PHASE 3 PROJECT

SYRIATEL CUSTOMER CHURN

Student: Lilian Ngige

Project Overview

The project aims at analysing SyriaTel data and building models that predict whether a customer will churn or not.

Business Problem

SyriaTel, a telecommunications company, is facing the challenge of customer churn. The company wants to predict whether a customer is likely to stop doing business with them in the near future. Reducing customer churn is essential for maintaining revenue and profitability.

Project Objective

Build a binary classification model to predict customer churn. The model will identify customers who are likely to churn, to enable SyriaTel to take proactive measures to retain them.

In [4]:

```
# Importing relevant libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.cm as cm
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.model_selection import GridSearchCV

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

In [5]:

```
# install imblearn library
!pip install imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in c:\users\dell\documents\llian dsf\env
s\learn-env\lib\site-packages (0.8.0)
Requirement already satisfied: numpy>=1.13.3 in c:\users\dell\documents\llian dsf\envs\l
earn-env\lib\site-packages (from imbalanced-learn) (1.18.5)
Requirement already satisfied: joblib>=0.11 in c:\users\dell\documents\llian dsf\envs\le
arn-env\lib\site-packages (from imbalanced-learn) (1.3.2)
Requirement already satisfied: scikit-learn>=0.24 in c:\users\dell\documents\llian dsf\e
nvs\learn-env\lib\site-packages (from imbalanced-learn) (1.3.1)
Requirement already satisfied: scipy>=0.19.1 in c:\users\dell\documents\llian dsf\envs\l
earn-env\lib\site-packages (from imbalanced-learn) (1.5.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\dell\documents\llian dsf
\envs\learn-env\lib\site-packages (from scikit-learn>=0.24->imbalanced-learn) (2.1.0)
```

Loading Data

In [8]:

```
df=pd.read_csv("C:/Users/Dell/Desktop/PHASE 3_Churn_Data _set/SyriaTel_data_set.csv")
```

Data understanding & Exploration

In [9]:
```
#  Exploring the first top rows of the data
df.head(5)
```

Out[9]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...	total eve calls	tc (char
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12

5 rows × 21 columns

In [11]:
```
# checking overview of the data
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
```

In [12]:
```
# checking for statistical summary of the data
df.describe()
```

Out[12]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	to
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.(
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	200.980348	100.
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50.713844	19.!
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.(
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166.600000	87.(
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201.400000	100.(
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235.300000	114.(
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363.700000	170.(

In [13]:

```
#Identifying the target variable
print(df['churn'].unique())
#Target variable = Churn
```

```
[False  True]
```

Data Preprocessing and Cleaning

In [14]:

```
#Getting count of missing values in the data
df.isna().sum()
```

Out[14]:

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

In [15]:

```
# finding the colleration of the features to target variable
correlation_matrix = df.corr()
target_correlation = correlation_matrix['churn'].abs().sort_values(ascending=False)
target_correlation
```

Out[15]:

```
churn                     1.000000
customer service calls    0.208750
total day minutes         0.205151
```

```
total day charge          0.205151
total eve minutes         0.092796
total eve charge          0.092786
number vmail messages     0.089728
total intl charge         0.068259
total intl minutes        0.068239
total intl calls          0.052844
total night charge        0.035496
total night minutes       0.035493
total day calls           0.018459
account length            0.016541
total eve calls           0.009233
area code                 0.006174
total night calls         0.006141
Name: churn, dtype: float64
```

Encoding of categorical variables

In [16]:

```
#Identify categorical columns
categorical_columns = df.select_dtypes(include=['object']).columns
# Display the list of categorical columns
print("Categorical Columns:")
print(categorical_columns)
```

```
Categorical Columns:
Index(['state', 'phone number', 'international plan', 'voice mail plan'], dtype='objec
t')
```

In [17]:

```
#Perform one-hot encoding for categorical variables
df= pd.get_dummies(df, columns=categorical_columns)
```

In [18]:

```
# Split the data into features (X) and the target variable (y)

X = df.drop('churn',axis=1)  # X contains all columns except 'churn'
y =df['churn']  # y is the 'churn' column
```

In [19]:

```
# split the data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=
```

In [20]:

```
# preview of X_train
X_train.head()
```

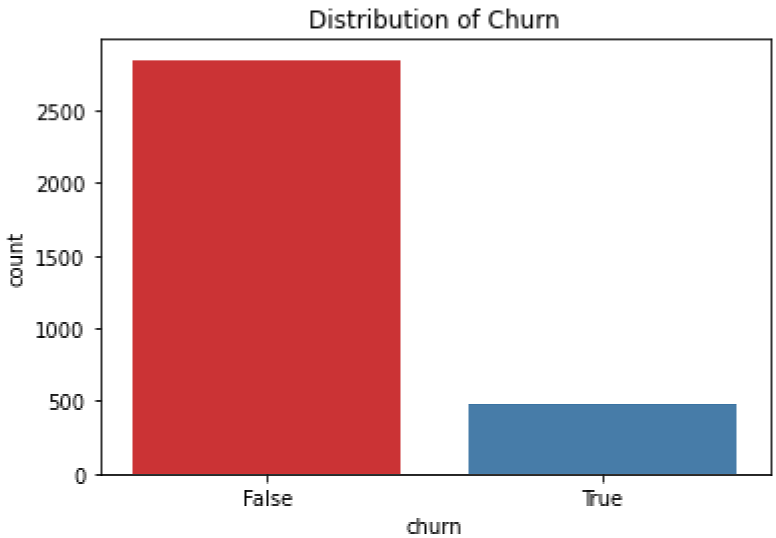
Out[20]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	total eve charge	total night minutes	...	phc number_4: 66
1066	117	510	25	216.0	140	36.72	224.1	69	19.05	267.9	...	
1553	86	415	0	217.8	93	37.03	214.7	95	18.25	228.7	...	
2628	37	415	0	221.0	126	37.57	204.5	110	17.38	118.0	...	
882	130	415	0	162.8	113	27.68	290.3	111	24.68	114.9	...	
984	77	415	0	142.3	112	24.19	306.3	111	26.04	196.5	...	

5 rows × 3404 columns

Exploratory data analysis

In [22]:
```
#Visualize the distribution of the target variable "churn"
plt.figure(figsize=(6, 4))
sns.countplot(df['churn'], palette='Set1')
plt.title("Distribution of Churn")
plt.show()
```



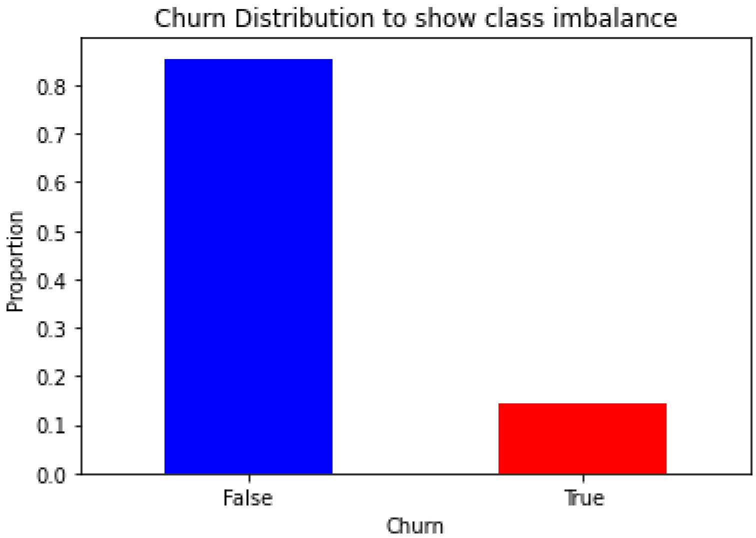
In [23]:
```
#Exploring the columns for Training_data
column_names = df.columns
#Target variable
#our target variable is churn
df['churn'].value_counts()
```

Out[23]:
```
False    2850
True      483
Name: churn, dtype: int64
```

In [24]:
```
df.churn.value_counts(normalize=True)
```

Out[24]:
```
False    0.855086
True     0.144914
Name: churn, dtype: float64
```

In [25]:
```
# Create a bar plot for the churn distribution
churn_counts = df['churn'].value_counts(normalize=True)
churn_counts.plot(kind='bar', color=['blue', 'red'])

# Set plot labels and title
plt.xlabel('Churn')
plt.ylabel('Proportion')
plt.title('Churn Distribution to show class imbalance')

# Set custom labels for the x-axis (True and False)
plt.xticks([0, 1], ['False', 'True'], rotation=0)

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



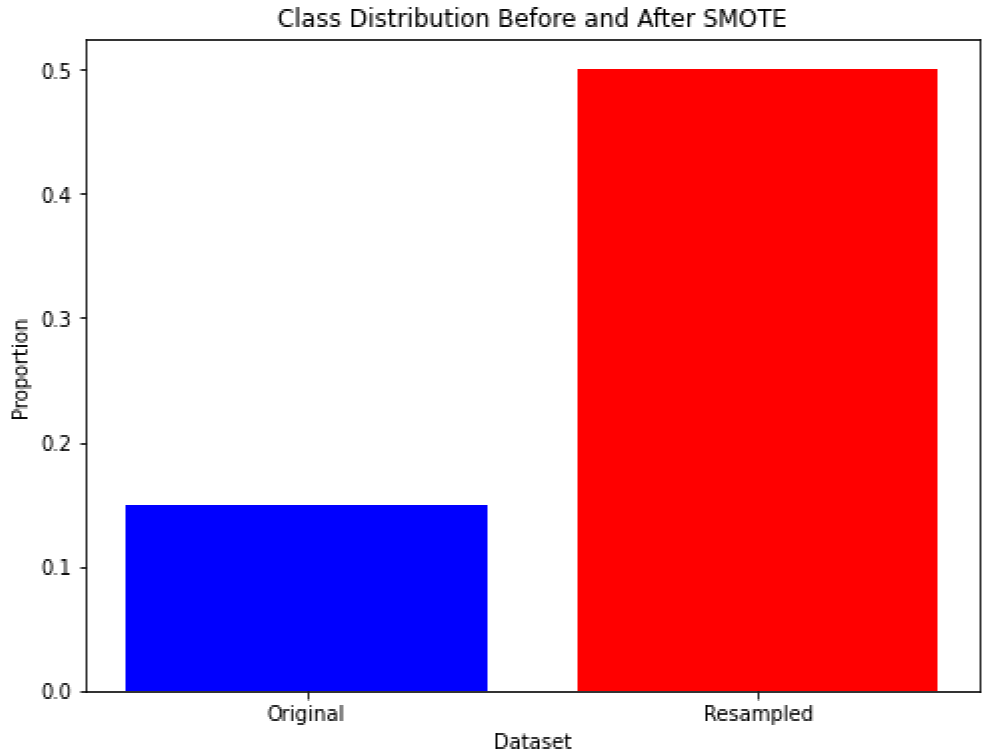
The data set contains 333 entries and 21 columns, with the target variable being churn. This dataset has some class imbalances that would have to be addressed during modeling.This is binary dataset, one class false takes up 86% of the dataset while false is only 14.4%.

In [27]:
```
#working on the class imbalance , import smote

from imblearn.over_sampling import SMOTE
oversample = SMOTE(k_neighbors=5)
X_smote, y_smote = oversample.fit_resample(X, y)
```

In [28]:
```
# Fit SMOTE to training data
smote = SMOTE(random_state=123)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)

# Preview synthetic sample class distribution
print(pd.Series(y_train_resampled).value_counts(normalize=True))
```

```
True     0.5
False    0.5
Name: churn, dtype: float64
```

In [29]:
```
# Calculate the class distribution after SMOTE
churn_counts_resampled = y_train_resampled.value_counts(normalize=True)
churn_counts_original = y_train.value_counts(normalize=True)

# Create a bar plot to compare the original and resampled class distributions
plt.figure(figsize=(8, 6))
plt.bar(['Original', 'Resampled'], [churn_counts_original[1], churn_counts_resampled[1]
plt.xlabel('Dataset')
plt.ylabel('Proportion')
plt.title('Class Distribution Before and After SMOTE')
plt.show()
```



In [30]:
```
# Split into training and test sets

X_train, X_test, y_train, y_test = train_test_split(X_smote,y_smote, test_size=0.25, ra
# Preview synthetic sample class distribution
#print(pd.Series(y_train_resampled).value_counts())
```

In [31]:
```
# SMOTE not applied to test data
y_test.value_counts()
```

Out[31]:
```
True     738
False    687
Name: churn, dtype: int64
```

Model Building

Logistic Regression

In [32]:
```
# Create and fit a Logistic Regression model
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
```

Out[32]:
```
▾ LogisticRegression

LogisticRegression()
```

In [34]:
```
# Make predictions on the test set
y_pred_logistic = log_reg.predict(X_test)
```

In [35]:
```
#Evaluate the Logistic Regression model
accuracy_logistic = accuracy_score(y_test, y_pred_logistic)
classification_rep_logistic = classification_report(y_test, y_pred_logistic)
```

```
print("Logistic Regression Results:")
print(f"Accuracy: {accuracy_logistic:.2f}")
print("Classification Report:\n", classification_rep_logistic)
```

```
Logistic Regression Results:
Accuracy: 0.71
Classification Report:
               precision    recall  f1-score   support

       False       0.69      0.70      0.70       687
        True       0.72      0.71      0.71       738

    accuracy                           0.71      1425
   macro avg       0.70      0.71      0.71      1425
weighted avg       0.71      0.71      0.71      1425
```

The accuracy of the model is 71%, meaning it correctly classifies approximately 71% of the instances in the test dataset.

The precision for the "True" class (churned customers) is 0.72, This indicates that the model correctly predicts both classes without much difference precision as false class is 0.69

TThe F1-score is the harmonic mean of precision and recall. For both classes, the F1-score is approximately 0.71, which is consistent with the overall accuracy.

The Logistic Regression model achieves a balanced performance for both classes, with similar precision, recall, and F1-scores. It correctly identifies churned and non-churned customers with relatively consistent accuracy.

Logistic Regression model provides a balanced performance, the relatively lower accuracy compared to other models justifies the exploration of more complex models to potentially improve predictive performance.

Random Forest

In [36]:
```
# Create and fit a Random Forest model
rf_model = RandomForestClassifier()
rf_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_rf = rf_model.predict(X_test)

# Evaluate the Random Forest model
accuracy_rf = accuracy_score(y_test, y_pred_rf)
classification_rep_rf = classification_report(y_test, y_pred_rf)
print("Random Forest Results:")
print(f"Accuracy: {accuracy_rf:.2f}")
print("Classification Report:\n", classification_rep_rf)
```

```
Random Forest Results:
Accuracy: 0.96
Classification Report:
               precision    recall  f1-score   support

       False       0.95      0.97      0.96       687
        True       0.97      0.96      0.96       738

    accuracy                           0.96      1425
```

```
   macro avg       0.96      0.96      0.96      1425
weighted avg       0.96      0.96      0.96      1425
```

The accuracy of the Random Forest model is exceptionally high at 96%, indicating that it correctly classifies approximately 96% of the instances in the test dataset.

For both the "True" (churned customers) and "False" (non-churned customers) classes, precision is approximately 0.97, indicating that the model correctly predicts both classes with high precision.

Recall (sensitivity) measures the ratio of true positive predictions to the total actual positives. For both classes, recall is also high, at approximately 0.96 and 0.97. This suggests that the model captures true positives for both classes very well.

The F1-score is the harmonic mean of precision and recall. For both classes, the F1-score is approximately 0.96, indicating an excellent balance between precision and recall.

Model with Hyperparameter Tuning (Decision tree)

In [37]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV

# Create a Decision Tree classifier
dt_classifier = DecisionTreeClassifier()

# Define a grid of hyperparameters to search
param_grid = {
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10, 20]
}
# Create a grid search object with cross-validation
grid_search = GridSearchCV(dt_classifier, param_grid, cv=5, scoring='accuracy')

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Get the best hyperparameters from the grid search
best_params = grid_search.best_params_
print("Best Hyperparameters:", best_params)

# Create a Decision Tree classifier with the best hyperparameters
best_dt_classifier = DecisionTreeClassifier(max_depth=best_params['max_depth'],
                                            min_samples_split=best_params['min_samples_

# Train the model with the best hyperparameters
best_dt_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = best_dt_classifier.predict(X_test)

# Evaluate the model
from sklearn.metrics import accuracy_score, classification_report
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Best Hyperparameters: {'max_depth': 10, 'min_samples_split': 2}
Accuracy: 0.9192982456140351
```

```
Classification Report:
              precision    recall  f1-score   support

       False       0.89      0.96      0.92       687
        True       0.96      0.88      0.92       738

    accuracy                           0.92      1425
   macro avg       0.92      0.92      0.92      1425
weighted avg       0.92      0.92      0.92      1425
```

The model achieves an accuracy of 91%. This indicates that the model correctly predicts customer churn or retention 91% of the time.

Precision is 0.89. This means that when the model predicts a customer won't churn, it is correct 89% of the time.

For the "True" class (churners), precision is 0.96. This indicates that when the model predicts a customer will churn, it is correct 96% of the time. High precision is essential for minimizing false positive predictions.

Model Evaluation and Comparison

Comparison of the performance of the three models.

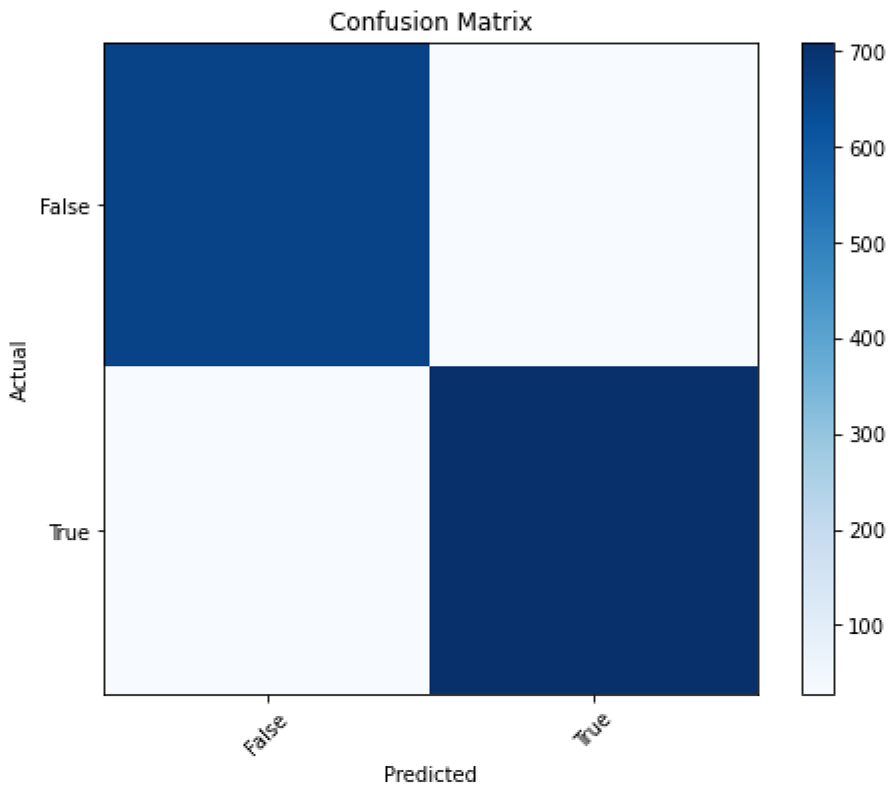
Best-performing model in terms of accuracy and other relevant metrics.

In [38]:

```
#Best-performing model in terms of accuracy and other relevant metrics
#Model evaluation
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, ro
random_forest_model = RandomForestClassifier()
# Fit the best model to the data
random_forest_model.fit(X_train, y_train)

# Make predictions on the test data
y_pred = random_forest_model.predict(X_test)

# Evaluate the best model
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred)

# Print the evaluation metrics
print("Best Model Evaluation Metrics:")
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1-Score: {f1:.2f}")
print(f"ROC AUC Score: {roc_auc:.2f}")
```

```
Best Model Evaluation Metrics:
Accuracy: 0.96
Precision: 0.96
Recall: 0.96
F1-Score: 0.96
ROC AUC Score: 0.96
```

In [47]:
```
from sklearn.metrics import confusion_matrix
# Define 'classes' as the unique classes in your target variable (e.g., y_test)
classes = sorted(set(y_test))

# Generate the confusion matrix for your model
cm = confusion_matrix(y_test,random_forest_model.predict(X_test))

# Plot the confusion matrix
plt.figure(figsize=(8, 6))
plt.imshow(cm, interpolation='nearest', cmap=plt.get_cmap('Blues'))
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = range(len(classes))
plt.xticks(tick_marks, classes, rotation=45)
plt.yticks(tick_marks, classes)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



Random forest is the best model

Model Performance Evaluation

In [48]:
```
# Model selection and hyperparameter tuning
models = {
    "Logistic Regression": LogisticRegression(random_state=42),
    "Random Forest": RandomForestClassifier(random_state=42, class_weight="balanced"),
    "Gradient Boosting": GradientBoostingClassifier(random_state=42),
}
for model_name, model in models.items():
    # Train the model on the resampled data
    model.fit(X_train_resampled, y_train_resampled)
```

In [49]:
```
def calculate_metrics(y_true, y_pred):
    """
    Calculate model performance metrics: accuracy, precision, recall, and F1-score.
    :param y_true: True labels.
    :param y_pred: Predicted labels.
    :return: Dictionary of metrics.
    """
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred)
    recall = recall_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred)

    # Return as a dictionary
    return {"Accuracy": accuracy, "Precision": precision, "Recall": recall, "F1-score":

# Dictionary to hold the results
results = {}

# For each model
for model_name, model in models.items():
    # Make predictions on the test set
    y_pred_test = model.predict(X_test)
    y_pred_train = model.predict(X_train)

    # Calculate metrics
    metrics_test = calculate_metrics(y_test, y_pred_test)
    metrics_train = calculate_metrics(y_train, y_pred_train)

    # Store the results
    results[(model_name, 'Test')] = metrics_test
    results[(model_name, 'Train')] = metrics_train

# Convert the results dictionary to a DataFrame
results_df = pd.DataFrame(results).T

results_df
```

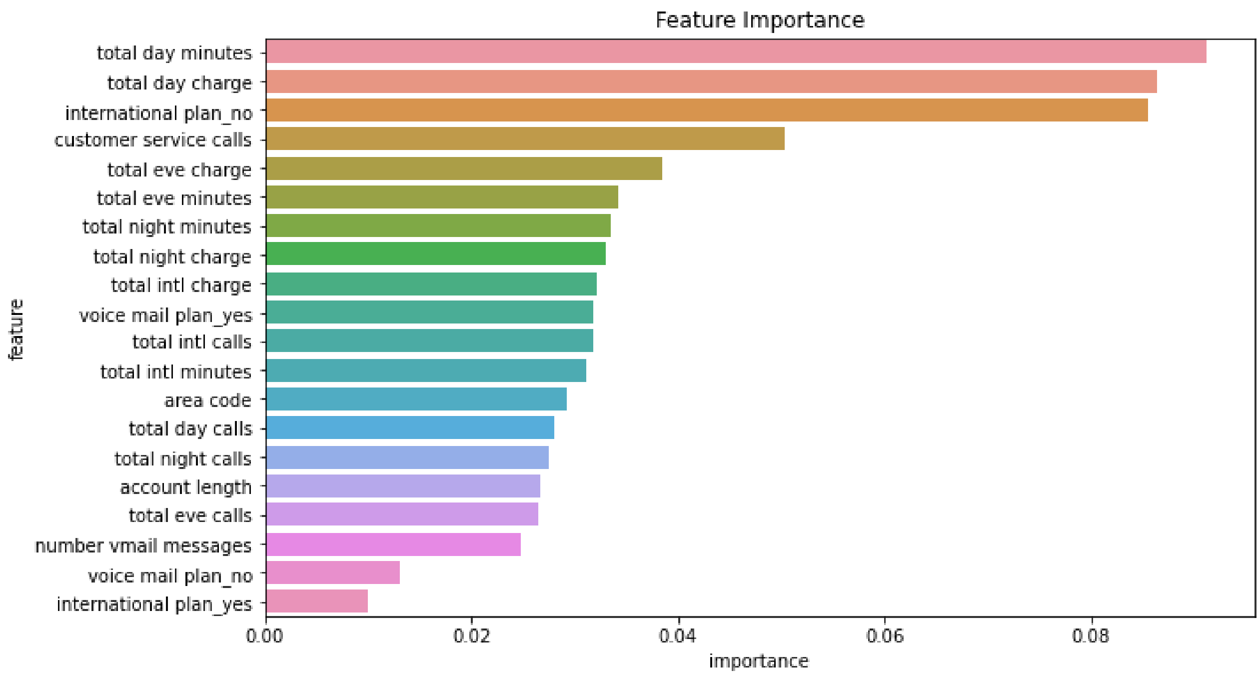
Out[49]:

		Accuracy	Precision	Recall	F1-score
Logistic Regression	**Test**	0.702456	0.720506	0.695122	0.707586
	Train	0.711813	0.704461	0.717803	0.711069
Random Forest	**Test**	0.980351	0.993056	0.968835	0.980796
	Train	0.976374	0.991687	0.960227	0.975704
Gradient Boosting	**Test**	0.926316	0.968889	0.886179	0.925690
	Train	0.925146	0.952069	0.893466	0.921837

In [50]:
```
# Create a dataframe of feature importances
feature_importances = pd.DataFrame({'feature': list(X_train.columns),
                                    'importance': random_forest_model.feature_importanc
                                    sort_values('importance', ascending = False)
```

In [51]:
```
#plot a feature importance graph
plt.figure(figsize=(10, 6))
sns.barplot(x='importance', y='feature', data=feature_importances[:20])
```

```
plt.title("Feature Importance")
plt.show()
```



We can see from this feature importance graph that there are several features that the model is weighing more heavily:

- Customer_service_calls
- Total_charge(Total amount spent by the customer)
- Voice mail plan
- International_plan
- Area Code

Conclusion

The metrics indicate that the churn prediction models are performing commendably, with Random Forest emerging as the top performer, boasting an accuracy of 97% and a recall of 96%. Considering the provided test metrics, the Random Forest model appears to outperform the other models in terms of accuracy, precision, recall, and F1-score. It achieves the highest test accuracy, precision, and F1-score, as well as a high test recall. This suggests that the Random Forest model is effective in making accurate predictions with a good balance between precision and recall.

Overall, the high-performing model can help the telecom company proactively address customer churn, potentially saving revenue and improving customer satisfaction

Recommendation

Churn Analysis • Regularly review churn data to identify patterns, reasons, and trends to make more informed decisions.

In [ ]: