Business understanding

Telecommunication market is expanding day by day. Companies are facing a severe loss of revenue due to increasing competition hence the loss of customers. They are trying to find the reasons of losing customers by measuring customer loyalty to regain the lost customers. The customers leaving the current company and moving to another telecom company are called churn

Objectives

1.How to reduce churn and increase retention by predicting high-risk customers and what makes them churn?

2.How can i optimize model performance with the right balance between precision and recall?

3.Building models that Minimize false positives.

4.How class imbalance can be handled to ensure accurate predictions for churners?

5.Develop targeted campaigns based on the model's predictions.

Data understanding

In [52]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings

warnings.filterwarnings('ignore')
```

In [53]:
```
df= pd.read_csv('bigml_59c28831336c6604c800002a.csv')
```

In [54]:
```
df.tail(10)
```

Out[54]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	c
3323	IN	117	415	362-5899	no	no	0	118.4	126	
3324	WV	159	415	377-1164	no	no	0	169.8	114	
3325	OH	78	408	368-8555	no	no	0	193.4	99	
3326	OH	96	415	347-6812	no	no	0	106.6	128	
3327	SC	79	415	348-3830	no	no	0	134.7	98	
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	

10 rows × 21 columns

In [55]:
```
df.head(10)
```

Out[55]:

	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.(
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	AL	118	510	391-8027	yes	no	0	223.4	98	37.9
6	MA	121	510	355-9993	no	yes	24	218.2	88	37.(
7	MO	147	415	329-9001	yes	no	0	157.0	79	26.(
8	LA	117	408	335-4719	no	no	0	184.5	97	31.3
9	WV	141	415	330-8173	yes	yes	37	258.6	84	43.9

10 rows × 21 columns

In [56]:
```
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
```

i am trying to understand the data if some coulmm have unique values so as to trasform them to categorical datatype

In [57]:
```
df["state"].unique()
```

Out[57]:
```
array(['KS', 'OH', 'NJ', 'OK', 'AL', 'MA', 'MO', 'LA', 'WV', 'IN', 'RI',
       'IA', 'MT', 'NY', 'ID', 'VT', 'VA', 'TX', 'FL', 'CO', 'AZ', 'SC',
       'NE', 'WY', 'HI', 'IL', 'NH', 'GA', 'AK', 'MD', 'AR', 'WI', 'OR',
       'MI', 'DE', 'UT', 'CA', 'MN', 'SD', 'NC', 'WA', 'NM', 'NV', 'DC',
       'KY', 'ME', 'MS', 'TN', 'PA', 'CT', 'ND'], dtype=object)
```

In [58]:
```
df["international plan"].unique()
```

Out[58]:
```
array(['no', 'yes'], dtype=object)
```

In [59]:
```
df["voice mail plan"].unique()
```

Out[59]:
```
array(['yes', 'no'], dtype=object)
```

In [60]:
```
df["churn"].unique()
```

Out[60]:
```
array([False,  True])
```

so after checking the data, i want to change the state, voice mail plan and international plan and churn to categorical datadype. later depending on the model i might change them to one-hot encoder.

coverting data type

In [61]:
```
df1=df
df1['state'] = df1['state'].astype('category')
df1['international plan'] = df1['international plan'].astype('category')
df1['voice mail plan'] = df1['voice mail plan'].astype('category')
df1['churn'] = df1['churn'].map({True: 'Yes', False: 'No'})
df1['churn'] = pd.Categorical(df1['churn'])
```

In [62]:
```
df1.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   category
 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   category
 5   voice mail plan         3333 non-null   category
 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   category
dtypes: category(4), float64(8), int64(8), object(1)
memory usage: 458.6+ KB
```

Data cleaning

handling missing value

In [63]:
```
df1.isna().sum()
```

Out[63]:
```
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 [64]:
```
### checking duplicates
```

In [65]:
```
df1[df1.duplicated()].count()
```

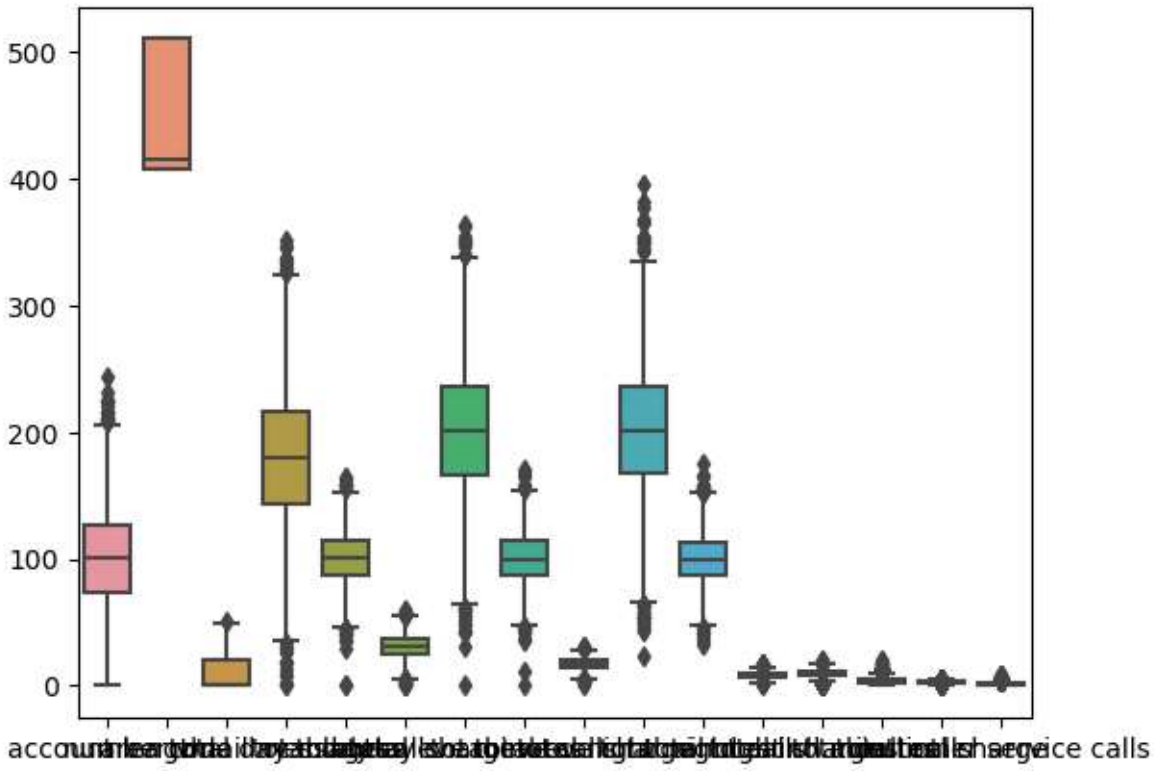
Out[65]:
```
state                     0
account length            0
area code                 0
phone number              0
international plan        0
voice mail plan           0
number vmail messages     0
total day minutes         0
total day calls           0
total day charge          0
total eve 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 [66]:
```
# dropping column whuich is deemed useless
df1= df1.drop('phone number', axis=1)
```

In [67]:
```
### checking outliers
```

In [68]:
```
sns.boxplot(df1)
```

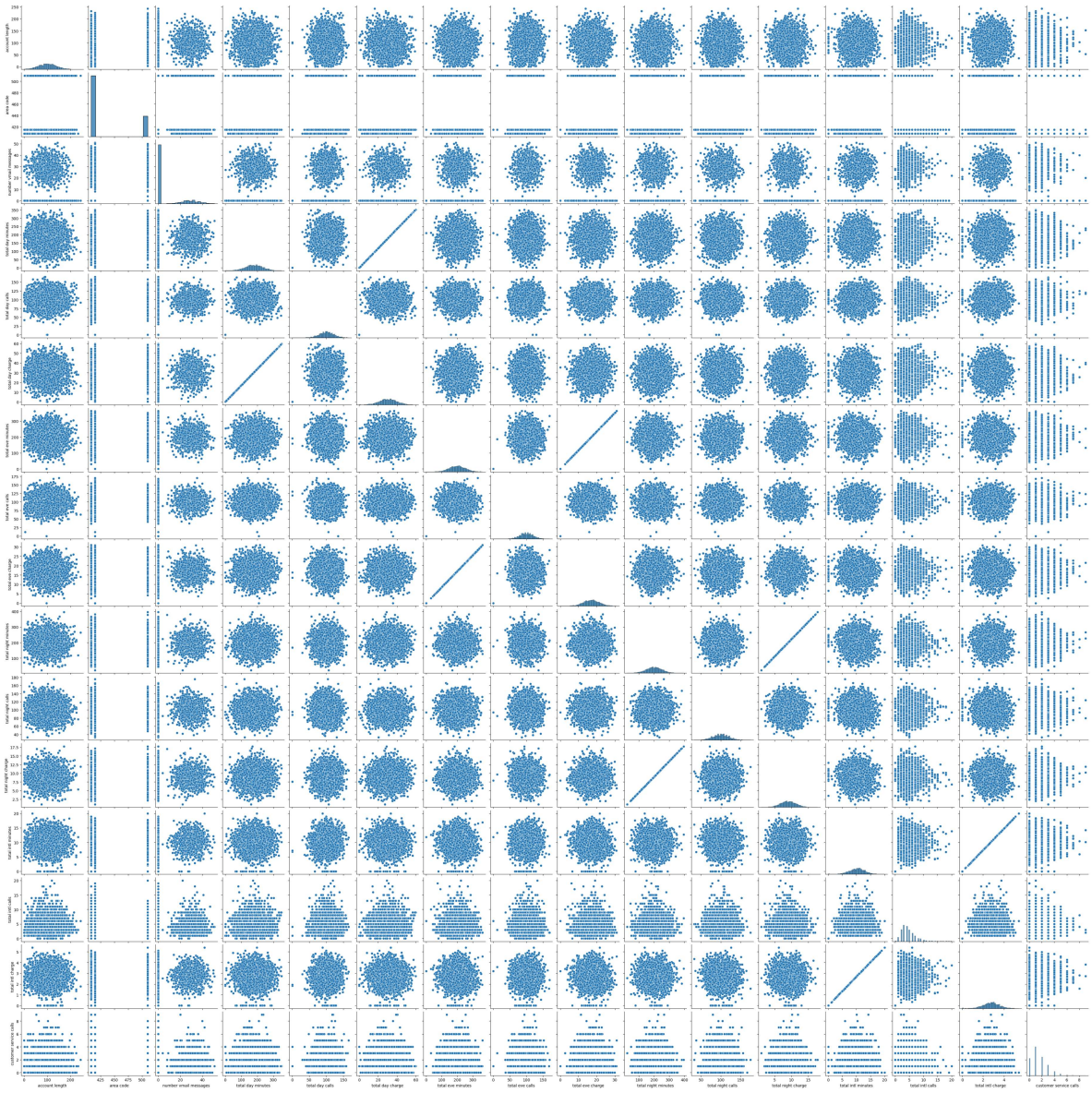
Out[68]:
```
<Axes: >
```



i have outliers but are not very extreme, hence i am going to keep them

In [69]:
```
sns.pairplot(df1)
```

Out[69]:
```
<seaborn.axisgrid.PairGrid at 0x13b2028b490>
```



computing the correlation between numerical columns

In [96]:
```
correlation_matrix = df1.select_dtypes(include=['number']).corr()

# the correlation matrix
print(correlation_matrix)

# correlation matrix using a heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f",
            linewidths=0.5, vmin=-1, vmax=1, cbar_kws={"shrink": 0.75})

plt.title('Correlation Matrix of Features')
plt.show()
```

	account length	area code	number vmail messages	\
account length	1.000000	-0.012463	-0.004628	
area code	-0.012463	1.000000	-0.001994	
number vmail messages	-0.004628	-0.001994	1.000000	
total day minutes	0.006216	-0.008264	0.000778	
total day calls	0.038470	-0.009646	-0.009548	
total day charge	0.006214	-0.008264	0.000776	
total eve minutes	-0.006757	0.003580	0.017562	
total eve calls	0.019260	-0.011886	-0.005864	
total eve charge	-0.006745	0.003607	0.017578	
total night minutes	-0.008955	-0.005825	0.007681	
total night calls	-0.013176	0.016522	0.007123	
total night charge	-0.008960	-0.005845	0.007663	
total intl minutes	0.009514	-0.018288	0.002856	
total intl calls	0.020661	-0.024179	0.013957	
total intl charge	0.009546	-0.018395	0.002884	
customer service calls	-0.003796	0.027572	-0.013263	

	total day minutes	total day calls	total day charge	\
account length	0.006216	0.038470	0.006214	
area code	-0.008264	-0.009646	-0.008264	
number vmail messages	0.000778	-0.009548	0.000776	
total day minutes	1.000000	0.006750	1.000000	
total day calls	0.006750	1.000000	0.006753	
total day charge	1.000000	0.006753	1.000000	
total eve minutes	0.007043	-0.021451	0.007050	
total eve calls	0.015769	0.006462	0.015769	
total eve charge	0.007029	-0.021449	0.007036	
total night minutes	0.004323	0.022938	0.004324	
total night calls	0.022972	-0.019557	0.022972	
total night charge	0.004300	0.022927	0.004301	
total intl minutes	-0.010155	0.021565	-0.010157	
total intl calls	0.008033	0.004574	0.008032	
total intl charge	-0.010092	0.021666	-0.010094	
customer service calls	-0.013423	-0.018942	-0.013427	

	total eve minutes	total eve calls	total eve charge	\
account length	-0.006757	0.019260	-0.006745	
area code	0.003580	-0.011886	0.003607	
number vmail messages	0.017562	-0.005864	0.017578	
total day minutes	0.007043	0.015769	0.007029	
total day calls	-0.021451	0.006462	-0.021449	
total day charge	0.007050	0.015769	0.007036	
total eve minutes	1.000000	-0.011430	1.000000	
total eve calls	-0.011430	1.000000	-0.011423	
total eve charge	1.000000	-0.011423	1.000000	
total night minutes	-0.012584	-0.002093	-0.012592	
total night calls	0.007586	0.007710	0.007596	
total night charge	-0.012593	-0.002056	-0.012601	
total intl minutes	-0.011035	0.008703	-0.011043	
total intl calls	0.002541	0.017434	0.002541	
total intl charge	-0.011067	0.008674	-0.011074	
customer service calls	-0.012985	0.002423	-0.012987	

	total night minutes	total night calls	\
account length	-0.008955	-0.013176	
area code	-0.005825	0.016522	
number vmail messages	0.007681	0.007123	
total day minutes	0.004323	0.022972	
total day calls	0.022938	-0.019557	

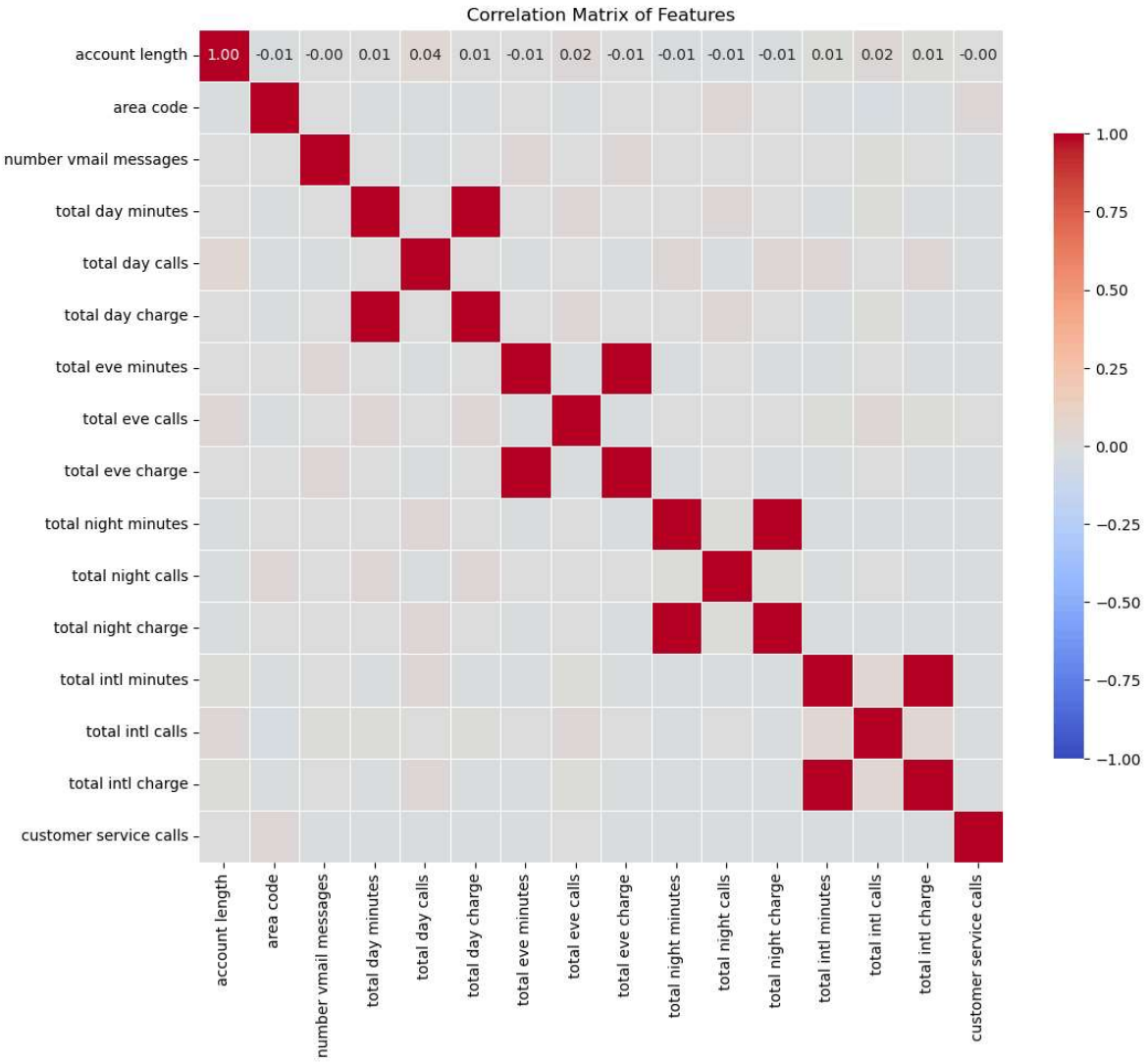
total day charge	0.004324	0.022972
total eve minutes	-0.012584	0.007586
total eve calls	-0.002093	0.007710
total eve charge	-0.012592	0.007596
total night minutes	1.000000	0.011204
total night calls	0.011204	1.000000
total night charge	0.999999	0.011188
total intl minutes	-0.015207	-0.013605
total intl calls	-0.012353	0.000305
total intl charge	-0.015180	-0.013630
customer service calls	-0.009288	-0.012802

	total night charge	total intl minutes	\
account length	-0.008960	0.009514	
area code	-0.005845	-0.018288	
number vmail messages	0.007663	0.002856	
total day minutes	0.004300	-0.010155	
total day calls	0.022927	0.021565	
total day charge	0.004301	-0.010157	
total eve minutes	-0.012593	-0.011035	
total eve calls	-0.002056	0.008703	
total eve charge	-0.012601	-0.011043	
total night minutes	0.999999	-0.015207	
total night calls	0.011188	-0.013605	
total night charge	1.000000	-0.015214	
total intl minutes	-0.015214	1.000000	
total intl calls	-0.012329	0.032304	
total intl charge	-0.015186	0.999993	
customer service calls	-0.009277	-0.009640	

	total intl calls	total intl charge	\
account length	0.020661	0.009546	
area code	-0.024179	-0.018395	
number vmail messages	0.013957	0.002884	
total day minutes	0.008033	-0.010092	
total day calls	0.004574	0.021666	
total day charge	0.008032	-0.010094	
total eve minutes	0.002541	-0.011067	
total eve calls	0.017434	0.008674	
total eve charge	0.002541	-0.011074	
total night minutes	-0.012353	-0.015180	
total night calls	0.000305	-0.013630	
total night charge	-0.012329	-0.015186	
total intl minutes	0.032304	0.999993	
total intl calls	1.000000	0.032372	
total intl charge	0.032372	1.000000	
customer service calls	-0.017561	-0.009675	

	customer service calls
account length	-0.003796
area code	0.027572
number vmail messages	-0.013263
total day minutes	-0.013423
total day calls	-0.018942
total day charge	-0.013427
total eve minutes	-0.012985
total eve calls	0.002423
total eve charge	-0.012987
total night minutes	-0.009288
total night calls	-0.012802

```
total night charge          -0.009277
total intl minutes          -0.009640
total intl calls            -0.017561
total intl charge           -0.009675
customer service calls       1.000000
```

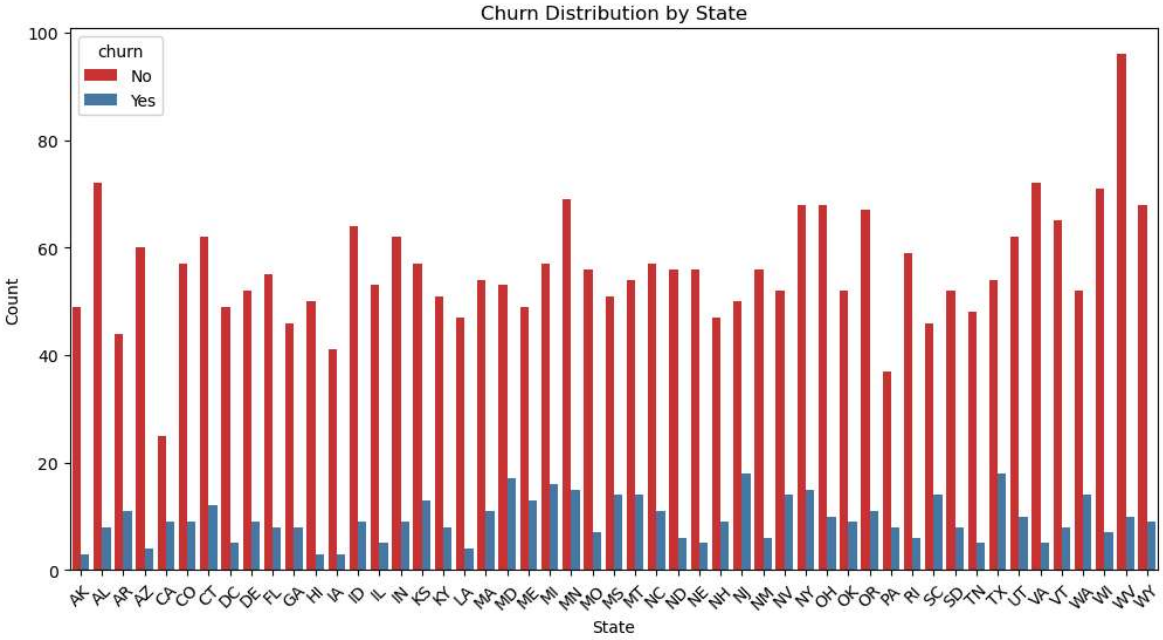


it can be seen that the minutes for whatever type of call the respective charges gave a 1 to 1 relationships. which this might indicate that a model that support linear relationship can be used.

plotting of data

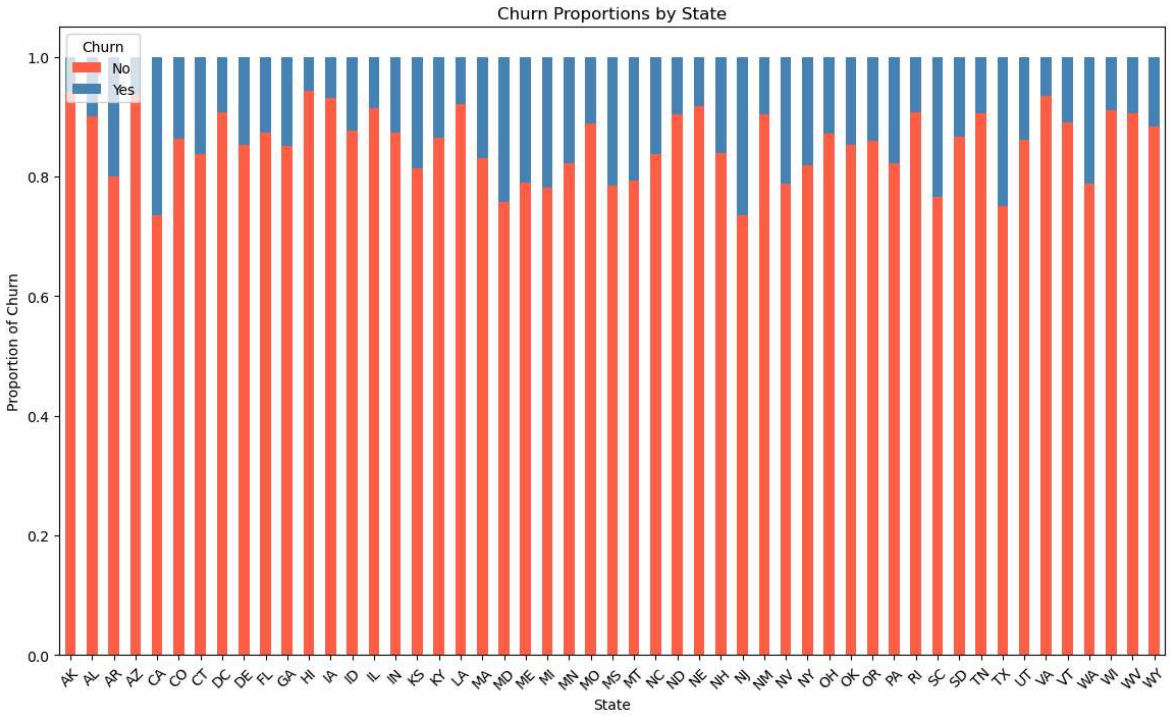
this plot shows the churn count by each state

In [70]:
```
plt.figure(figsize=(12, 6))
sns.countplot(x='state', hue='churn', data=df1, palette='Set1')
plt.title('Churn Distribution by State')
plt.xlabel('State')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



it can be seen that WV has the highest false churn in terms of counts, but this value in only absolute, so make a comparisone there is a need to have a relative count in relation to other states. To address this, you should consider normalizing the data to show the proportion of churn within each state (both for True and False churn) so you can better compare states of different sizes.To address this, you should consider normalizing the data to show the proportion of churn within each state (both for True and False churn) so you can better compare states of different sizes.To address this, you should consider normalizing the data to show the proportion of churn within each state (both for True and False churn) so you can better compare states of different sizes.To address this each state is normaziled within each state, so that the proportions.

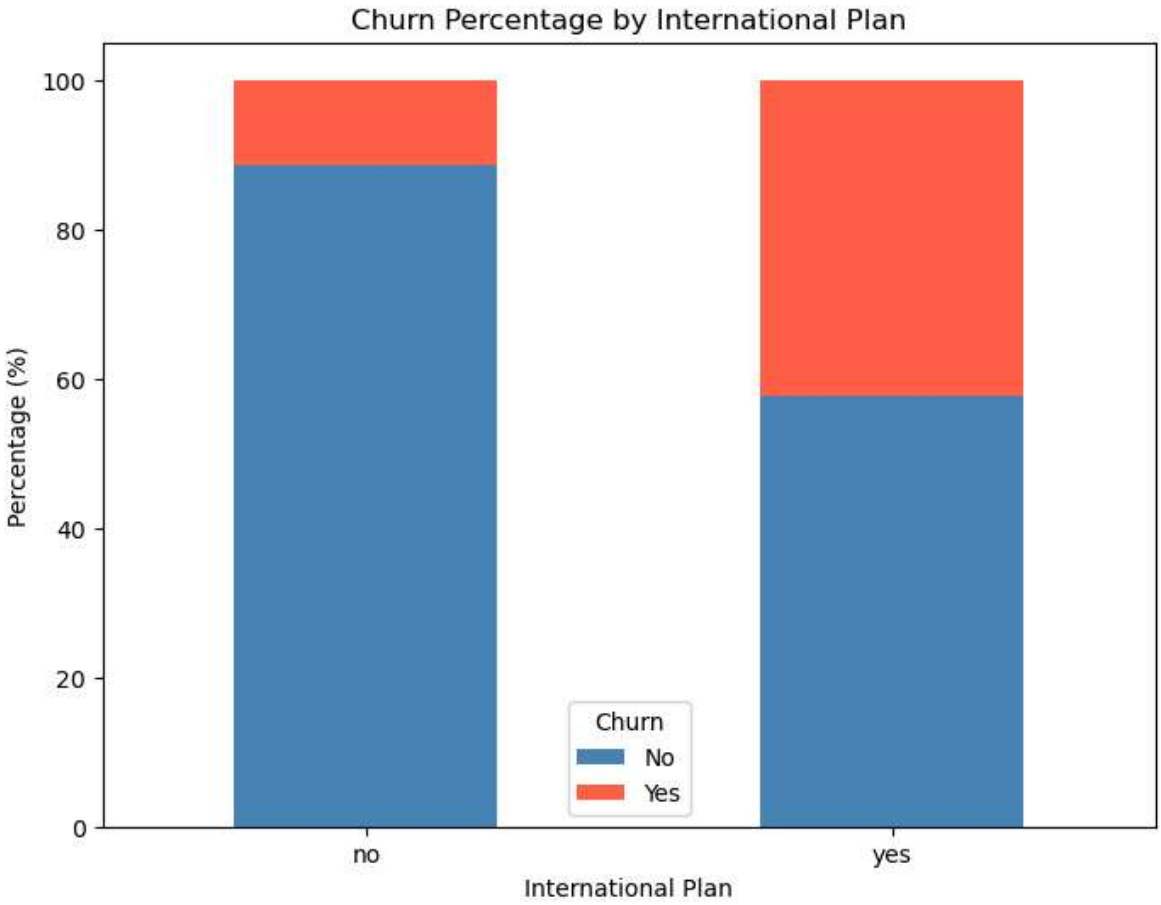
In [71]:
```
# Calculate churn proportions per state
churn_state_counts = df1.groupby(['state', 'churn']).size().unstack()

# Normalize by dividing by the total count of each state
churn_state_proportions = churn_state_counts.div(churn_state_counts.sum(axis=1),

# Plot the stacked bar plot of churn proportions by state
churn_state_proportions.plot(kind='bar', stacked=True, figsize=(14, 8), color=['
plt.title('Churn Proportions by State')
plt.xlabel('State')
plt.ylabel('Proportion of Churn')
plt.xticks(rotation=45)
plt.legend(title='Churn', loc='upper left',labels=['No', 'Yes'])
plt.show()
```



it can be concluded that some states like NJ and CA have the highest churn

this plot explores the relationship between international calls and churn

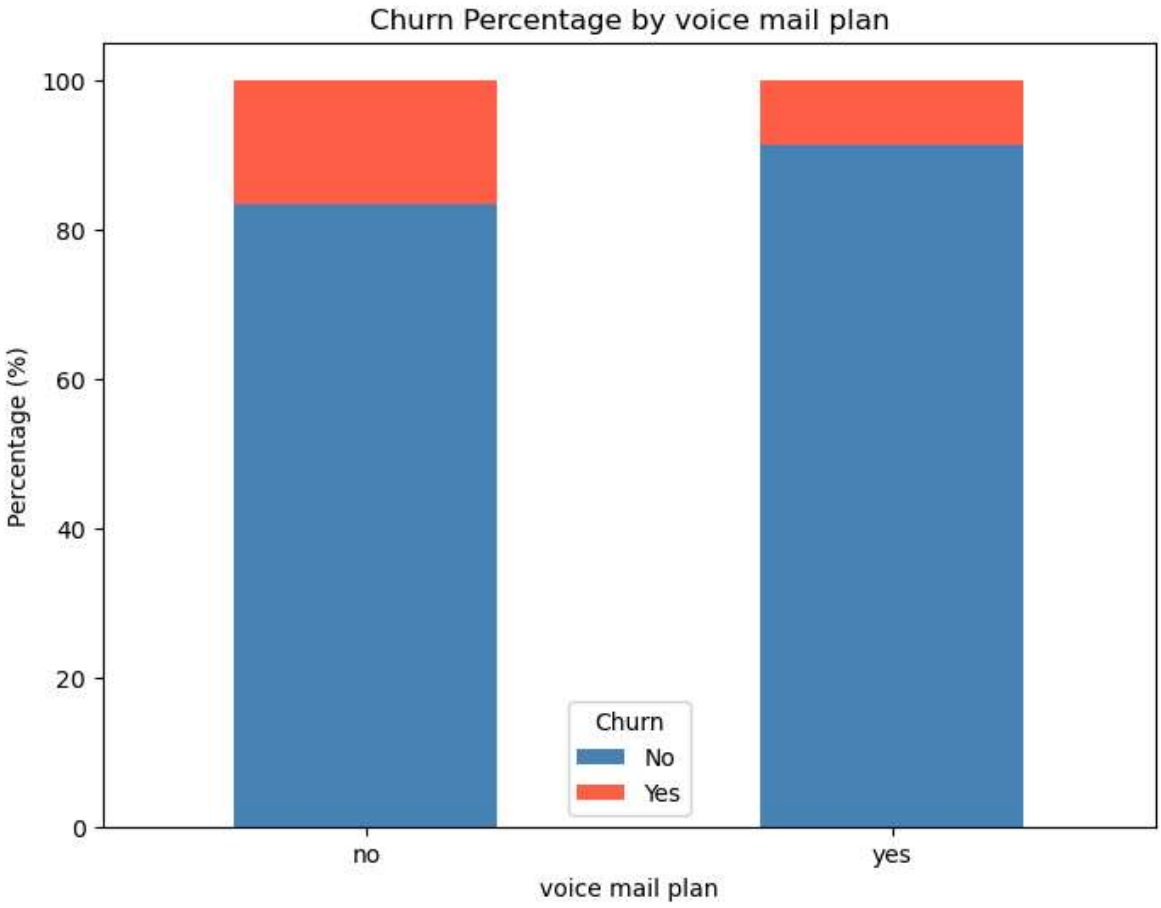
In [72]:
```
counts = df.groupby(['international plan', 'churn']).size().unstack()
# Calculate percentages
percentages = counts.div(counts.sum(axis=1), axis=0) * 100
# stacked bar chart
percentages.plot(kind='bar', stacked=True, figsize=(8, 6), color=['#4682B4', '#F
# Title and labels
plt.title('Churn Percentage by International Plan')
plt.xlabel('International Plan')
plt.ylabel('Percentage (%)')
plt.xticks(rotation=0)
plt.legend(title='Churn', labels=['No', 'Yes'])
plt.show()
```



it can be concluded that people that have international calls tend to churn more than the people who don`t have.

this plot shows the churn in relation to people having voice mail plan

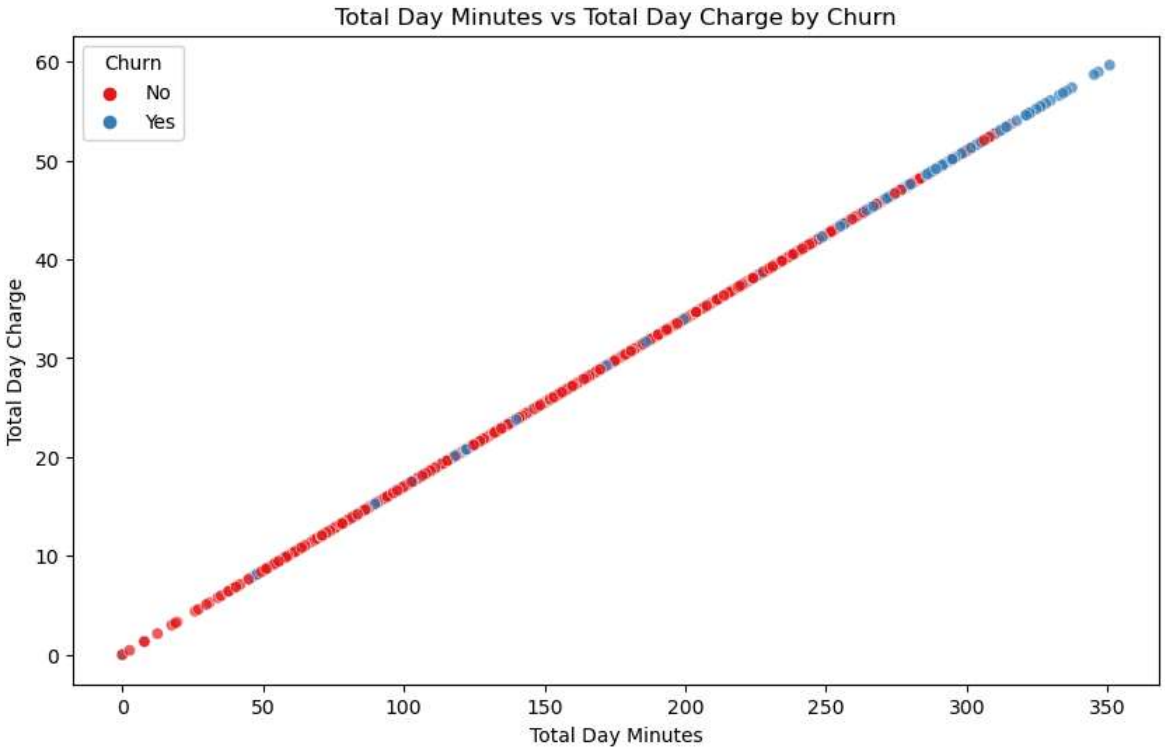
In [73]:
```
counts = df.groupby(['voice mail plan', 'churn']).size().unstack()
# Calculate percentages
percentages = counts.div(counts.sum(axis=1), axis=0) * 100
# stacked bar chart
percentages.plot(kind='bar', stacked=True, figsize=(8, 6), color=['#4682B4', '#F
# Title and labels
plt.title('Churn Percentage by voice mail plan')
plt.xlabel('voice mail plan')
plt.ylabel('Percentage (%)')
plt.xticks(rotation=0)
plt.legend(title='Churn', labels=['No', 'Yes'])
plt.show()
```



it can be concluded that people that don`t have voice mail plan tend to churn more.

this plot is total day minutes against day charge and colored by churn

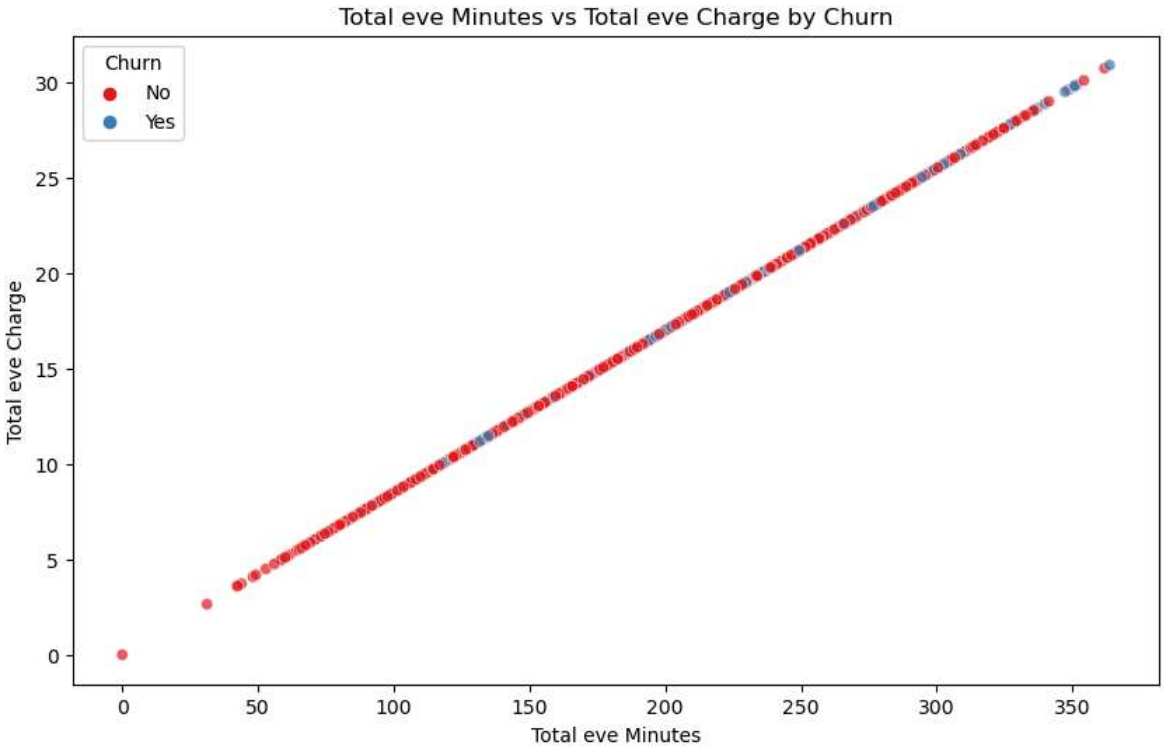
In [74]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(
    data=df1,
    x='total day minutes',
    y='total day charge',
    hue='churn',
    palette='Set1',
    alpha=0.7
)

plt.title('Total Day Minutes vs Total Day Charge by Churn')
plt.xlabel('Total Day Minutes')
plt.ylabel('Total Day Charge')
plt.legend(title='Churn')
plt.show()
```



it can be concluded that the relationship is 1 to 1, and as the charges or minutes are high the people tend to churn more.

this plot is total eve minutes agains eve charge and coloured by churn

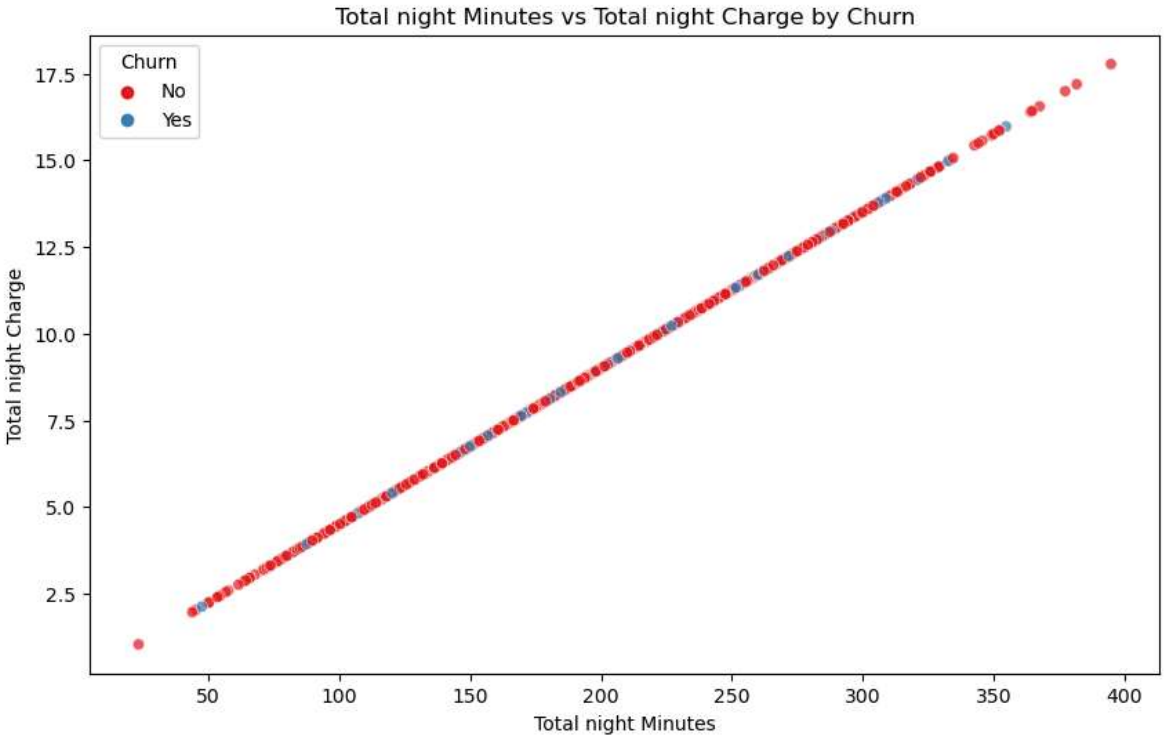
In [75]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(
    data=df1,
    x='total eve minutes',
    y='total eve charge',
    hue='churn',
    palette='Set1',
    alpha=0.7
)

plt.title('Total eve Minutes vs Total eve Charge by Churn')
plt.xlabel('Total eve Minutes')
plt.ylabel('Total eve Charge')
plt.legend(title='Churn')
plt.show()
```



it can be concluded that the relationship is 1 to 1, but there is no particular relationship with churn

this plot is total night minutes agains night charge and coloured by churn

In [76]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(
    data=df1,
    x='total night minutes',
    y='total night charge',
    hue='churn',
    palette='Set1',
    alpha=0.7
)

plt.title('Total night Minutes vs Total night Charge by Churn')
plt.xlabel('Total night Minutes')
plt.ylabel('Total night Charge')
plt.legend(title='Churn')
plt.show()
```



it can be concluded that the relationship is 1 to 1, but there is no particular relationship with churn

Data Preprocessing

In [77]:
```
#library
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
# seperating the categorical form numerical features except for the target varia
numerical_features = df1.select_dtypes(include=['int64', 'float64']).columns.tol
categorical_features = df1.select_dtypes(include=['category']).columns.tolist()
target_column = 'churn'
categorical_features.remove(target_column)
#standardizing the numerical features and apply onehot encoder on the categorica
preprocessor = ColumnTransformer(transformers=[('num', StandardScaler(), numeric
```

Modelling using pipeline

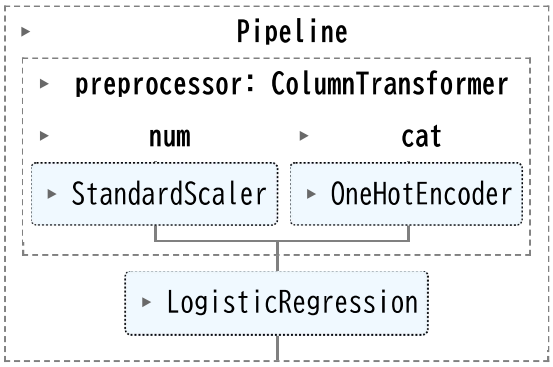
logistic regression

In [78]:
```
#importing of libraries
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_auc_score, roc_curve, accuracy_score, auc
```

In [79]:
```
# Full pipeline
pipeline = Pipeline(steps=[('preprocessor', preprocessor),('classifier', Logisti
```

In [80]:
```
# definig x and y and then applying fit
X = df1.drop('churn', axis=1)
y = df1['churn'].map({'No': 0, 'Yes': 1})
pipeline.fit(X, y)
```

Out[80]:



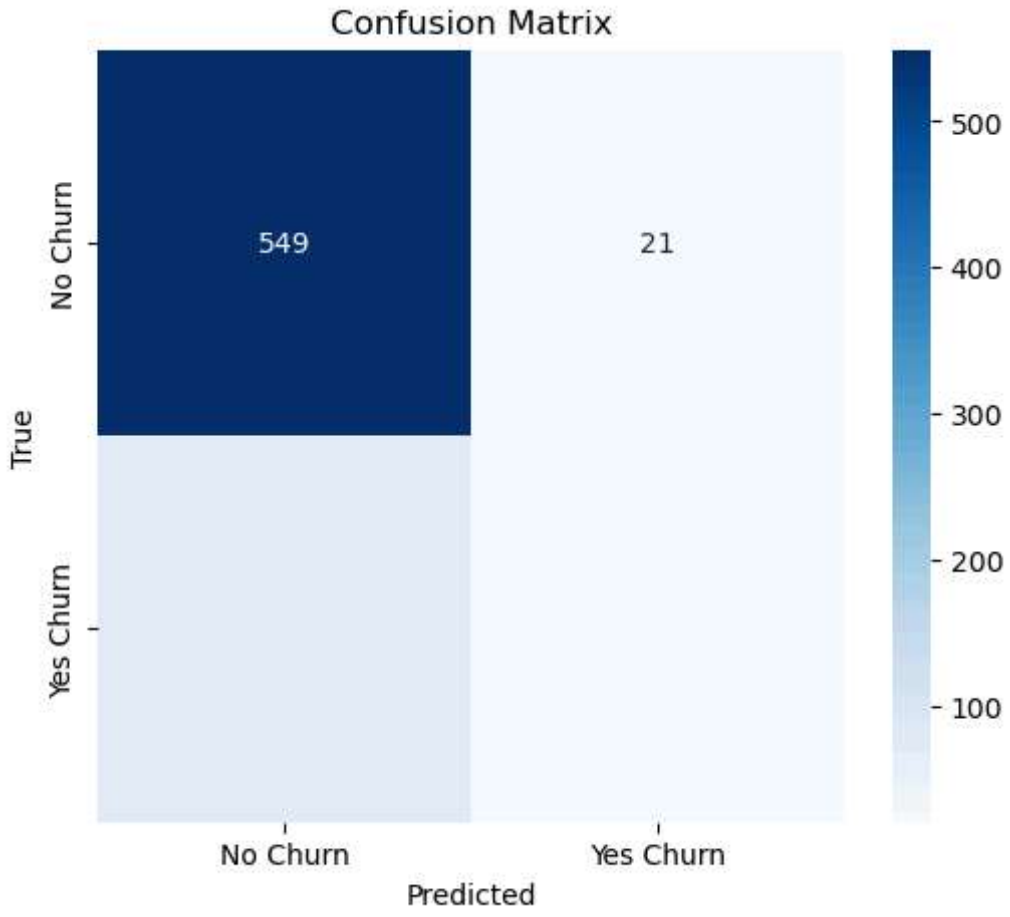
In [81]:
```
#splitting the data into train and test , with 0.2 test data and keeps the same
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

In [82]:
```
#fitting
pipeline.fit(X_train, y_train)
#predicting
y_pred = pipeline.predict(X_test)
#confusion matrix
print(confusion_matrix(y_test, y_pred))
cm=confusion_matrix(y_test, y_pred)
print(classification_report(y_test, y_pred))
#crossvalidation scores
scores = cross_val_score(pipeline, X, y, cv=5, scoring='accuracy')
print("Cross-validation accuracy scores:", scores)
print("Mean accuracy:", scores.mean())
```

```
[[549  21]
 [ 72  25]]
              precision    recall  f1-score   support

           0       0.88      0.96      0.92       570
           1       0.54      0.26      0.35        97

    accuracy                           0.86       667
   macro avg       0.71      0.61      0.64       667
weighted avg       0.83      0.86      0.84       667

Cross-validation accuracy scores: [0.85307346 0.85607196 0.86056972 0.86336336 0.
86336336]
Mean accuracy: 0.8592883738311026
```

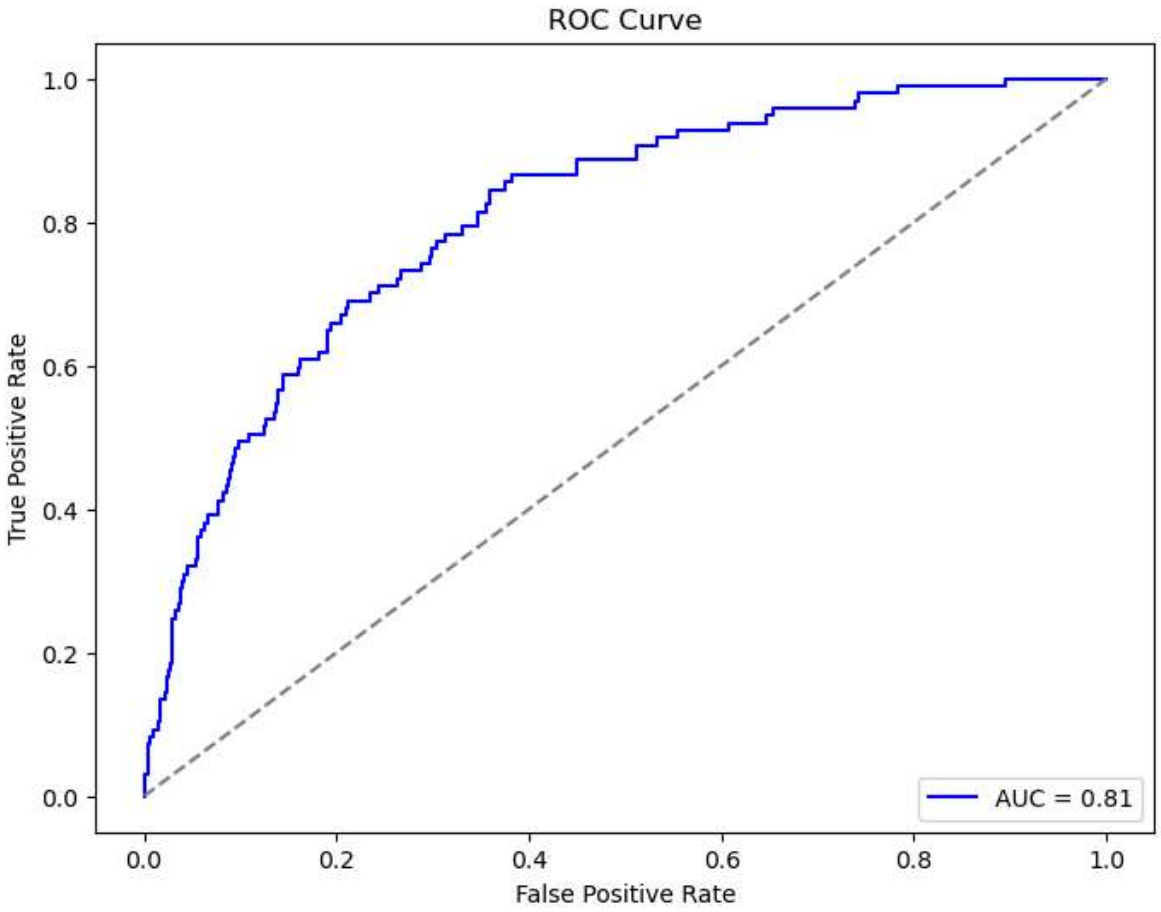
the model has an accuracy of 86% and a recall of 99% for no churn and a 26% for yes churn

In [83]:
```
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['No Churn', 'Yes
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```



In [84]:
```
y_prob = pipeline.predict_proba(X_test)[:, 1]
# AUC-ROC score
auc_score = roc_auc_score(y_test, y_prob)
print("AUC-ROC Score:", auc_score)
# ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label=f'AUC = {auc_score:.2f}')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```

```
AUC-ROC Score: 0.8092060047024778
```



In [85]:
```
# Get model coefficients
coefficients = pipeline.named_steps['classifier'].coef_[0]
# Print coefficients
for feature, coef in zip(X_train.columns, coefficients):
    print(f'{feature}: {coef}')
```

```
state: 0.038833625647567295
account length: -0.03157745768543498
area code: 0.34943081769463286
international plan: 0.3324505906537912
voice mail plan: 0.09105270144168924
number vmail messages: 0.33343549696565206
total day minutes: 0.19796276327637982
total day calls: 0.04982795819560248
total day charge: 0.19827065372629663
total eve minutes: 0.06001054424572813
total eve calls: -0.0023587409624517813
total eve charge: 0.07413875845994657
total night minutes: 0.10378678691796299
total night calls: -0.21182329849498716
total night charge: 0.1350395587546658
total intl minutes: 0.7535071759927707
total intl calls: -0.48975727317473905
total intl charge: -0.03372248673020865
customer service calls: -0.3861077146528432
```

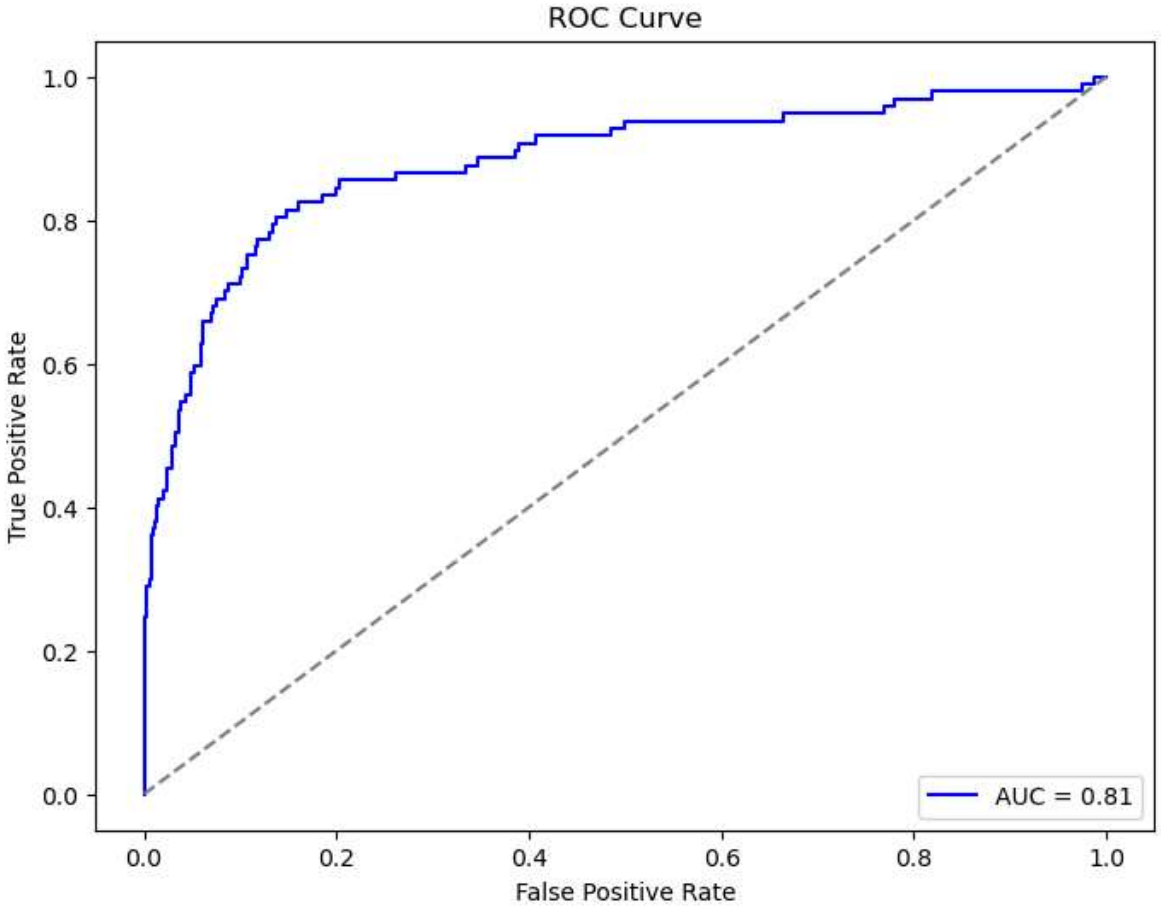
it can be seen from the coefficients that total intl minutes has the highest positive impact on the prediction, total evening calls have almost close to zero effect and total intl calls have the highest negative impacts

SVM

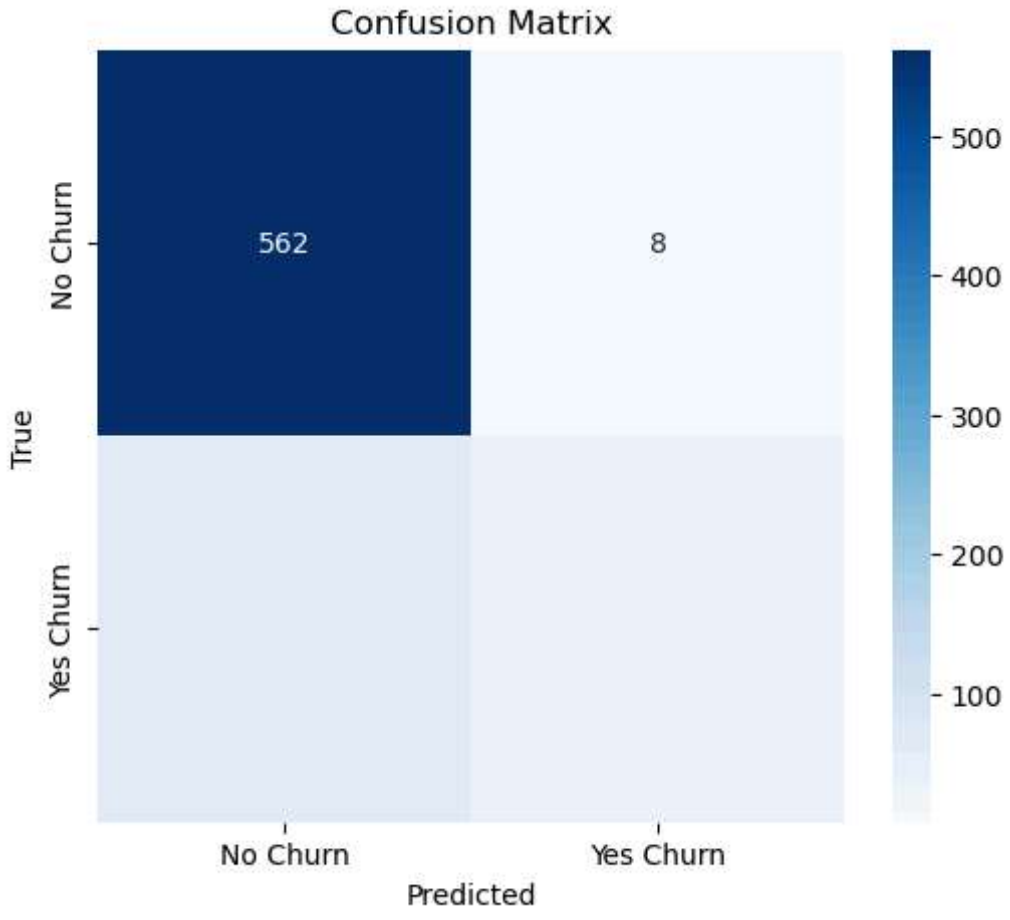
In [86]:
```
# importing lybrary
from sklearn.svm import SVC
```

In [87]:
```
svm_model = Pipeline(steps=[('preprocessor', preprocessor),('classifier', SVC(ra
# Train the SVM model
svm_model.fit(X_train, y_train)
# Make predictions on the test set
y_pred = svm_model.predict(X_test)
# Evaluate the model using classification report
print("Classification Report:\n", classification_report(y_test, y_pred))
# Calculate and print the AUC-ROC score
y_prob = svm_model.predict_proba(X_test)[:, 1]
print("AUC-ROC Score:", roc_auc_score(y_test, y_prob))
# ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label=f'AUC = {auc_score:.2f}')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
#Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", cm)
#Visualize the confusion matrix
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['No Churn', 'Yes
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

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

           0       0.90      0.99      0.94       570
           1       0.82      0.38      0.52        97

    accuracy                           0.90       667
   macro avg       0.86      0.68      0.73       667
weighted avg       0.89      0.90      0.88       667

AUC-ROC Score: 0.880774100198951
```




```
Confusion Matrix:
 [[562   8]
 [ 60  37]]
```



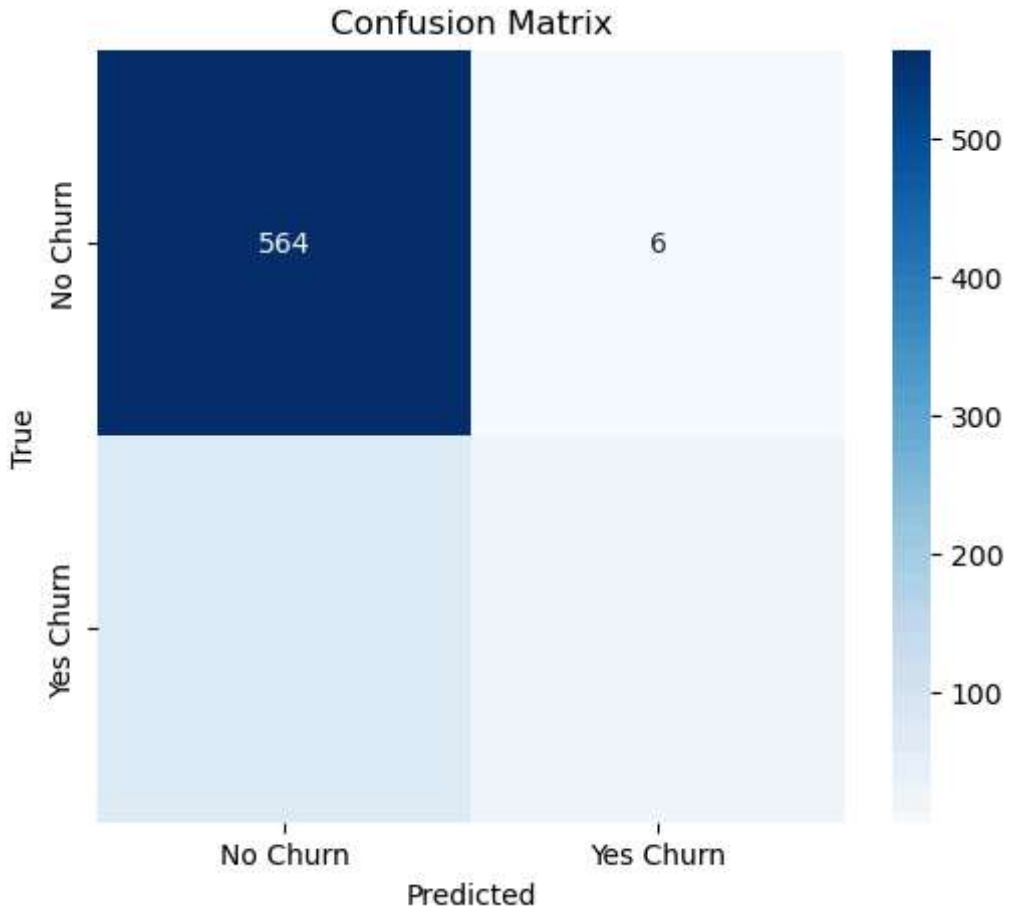
the accuracy is 90% and the recall of no churn is 99% while for yes churn is 38%

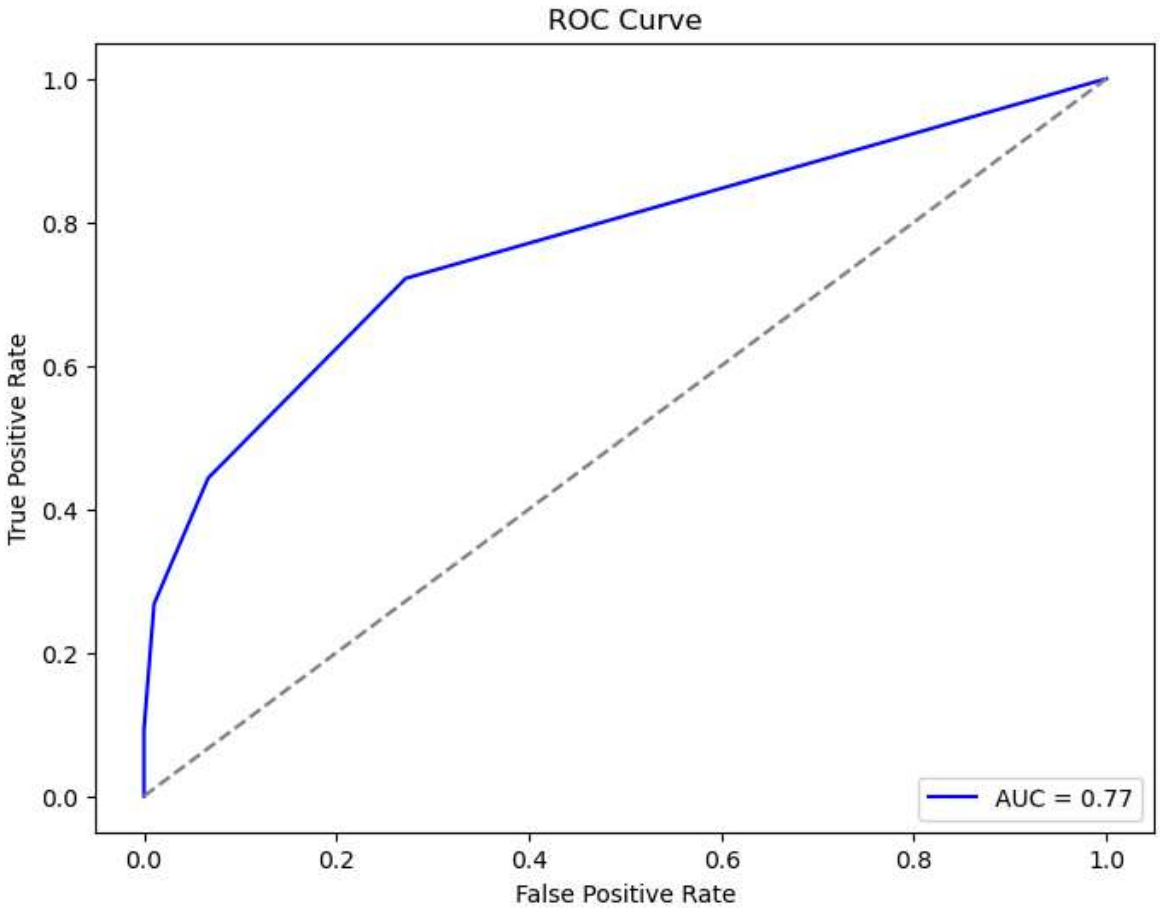
KNN

In [88]:
```
#importing library
from sklearn.neighbors import KNeighborsClassifier
```

In [89]:
```
#  the number of neighbors
knn_model = KNeighborsClassifier(n_neighbors=5)

# Create a pipeline
pipeline = Pipeline(steps=[('preprocessor', preprocessor),('classifier', knn_mod
pipeline.fit(X_train, y_train)
y_pred = pipeline.predict(X_test)
#accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", cm)

# Visualize the confusion matrix
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['No Churn', 'Yes
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

# Calculate ROC curve and AUC
y_prob = pipeline.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
auc_score = auc(fpr, tpr)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label=f'AUC = {auc_score:.2f}')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
# Classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.8846
Confusion Matrix:
 [[564   6]
 [ 71  26]]
```


Confusion Matrix
564
6
No Churn
Yes Churn
True
No Churn
Yes Churn
Predicted
500
400
300
200
100


ROC Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
AUC = 0.77

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

           0       0.89      0.99      0.94       570
           1       0.81      0.27      0.40        97

    accuracy                           0.88       667
   macro avg       0.85      0.63      0.67       667
weighted avg       0.88      0.88      0.86       667
```

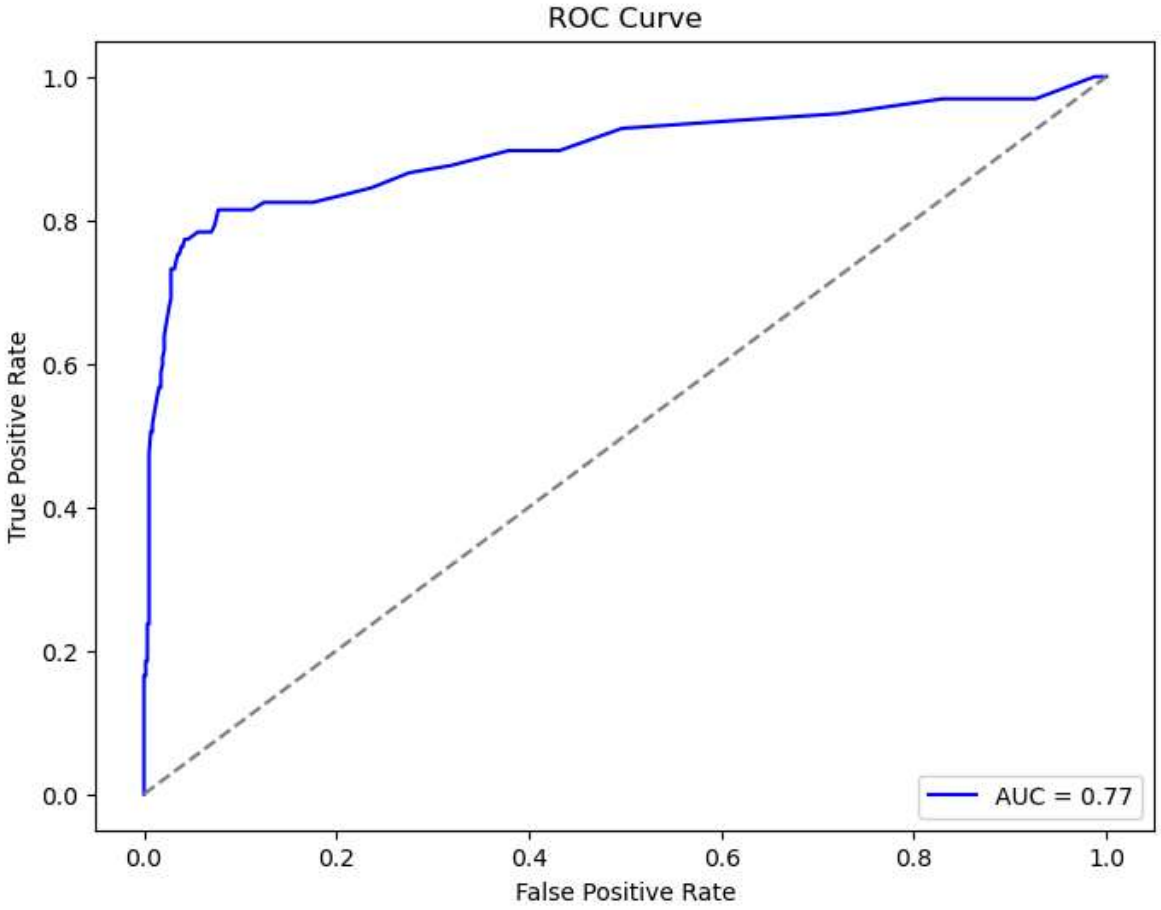
the accuracy is 88% and the recall of no church is 99% while for yes churn is 27%

Random Forest

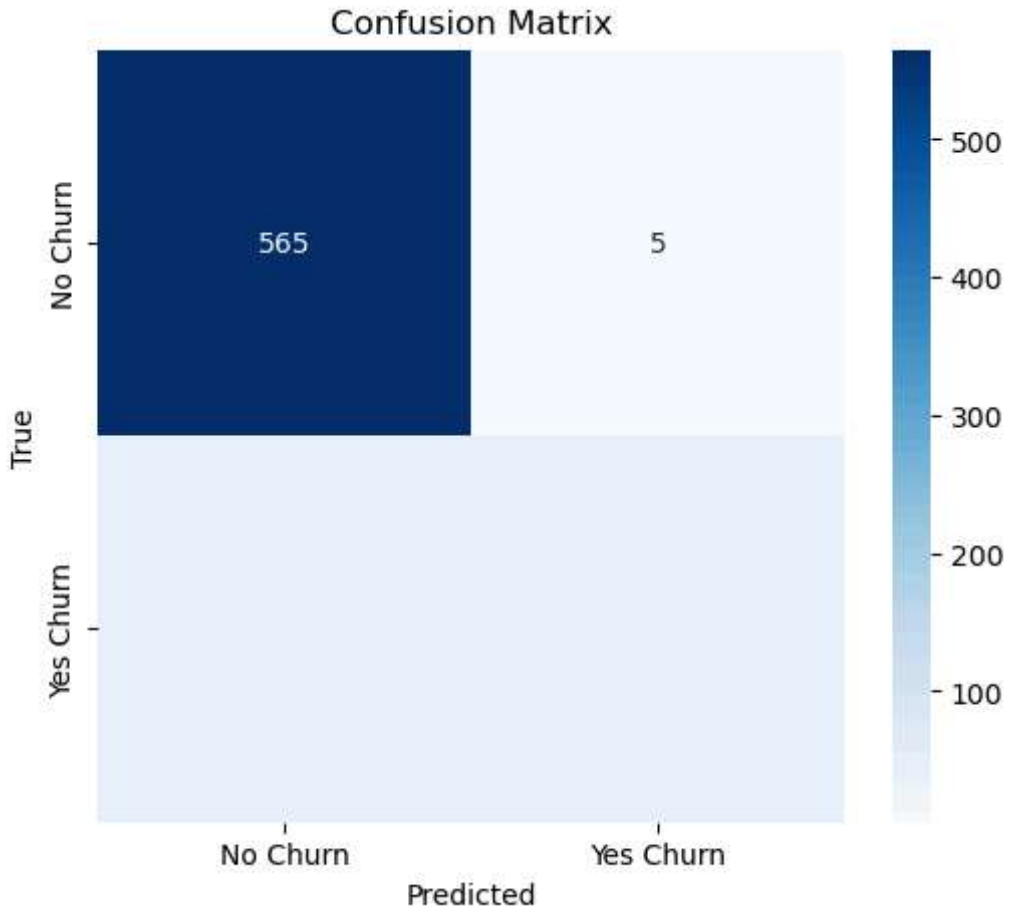
In [90]:
```
# importing of library
from sklearn.ensemble import RandomForestClassifier
```

In [91]:
```
rf_model = Pipeline(steps=[('preprocessor', preprocessor),('classifier', RandomF
# Train the Random Forest model
rf_model.fit(X_train, y_train)
# Make predictions on the test set
y_pred = rf_model.predict(X_test)
# Evaluate the model using classification report
print("Classification Report:\n", classification_report(y_test, y_pred))
# Calculate and print the AUC-ROC score
y_prob = rf_model.predict_proba(X_test)[:, 1]
print("AUC-ROC Score:", roc_auc_score(y_test, y_prob))
# ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label=f'AUC = {auc_score:.2f}')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", cm)
# Visualize the confusion matrix
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['No Churn', 'Yes
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

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

           0       0.92      0.99      0.96       570
           1       0.91      0.52      0.66        97

    accuracy                           0.92       667
   macro avg       0.92      0.75      0.81       667
weighted avg       0.92      0.92      0.91       667

AUC-ROC Score: 0.8959757641526496
```




```
Confusion Matrix:
 [[565   5]
 [ 47  50]]
```



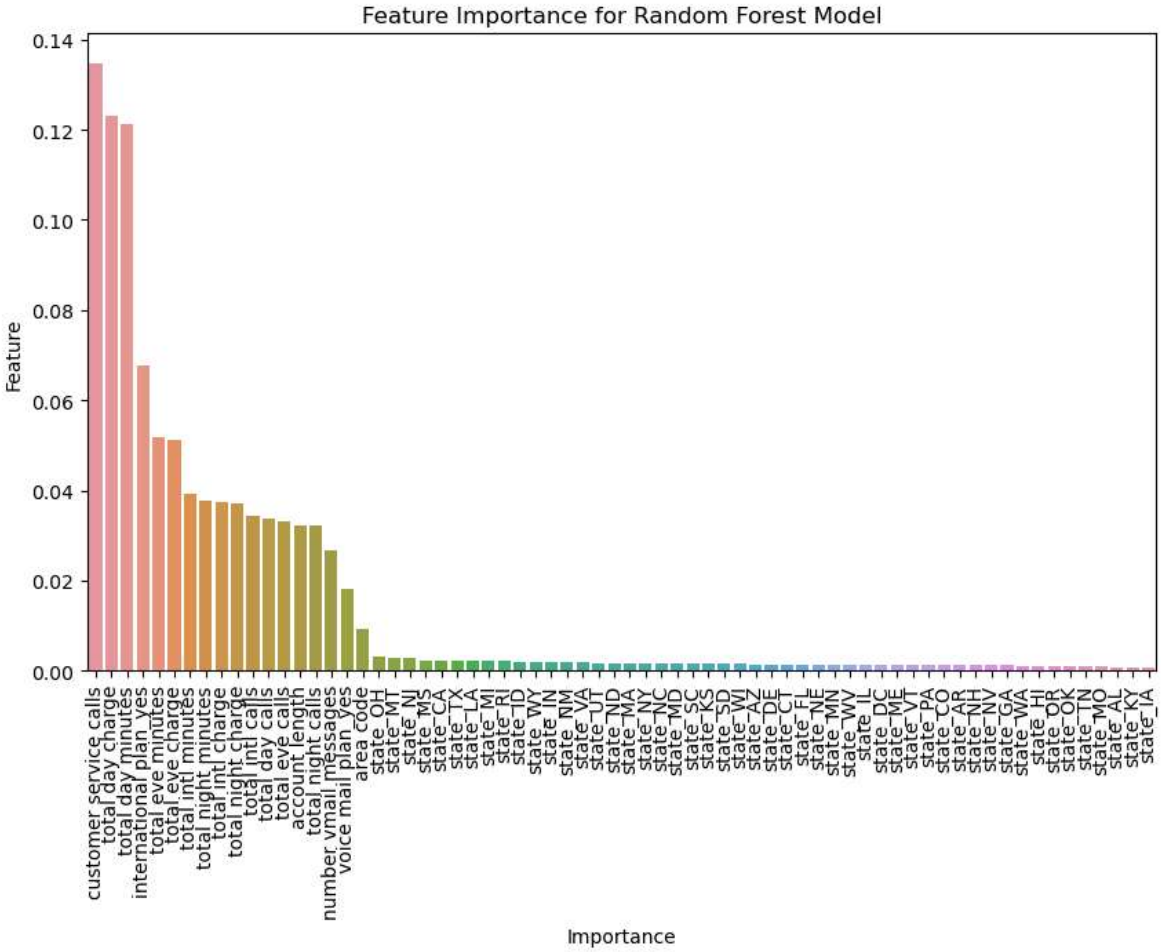
the accuracy is 92% and the recall of no churn is 99% while for yes churn is 59%

the best performing model is random forest with the accuracy is 92% and the recall of no church is 99% while for yes churn is 59%

to understand which features were important in the building of the random forest model, which is the better performing model the feature importance is computed

In [92]:
```
importances = rf_model.named_steps['classifier'].feature_importances_

# Get the numerical and categorical feature names
num_features = numerical_features
cat_features = preprocessor.transformers_[1][1].get_feature_names_out(categorica

# Combine the numerical and one-hot encoded categorical feature names
all_feature_names = np.concatenate([num_features, cat_features])

# Create a DataFrame to display the feature importances with their corresponding
feature_importance_df = pd.DataFrame({'Feature': all_feature_names,'Importance':
# Sort the features by importance in descending order
feature_importance_df = feature_importance_df.sort_values(by='Importance', ascen
# Plot the top features by importance
plt.figure(figsize=(10, 6))
sns.barplot(x='Feature', y='Importance', data=feature_importance_df)
plt.xticks(rotation=90)
plt.title('Feature Importance for Random Forest Model')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
```

```
# print the feature importance table
print(feature_importance_df)
```




```
                  Feature  Importance
15  customer service calls    0.134600
5         total day charge    0.123191
3        total day minutes    0.121110
66  international plan_yes    0.067745
6        total eve minutes    0.051861
..                     ...         ...
57                state_TN    0.000947
39                state_MO    0.000885
16                state_AL    0.000868
32                state_KY    0.000709
27                state_IA    0.000630

[68 rows x 2 columns]
```

From the feature importance it can be seen that customer service calls, total day charge and total day minutes have the most importance in estimating the churn.

It can be seen that for all the models there is an imbalance in class, meaning that the entries for people who churn are very few to the people who don't churn. And my interest is in the people who churn to understand why they do it, and what factors are leading them to that. To solve this imbalance i have decided a model which is good in handling class imbalance which is the CatBoost.

CatBoost

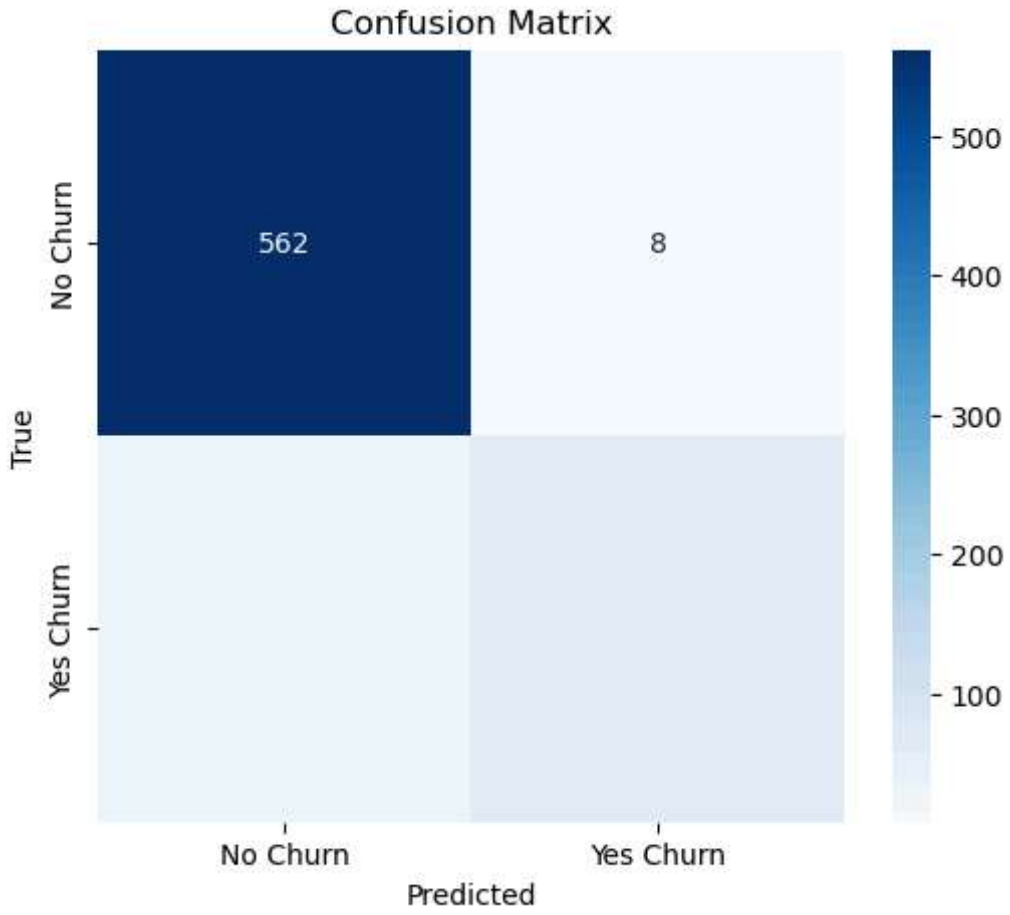
In [93]:
```
#importing library
!pip install catboost
from catboost import CatBoostClassifier
```

```
Requirement already satisfied: catboost in c:\users\admin\anaconda3\lib\site-pack
ages (1.2.7)
Requirement already satisfied: graphviz in c:\users\admin\anaconda3\lib\site-pack
ages (from catboost) (0.20.3)
Requirement already satisfied: matplotlib in c:\users\admin\anaconda3\lib\site-pa
ckages (from catboost) (3.8.0)
Requirement already satisfied: numpy<2.0,>=1.16.0 in c:\users\admin\anaconda3\lib
\site-packages (from catboost) (1.26.4)
Requirement already satisfied: pandas>=0.24 in c:\users\admin\anaconda3\lib\site-
packages (from catboost) (2.1.4)
Requirement already satisfied: scipy in c:\users\admin\anaconda3\lib\site-package
s (from catboost) (1.11.4)
Requirement already satisfied: plotly in c:\users\admin\anaconda3\lib\site-packag
es (from catboost) (5.9.0)
Requirement already satisfied: six in c:\users\admin\anaconda3\lib\site-packages
(from catboost) (1.16.0)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\admin\anaconda3
\lib\site-packages (from pandas>=0.24->catboost) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in c:\users\admin\anaconda3\lib\site-
packages (from pandas>=0.24->catboost) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in c:\users\admin\anaconda3\lib\sit
e-packages (from pandas>=0.24->catboost) (2023.3)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\admin\anaconda3\lib\s
ite-packages (from matplotlib->catboost) (1.2.0)
Requirement already satisfied: cycler>=0.10 in c:\users\admin\anaconda3\lib\site-
packages (from matplotlib->catboost) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\admin\anaconda3\lib
\site-packages (from matplotlib->catboost) (4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\admin\anaconda3\lib
\site-packages (from matplotlib->catboost) (1.4.4)
Requirement already satisfied: packaging>=20.0 in c:\users\admin\anaconda3\lib\si
te-packages (from matplotlib->catboost) (23.1)
Requirement already satisfied: pillow>=6.2.0 in c:\users\admin\anaconda3\lib\site
-packages (from matplotlib->catboost) (10.2.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\admin\anaconda3\lib\s
ite-packages (from matplotlib->catboost) (3.0.9)
Requirement already satisfied: tenacity>=6.2.0 in c:\users\admin\anaconda3\lib\si
te-packages (from plotly->catboost) (8.2.2)
```

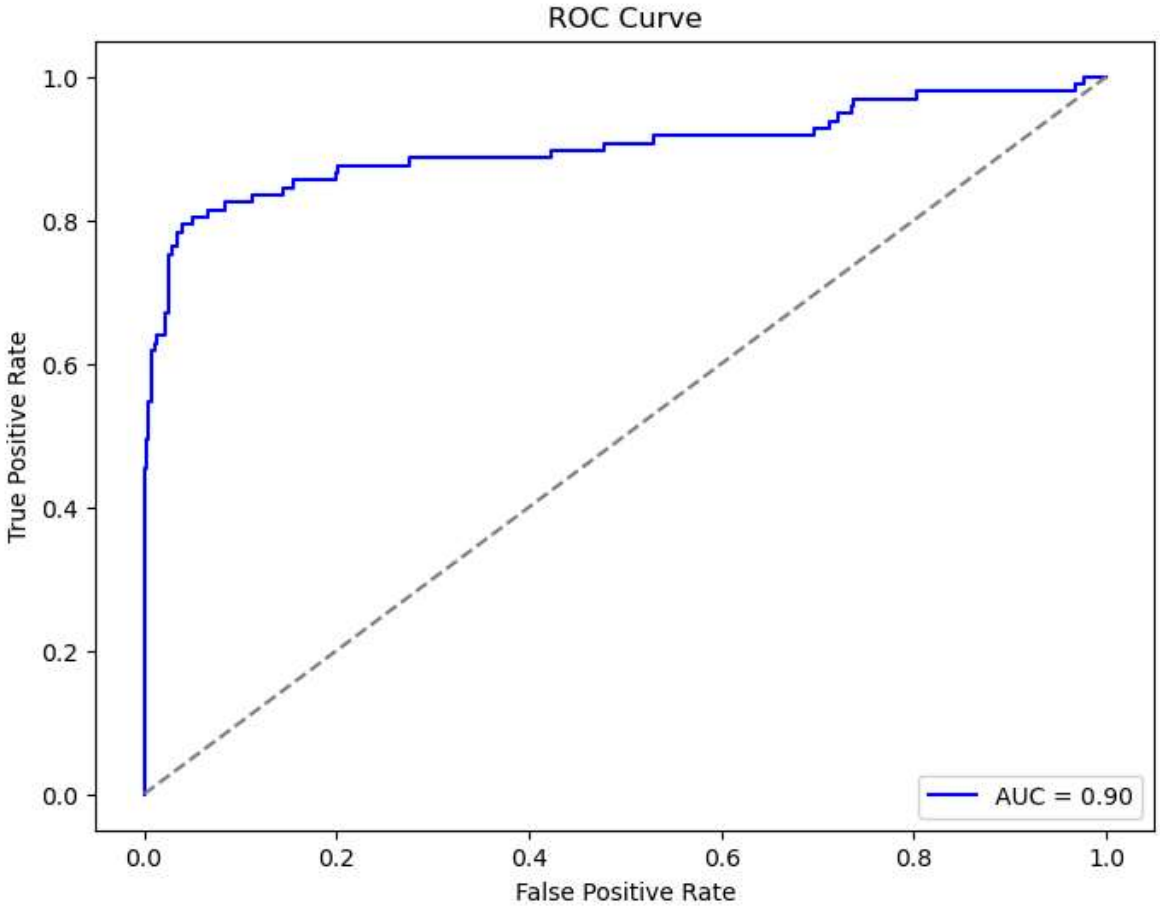
In [94]:
```
scaler = StandardScaler()
X_train_scaled_num = pd.DataFrame(scaler.fit_transform(X_train[numerical_feature
X_test_scaled_num = pd.DataFrame(scaler.transform(X_test[numerical_features]),co

# Keep categorical features as they are no need for onehotencoder
X_train_cat = X_train[categorical_features].astype(str)
X_test_cat = X_test[categorical_features].astype(str)

# Combine scaled numerical and categorical features
X_train_final = pd.concat([X_train_scaled_num, X_train_cat], axis=1)
X_test_final = pd.concat([X_test_scaled_num, X_test_cat], axis=1)

# Get list of categorical feature names after combining them
cat_features = categorical_features
```

```
# Define CatBoost model 100 iteration are considered
catboost_model = CatBoostClassifier(iterations=100,learning_rate=0.1,depth=6,eva
# Train model
catboost_model.fit(X_train_final, y_train,cat_features=cat_features,eval_set=(X_
# Predict
y_pred = catboost_model.predict(X_test_final)
y_prob = catboost_model.predict_proba(X_test_final)[:, 1]

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['No Churn', 'Yes
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

# AUC-ROC score
auc_score = roc_auc_score(y_test, y_prob)
print("AUC-ROC Score:", auc_score)

# ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label=f'AUC = {auc_score:.2f}')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()

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

```
0:      test: 0.7904865 best: 0.7904865 (0)     total: 57.6ms   remaining: 5.71s
99:     test: 0.8969976 best: 0.9011575 (68)    total: 4.93s    remaining: 0us

bestTest = 0.901157533
bestIteration = 68

Shrink model to first 69 iterations.
```




```
AUC-ROC Score: 0.9011575330077771
```



	precision	recall	f1-score	support
0	0.94	0.99	0.96	570
1	0.89	0.64	0.74	97
accuracy			0.94	667
macro avg	0.91	0.81	0.85	667
weighted avg	0.93	0.94	0.93	667

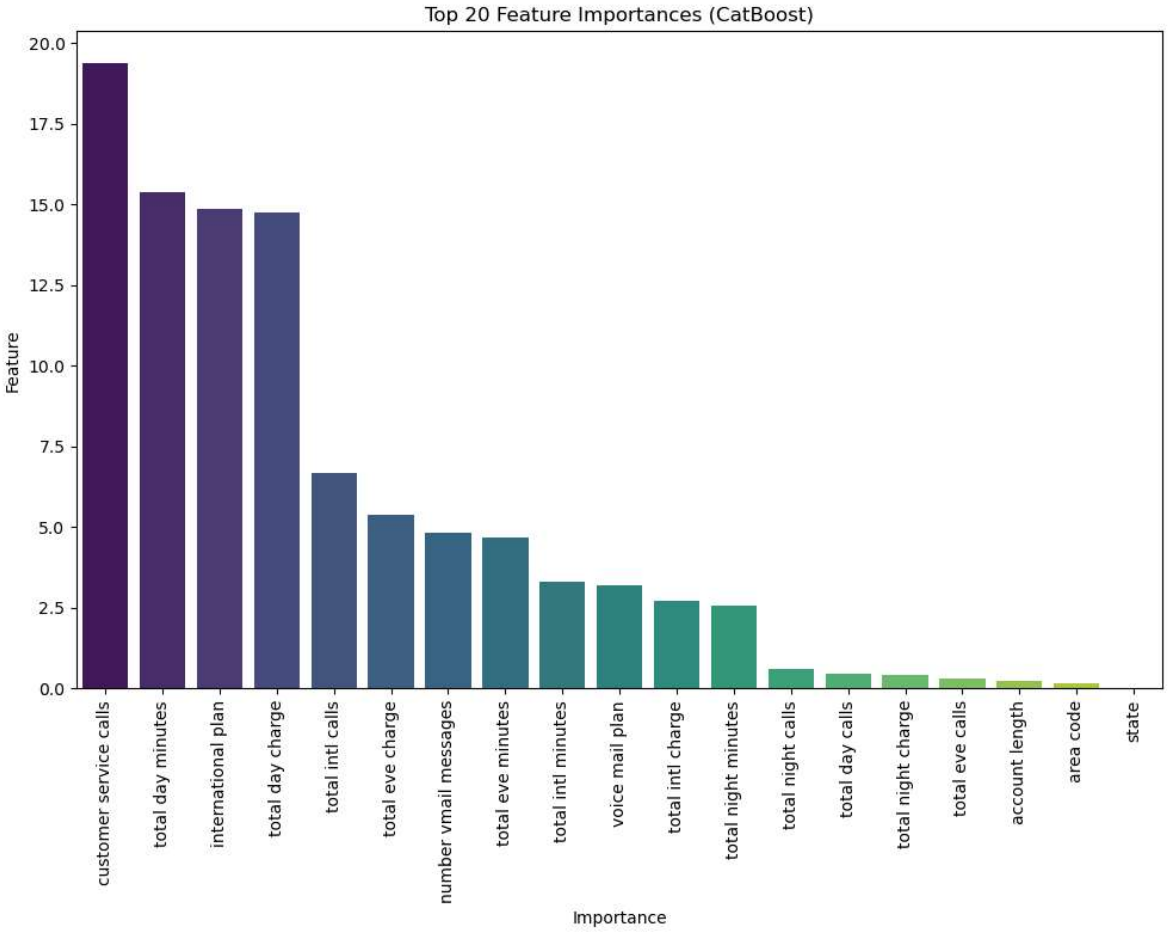
it can be seen that the accuracy has improved to 94% and the recall for the 0 is 99% while for the 1 is 64%.

This means that out of all the models this one performs best, because our interest is in the people who churn, and the recall for them is much improved in comparison to the other models.

this is the feature importance for the CatBoost

In [95]:
```
# Get feature importances
importances = catboost_model.get_feature_importance()
feature_names = X_train_final.columns

# Create a DataFrame for easy viewing
feat_importance_df = pd.DataFrame({'Feature': feature_names,'Importance': import

# Display top features
print(feat_importance_df.head(20))

# Plot feature importance
plt.figure(figsize=(10, 8))
sns.barplot(x='Feature', y='Importance', data=feat_importance_df.head(20), palet
plt.title('Top 20 Feature Importances (CatBoost)')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```

	Feature	Importance
15	customer service calls	19.402913
3	total day minutes	15.401454
17	international plan	14.862018
5	total day charge	14.773028
13	total intl calls	6.674265
8	total eve charge	5.397455
2	number vmail messages	4.809905
6	total eve minutes	4.670053
12	total intl minutes	3.307359
18	voice mail plan	3.207915
14	total intl charge	2.715849
9	total night minutes	2.585217
10	total night calls	0.602902
4	total day calls	0.471257
11	total night charge	0.435061
7	total eve calls	0.296086
0	account length	0.219037
1	area code	0.168224
16	state	0.000000



the features that are important for the estimation are customer service calls, total day minutes, international plan and total day charge.

Conclusion

1.Logistic regression,SVM model,KNN model,Random forest and CatBoost have been tried to predict churn,Random forest and Catboost are considered to be the most suitable models based on the accuracy: Random forest(the accuracy is 92% and the recall

of no churn is 99% while for yes churn is 59%). CatBoost(the accuracy is 94% and the recall for the 0 is 99% while for the 1 is 64%). They also handled class imbalance

2.Feature importance was done for this 2 models(Random forest and CatBoost)and the features with the highest importance for Random Forest was customer service calls,total day charge and total day minutes. For the CatBoost was customer service calls,total day minutes,international plan and total day charge.

3.While interpreting results of random forest and catboost, as it has been mentioned that some features are more important for the churn modelling. Which means that such features should be considered while dealing with at risk customer, by offering discounts or personalizing plan. Focusing on such features can be useful on devising the plan to reduce churn.