Customer Churn Analysis ¶

Business Understanding

Problem Statement: Predicting Customer Churn for SyriaTel

1. Overview

SyriaTel, a telecommunications company, faces customer churn, where users discontinue their services. High churn rates lead to revenue loss, increased acquisition costs, and lower profitability. Understanding and predicting churn allows SyriaTel to take proactive measures to retain customers, optimize marketing strategies, and improve service offerings.

2. Business Problem

SyriaTel wants to identify customers who are likely to churn in the near future. By accurately predicting churn, the company can take targeted actions such as personalized offers, improved customer service, and technical support to retain these customers.

3. Why Machine Learning?

Traditional approaches to reducing churn—such as generalized promotions or mass discounts—are often inefficient and costly. Machine learning enables SyriaTel to:

Objectives

- Identify high-risk customers early based on behavioral patterns.
- Pinpoint key churn drivers, such as call patterns, data usage, and customer support interactions.
- Optimize retention strategies by offering personalized incentives only to customers who are at risk.

4. Key Stakeholder

The primary stakeholder is SyriaTel's Customer Retention & Marketing Department, which is responsible for reducing churn and maximizing customer lifetime value. Other relevant stakeholders include:

- Sales & Marketing Team: To design targeted campaigns based on churn predictions.
- Customer Support Team: To enhance service quality for high-risk customers.
- Network Operations Team: To address technical issues leading to churn.\

5. Success Metrics

The success of this project will be evaluated based on:

- Model performance: Accuracy, recall, precision, F1-score, and AUC-ROC for churn classification.
- Business impact: Reduction in churn rate after implementing model-driven interventions.
- Cost-effectiveness: Higher ROI from retention efforts by focusing on high-risk customers instead of mass offers.

Data Understanding

1.0 Import libraries

In [160]:

```
#Data Manipulation $ Visualizations
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

#Modelling
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classific
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV

from imblearn.over_sampling import SMOTE
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier
```

1.1 Load dataset

In [128]:
```
#Load Data and creating a dataframe
df= pd.read_csv("bigml_59c28831336c6604c800002a.csv")

#checking first five rows
df.head()
```

Out[128]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	tot da charg
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.0
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.4
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.3
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.9
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.3

5 rows × 21 columns

In [129]:
```
df.tail()
```

Out[129]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	ch
3328	AZ	192	415	414-4276	no	yes	36	156.2	77	
3329	WV	68	415	370-3271	no	no	0	231.1	57	
3330	RI	28	510	328-8230	no	no	0	180.8	109	
3331	CT	184	510	364-6381	yes	no	0	213.8	105	
3332	TN	74	415	400-4344	no	yes	25	234.4	113	

5 rows × 21 columns

In [130]:
```
df.shape
```

Out[130]: (3333, 21)

Observation:

Data is uniform from top to bottom.

In [131]:

```
#check the datatypes
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 [132]:

```
#check columns
df.columns
```

Out[132]:

```
Index(['state', 'account length', 'area code', 'phone number',
       'international plan', 'voice mail plan', 'number vmail message
s',
       '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 charg
e',
       'total intl minutes', 'total intl calls', 'total intl charge',
       'customer service calls', 'churn'],
      dtype='object')
```

In [133]:
```
df.describe(include= 'all')
```

Out[133]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	
count	3333	3333.000000	3333.000000	3333	3333	3333	3333.000000	333
unique	51	NaN	NaN	3333	2	2	NaN	
top	WV	NaN	NaN	401-6977	no	no	NaN	
freq	106	NaN	NaN	1	3010	2411	NaN	
mean	NaN	101.064806	437.182418	NaN	NaN	NaN	8.099010	17
std	NaN	39.822106	42.371290	NaN	NaN	NaN	13.688365	5
min	NaN	1.000000	408.000000	NaN	NaN	NaN	0.000000	
25%	NaN	74.000000	408.000000	NaN	NaN	NaN	0.000000	14
50%	NaN	101.000000	415.000000	NaN	NaN	NaN	0.000000	17
75%	NaN	127.000000	510.000000	NaN	NaN	NaN	20.000000	21
max	NaN	243.000000	510.000000	NaN	NaN	NaN	51.000000	35

11 rows × 21 columns

In [134]:
```
#checking the categories for object data types
print(df['international plan'].unique())
print(df['voice mail plan'].unique())
print(df['churn'].unique())
```

```
['no' 'yes']
['yes' 'no']
[False  True]
```

Observation-

The dataset includes categorical and numerical variables.

The target variable is "churn", a boolean column indicating whether a customer churned (True) or not (False).

phone number: which is an identifier, should be dropped for modeling.

Data Prep

1.0 Data Cleaning

In [135]:
```
#checking for missing values
df.isna().sum()
```

Out[135]:
```
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 [136]:
```
#checking for duplicates
df.duplicated().sum()
```

Out[136]: 0

In [137]:
```
# Remove customer number feature it is contact information on the clier
# Recheck dataframe
df.drop(['phone number'],axis=1,inplace=True)
df.head()
```

