# Final phase 03 Project Submission

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- Student pace: full time
- Dataset: SyriaTel Customer Churn
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# Executive summary

The project's objective is to utilize data analytics and machine learning methods to improve customer experiences and decrease churn for Syriatel, a top mobile network provider in Syria. In the competitive telecommunications sector, retaining current customers and ensuring their satisfaction are crucial for Syriatel's long-term success and growth. The goals of this project include:

- Determining whether customers are indeed leaving
- How can we best predict the amount of customers leaving
- How can this data assist Syriatel improve customer satisfaction

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# 1. Business understanding

## 1.1 About Syriatel

Syriatel (Arabic: سيريتل) is a leading mobile network provider in Syria, established in January 2000 with its headquarters in Damascus. It is one of the only two mobile service providers in the country, alongside MTN Syria. In 2022, Wafa Telecom was awarded the third telecom license by the Syrian telecommunications authority. Syriatel offers LTE services under the brand name Super Surf, providing speeds up to 150 Mb/s.

Initially, Syriatel operated under a Build-Own-Transfer (BOT) contract for 15 years, with management provided by Orascom. In 2017, the company introduced 4G services. On June 5, 2020, a Syrian court placed Syriatel under judicial custody.

## 1.2 Stakeholders

- **Customers:** Existing customers are directly affected by the company's efforts to reduce churn, which often lead to improved services, better customer support, and enhanced loyalty programs. Customers who experience better service are less likely to leave
- **Management:** Responsible for strategic decision-making, they are directly impacted by customer churn as it affects the company's revenue, profitability, and market position. High churn rates can indicate issues with customer satisfaction or service quality, prompting them to implement corrective measures
- **Employees:** Job security and career growth for employees can be affected by churn. If high churn rates lead to financial losses, it might result in cost-cutting measures, including layoffs or reduced resources for employee development

## 1.3 Business Problem

Customer churn or attrition, is where customers stop doing business with a company or service provider over a given period.For Syriatel, customer churn happens when subscribers cancel their services or switch to a competitor. High churn rates can significantly impact the company's revenue and growth, making it crucial for businesses to implement strategies to reduce churn and retain customers.

Churn can be categorized into two types:

1. **Voluntary Churn:** This occurs when customers choose to leave a service on their own, often due to dissatisfaction with the service quality, better offers from competitors, or changes in their personal needs.

2. **Involuntary Churn:** This happens when the company terminates the customer's service, often due to non-payment or breaches of contract terms.

Understanding and addressing the factors contributing to churn is essential for Syriatel to maintain a stable customer base and ensure long-term success.

## 1.4 Objectives

- Understand what is causing churn
- Predict church
- Mitigate churn

# 2. Data Understanding

```
#Imports
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objs as go

from imblearn.over_sampling import SMOTE
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.preprocessing import LabelEncoder
from imblearn.pipeline import Pipeline
from sklearn.dummy import DummyClassifier
from sklearn.model_selection import train_test_split, cross_val_score,
GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import MinMaxScaler
from sklearn.compose import ColumnTransformer

from sklearn.metrics import confusion_matrix, plot_confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import precision_score, recall_score,
accuracy_score, f1_score, log_loss
from sklearn.metrics import roc_curve, roc_auc_score

import pickle

# Loading Dataset
df = pd.read_csv('bigml_59c28831336c6604c800002a.csv')

df.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]

# Checking for information on data types and column names
df.info()
```

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

```python
#Checking data shape
df.shape
```

```
(3333, 21)
```

```python
# Checking dataset using descriptive statistics
df.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
```

```
# Checking for missing values
df.isna().sum()
```

```
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
```

```
# Checking for duplicate values
df.duplicated().sum()
```

```
0
```

## 2.1 Data Cleaning

```
def data_cleaning(df):
    missing = df.isna().sum().sum()
    duplicates = df.duplicated().sum()
    return (f"There are {missing} missing values and {duplicates}
duplicated values in the dataset")

data_cleaning(df)
```

```
'There are 0 missing values and 0 duplicated values in the dataset'
```

```
#Dropping Phone number column as it is not useful
df.drop('phone number', axis=1, inplace=True)
```

```
# Checking that the column it's dropped.
df.columns
```

```
Index(['state', 'account length', 'area code', 'international plan',
       'voice mail plan', 'number vmail messages', 'total day
minutes',
       'total day calls', 'total day charge', 'total eve minutes',
       'total eve calls', 'total eve charge', 'total night minutes',
       'total night calls', 'total night charge', 'total intl
minutes',
       'total intl calls', 'total intl charge', 'customer service
calls',
       'churn'],
      dtype='object')
```

# 3. EDA

## 3.1 Univariate analysis

### Distribution of Churn

```
# Plotting the target variable distribution
class_counts = df.groupby("churn").size()

fig = go.Figure(
    data=[go.Bar(x=class_counts.index, y=class_counts.values)],
    layout=go.Layout(title="Churn Distribution",
xaxis=dict(tickvals=[0, 1], ticktext=["Not Churn", "Churn"]),
          hovermode = 'closest',width=600)
)

# Show the chart
fig.show()
```


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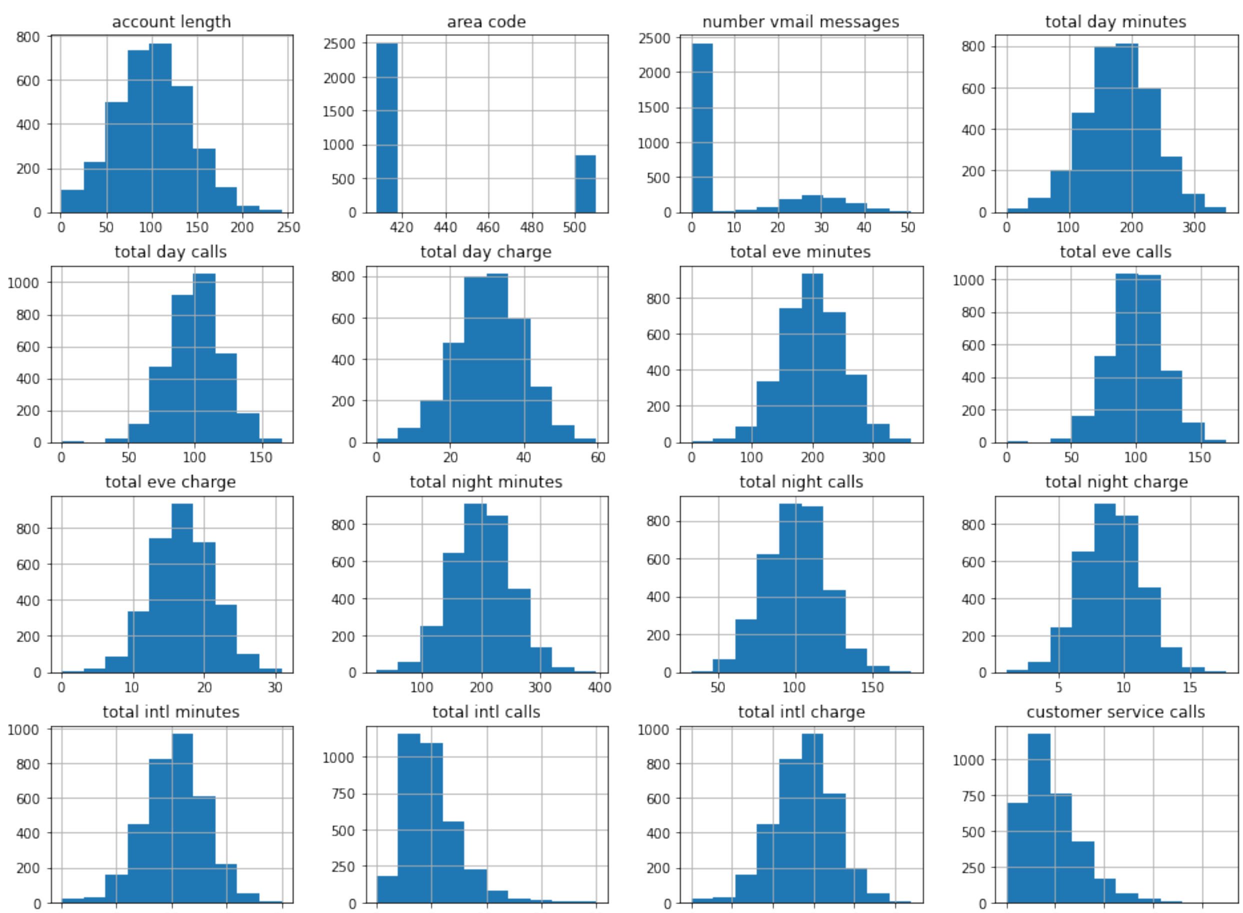
```

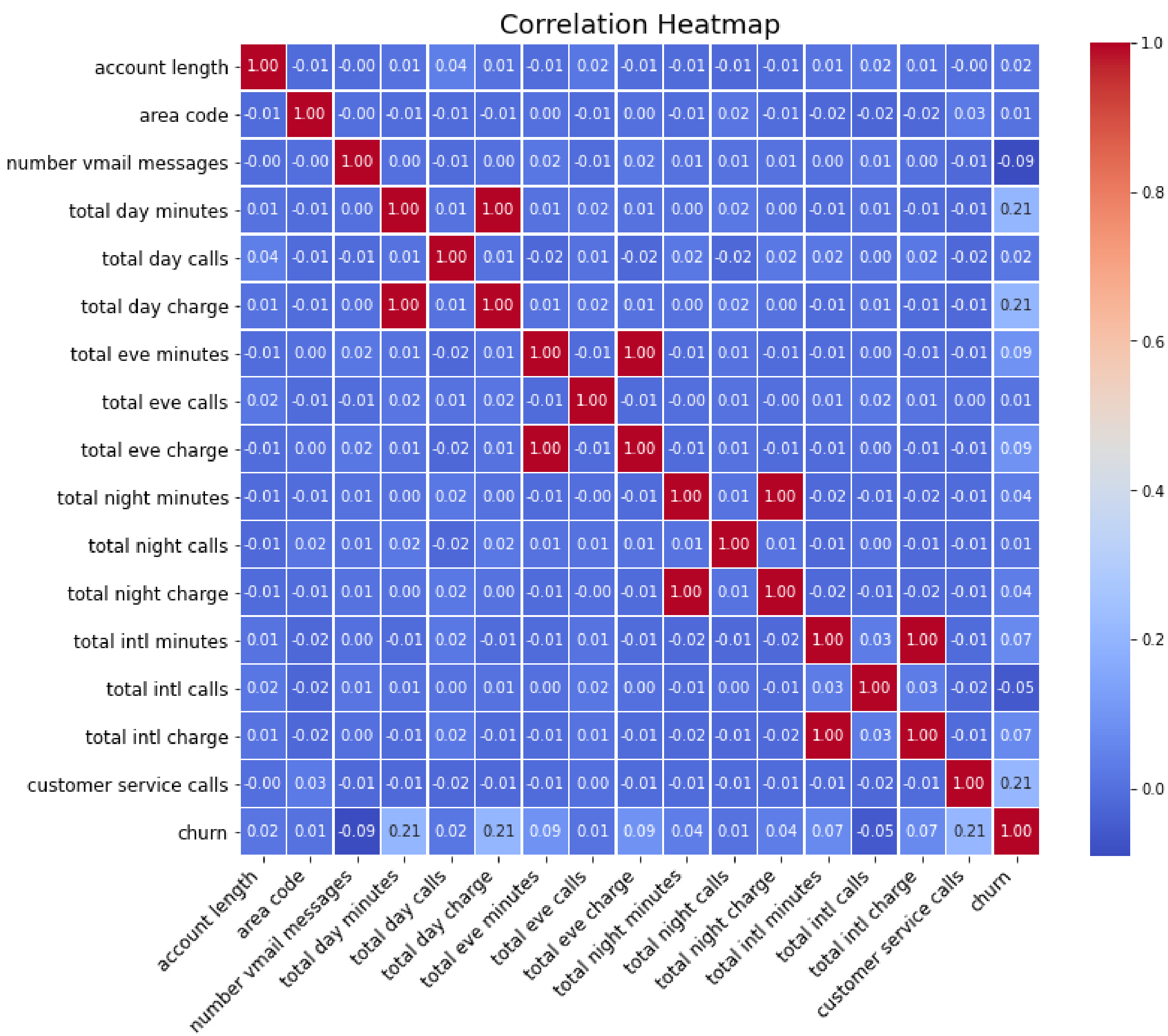

## Distribution of each predictor column

```
pd.plotting.hist_frame(df.drop('churn',axis=1),figsize=(16,12));
```



## 3.2 Bivariate analysis

```python
# Correlation matrix
corr_matrix = df.corr()

plt.figure(figsize=(12, 10))

sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap='coolwarm',
linewidths=0.5)

plt.title('Correlation Heatmap', fontsize=18)
plt.xticks(rotation=45, ha='right', fontsize=12)
plt.yticks(rotation=0, fontsize=12)

plt.show()
```



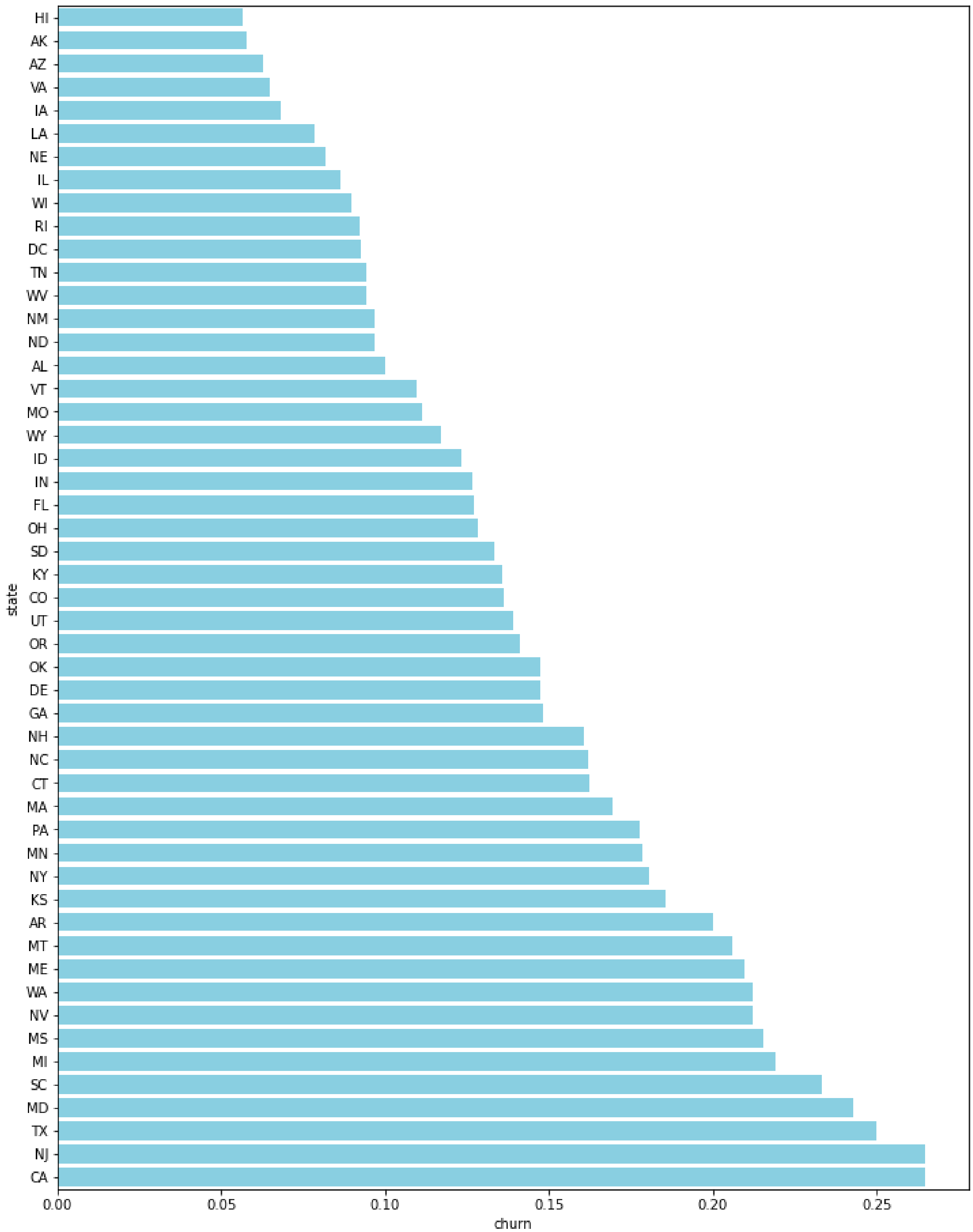
The majority of features do not show strong correlations, but some demonstrate perfect correlations:

- The features "Total day charge" and "total day minutes" are fully positively correlated.
- The features "Total eve charge" and "total eve minutes" are fully positively correlated.
- The features "Total night charge" and "total night minutes" are fully positively correlated.
- The features "Total int charge" and "total int minutes" are fully positively correlated.

This perfect correlation can be explained by the direct influence of minutes used on the charge.

## Comparing the churn rates for each state

```
states = df.groupby('state').churn.agg(np.mean)
states.sort_values(ascending=True, inplace=True)
fig,ax = plt.subplots(figsize=(12,16))
sns.barplot(x=states,y=states.index,ax=ax,color='#7ad7f0');
```



HI
AK
AZ
VA
IA
LA
NE
IL
WI
RI
DC
TN
WV
NM
ND
AL
VT
MO
WY
ID
IN
FL
OH
SD
KY
CO
UT
OR
OK
DE
GA
NH
NC
CT
MA
PA
MN
NY
KS
AR
MT
ME
WA
NV
MS
MI
SC
MD
TX
NJ
CA
state
0.00
0.05
0.10
0.15
0.20
0.25
churn

## International plan correlated to churn

```
print(df.groupby('international plan')['churn'].agg(np.mean))
print(df.groupby('international plan')['churn'].agg(np.std))
```

```
international plan
no     0.114950
yes    0.424149
Name: churn, dtype: float64
international plan
no     0.319015
yes    0.494980
Name: churn, dtype: float64
```

## Voice mail plan correlated to churn

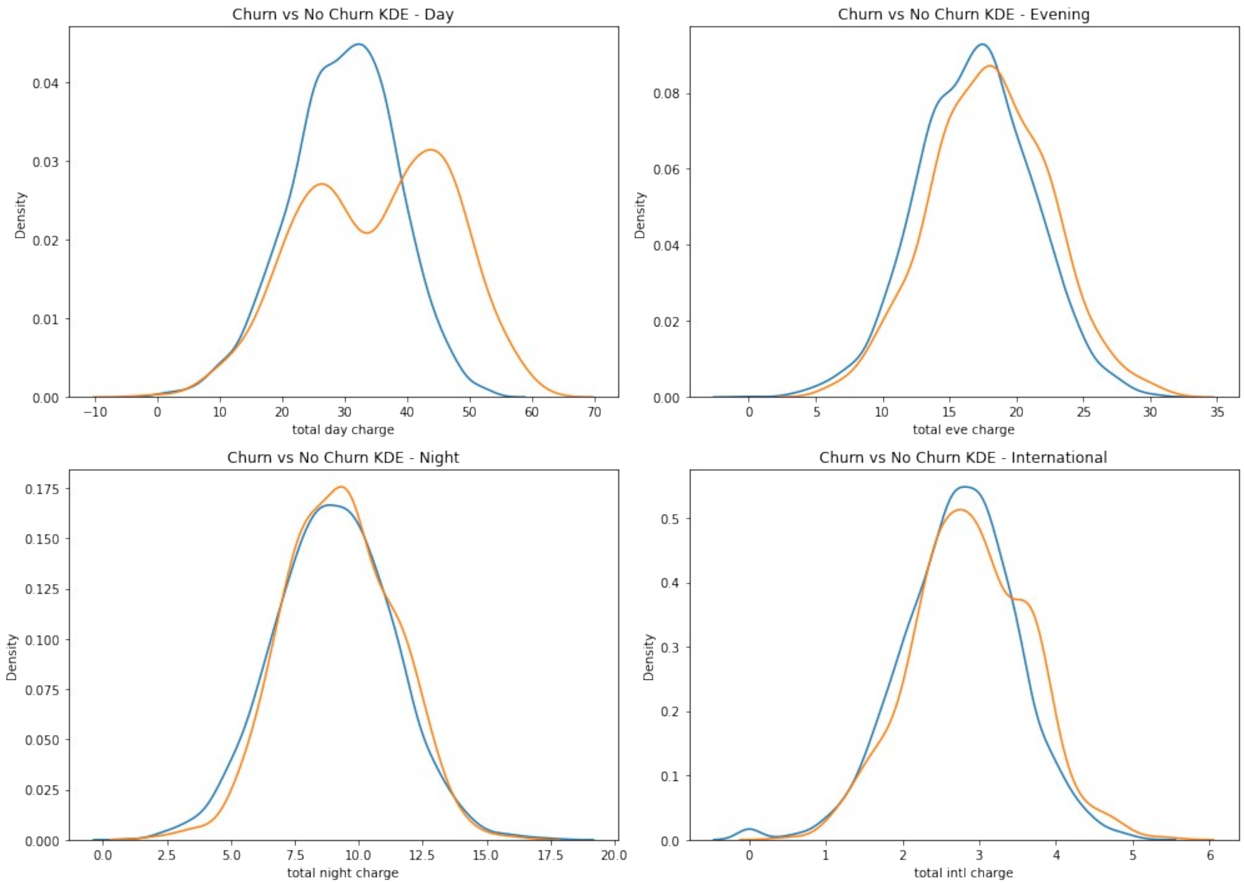
```
print(df.groupby('voice mail plan')['churn'].agg(np.mean))
print(df.groupby('voice mail plan')['churn'].agg(np.std))
```

```
voice mail plan
no     0.167151
yes    0.086768
Name: churn, dtype: float64
voice mail plan
no     0.373188
yes    0.281647
Name: churn, dtype: float64
```

## Churn by charges

```
def plot_churn_kde(data, feature, label, ax):
    """Plot KDE for churn vs non-churn for a given feature."""
    sns.kdeplot(data[data['churn'] == False][feature], label=f'No Churn - {label}', ax=ax)
    sns.kdeplot(data[data['churn'] == True][feature], label=f'Churn - {label}', ax=ax)
    ax.set_title(f'Churn vs No Churn KDE - {label}')
    ax.set_xlabel(feature)
    ax.set_ylabel('Density')

# Create a figure with multiple subplots
fig, axs = plt.subplots(2, 2, figsize=(14, 10))

# Plot each feature in a different subplot
plot_churn_kde(df, 'total day charge', 'Day', axs[0, 0])
plot_churn_kde(df, 'total eve charge', 'Evening', axs[0, 1])
plot_churn_kde(df, 'total night charge', 'Night', axs[1, 0])
plot_churn_kde(df, 'total intl charge', 'International', axs[1, 1])

# Adjust layout
```

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




All these show that the higher the charger the higher the churn

# 3.3 Encoding

## 3.3.1 Label encoding

```
label_encoder = LabelEncoder()

for column in df.columns:
    if df[column].dtype == object and set(df[column].unique()) == 
{'yes', 'no'}:
        df[column] = label_encoder.fit_transform(df[column])

print("\nEncoded DataFrame:")
print(df)


Encoded DataFrame:
     state  account length  area code  international plan  voice mail 
plan  \
```

```
0       KS             128        415                    0
1
1       OH             107        415                    0
1
2       NJ             137        415                    0
0
3       OH              84        408                    1
0
4       OK              75        415                    1
0
...    ...             ...        ...                  ...
...
3328    AZ             192        415                    0
1
3329    WV              68        415                    0
0
3330    RI              28        510                    0
0
3331    CT             184        510                    1
0
3332    TN              74        415                    0
1

      number vmail messages  total day minutes  total day calls  \
0                        25              265.1              110
1                        26              161.6              123
2                         0              243.4              114
3                         0              299.4               71
4                         0              166.7              113
...                     ...                ...              ...
3328                     36              156.2               77
3329                      0              231.1               57
3330                      0              180.8              109
3331                      0              213.8              105
3332                     25              234.4              113

      total day charge  total eve minutes  total eve calls  total eve
charge  \
0                45.07              197.4               99
16.78
1                27.47              195.5              103
16.62
2                41.38              121.2              110
10.30
3                50.90               61.9               88
5.26
4                28.34              148.3              122
12.61
...                ...                ...              ...
```

```
...
3328              26.55              215.5              126
18.32
3329              39.29              153.4               55
13.04
3330              30.74              288.8               58
24.55
3331              36.35              159.6               84
13.57
3332              39.85              265.9               82
22.60

      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
...                   ...                ...                 ...
3328                279.1                 83               12.56
3329                191.3                123                8.61
3330                191.9                 91                8.64
3331                139.2                137                6.26
3332                241.4                 77               10.86

      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
...                  ...               ...                ...
3328                 9.9                 6               2.67
3329                 9.6                 4               2.59
3330                14.1                 6               3.81
3331                 5.0                10               1.35
3332                13.7                 4               3.70

      customer service calls  churn
0                          1  False
1                          1  False
2                          0  False
3                          2  False
4                          3  False
...                      ...    ...
3328                       2  False
3329                       3  False
3330                       2  False
3331                       2  False
3332                       0  False
```

```
[3333 rows x 20 columns]
```

### 3.3.2 One-Hot encoding

```
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(sparse=False, drop='first'),
categorical_columns)
    ],
    remainder='passthrough'
)

X_transformed = preprocessor.fit_transform(X)

scaler = MinMaxScaler()

def scaling(columns):
    return scaler.fit_transform(df[columns].values.reshape(-1,1))

for i in df.select_dtypes(include=[np.number]).columns:
    df[i] = scaling(i)
df.head()
```

```
  state  account length  area code  international plan  voice mail
plan  \
0    KS        0.524793   0.068627                 0.0
1.0
1    OH        0.438017   0.068627                 0.0
1.0
2    NJ        0.561983   0.068627                 0.0
0.0
3    OH        0.342975   0.000000                 1.0
0.0
4    OK        0.305785   0.068627                 1.0
0.0

   number vmail messages  total day minutes  total day calls  \
0               0.490196           0.755701         0.666667
1               0.509804           0.460661         0.745455
2               0.000000           0.693843         0.690909
3               0.000000           0.853478         0.430303
4               0.000000           0.475200         0.684848

   total day charge  total eve minutes  total eve calls  total eve
charge  \
0          0.755701           0.542755         0.582353
0.542866
1          0.460597           0.537531         0.605882
0.537690
```

```
2          0.693830          0.333242         0.647059
0.333225
3          0.853454          0.170195         0.517647
0.170171
4          0.475184          0.407754         0.717647
0.407959

   total night minutes  total night calls  total night charge  \
0             0.595750           0.408451            0.595935
1             0.621840           0.492958            0.622236
2             0.374933           0.500000            0.375374
3             0.467187           0.394366            0.467424
4             0.440290           0.619718            0.440526

   total intl minutes  total intl calls  total intl charge  \
0               0.500              0.15           0.500000
1               0.685              0.15           0.685185
2               0.610              0.25           0.609259
3               0.330              0.35           0.329630
4               0.505              0.15           0.505556

   customer service calls  churn
0                0.111111  False
1                0.111111  False
2                0.000000  False
3                0.222222  False
4                0.333333  False
```

# 4. Modeling

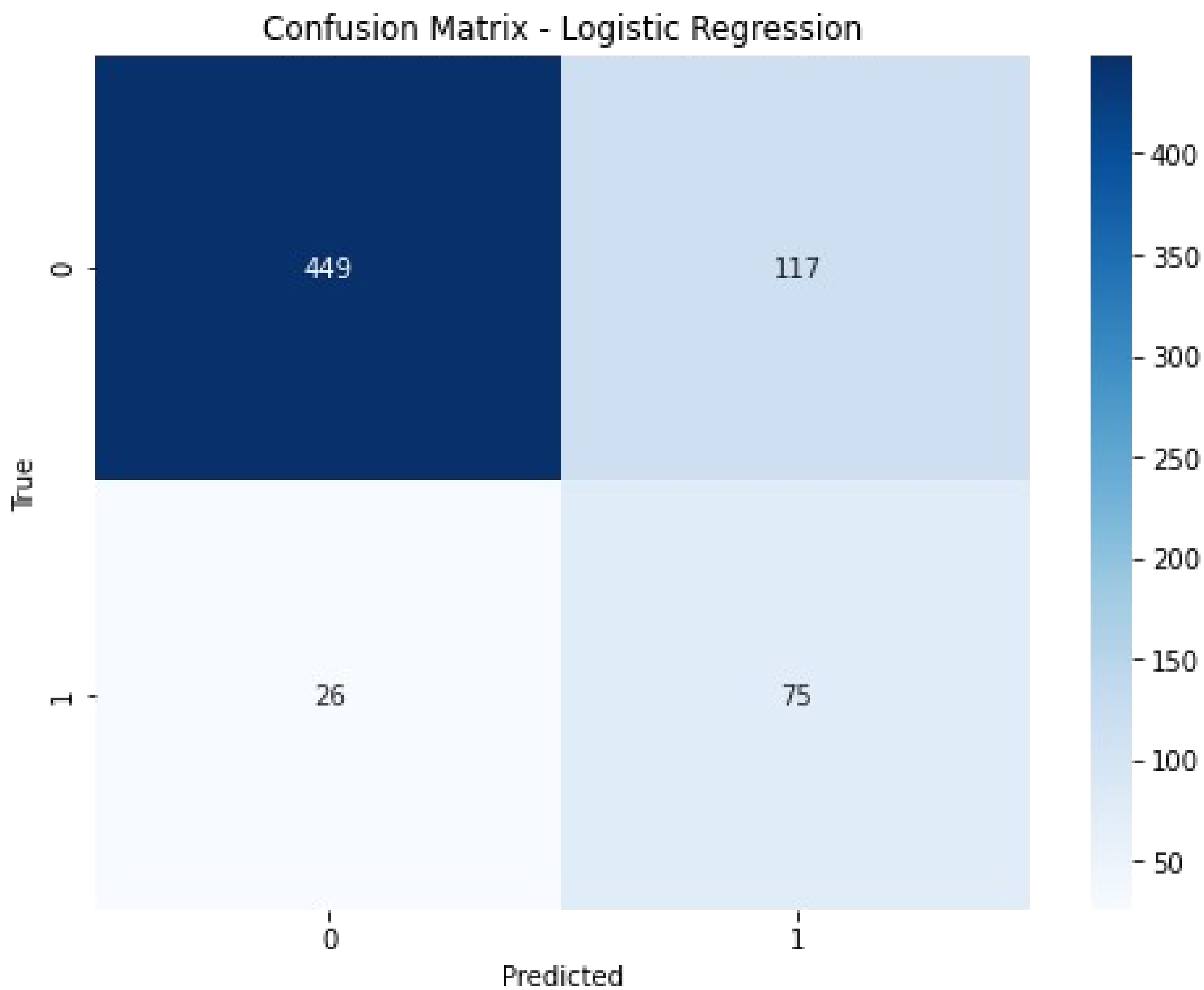
## 4.1 Base modeling

```
#Defining X and y
X = df.drop("churn", axis=1)
y = df["churn"]

# Performing a test split for the data
X_train, X_test, y_train, y_test = train_test_split(X_transformed, y,
test_size=0.2, random_state=42)

sm = SMOTE(random_state=42)
X_train_resample, y_train_resample = sm.fit_resample(X_train, y_train)
```

## 4.2 Logistic Regression

```
logreg = LogisticRegression(random_state=110)
logreg.fit(X_train_resample, y_train_resample)
y_pred_log = logreg.predict(X_test)

accuracy = accuracy_score(y_test, y_pred_log)
precision = precision_score(y_test, y_pred_log, average='binary')
recall = recall_score(y_test, y_pred_log, average='binary')
f1 = f1_score(y_test, y_pred_log, average='binary')

print('Logistic Regression:')
print('Accuracy:', accuracy)
print('Precision:', precision)
print('Recall:', recall)
print('F1 Score:', f1)

cm = confusion_matrix(y_test, y_pred_log)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, cmap='Blues', fmt='d')
plt.title('Confusion Matrix - Logistic Regression')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```

```
Logistic Regression:
Accuracy: 0.7856071964017991
Precision: 0.390625
Recall: 0.7425742574257426
F1 Score: 0.5119453924914675
```

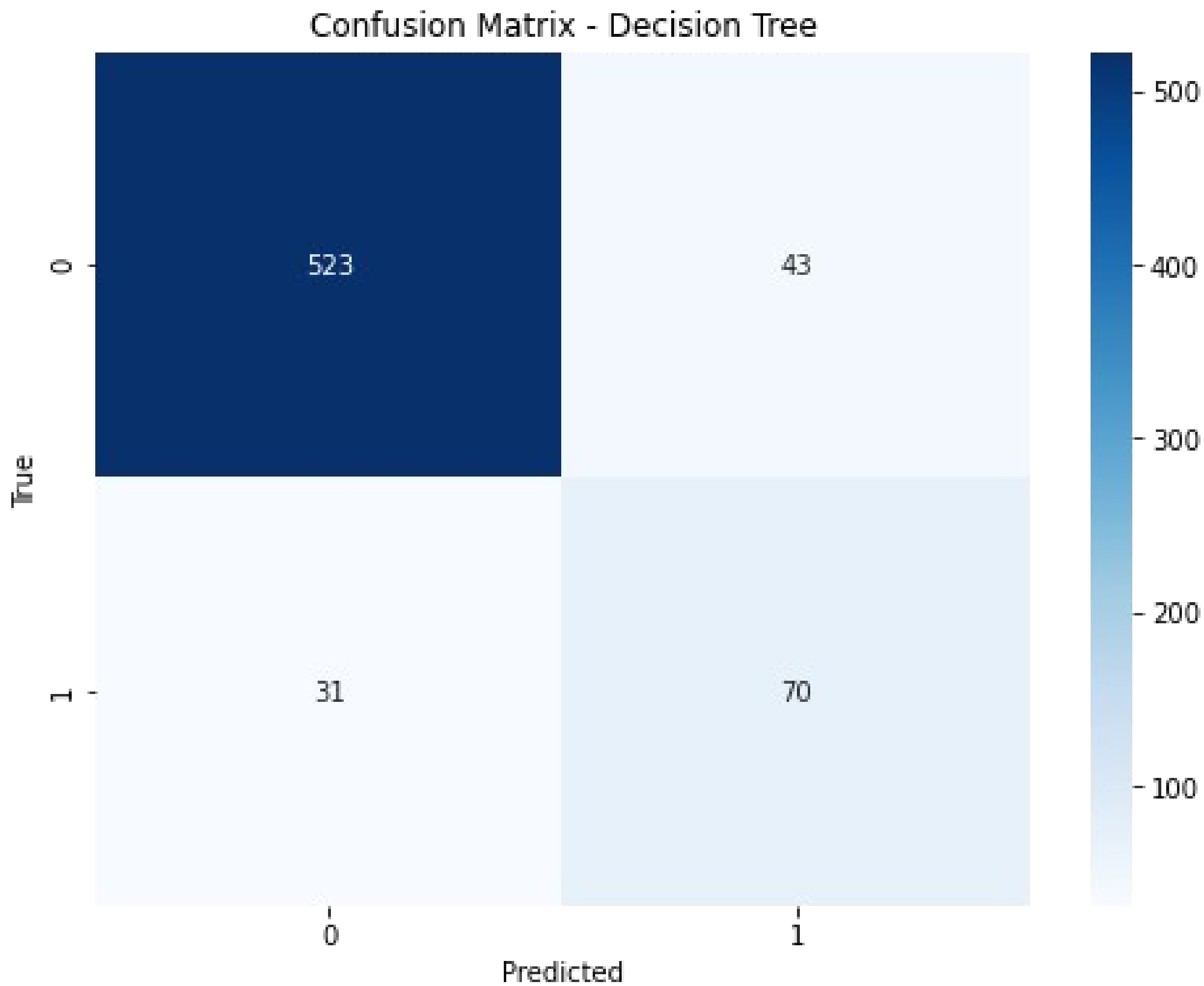



## 4.3 Decision Tree

```
# Decision tree model classifier
dt = DecisionTreeClassifier(random_state=110)
dt.fit(X_train_resample, y_train_resample)
y_pred_dt = dt.predict(X_test)

accuracy = accuracy_score(y_test, y_pred_dt)
precision = precision_score(y_test, y_pred_dt)
recall = recall_score(y_test, y_pred_dt)
f1 = f1_score(y_test, y_pred_dt)

print('Decision Tree:')
print('Accuracy:', accuracy)
print('Precision:', precision)
print('Recall:', recall)
print('F1 Score:', f1)

cm = confusion_matrix(y_test, y_pred_dt)
```

```
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, cmap='Blues', fmt='d')
plt.title('Confusion Matrix - Decision Tree')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```

```
Decision Tree:
Accuracy: 0.889055472263868
Precision: 0.6194690265486725
Recall: 0.693069306930693
F1 Score: 0.6542056074766355
```

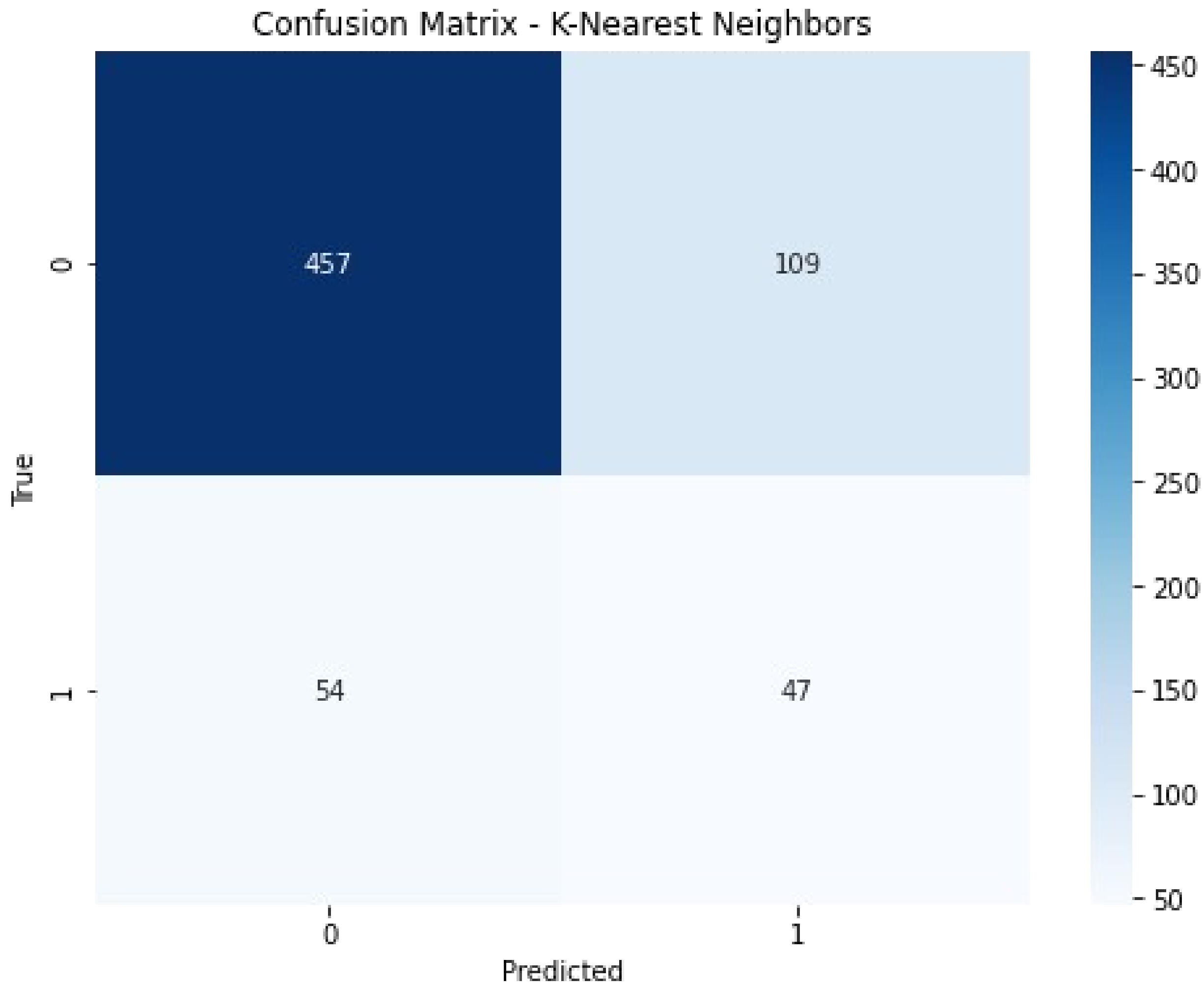



## 4.4 K-nearest neighbors

```
# KNN classifier
knn = KNeighborsClassifier(n_neighbors=5)
```

```
knn.fit(X_train_resample, y_train_resample)
y_pred_knn = knn.predict(X_test)

accuracy = accuracy_score(y_test, y_pred_knn)
precision = precision_score(y_test, y_pred_knn)
recall = recall_score(y_test, y_pred_knn)
f1 = f1_score(y_test, y_pred_knn)

print('K-Nearest Neighbors:')
print('Accuracy:', accuracy)
print('Precision:', precision)
print('Recall:', recall)
print('F1 Score:', f1)

cm = confusion_matrix(y_test, y_pred_knn)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, cmap='Blues', fmt='d')
plt.title('Confusion Matrix - K-Nearest Neighbors')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```

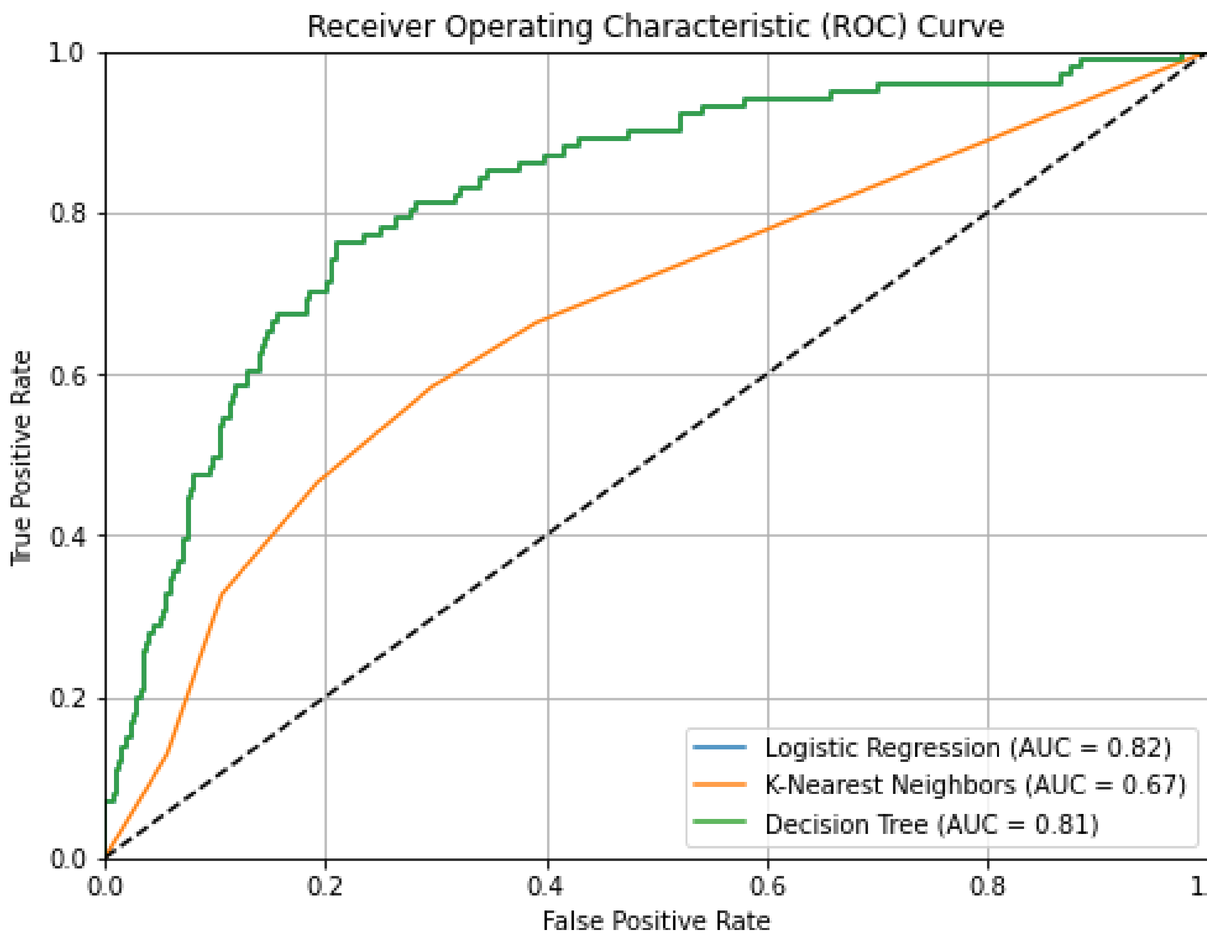
```
K-Nearest Neighbors:
Accuracy: 0.7556221889055472
Precision: 0.30128205128205127
Recall: 0.46534653465346537
F1 Score: 0.3657587548638132
```




## 4.5 ROC curve

```
# Logistic Regression
logreg_proba = logreg.predict_proba(X_test)[:, 1]
logreg_fpr, logreg_tpr, _ = roc_curve(y_test, logreg_proba)
logreg_auc = roc_auc_score(y_test, logreg_proba)

# Decision Tree
dt_proba = dt.predict_proba(X_test)[:, 1]
dt_fpr, dt_tpr, _ = roc_curve(y_test, logreg_proba)
dt_auc = roc_auc_score(y_test, dt_proba)
# KNN
knn_proba = knn.predict_proba(X_test)[:, 1]
knn_fpr, knn_tpr, _ = roc_curve(y_test, knn_proba)
knn_auc = roc_auc_score(y_test, knn_proba)

plt.figure(figsize=(8, 6))
plt.plot(logreg_fpr, logreg_tpr, label='Logistic Regression (AUC =
{:.2f})'.format(logreg_auc))
```

```
plt.plot(knn_fpr, knn_tpr, label='K-Nearest Neighbors (AUC =
{:.2f})'.format(knn_auc))
plt.plot(dt_fpr, dt_tpr, label='Decision Tree (AUC =
{:.2f})'.format(dt_auc))
plt.plot([0, 1], [0, 1], 'k--')  # Random guessing line
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```




Out of one simple (logistic regression) the two complex models (KNN and Decision trees) Decision Trees is the best option to us as it is 89% accurate and has an ROC AUC socre f 81%

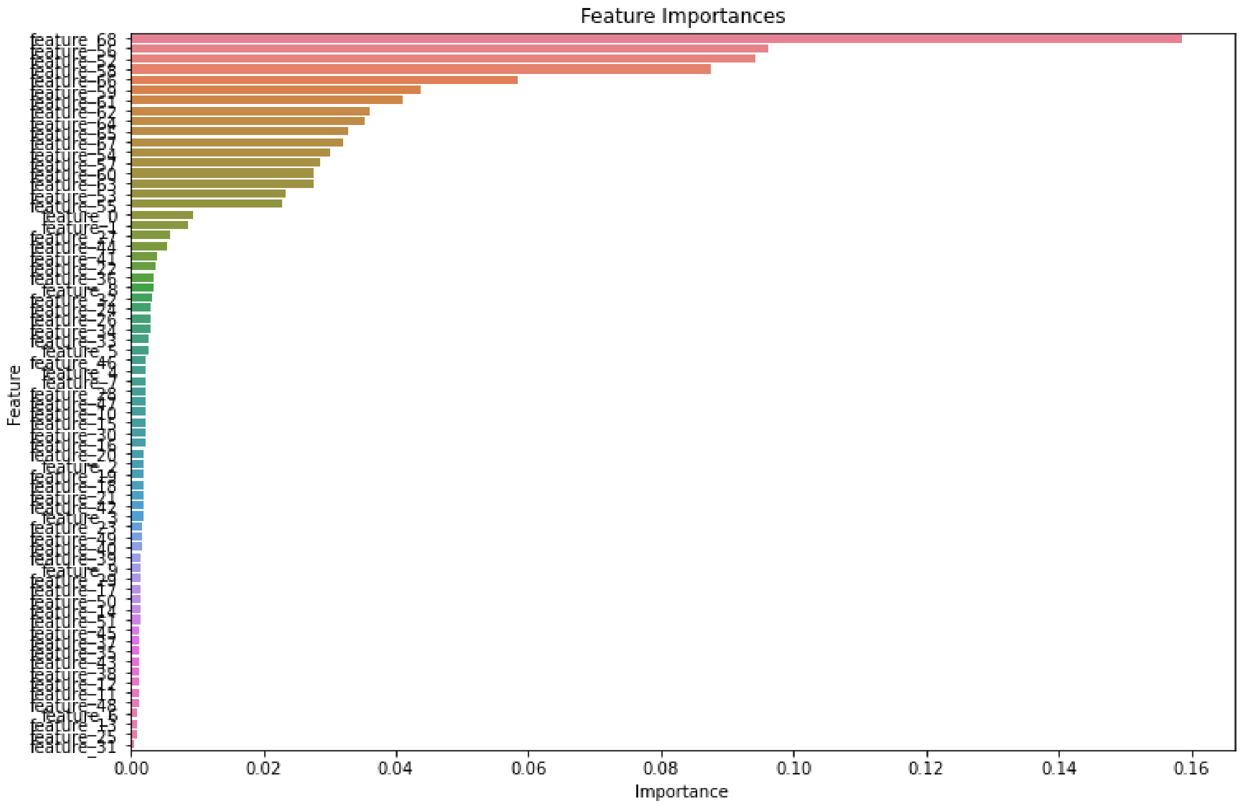
```
pipeline = Pipeline(steps=[('preprocessor', preprocessor),
                           ('classifier',
DecisionTreeClassifier(random_state=110))])
```

```
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 5, 10],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

dt_classifier = DecisionTreeClassifier()

grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5)
grid_search.fit(X_train_resample, y_train_resample)

best_params = grid_search.best_params_
best_score = grid_search.best_score_

print("Best Parameters:", best_params)
print("Best Score:", best_score)
```

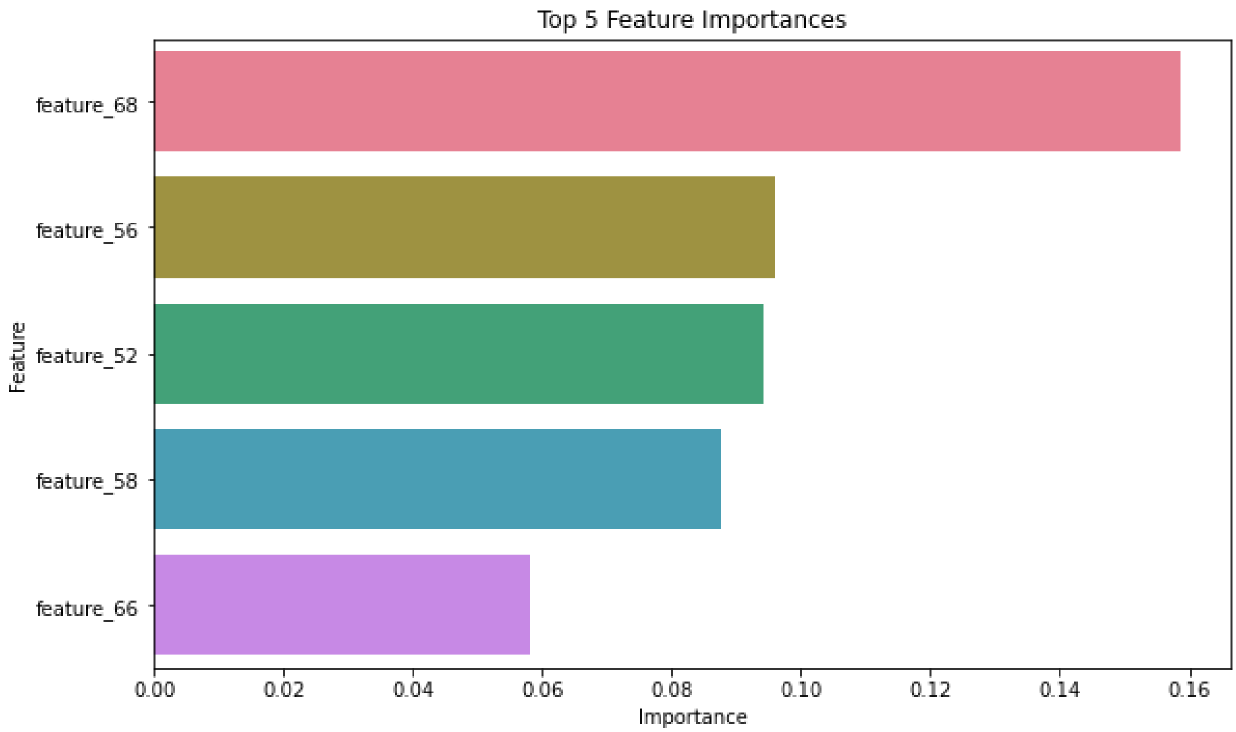
```
Best Parameters: {'max_depth': None, 'min_samples_leaf': 1,
'min_samples_split': 2, 'n_estimators': 300}
Best Score: 0.9441804616516594
```

## 4.6 Feature Importance (all features)

```
if isinstance(X_test, np.ndarray):
    feature_names = [f'column_{i}' for i in range(X_test.shape[1])]
    X_test = pd.DataFrame(X_test, columns=feature_names)
else:
    feature_names = X_test.columns

importances = grid_search.best_estimator_.feature_importances_

feature_importances = pd.DataFrame({'Feature': feature_names,
'Importance': importances})
feature_importances = feature_importances.sort_values('Importance',
ascending=False)

colors = sns.color_palette('husl', len(importances))

plt.figure(figsize=(12, 8))
sns.barplot(x='Importance', y='Feature', data=feature_importances,
palette = colors)
plt.title('Feature Importances')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
```




```
top_features = feature_importances.head(5)

colors = sns.color_palette('husl', len(top_features))

plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=top_features,
palette=colors)
plt.title('Top 5 Feature Importances')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
```




```
feature_index_mapping = {index: name for index, name in
enumerate(feature_names)}
print(feature_index_mapping)
```

```
{0: 'feature_0', 1: 'feature_1', 2: 'feature_2', 3: 'feature_3', 4:
'feature_4', 5: 'feature_5', 6: 'feature_6', 7: 'feature_7', 8:
'feature_8', 9: 'feature_9', 10: 'feature_10', 11: 'feature_11', 12:
'feature_12', 13: 'feature_13', 14: 'feature_14', 15: 'feature_15',
16: 'feature_16', 17: 'feature_17', 18: 'feature_18', 19:
'feature_19', 20: 'feature_20', 21: 'feature_21', 22: 'feature_22',
23: 'feature_23', 24: 'feature_24', 25: 'feature_25', 26:
'feature_26', 27: 'feature_27', 28: 'feature_28', 29: 'feature_29',
30: 'feature_30', 31: 'feature_31', 32: 'feature_32', 33:
'feature_33', 34: 'feature_34', 35: 'feature_35', 36: 'feature_36',
37: 'feature_37', 38: 'feature_38', 39: 'feature_39', 40:
'feature_40', 41: 'feature_41', 42: 'feature_42', 43: 'feature_43',
44: 'feature_44', 45: 'feature_45', 46: 'feature_46', 47:
'feature_47', 48: 'feature_48', 49: 'feature_49', 50: 'feature_50',
51: 'feature_51', 52: 'feature_52', 53: 'feature_53', 54:
'feature_54', 55: 'feature_55', 56: 'feature_56', 57: 'feature_57',
58: 'feature_58', 59: 'feature_59', 60: 'feature_60', 61:
'feature_61', 62: 'feature_62', 63: 'feature_63', 64: 'feature_64',
65: 'feature_65', 66: 'feature_66', 67: 'feature_67', 68:
'feature_68'}
```

Model saved for use later

```
filename = 'decision_tree_model.pkl'

with open(filename, 'wb') as file:
    pickle.dump(dt, file)

print(f"Model saved to {filename}")
```

```
Model saved to decision_tree_model.pkl
```

# 5. Evaluation & Recommendations

## 5.1 Churn prediction

The decision tree model is 89% accurate and which is a good predictor of Syriatel's customer churn

## 5.2 Churn Mitigation:

- Focus on lower charges as the higher the charge the higher the churn
- Provide lower rates for the states with higher churn rates
- Make international calls cheaper or use dynamic pricing to cater to those less willing to spend on calls

## 5.3 Other recommendations:

- Prioritize efforts to retain customers with high predicted churn probabilities.
- Provide tailored incentives and enhance service quality in identified weak areas.
- Ensure top-notch services for high-usage customers who contribute significantly to revenue.
- Expand voice mail plan availability based on its observed impact on churn reduction.
- Actively engage with customers through increased customer service calls to solicit feedback and implement suggestions, as evident by the observed reduction in churn with higher call frequencies.