"ticks":""}},"type":"scatter3d"}],"scattercarpet":
[{"marker":{"colorbar":
{"outlinewidth":0,"ticks":""}},"type":"scattercarpet"}],"scattergeo":
[{"marker":{"colorbar":
{"outlinewidth":0,"ticks":""}},"type":"scattergeo"}],"scattergl":
[{"marker":{"colorbar":
{"outlinewidth":0,"ticks":""}},"type":"scattergl"}],"scattermapbox":
[{"marker":{"colorbar":
{"outlinewidth":0,"ticks":""}},"type":"scattermapbox"}],"scatterpolar"
:[{"marker":{"colorbar":
{"outlinewidth":0,"ticks":""}},"type":"scatterpolar"}],"scatterpolargl
":[{"marker":{"colorbar":
{"outlinewidth":0,"ticks":""}},"type":"scatterpolargl"}],"scatterterna
ry":[{"marker":{"colorbar":
{"outlinewidth":0,"ticks":""}},"type":"scatterternary"}],"surface":
[{"colorbar":{"outlinewidth":0,"ticks":""},"colorscale":
[[0,"#0d0887"],[0.1111111111111111,"#46039f"],
[0.2222222222222222,"#7201a8"],[0.3333333333333333,"#9c179e"],
[0.4444444444444444,"#bd3786"],[0.5555555555555556,"#d8576b"],
[0.6666666666666666,"#ed7953"],[0.7777777777777778,"#fb9f3a"],
[0.8888888888888888,"#fdca26"],
[1,"#f0f921"]],"type":"surface"}],"table":[{"cells":{"fill":
{"color":"#EBF0F8"},"line":{"color":"white"}},"header":{"fill":
{"color":"#C8D4E3"},"line":
{"color":"white"}},"type":"table"}]},"layout":{"annotationdefaults":
{"arrowcolor":"#2a3f5f","arrowhead":0,"arrowwidth":1},"coloraxis":
{"colorbar":{"outlinewidth":0,"ticks":""}},"colorscale":{"diverging":
[[0,"#8e0152"],[0.1,"#c51b7d"],[0.2,"#de77ae"],[0.3,"#f1b6da"],
[0.4,"#fde0ef"],[0.5,"#f7f7f7"],[0.6,"#e6f5d0"],[0.7,"#b8e186"],
[0.8,"#7fbc41"],[0.9,"#4d9221"],[1,"#276419"]],"sequential":
[[0,"#0d0887"],[0.1111111111111111,"#46039f"],
[0.2222222222222222,"#7201a8"],[0.3333333333333333,"#9c179e"],
[0.4444444444444444,"#bd3786"],[0.5555555555555556,"#d8576b"],
[0.6666666666666666,"#ed7953"],[0.7777777777777778,"#fb9f3a"],
[0.8888888888888888,"#fdca26"],[1,"#f0f921"]],"sequentialminus":
[[0,"#0d0887"],[0.1111111111111111,"#46039f"],
[0.2222222222222222,"#7201a8"],[0.3333333333333333,"#9c179e"],
[0.4444444444444444,"#bd3786"],[0.5555555555555556,"#d8576b"],
[0.6666666666666666,"#ed7953"],[0.7777777777777778,"#fb9f3a"],
[0.8888888888888888,"#fdca26"],[1,"#f0f921"]]},"colorway":
["#636efa","#EF553B","#00cc96","#ab63fa","#FFA15A","#19d3f3","#FF6692"
,"#B6E880","#FF97FF","#FECB52"],"font":{"color":"#2a3f5f"},"geo":
{"bgcolor":"white","lakecolor":"white","landcolor":"#E5ECF6","showlake
s":true,"showland":true,"subunitcolor":"white"},"hoverlabel":
```

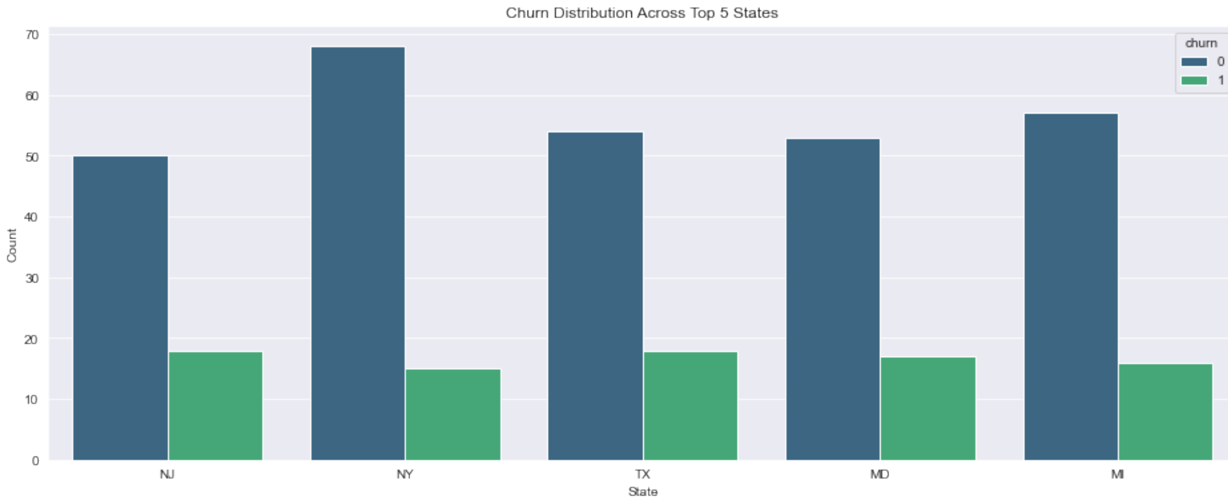
```
{"align":"left"},"hovermode":"closest","mapbox":
{"style":"light"},"paper_bgcolor":"white","plot_bgcolor":"#E5ECF6","po
lar":{"angularaxis":
{"gridcolor":"white","linecolor":"white","ticks":""},"bgcolor":"#E5ECF
6","radialaxis":
{"gridcolor":"white","linecolor":"white","ticks":""}},"scene":
{"xaxis":
{"backgroundcolor":"#E5ECF6","gridcolor":"white","gridwidth":2,"lineco
lor":"white","showbackground":true,"ticks":"","zerolinecolor":"white"}
,"yaxis":
{"backgroundcolor":"#E5ECF6","gridcolor":"white","gridwidth":2,"lineco
lor":"white","showbackground":true,"ticks":"","zerolinecolor":"white"}
,"zaxis":
{"backgroundcolor":"#E5ECF6","gridcolor":"white","gridwidth":2,"lineco
lor":"white","showbackground":true,"ticks":"","zerolinecolor":"white"}
},"shapedefaults":{"line":{"color":"#2a3f5f"}},"ternary":{"aaxis":
{"gridcolor":"white","linecolor":"white","ticks":""},"baxis":
{"gridcolor":"white","linecolor":"white","ticks":""},"bgcolor":"#E5ECF
6","caxis":
{"gridcolor":"white","linecolor":"white","ticks":""}},"title":
{"x":5.0e-2},"xaxis":
{"automargin":true,"gridcolor":"white","linecolor":"white","ticks":"",
"title":
{"standoff":15},"zerolinecolor":"white","zerolinewidth":2},"yaxis":
{"automargin":true,"gridcolor":"white","linecolor":"white","ticks":"",
"title":
{"standoff":15},"zerolinecolor":"white","zerolinewidth":2}}},"title":
{"text":"Distribution of Area Code Feature"}}}
```


3.4 Bivariate analysis

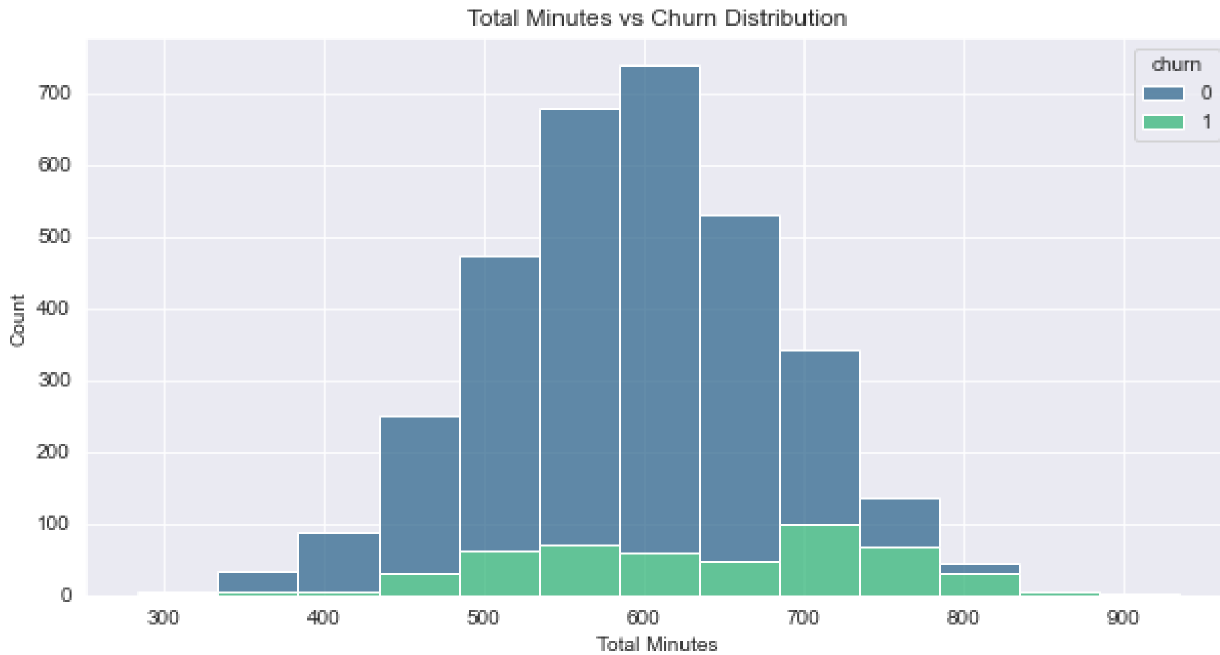
```
# Churn vs States

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

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

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

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



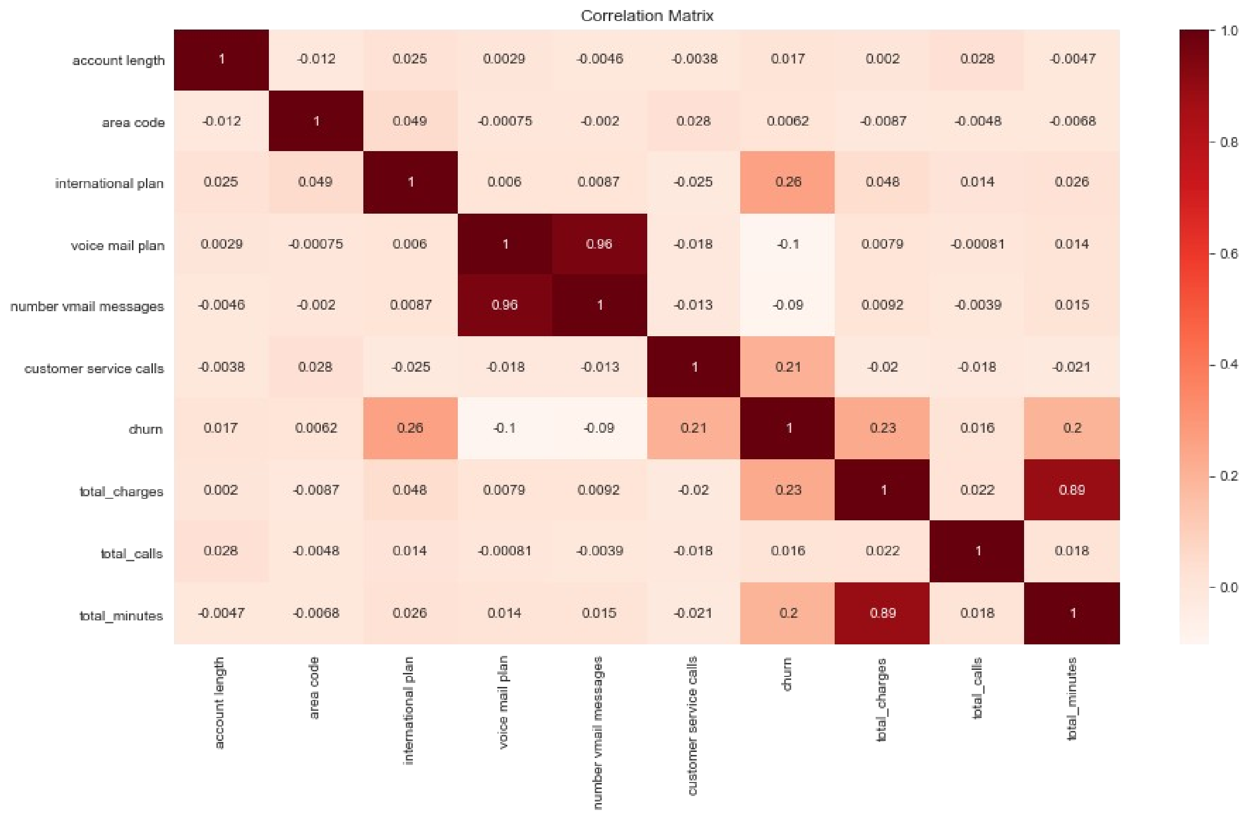

```python
# Calculate the total number of churns for each state
state_churn_counts = data.groupby('state')['churn'].sum()

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

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

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

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

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




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

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

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

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




```
#Calculate the correlation matrix using the corr() method
correlation_matrix = data_copy.corr()

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



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

4. MODELLING

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

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

```
      account length  international plan  voice mail plan  \
362               39                   0                1
2611             135                   0                0
3068              78                   0                1
2934              24                   0                0
2198             127                   0                0
2214              90                   0                0
82                55                   0                1
3046             110                   0                0
2587             105                   0                0
3094              91                   0                0
```

```
      number vmail messages  customer service calls  churn
total_charges  \
362                      36                       1      0
57.0
2611                      0                       0      0
54.0
3068                     21                       2      0
54.0
2934                      0                       2      1
50.0
2198                      0                       0      0
65.0
2214                      0                       1      0
64.0
82                       25                       3      0
51.0
3046                      0                       1      0
34.0
2587                      0                       3      0
66.0
3094                      0                       1      0
48.0

      total_calls  total_minutes  state_AL  ...  state_TX  state_UT
state_VA  \
362           370          608.0         0  ...         0         0
0
2611          282          529.0         0  ...         0         0
0
3068          257          517.0         0  ...         0         0
0
2934          226          527.0         0  ...         0         0
0
2198          348          548.0         0  ...         0         0
0
2214          355          625.0         0  ...         0         0
0
82            310          488.0         0  ...         0         0
0
3046          251          402.0         0  ...         0         0
0
2587          362          641.0         0  ...         0         0
0
3094          251          493.0         0  ...         0         0
0

      state_VT  state_WA  state_WI  state_WV  state_WY  area code_415
\
362          0         0         0         0         0              1
```

```
2611          0         0         0         0         0              0
3068          0         0         0         0         0              1
2934          0         0         0         0         0              0
2198          0         0         0         0         0              1
2214          0         0         0         0         0              1
82            0         0         0         0         0              0
3046          0         0         0         0         0              0
2587          0         0         0         0         0              0
3094          0         0         0         0         0              1

      area code_510
362               0
2611              1
3068              0
2934              0
2198              0
2214              0
82                0
3046              1
2587              1
3094              0

[10 rows x 61 columns]
```

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

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

```
      account length  international plan  voice mail plan  \
2742        0.595041                 0.0              1.0
281         0.330579                 0.0              0.0
1508        0.380165                 0.0              0.0
```

```
2658       0.413223                 0.0               0.0
2112       0.615702                 0.0               0.0
2323       0.123967                 0.0               0.0
2739       0.413223                 0.0               1.0
2636       0.425620                 0.0               0.0
1460       0.326446                 0.0               0.0
115        0.144628                 1.0               1.0

      number vmail messages  customer service calls  churn
total_charges  \
2742               0.607843                0.222222    0.0
0.630137
281                0.000000                0.222222    0.0
0.547945
1508               0.000000                0.333333    0.0
0.534247
2658               0.000000                0.000000    0.0
0.616438
2112               0.000000                0.444444    1.0
0.397260
2323               0.000000                0.111111    0.0
0.465753
2739               0.176471                0.000000    0.0
0.424658
2636               0.000000                0.222222    0.0
0.452055
1460               0.000000                0.333333    0.0
0.479452
115                0.823529                0.000000    1.0
0.602740

      total_calls  total_minutes  state_AL  ...  state_TX  state_UT
state_VA  \
2742     0.604444       0.668885       0.0  ...       0.0       0.0
0.0
281      0.386667       0.547421       0.0  ...       0.0       0.0
0.0
1508     0.426667       0.668885       0.0  ...       0.0       0.0
0.0
2658     0.551111       0.465890       0.0  ...       0.0       0.0
0.0
2112     0.364444       0.391015       0.0  ...       0.0       0.0
0.0
2323     0.293333       0.490849       0.0  ...       0.0       0.0
0.0
2739     0.533333       0.392679       0.0  ...       0.0       0.0
0.0
2636     0.262222       0.462562       0.0  ...       0.0       0.0
0.0
```

```
1460     0.600000       0.435940       0.0  ...       0.0       0.0
0.0
115      0.675556       0.542429       0.0  ...       0.0       0.0
0.0

      state_VT  state_WA  state_WI  state_WV  state_WY  area code_415
\
2742       0.0       0.0       0.0       1.0       0.0            0.0

281        0.0       0.0       0.0       0.0       0.0            1.0

1508       0.0       0.0       0.0       0.0       0.0            0.0

2658       0.0       0.0       0.0       0.0       0.0            1.0

2112       0.0       0.0       0.0       0.0       0.0            1.0

2323       0.0       0.0       0.0       0.0       0.0            0.0

2739       0.0       0.0       0.0       0.0       1.0            0.0

2636       0.0       0.0       0.0       0.0       0.0            0.0

1460       0.0       0.0       0.0       0.0       0.0            1.0

115        0.0       0.0       0.0       0.0       0.0            0.0


      area code_510
2742            0.0
281             0.0
1508            0.0
2658            0.0
2112            0.0
2323            1.0
2739            1.0
2636            0.0
1460            0.0
115             1.0

[10 rows x 61 columns]
```

4.1 train test split

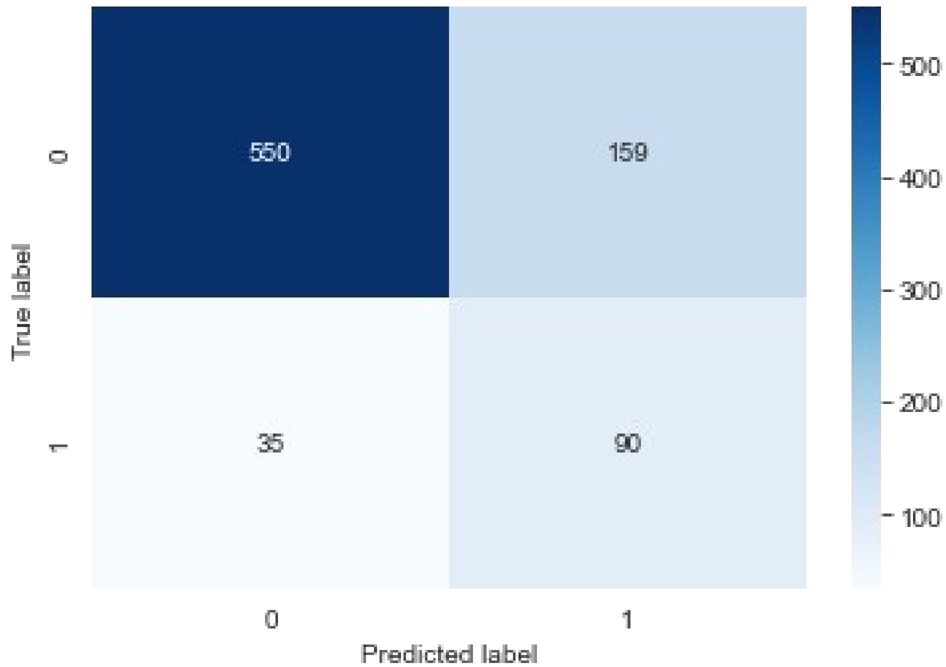
```
#Defining X(independent variables) and y(target variable)
X = data_copy.drop("churn", axis=1)
y = data_copy["churn"]

#train test split
X_train, X_test, y_train, y_test = train_test_split(X,y,
test_size=0.25, random_state=42)
```

4.2 SMOTE/SMOTENC technique

```
#SMOTE to fix the class imbalancemnt found during the decison tree
classification

#instantiate SMOTENC

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

4.3 Logistic Regression

```
#logistic regression
logreg =LogisticRegression(random_state=42)

#fit the model
logreg.fit(resampled_X_train, resampled_y_train)
#predict on the labels
y_pred_log = logreg.predict(X_test)

def plot_confusion_matrix(y_true, y_pred, classes):
    #plots confusion matrix

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

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




```
print(classification_report(y_test,y_pred_log))
```

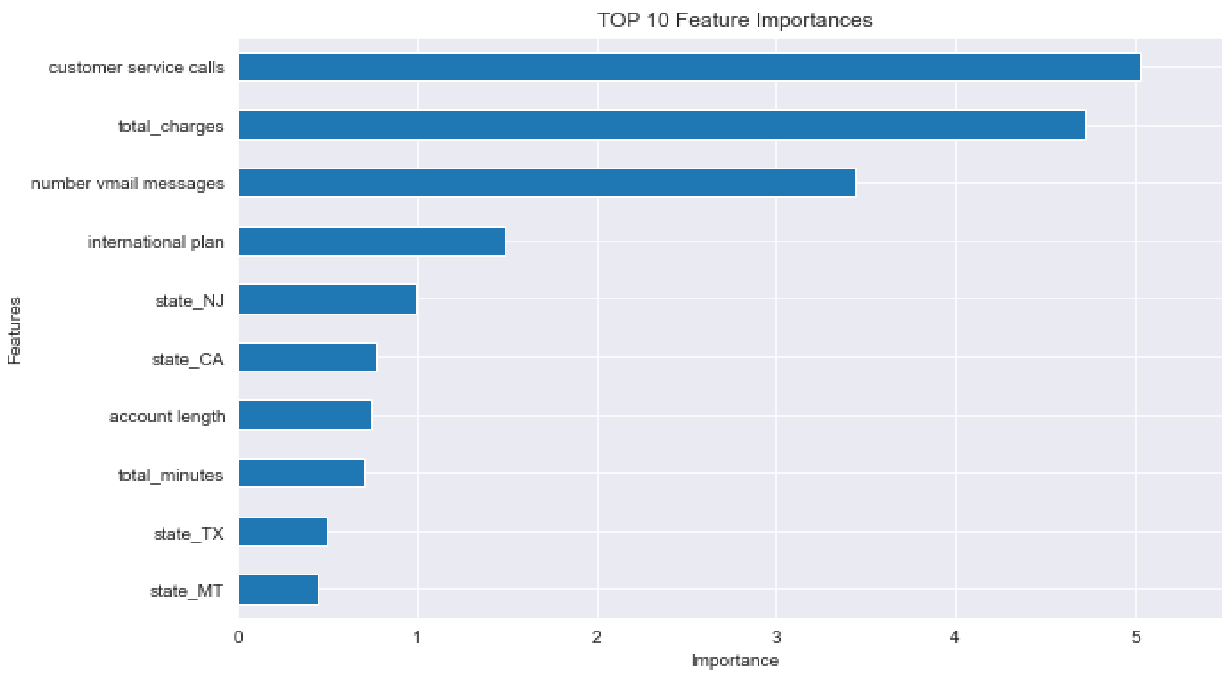
```
              precision    recall  f1-score   support

         0.0       0.94      0.78      0.85       709
         1.0       0.36      0.72      0.48       125

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

The classification report of the logistic regression model in summary:

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

```
#Feature Importance in the logistics Regression

importance_logreg = logreg.coef_[0]
Feature_names = resampled_X_train.columns
Feature_importances = pd.Series(importance_logreg,index=Feature_names)
Feature_importances = Feature_importances.sort_values(ascending=False)
plt.figure(figsize=(10,6))
top_features = Feature_importances[:10] #selecting the top 10
top_features.sort_values().plot(kind='barh')
plt.xlabel('Importance')
plt.ylabel('Features')
```

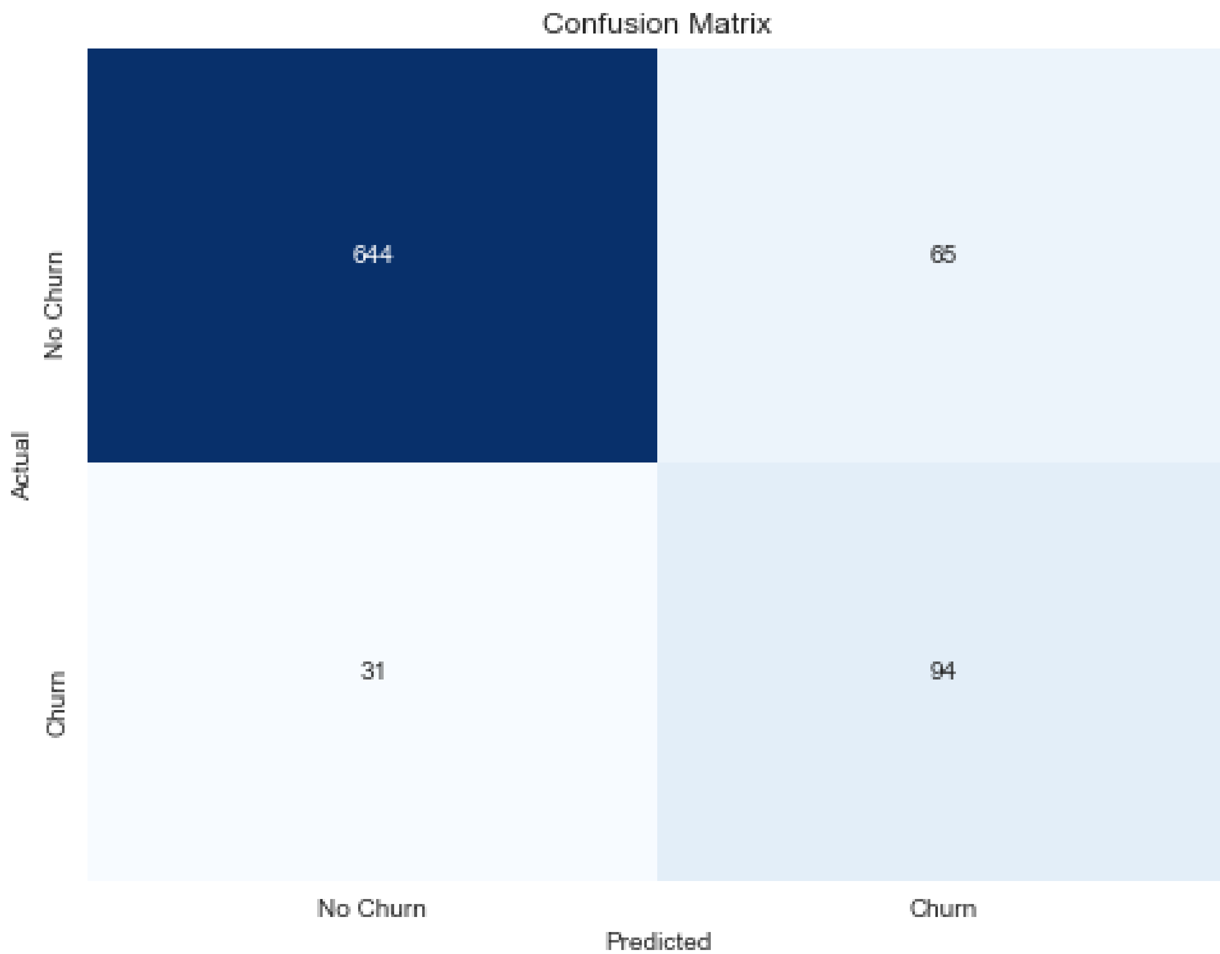
```python
plt.title('TOP 10 Feature Importances')
plt.xlim(0, max(top_features)*1.1) #setting nthe xlim to the max importance vakue
plt.show()
```



4.3 Decision Tree Classification

```python
#Decision Tree

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

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

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

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

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

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

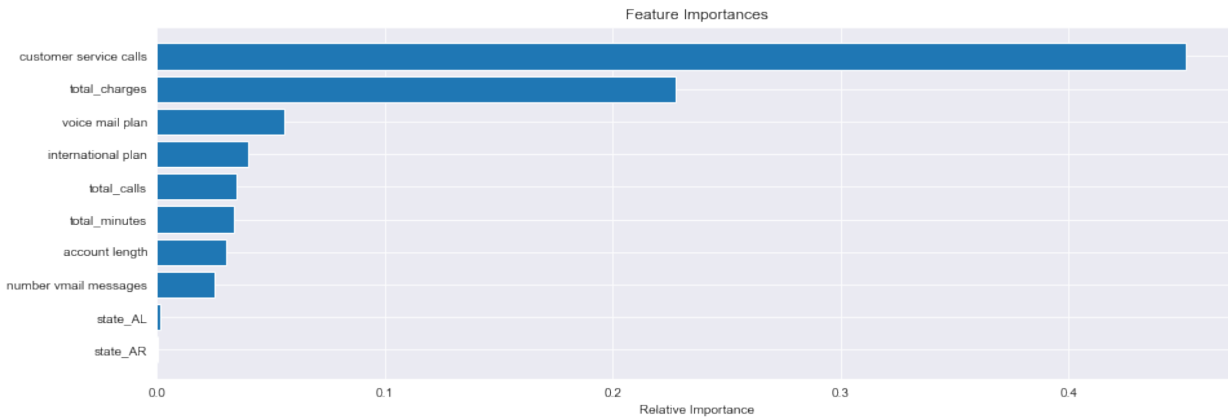
```
# Calculate the confusion matrix
cm = confusion_matrix(y_test, y_pred)

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

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

Accuracy:0.88

Classfication Report:
              precision    recall  f1-score   support

         0.0       0.95      0.91      0.93       709
         1.0       0.59      0.75      0.66       125

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


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



Classification report of Decision Tree in summary:

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

```
#Feature Importance in the Decision Tree

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

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



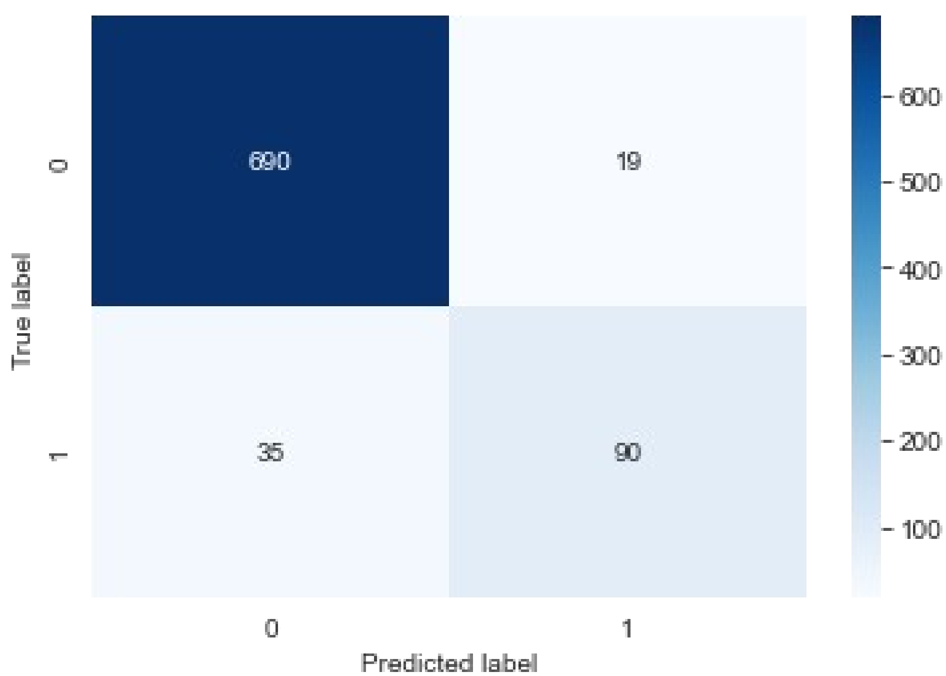
4.4 Random Tree Classifier

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

```
RandomForestClassifier(random_state=42)
```

```
#predict on the test data
y_pred_rf = rf.predict(X_test)
```

```
#rf confusion matrix

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



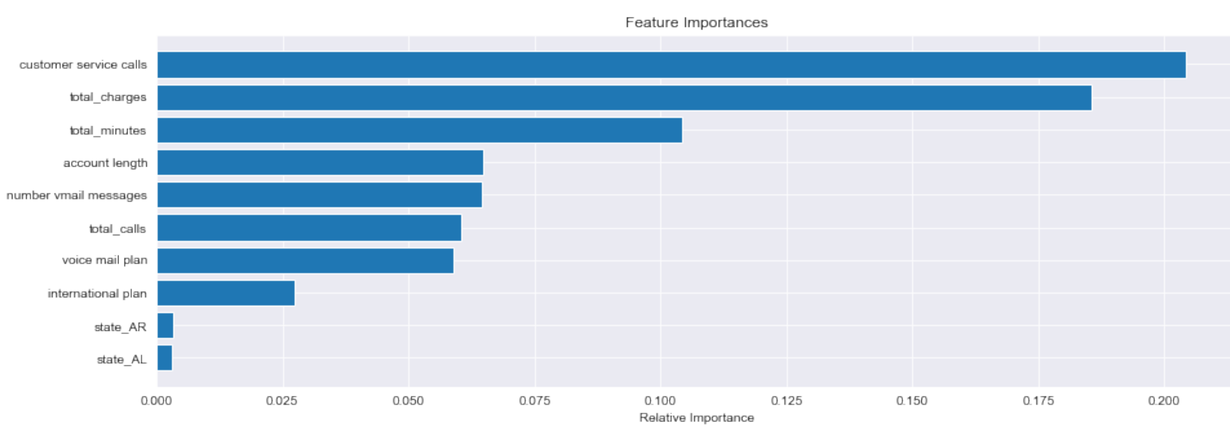
```python
print(classification_report(y_test, y_pred_rf))
```

```
              precision    recall  f1-score   support

         0.0       0.95      0.97      0.96       709
         1.0       0.83      0.72      0.77       125

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

Classification report of Random Tree Classsifier in summary:

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

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

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



5. EVALUATION

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

5.1 Recall Score

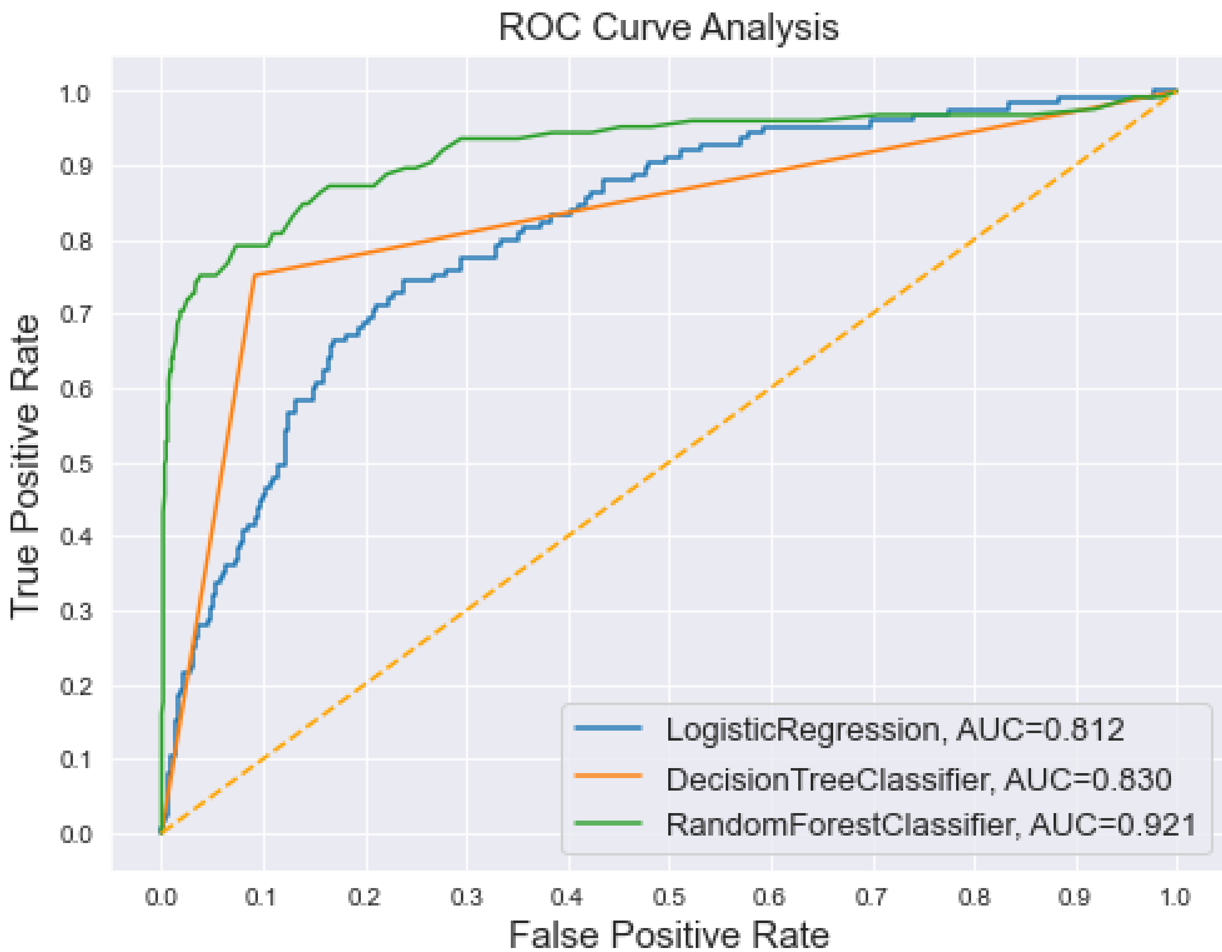
This is a measure of how many positive instances the model correctly indetifies. The higher the recall score the better the model.

```
np.random.seed(42)

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

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

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

    recall = recall_score(y_test, y_pred)

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

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

result_table
```

	recall
classifiers	
LogisticRegression	0.720
DecisionTreeClassifier	0.752
RandomForestClassifier	0.720

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

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

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

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

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

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

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

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

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

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

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

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

plt.show()
```



- The ROC curve shows that the RandomForestClassifier has the best performance among our three models with a score of 0.921 and LogisticRgression with the lowest performance with a score of 0.812.
- The ROC curve essential show us the trade-off between the (TPR) true positive rate and (FPR) false positive rate for our binary classifiers.
- TPR = those positive instances correctly classified as such
- FPR = those negatives instances incorrectly classifies as positives

5.2 Model Tuning

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

```
#Tuning RandomForestClassification

#Define the grid
param_grid = {
```

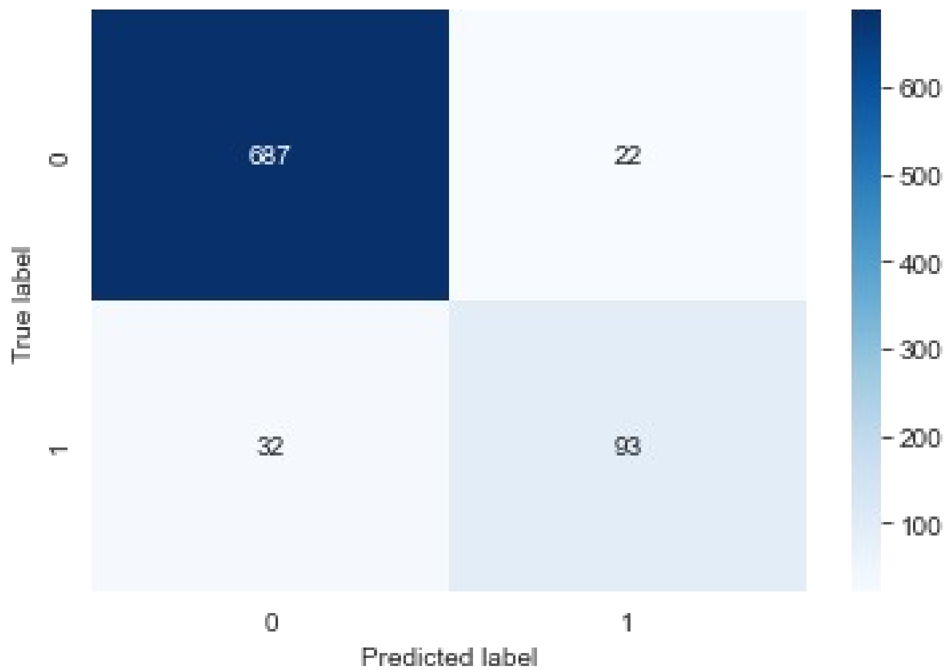
```
    "n_estimators": [50, 100],
    "max_depth": [15, 20, 35],
    "min_samples_split":[5, 10, 15],
    "min_samples_leaf":[2, 4, 10],
    "criterion":['entropy','gini']
}

#Create a RandomForestClassifier instance
rf_classifier = RandomForestClassifier(random_state=42)
grid_search = GridSearchCV(estimator=rf_classifier,
param_grid=param_grid, scoring="recall", cv=5, n_jobs=-1)
grid_search.fit(resampled_X_train, resampled_y_train)
best_params = grid_search.best_params_
best_rf_classifier = grid_search.best_estimator_
#Evaluate
y_pred_grid = best_rf_classifier.predict(X_test)
#Display the best parameters
print("Best Parameters:", best_params)

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

```
Best Parameters: {'criterion': 'entropy', 'max_depth': 35,
'min_samples_leaf': 2, 'min_samples_split': 15, 'n_estimators': 100}

Classification Report:
              precision    recall  f1-score   support

         0.0       0.96      0.97      0.96       709
         1.0       0.81      0.74      0.78       125

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

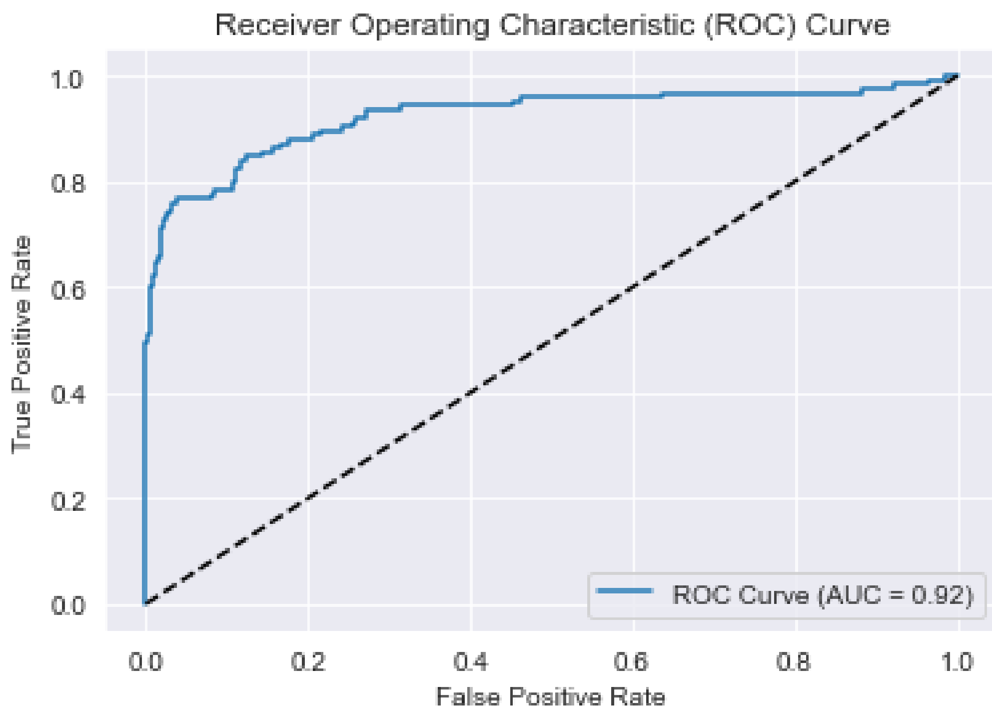
classification_report of RandomForestClassifier after tuning:

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

```
#Confusion matrix
plot_confusion_matrix(y_test, y_pred_grid,[0,1])
```




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

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

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

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



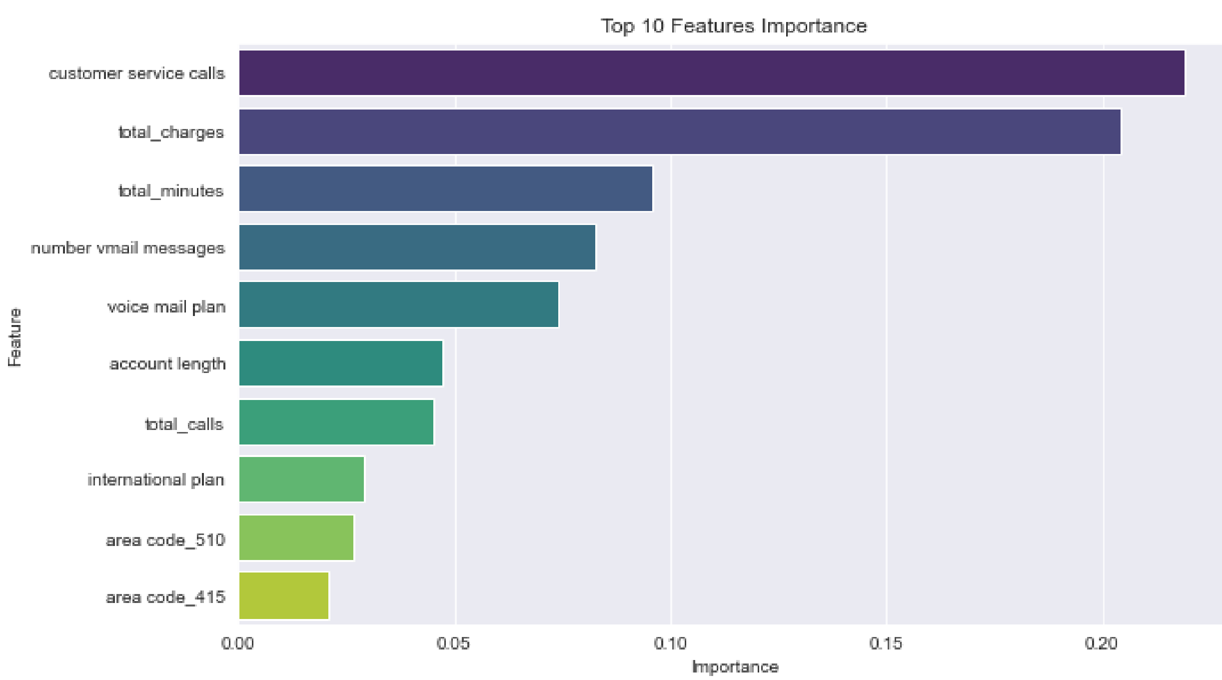
For 'Churn' predictions, recall is 74% indicating that the model identified 74% of the actual 'Churn' instances. This as close as to the 0.8 recall score we needed to make our model effective.

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

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

# Get feature importances
feature_importances = best_rf_classifier.feature_importances_

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

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

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

import matplotlib.pyplot as plt
import seaborn as sns

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

# Create a bar plot of the top 10 features
```

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

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

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

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



6. CONCLUSION

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

6.1 Reccomendations

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

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

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