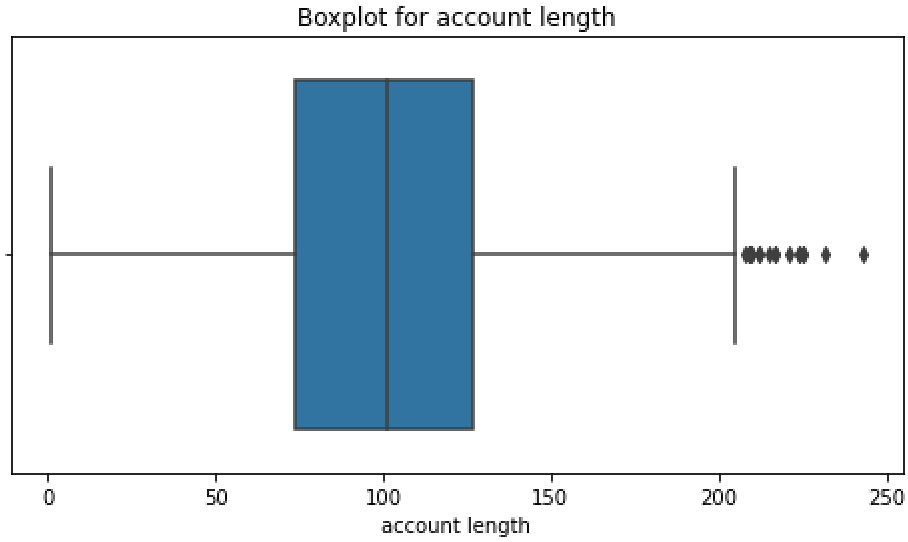
Out[137]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	tot ev minute
0	KS	128	415	no	yes	25	265.1	110	45.07	197
1	OH	107	415	no	yes	26	161.6	123	27.47	195
2	NJ	137	415	no	no	0	243.4	114	41.38	121
3	OH	84	408	yes	no	0	299.4	71	50.90	61
4	OK	75	415	yes	no	0	166.7	113	28.34	148

In [138]:
```
#checking for outliers
df.skew()
```

Out[138]:
```
account length            0.096606
area code                 1.126823
number vmail messages     1.264824
total day minutes        -0.029077
total day calls          -0.111787
total day charge         -0.029083
total eve minutes        -0.023877
total eve calls          -0.055563
total eve charge         -0.023858
total night minutes       0.008921
total night calls         0.032500
total night charge        0.008886
total intl minutes       -0.245136
total intl calls          1.321478
total intl charge        -0.245287
customer service calls    1.091359
churn                     2.018356
dtype: float64
```

In [139]:
```
#visualize the outliers
for col in df.select_dtypes(include=['number']).columns:
    plt.figure(figsize=(8, 4))
    sns.boxplot(x=df[col])
    plt.title(f'Boxplot for {col}')
    plt.show()
```



Boxplot for area code

In [140]:
```
#remove the outliers using Interquartile Range
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1

df_cleaned = df[~((df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))).ar
df_cleaned.to_csv("cleaned_dataset.csv", index=False)
```

In [141]:
```
df1=pd.read_csv("cleaned_dataset.csv")
df1.head()
```

Out[141]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	tot ev minute
0	KS	128	415	no	yes	25	265.1	110	45.07	197
1	OH	107	415	no	yes	26	161.6	123	27.47	195
2	NJ	137	415	no	no	0	243.4	114	41.38	121
3	OK	75	415	yes	no	0	166.7	113	28.34	148
4	AL	118	510	yes	no	0	223.4	98	37.98	220

In [142]:
```
df1.shape
```

Out[142]: (2499, 20)

Obsevation- Removing Outliers affects the dataset by removing important data, thus i proceed with the original dataset

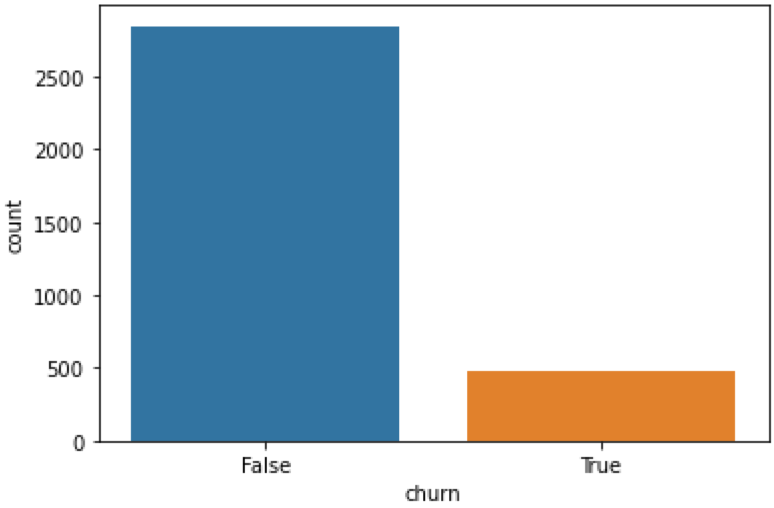
EDA

Analysis on 'churn' Feature

- Churn will be used as the dependent variable in this analysis.
- Churn indicates if a customer has terminated their contract with SyriaTel. True indicates they have terminated and false indicates they have not and have an existing account.

In [143]:
```
# Countplot of churn feature
print(df.churn.value_counts())
sns.countplot(data=df, x='churn');
```

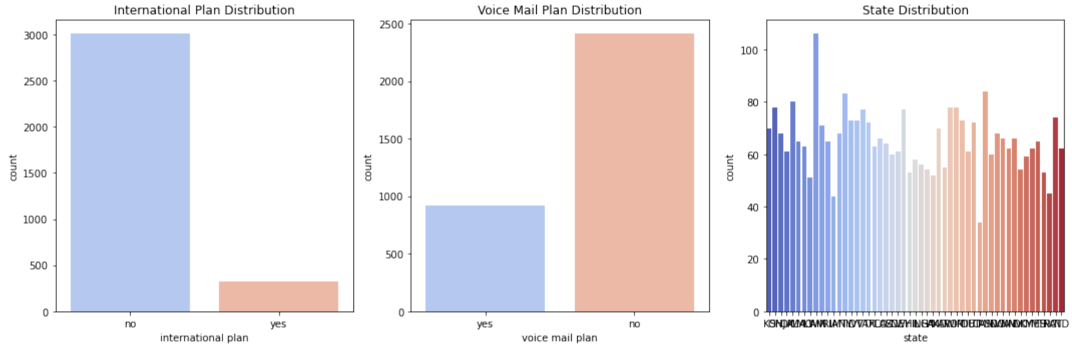
```
False    2850
True      483
Name: churn, dtype: int64
```



- Of the 3,333 customers in the dataset, 483 have terminated their contract with SyriaTel. That is 14.5% of customers lost.
- The distribution of the binary classes shows a data imbalance. This needs to be addressed before modeling as an unbalanced feature can cause the model to make false predictions.

In [144]:

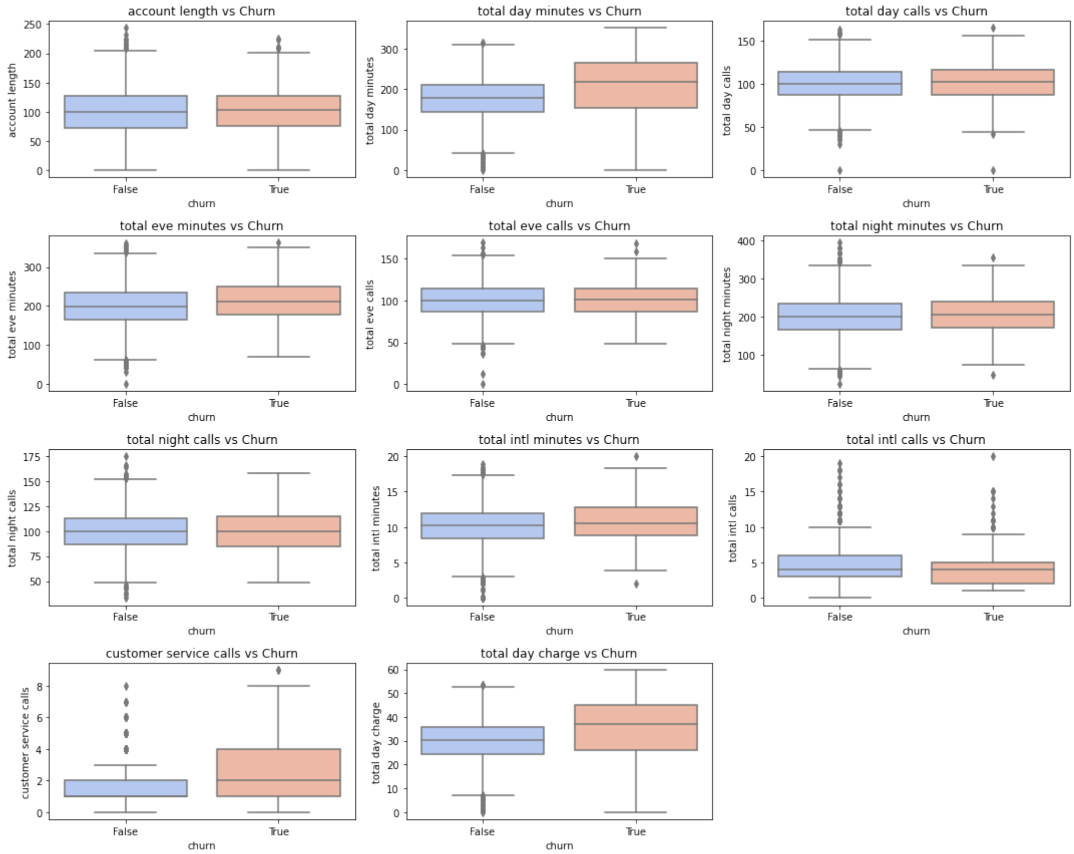
```
# Univariate Analysis-: Categorical Variables

fig, axes = plt.subplots(1, 3, figsize=(15, 5))

# Plot categorical feature distributions
sns.countplot(x="international plan", data=df, ax=axes[0], palette="coo
sns.countplot(x="voice mail plan", data=df, ax=axes[1], palette="coolwa
sns.countplot(x="state", data=df, ax=axes[2], palette="coolwarm")

# Titles
axes[0].set_title("International Plan Distribution")
axes[1].set_title("Voice Mail Plan Distribution")
axes[2].set_title("State Distribution")

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



- The plots show the number of customers who have subscribed to an international plan, voice mail plan and number of customers in each state
- If churn is high among customers with an international plan , it may indicate dissatisfaction with international service pricing or quality
- States with a higher customer base, could be useful for targeted marketing strategies

In [145]:

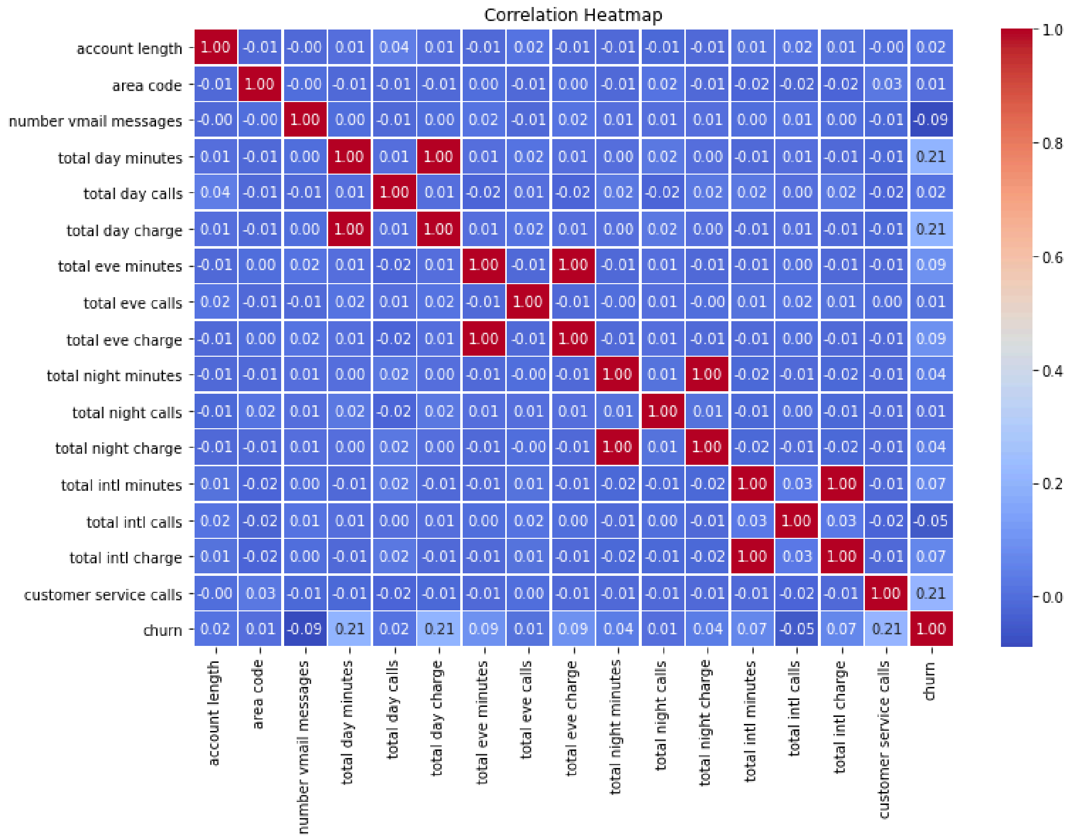
```
# Bivariate Analysis-: Boxplots of numerical features against churn

num_features = [
    "account length", "total day minutes", "total day calls",
    "total eve minutes", "total eve calls", "total night minutes",
    "total night calls", "total intl minutes", "total intl calls",
    "customer service calls", "total day charge"
]

plt.figure(figsize=(15, 12))
for i, col in enumerate(num_features, 1):
    plt.subplot(4, 3, i)
    sns.boxplot(x=df["churn"], y=df[col], palette="coolwarm")
    plt.title(f"{col} vs Churn")

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



- High usage ,especially during the day, may increase churn risk—possibly due to pricing concerns.
- More customer service calls are likely correlated with churn, suggesting dissatisfaction.
- International call patterns may indicate pricing concerns.
- Total day calls may not show a strong correlation with churn.

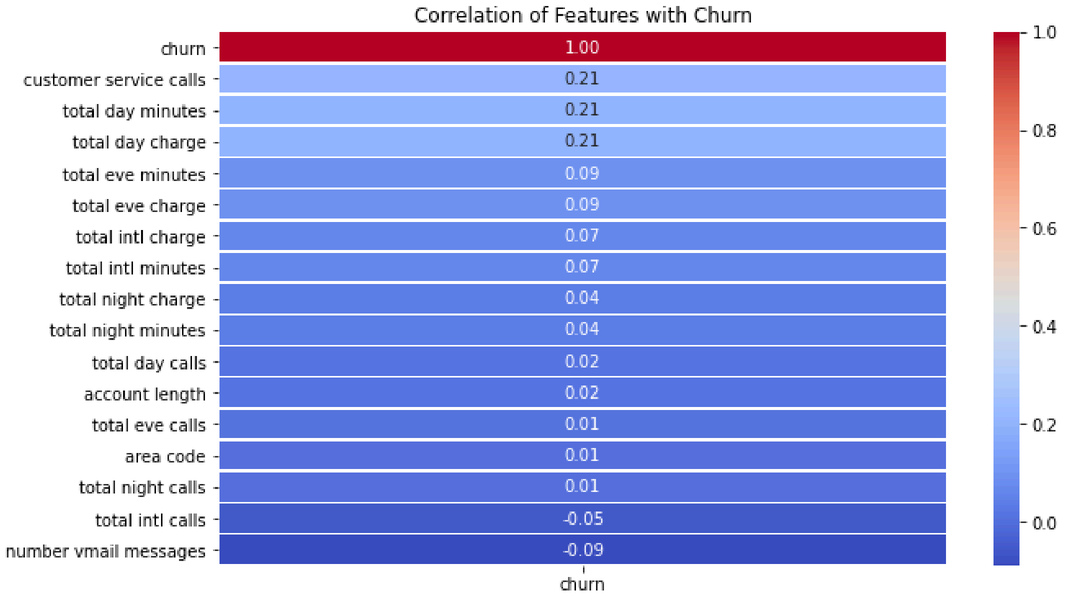
In [146]:

```
# Multivariate Analysis-: Correlation heatmap

plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, cmap="coolwarm", fmt=".2f", linewidt
plt.title("Correlation Heatmap")
plt.show()
```



In [147]:

```
# Compute correlation of all numerical features with churn
correlation_with_churn = df.corr()["churn"].sort_values(ascending=False

# Create a heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(correlation_with_churn, annot=True, cmap='coolwarm', linewi


plt.title("Correlation of Features with Churn")
plt.show()
```



- Strong internal correlations exist between total minutes and total charges, indicating redundancy in features.
- Pricing & Service Quality appear to be the biggest churn drivers—customers likely leave due to high costs and unresolved complaints.
- We can clearly state that the following three attributes contribute the most towards deciding whether a person will churn or not:

  -Customer service calls

  -Total day minutes

  -Total day charge

Data Preprocessing

In [148]:

```
#Drop highly correlated  features -to prevents data leakage and multico
df.drop(columns=["total day charge", "total eve charge", "total night c
                 "total intl charge", "area code", "state"], inplace=Tr
```

In [149]:
```
df.churn.unique()
```

Out[149]: array([False, True])

One Hot Encoding

In [150]:
```
df['churn'] =df['churn'].map({True: 1, False: 0}).astype('int')
df.head()
```

Out[150]:

	account length	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total eve minutes	total eve calls	total night minutes	tc ni ca
0	128	no	yes	25	265.1	110	197.4	99	244.7	
1	107	no	yes	26	161.6	123	195.5	103	254.4	1
2	137	no	no	0	243.4	114	121.2	110	162.6	1
3	84	yes	no	0	299.4	71	61.9	88	196.9	
4	75	yes	no	0	166.7	113	148.3	122	186.9	1

In [151]:
```
# Convert categorical features
df = pd.get_dummies(df, columns=["international plan", "voice mail plar
```

In [152]:
```
df.tail()
```

Out[152]:

	account length	number vmail messages	total day minutes	total day calls	total eve minutes	total eve calls	total night minutes	total night calls	total intl minutes	tota in call
3328	192	36	156.2	77	215.5	126	279.1	83	9.9	
3329	68	0	231.1	57	153.4	55	191.3	123	9.6	
3330	28	0	180.8	109	288.8	58	191.9	91	14.1	
3331	184	0	213.8	105	159.6	84	139.2	137	5.0	1
3332	74	25	234.4	113	265.9	82	241.4	77	13.7	

Scaling Numerical Features

In [153]:

```
# Normalize numerical features

scaler = StandardScaler()

numerical_features = [
    "account length", "number vmail messages", "total day minutes", "to
     "total eve minutes", "total eve calls",
    "total night minutes", "total night calls",
    "total intl minutes", "total intl calls",  "customer service calls'
]

df[numerical_features] = scaler.fit_transform(df[numerical_features])
```

Handling Class Imbalance for the target variable "Churn"

In [154]:

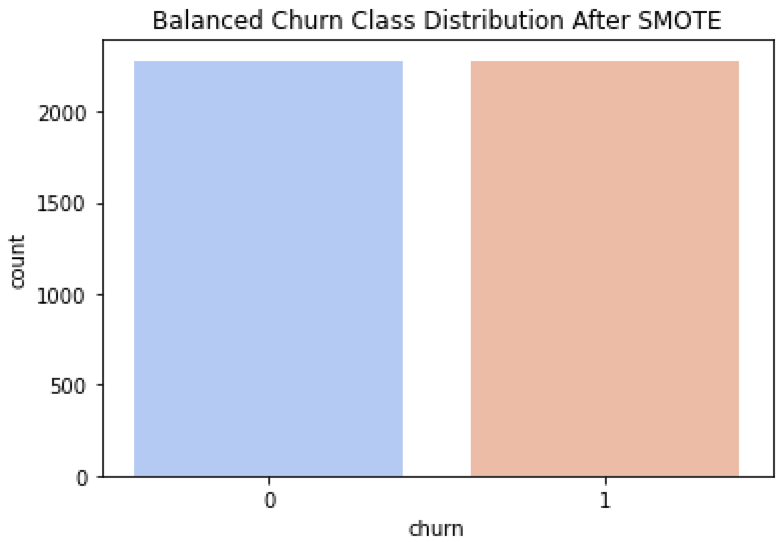
```
# Define features and target variable
X = df.drop(columns=["churn"])
y = df["churn"]
```

In [155]:

```
# Split the data before applying SMOTE
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2
```

In [156]:
```
# Apply SMOTE only on training data
smote = SMOTE(random_state=42)

X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_tr

# Check new class distribution
print("Class Distribution Before SMOTE:", y_train.value_counts())
print("Class Distribution After SMOTE:", y_train_resampled.value_counts

#check the visualization for new dustribution
plt.figure(figsize=(6, 4))
sns.countplot(x=y_train_resampled, palette="coolwarm")
plt.title("Balanced Churn Class Distribution After SMOTE")
plt.show()
```

```
Class Distribution Before SMOTE: 0    2280
1     386
Name: churn, dtype: int64
Class Distribution After SMOTE: 1    2280
0    2280
Name: churn, dtype: int64
```



Observation: Minority class observations have increased balancing the class distribution

Modelling

Model 1: Logistic Regression Classifier

- Logistic Regression is a simple linear model that performs well when the relationship between features and target is approximately linear.
- It provides probability estimates for churn prediction, making it useful for risk assessment.

In [157]:

```
# Initialize Logistic Regression
logreg = LogisticRegression(random_state=42)

# Train the model
logreg.fit(X_train_resampled, y_train_resampled)

# Make predictions on test data
y_pred = logreg.predict(X_test)
y_pred
```

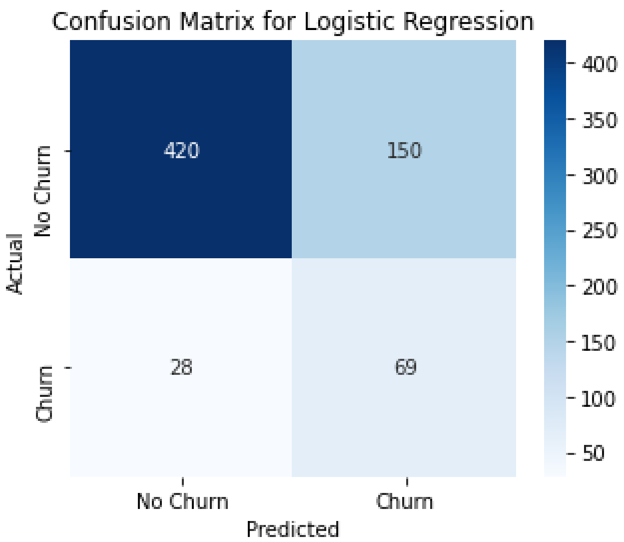
```
Out[157]: array([0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0,
          0,
                 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1,
          0,
                 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1,
          1,
                 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
          0,
                 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0,
          0,
                 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1,
          0,
                 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 1,
          0,
                 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1,
          0,
                 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0,
          0,
                 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
          0,
                 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0,
          1,
                 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1,
          0,
                 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0,
          1,
                 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0,
          0,
                 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,
          1,
                 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0,
          0,
                 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0,
          0,
                 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
          1,
                 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0,
          0,
                 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1,
          1,
                 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0,
          0,
                 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0,
          1,
                 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1,
          1,
                 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0,
          1,
                 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0,
          1,
                 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0,
          0,
                 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1,
          1,
                 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0,
          0,
                 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
          0,
                 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1,
```

```
1,
       0, 0, 0, 0, 0, 0, 1])
```

In [158]:

```
#Model Evaluation

# Classification report
print(classification_report(y_test, y_pred))


# Confusion Matrix
plt.figure(figsize=(5,4))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt="d", cmap
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix for Logistic Regression")
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.94      0.74      0.83       570
           1       0.32      0.71      0.44        97

    accuracy                           0.73       667
   macro avg       0.63      0.72      0.63       667
weighted avg       0.85      0.73      0.77       667
```



- The model correctly predicts 73% of cases overall.However, accuracy alone can be misleading
- The model is very confident when predicting non-churners but sacrifices recall slightly.
- High recall and low precision for Churn means it generates many false positives, flagging customers as potential churners when they aren’t.

- False positives are high, meaning the model incorrectly flags many non-churners as churners.This could lead to wasted resources if a business takes action on these false churn predictions.
- Thus we proceed by conducting hyperparameter tuning and try another model to improve performance

Model 2: Decision Tree Classifier

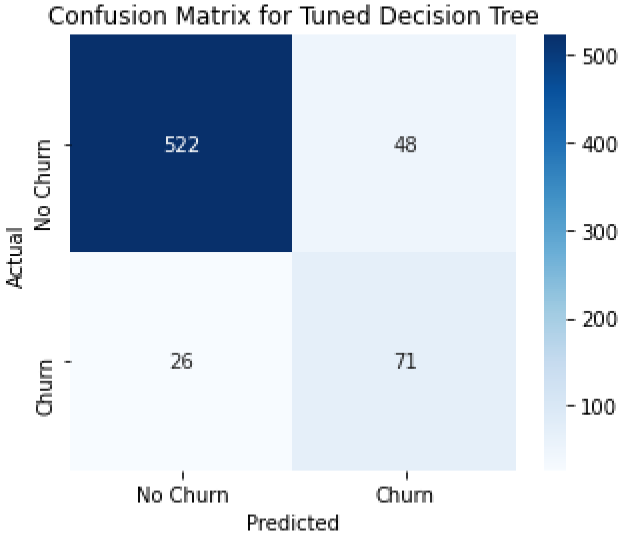
- Decision Tree models can capture complex relationships but are prone to overfitting.
- They provide clear decision rules, making them interpretable but sensitive to noisy data.

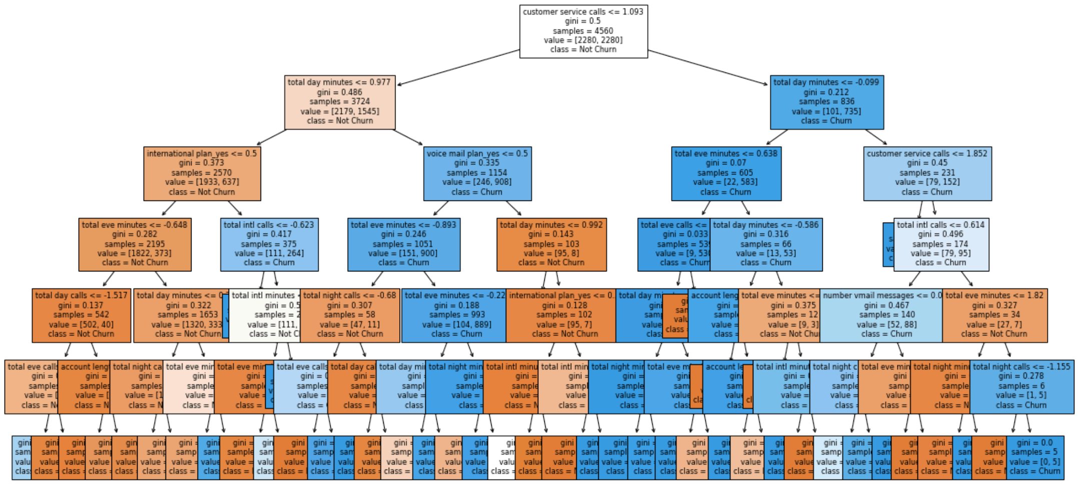
Hyperparameter Tuning & Model Building

In [159]:

```
# Define parameter grid
dt_params = {'max_depth': [5, 6, 4], 'min_samples_split': [2, 5, 10]}

# Initialize Decision Tree Classifier
dt= DecisionTreeClassifier(random_state=42)

#grid search
dt_grid = GridSearchCV(dt, dt_params, cv=5, scoring='accuracy', n_jobs=
dt_grid.fit(X_train_resampled, y_train_resampled)

#train model
best_dt = dt_grid.best_estimator_

#predictions
y_pred_dt = best_dt.predict(X_test)


print("Decision Tree Results:")

#tuned parameters
print("Best Parameters:", dt_grid.best_params_)

#accuracy score
print("Accuracy:", accuracy_score(y_test, y_pred_dt))

#classification report
print("Classification Report:\n", classification_report(y_test, y_pred_
print("-"*50)

# Confusion Matrix
plt.figure(figsize=(5,4))
sns.heatmap(confusion_matrix(y_test, y_pred_dt), annot=True, fmt="d", c
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix for Tuned Decision Tree")
plt.show()

# Visualizing Decision Tree

plt.figure(figsize=(20, 10))
plot_tree(best_dt, feature_names=X_train_resampled.columns, class_names
plt.show()
```

```
Decision Tree Results:
Best Parameters: {'max_depth': 6, 'min_samples_split': 2}
Accuracy: 0.889055472263868
Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.92      0.93       570
           1       0.60      0.73      0.66        97

    accuracy                           0.89       667
   macro avg       0.77      0.82      0.80       667
weighted avg       0.90      0.89      0.89       667

--------------------------------------------------
```





- The Decision Tree captures more complex patterns in the data, leading to a higher overall accuracy.
- Precision (Churn - 1) increased from 32% to 60% meaning there are Fewer false positives (incorrectly predicting churn).
- F1-score Indicates a better balance in model performance across both classes and a stronger ability to correctly classify customers.
- Recall remains high for churners (**73%**).
- However the model is prone to overfitting without proper pruning.

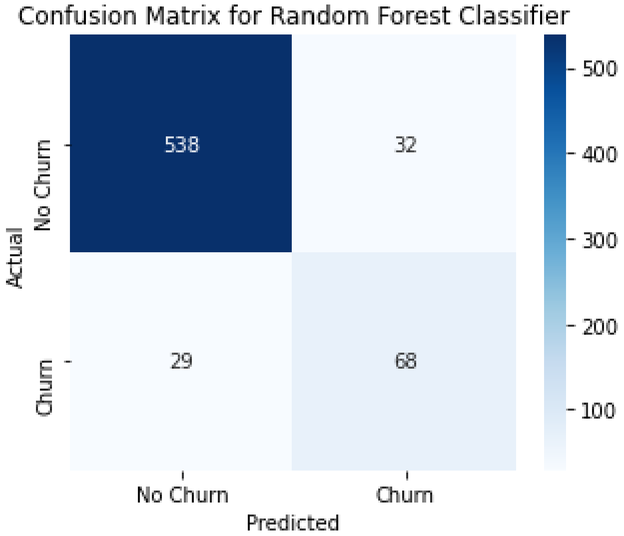
Model 3: Random Forest Classifier

- Random Forest is an ensemble of decision trees that reduces overfitting and improves generalization.
- It tends to have higher accuracy and robustness compared to individual decision trees.

In [161]:

```
#Define parameters
rf_params = {'n_estimators': [50, 100, 200], 'max_depth': [5, 10, 20],

# Initialize Random Forest Classifier
rf= RandomForestClassifier()

##grid search
rf_grid = GridSearchCV(rf, rf_params, cv=5, scoring='accuracy', n_jobs=
rf_grid.fit(X_train_resampled, y_train_resampled)

#train model
best_rf = rf_grid.best_estimator_

#predictions
y_pred_rf = best_rf.predict(X_test)


print("Random Forest Results:")
print("Best Parameters:", rf_grid.best_params_)

#accuracy score
print("Accuracy:", accuracy_score(y_test, y_pred_rf))

#classification report
print("Classification Report:\n", classification_report(y_test, y_pred_
print("-"*50)

#confusion matrix
plt.figure(figsize=(5,4))
sns.heatmap(confusion_matrix(y_test, y_pred_rf), annot=True, fmt="d", c
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix for Random Forest Classifier")
plt.show()
```

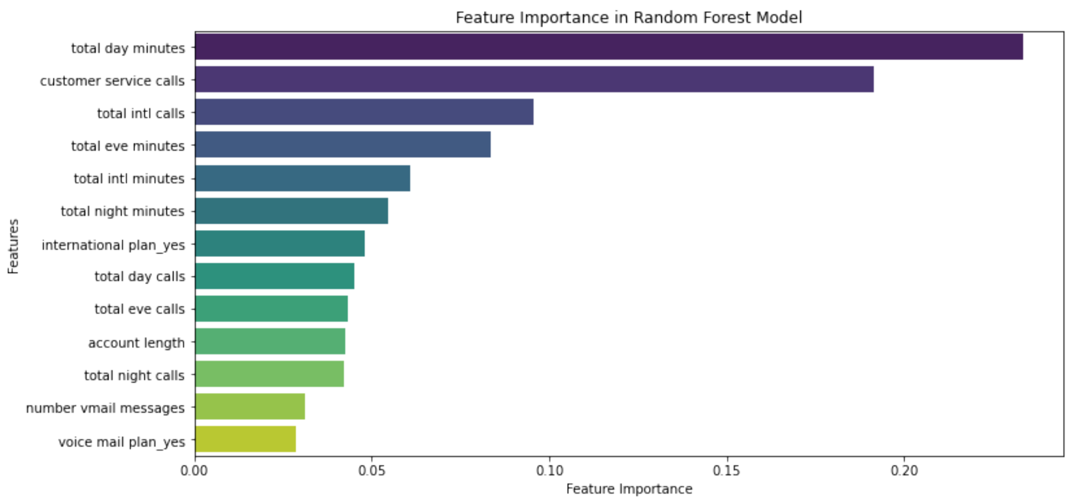
```
Random Forest Results:
Best Parameters: {'max_depth': 20, 'min_samples_split': 2, 'n_estimat
ors': 100}
Accuracy: 0.9085457271364318
Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.94      0.95       570
           1       0.68      0.70      0.69        97

    accuracy                           0.91       667
   macro avg       0.81      0.82      0.82       667
weighted avg       0.91      0.91      0.91       667

--------------------------------------------------
```



- Random Forest performed the best, with the highest accuracy and a good balance between precision and recall.
- It reduces overfitting by averaging multiple decision trees.
- Precision for churners improves to 70%, reducing false positives compared to the decision tree.

In [162]:

```
# Visualizing Feature Importance fro the Random Forest Model
plt.figure(figsize=(12, 6))
feature_importances = best_rf.feature_importances_
sorted_idx = np.argsort(feature_importances)[::-1]


sns.barplot(x=feature_importances[sorted_idx], y=np.array(X_train_resam
plt.xlabel("Feature Importance")
plt.ylabel("Features")
plt.title("Feature Importance in Random Forest Model")
plt.show()
```



- According to the random forest classifier, total day charge, customer service calles and "international plan is yes" features have the highest impact on the model.

In [ ]: