SyrialTel Customer Churn

Problem Statement: Predicting Customer Churn for SyriaTel

`Customer Churn` refers to the phenomenon where customers stop using a company's products or services. In telecommunications industry, churn occurs when a subscriber cancels their service, switches to a competitor, or stops engaging with the company altogether

For Syrialtel, a telcom provider, high churn rates lead to significant revenue losses, increased customer acquisition costs, and a weakened market position.Retaining existing customers is generally more cost-effective than acquiring new ones, making churn prediction a critical business priority.

Disadvantages of Customer Churn:

1. Revenue loss - Losing customers reduces recurring revenue, impacting overall profitability
2. Higher Acquisition Costs - Acquiring new customers is often more expensive than retaining existiong ones.
3. Reputational Damage - High churn ratess may inidcate poor service quality,leading to negative word-of-mouth
4. Reduced Customer Lifetime Value (CLV) - Frequent customer exits lower the long-tern revenue a company can generate from each user
5. Operational Inefficiencies - constantly replacing lost customers requires continous marketing and sales efforts, increase costs

Objective

The goal is to build a predictive model that identifies customers who are likely to churn in the near future. By analyzing patterns in customer behaviour, the company can implement targeted retetion strategies, such as personalized offers, improved customer support, or proactive engagement, to reduced churn and enhance customer loyalty

1.0 Import Libraries

In [78]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
import numpy as np

from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder,StandardScaler,FunctionTransformer
from sklearn.metrics import classification_report,roc_auc_score,accuracy_score,precision_score,recall_s
from sklearn.linear_model import LogisticRegression
from sklearn import svm
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImbPipeline
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.model_selection import cross_val_score,StratifiedKFold,GridSearchCV
from sklearn.inspection import permutation_importance
```

2.0 Understanding the dataset

In [2]:

```
#Read file from the csv as a dataframe and display the first 5 rows
df = pd.read_csv('CustomerChurnData.csv')
df.head()
```

Out[2]:

	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	total eve charge	total night minutes	total night calls	total night charge	mi
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16.78	244.7	91	11.01	
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16.62	254.4	103	11.45	
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10.30	162.6	104	7.32	
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.26	196.9	89	8.86	
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12.61	186.9	121	8.41	

5 rows × 21 columns

Data Description /Features in the Dataset

This features will help in determining if there is a pattern in customers that have churned versus customers that have not

- `state` : state the customer lives in
- `Account length` : The number of days the customer has had the account
- `Area code` : the area code of the customer
- `Phone number` : The phone number of the customer
- `Internation plan` : true if the customer has the international plan, otherwise false
- `Voice mail plan` : true if the customer has the voice mail plan, otherwise false
- `number vmail messages` : Number of voicemails the customer has sent
- `total day minutes` : total number of minutes the customer has used in calls made during the day

- `total day calls` : total number of calls the user has done during the day
- `total day charge` : total amount of money the customer was charged by the Telecom company for calls made during the day
- `total eve minutes` : total number of minutes the customer has used in calls made in the evening
- `total eve calls` : total number of calls the user has done in the evening
- `total eve charge` : total amount of money the customer was charged by the Telecom company for calls made in the evening
- `total night minutes` : total number of minutes the customer has used during the night
- `total night calls` : total number of calls the user has done during the night
- `total night charge` : total amount of money the customer was charged by the Telecom company for calls made at night`
- `total intl minutes` : total number of minutes the user has been in international calls
- `total intl calls` : total number of international calls the customer has done
- `total intl charge` : total amount of monye the customer was charged by the Telcom company for international calls
- `customer service calls` : number of calls the customer has mase to customer service
- `churn` - true if the customer terminated their contract, otherwise false

In [3]:

```python
# Check the number of records and features using the .shape method
print(f'The dataset has {df.shape[0]} rows')
print(f'The dataset has {df.shape[1]} columns')
```

```
The dataset has 3333 rows
The dataset has 21 columns
```

In [4]:
```python
#check information of the dataset
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
```

They are no missing values in the dataset.The object types colums will be one-hot encododed to integers prior to modelling

The target variable is churn. It is a binary variable(yes/no) hence we'll be solving a classification problem

In [5]:
```
#confirming they are no missing values
df.isna().sum()
```

Out[5]:
```
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 [6]:

```
#check data statistics for numerics
df.describe().T
```

Out[6]:

	count	mean	std	min	25%	50%	75%	max
account length	3333.0	101.064806	39.822106	1.00	74.00	101.00	127.00	243.00
area code	3333.0	437.182418	42.371290	408.00	408.00	415.00	510.00	510.00
number vmail messages	3333.0	8.099010	13.688365	0.00	0.00	0.00	20.00	51.00
total day minutes	3333.0	179.775098	54.467389	0.00	143.70	179.40	216.40	350.80
total day calls	3333.0	100.435644	20.069084	0.00	87.00	101.00	114.00	165.00
total day charge	3333.0	30.562307	9.259435	0.00	24.43	30.50	36.79	59.64
total eve minutes	3333.0	200.980348	50.713844	0.00	166.60	201.40	235.30	363.70
total eve calls	3333.0	100.114311	19.922625	0.00	87.00	100.00	114.00	170.00
total eve charge	3333.0	17.083540	4.310668	0.00	14.16	17.12	20.00	30.91
total night minutes	3333.0	200.872037	50.573847	23.20	167.00	201.20	235.30	395.00
total night calls	3333.0	100.107711	19.568609	33.00	87.00	100.00	113.00	175.00
total night charge	3333.0	9.039325	2.275873	1.04	7.52	9.05	10.59	17.77
total intl minutes	3333.0	10.237294	2.791840	0.00	8.50	10.30	12.10	20.00
total intl calls	3333.0	4.479448	2.461214	0.00	3.00	4.00	6.00	20.00
total intl charge	3333.0	2.764581	0.753773	0.00	2.30	2.78	3.27	5.40
customer service calls	3333.0	1.562856	1.315491	0.00	1.00	1.00	2.00	9.00

In [7]:

```
total_day_charge_per_min = (df['total day charge']/df['total day minutes']).mean()
total_eve_charge_per_min = (df['total eve charge']/df['total eve minutes']).mean()
total_night_charge_per_min = (df['total night charge']/df['total night minutes']).mean()
total_intl_charge_per_min = (df['total intl charge']/df['total intl minutes']).mean()
print(f'total_day_charge_per_min: {total_day_charge_per_min}')
print(f'total_eve_charge_per_min: {total_eve_charge_per_min}')
print(f'total_night_charge_per_min: {total_night_charge_per_min}')
print(f'total_intl_charge_per_min: {total_intl_charge_per_min}')
```

```
total_day_charge_per_min: 0.1700032343416007
total_eve_charge_per_min: 0.08500117298813906
total_night_charge_per_min: 0.045000345702212
total_intl_charge_per_min: 0.27005654558216496
```

- Customer that stayed for long with the company is 243 days and on average 101 days.
- on average voice mail messages 0 showing that voice mail messages are not as frequent
- Phone calls last longer in the evening and at night. We also see that that night time calling is the cheapest(0.045 Euros per min), followed by evening which is almost double(0.085 Euros per min) and during the days almost four times compared to night time(0.17 Euros per min). Lesser international calls are made probably due to high ratings(0.27 Euros per min)
- Customer service calls on average are low (1 call) whixh could mean overall customer satisafaction but maximum of 9 could show customer disatisfaction.
- We will also need to scale the data due to the different scales used in the dataset as shown by the min and max values for each columns

In [8]:

```
#statitiscs for strings
df.describe(include='O')
```

Out[8]:

	state	phone number	international plan	voice mail plan
count	3333	3333	3333	3333
unique	51	3333	2	2
top	WV	382-4657	no	no
freq	106	1	3010	2411

In [9]:

```
#value counts for categorical columns
print(df['international plan'].value_counts(normalize=True))
print(df['voice mail plan'].value_counts(normalize=True))
```

```
no     0.90309
yes    0.09691
Name: international plan, dtype: float64
no     0.723372
yes    0.276628
Name: voice mail plan, dtype: float64
```

Low subscriptions seen on international plan(almost 10% of customers have subscribed) and voice mail plan(almost 28% of customers have subscribed). Phone numbers does determine whether a customer churned or not we will drop that column. We will need to one hot encode this columms durig the modelling process

In [10]:

```
df['state'].value_counts(normalize=True)
```

```
Out[10]: WV    0.031803
         MN    0.025203
         NY    0.024902
         AL    0.024002
         WI    0.023402
         OH    0.023402
         OR    0.023402
         WY    0.023102
         VA    0.023102
         CT    0.022202
         MI    0.021902
         ID    0.021902
         VT    0.021902
         TX    0.021602
         UT    0.021602
         IN    0.021302
         MD    0.021002
         KS    0.021002
         NC    0.020402
         NJ    0.020402
         MT    0.020402
         CO    0.019802
         NV    0.019802
         WA    0.019802
         RI    0.019502
         MA    0.019502
         MS    0.019502
         AZ    0.019202
         FL    0.018902
         MO    0.018902
         NM    0.018602
         ME    0.018602
         ND    0.018602
         NE    0.018302
         OK    0.018302
         DE    0.018302
         SC    0.018002
         SD    0.018002
         KY    0.017702
         IL    0.017402
         NH    0.016802
         AR    0.016502
         GA    0.016202
```

```
DC    0.016202
HI    0.015902
TN    0.015902
AK    0.015602
LA    0.015302
PA    0.013501
IA    0.013201
CA    0.010201
Name: state, dtype: float64
```

We see an almost equal distribution in the number of states with WV having the highest number od customers

In [11]:

```
#Statistics for the churn column
df.describe(include='bool')
```

Out[11]:

	churn
count	3333
unique	2
top	False
freq	2850

In [12]:

```
#value count for churned column
df['churn'].value_counts(normalize = True)
```

Out[12]:

```
False    0.855086
True     0.144914
Name: churn, dtype: float64
```

Majority of customers did not churn(86%) indicating an imbalance in the traget variable . The class imbalance needs to be addressed during modelling to preveny overrepresenation fo the majority class and ensure accurate predictions

3.0 Data Cleaning

In [13]:
```
#check for duplicates
df.duplicated().sum()
```

Out[13]: 0

No duplicates in the dataset

In [14]:
```
#drop phone number and Area Code
df.drop(['phone number','area code'],axis=1,inplace=True)
#confirm drop
df.head()
```

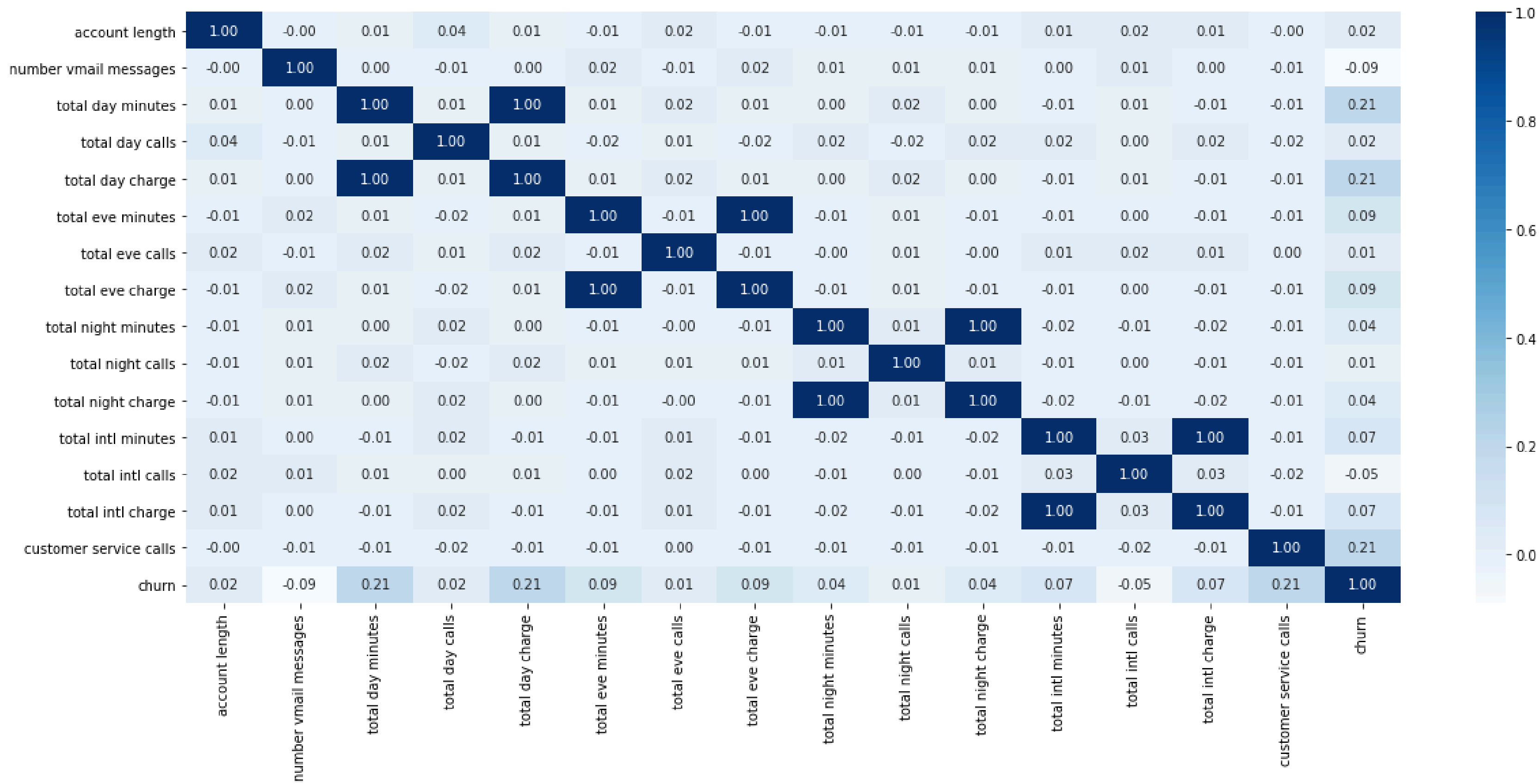
Out[14]:

	state	account length	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	total eve charge	total night minutes	total night calls	total night charge	total intl minutes	tot in call
0	KS	128	no	yes	25	265.1	110	45.07	197.4	99	16.78	244.7	91	11.01	10.0	
1	OH	107	no	yes	26	161.6	123	27.47	195.5	103	16.62	254.4	103	11.45	13.7	
2	NJ	137	no	no	0	243.4	114	41.38	121.2	110	10.30	162.6	104	7.32	12.2	
3	OH	84	yes	no	0	299.4	71	50.90	61.9	88	5.26	196.9	89	8.86	6.6	
4	OK	75	yes	no	0	166.7	113	28.34	148.3	122	12.61	186.9	121	8.41	10.1	

We drop the phone number and Area Code since they do not determine customer churn

In [15]:

```python
# check correlated features
plt.figure(figsize=(20,8))
sns.heatmap(df.corr(),annot=True,fmt='.2f',cmap='Blues');
```



- total day charge and total day minutes have a perfect correlation suggesting total day charge might be derived from total day minutes.similarly total evening/night/international minutes and their charges sre perfectly correlated.We will need to remove one of the features that are pefectly correlated ro remove multicolinearity in machine learning models
- total day minutes and customer service calls have highest correlation with churn in this dataset. This could mean that high usage could lead to higher bills,casuing dissatisfaction. High no of customer service calls also shows dissatisfaction which could lead to customer churn.

In [16]:

```python
# remove correlated features

#compute the correlation matrix
corr_matrix = df.corr().abs()

#set correlation threshold
threshold = 0.9

#create an upper triangle matrix to avoid duolicate checks
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape),k=1).astype(bool))
to_drop = [column for column in upper.columns if any(upper[column] > threshold)]

#drop correlated columns
df= df.drop(columns =to_drop)
print(f'Removed correlated features: {to_drop}')
```

```
Removed correlated features: ['total day charge', 'total eve charge', 'total night charge', 'total intl char
ge']
```

In [17]:

```python
# make a copy of the cleaned dataframe
customer_churn = df.copy(deep=True)
customer_churn
```

Out[17]:

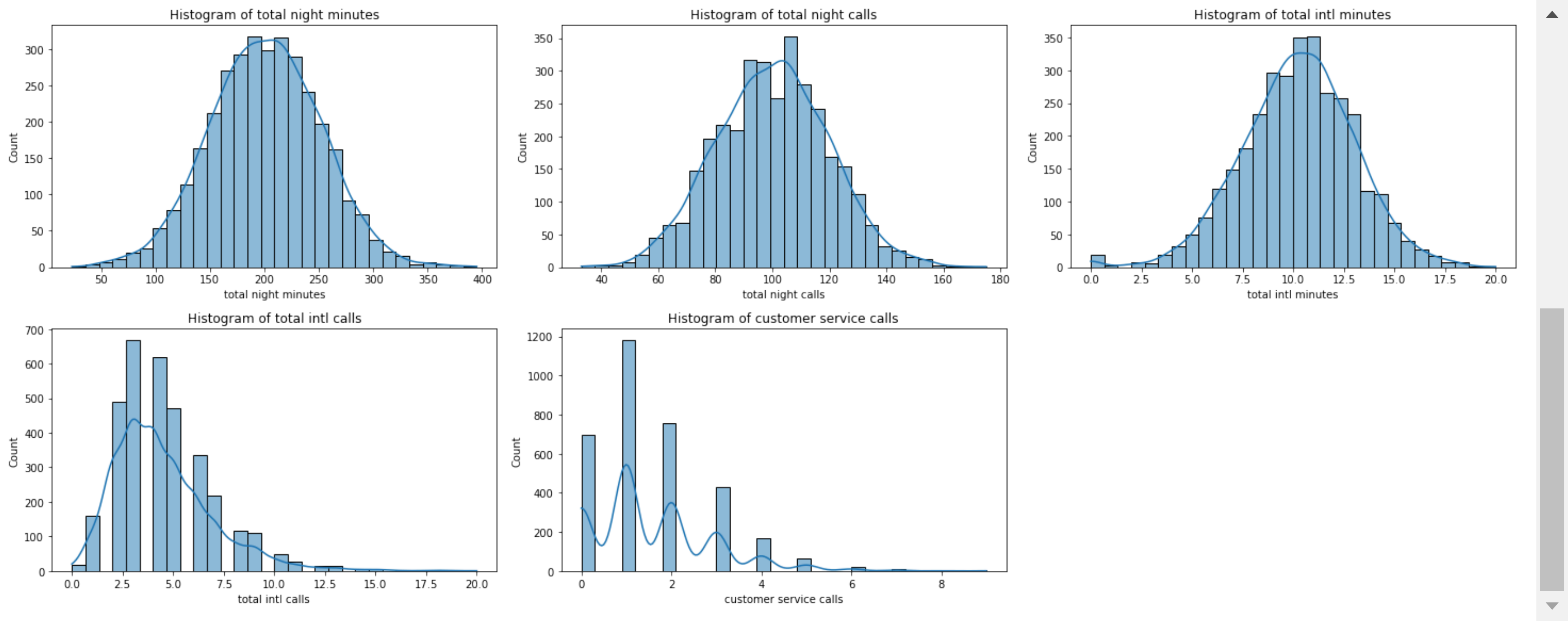
	state	account length	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total eve minutes	total eve calls	total night minutes	total night calls	total intl minutes	total intl calls	customer service calls	churn
0	KS	128	no	yes	25	265.1	110	197.4	99	244.7	91	10.0	3	1	False
1	OH	107	no	yes	26	161.6	123	195.5	103	254.4	103	13.7	3	1	False
2	NJ	137	no	no	0	243.4	114	121.2	110	162.6	104	12.2	5	0	False
3	OH	84	yes	no	0	299.4	71	61.9	88	196.9	89	6.6	7	2	False
4	OK	75	yes	no	0	166.7	113	148.3	122	186.9	121	10.1	3	3	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
3328	AZ	192	no	yes	36	156.2	77	215.5	126	279.1	83	9.9	6	2	False
3329	WV	68	no	no	0	231.1	57	153.4	55	191.3	123	9.6	4	3	False
3330	RI	28	no	no	0	180.8	109	288.8	58	191.9	91	14.1	6	2	False
3331	CT	184	yes	no	0	213.8	105	159.6	84	139.2	137	5.0	10	2	False

4.0 Exploratory Data Analysis

Visualize numeric variables

In [18]:

```python

 # Select numerical columns
numerical_columns = df.describe().columns

def plot_histograms(columns,cols_per_row = 3):
    num_cols = len(columns)
    num_rows = int(np.ceil(num_cols/cols_per_row)) #calculate required rows

    fig, ax = plt.subplots(nrows=num_rows,ncols=cols_per_row,figsize=(20,num_rows*4))
    ax = ax.flatten()

    for i,col in enumerate(columns):
        sns.histplot(df[col],bins=30,kde=True,ax=ax[i])
        ax[i].set_title(f'Histogram of {col}')

    #Hide any unused subplots (if number of columns is not a multiple of 3)
    for j in range(i+1, len(ax)):
        ax[j].axis('off')

        plt.tight_layout(); #prevents overlapping

#call function
plot_histograms(numerical_columns)
```

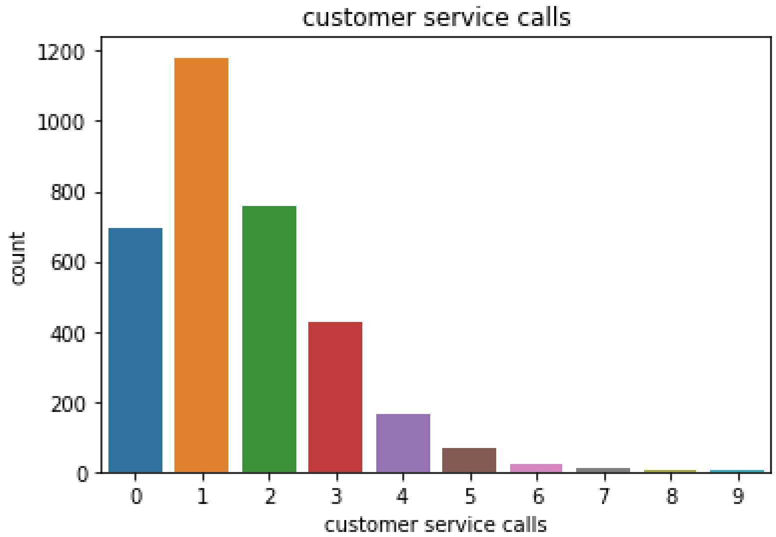


total day/evening/night calls/minutes- Distributions appear to be normally distributed,suggesting customers have a typical range of call durations

Number of voice mail mesages and customer sevice callsare right skewed meaning most customers have low values but few have higher counts

Total international calls and minutes are right-skewed indicating most customers make very few international calls

In [19]:
```python
#Distribution of customer service calls
#function to plot countplot
def countplot(x):
    sns.countplot(data=df,x=x);
    plt.title(x)

countplot('customer service calls')
```



Most customers called the customer service once(approximately 1200) customers.A significant number almost 800 customers never called at all. Only a few customers(less than 50) called the customer care more than 6 times. The distributiion is right skewd meaning that a small number of users call the customer care excessively

Visualize categorical variables

In [20]:

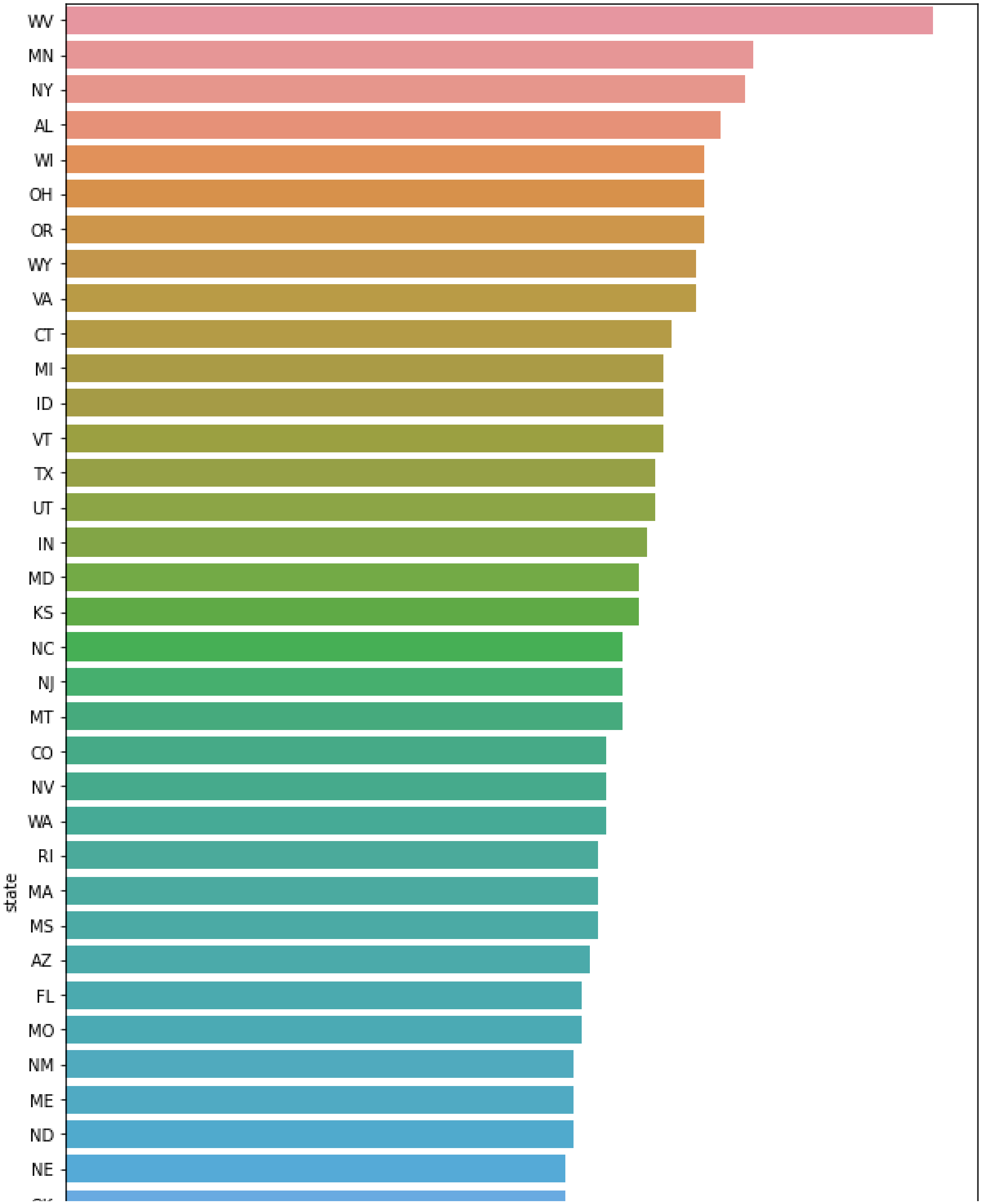
```
df.describe(include='O')
```

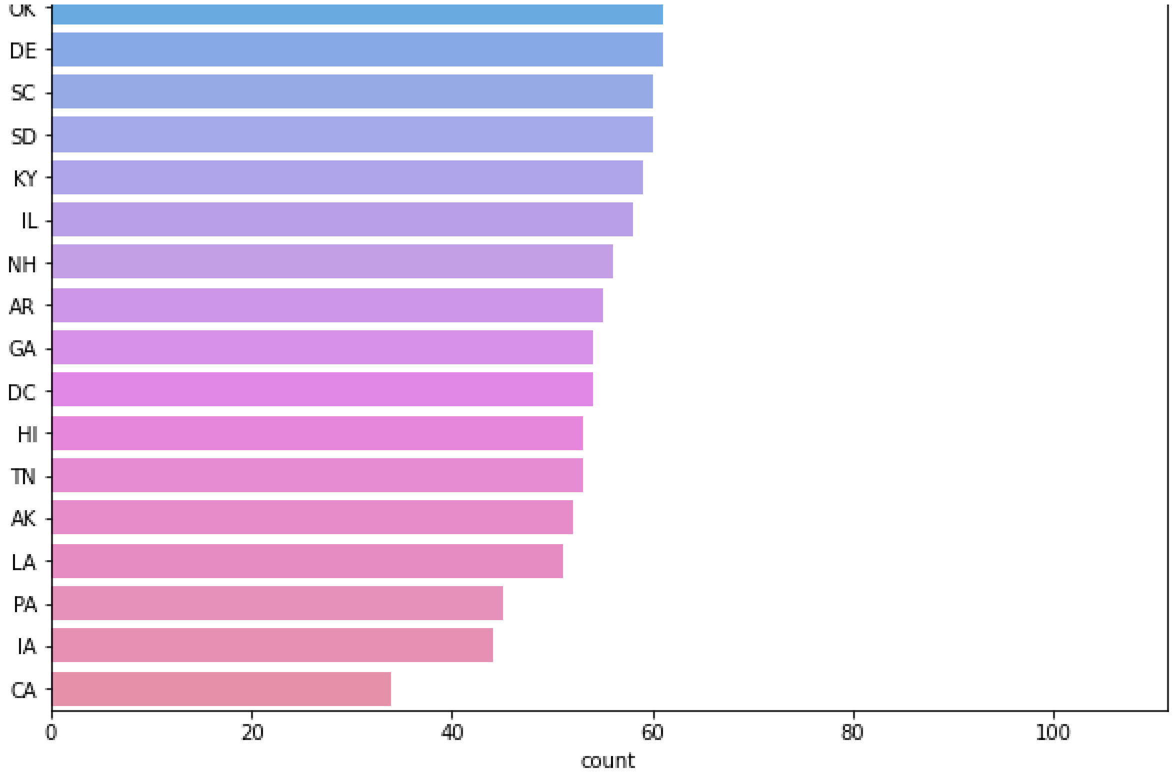
Out[20]:

	state	international plan	voice mail plan
count	3333	3333	3333
unique	51	2	2
top	WV	no	no
freq	106	3010	2411

In [21]:

```
#states
plt.figure(figsize=(10,20))
sns.countplot(data=df,y='state',order=df['state'].value_counts().index);
```

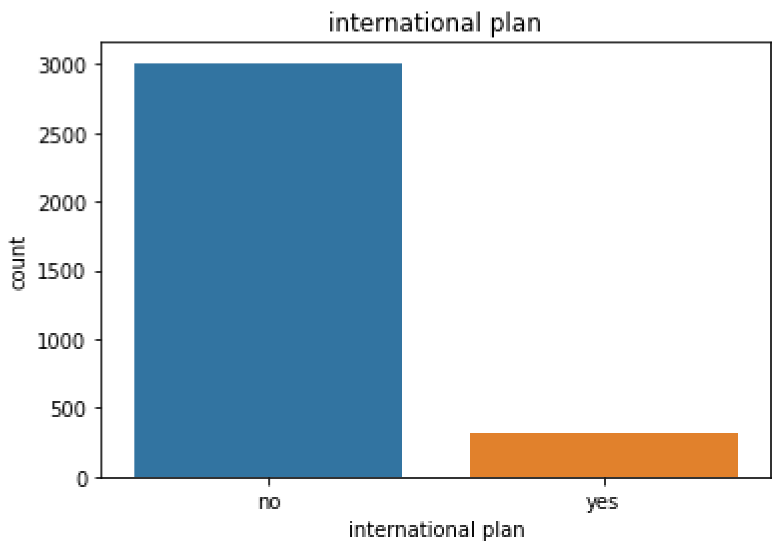

state
WV
MN
NY
AL
WI
OH
OR
WY
VA
CT
MI
ID
VT
TX
UT
IN
MD
KS
NC
NJ
MT
CO
NV
WA
RI
MA
MS
AZ
FL
MO
NM
ME
ND
NE



wv state has the highest number of customers while CA has the least, we will need to check if churn is affected by state a customer lives in

In [22]:

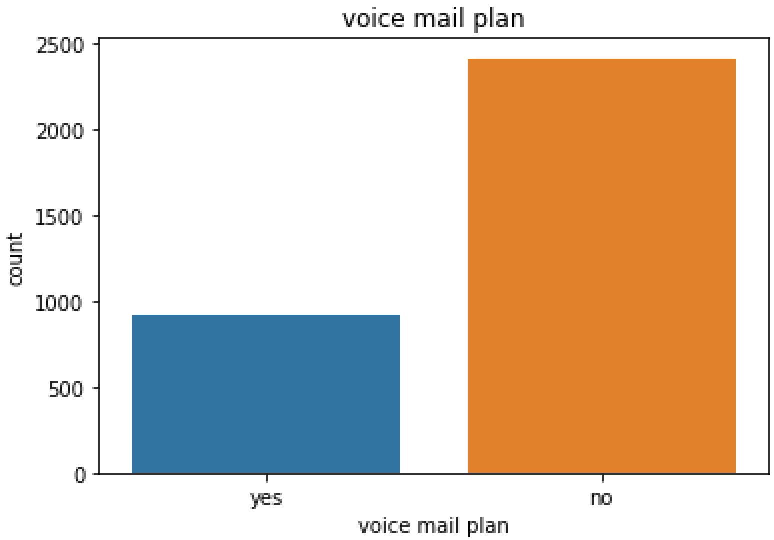
```
#international plan
countplot('international plan')
```



Majority of the customers donot gave an international plan

In [23]:

```
#voice mail plan
countplot('voice mail plan')
```

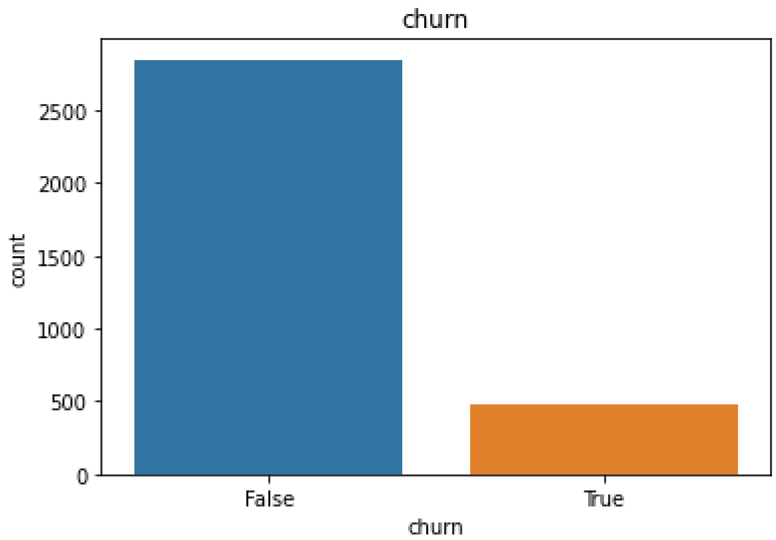


huge percentage of customers lack the voice mail plan

In [24]:

```
#churn
print(df.churn.value_counts(normalize=True))
countplot('churn')
```

```
False    0.855086
True     0.144914
Name: churn, dtype: float64
```

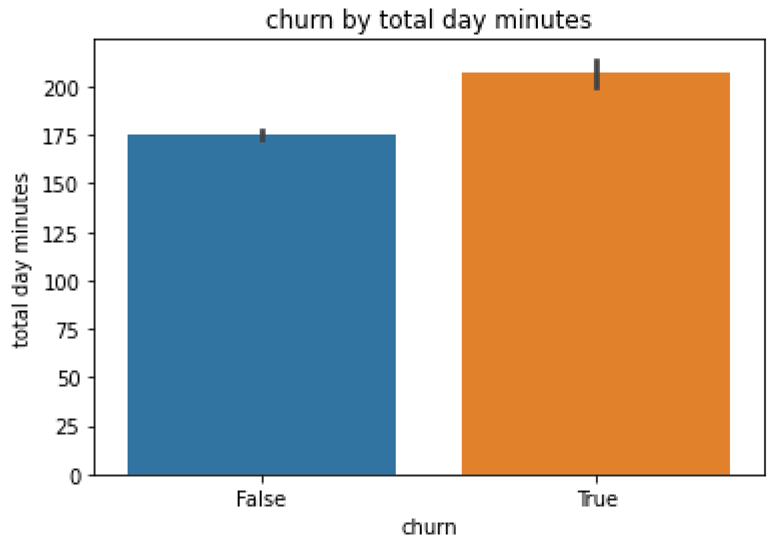


of the 3333 customers in the dataset, 14.5% have terminated their contact with the company.The distribution of the target variable shows data imbalance.This needs to be adresed before modeliing as an unbalanced feature may cause the model to make false predictions

Bivariate analysis

In [25]:

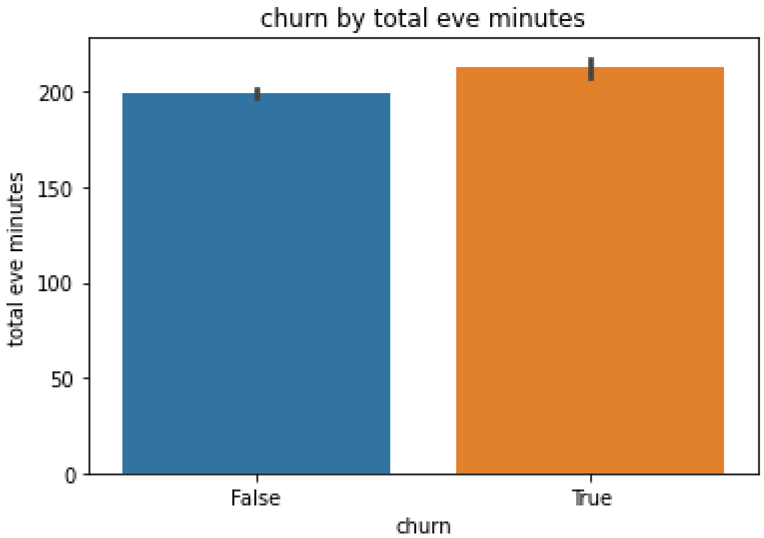
```python
#function to plot barplots for customer churn
def barplot(yaxis):
    sns.barplot(data=df, y=yaxis,x='churn')
    plt.title(f'churn by {yaxis}')
#total day minutes by churn
barplot('total day minutes')
```



Number of customers who churned actually had more day minutes

In [26]:

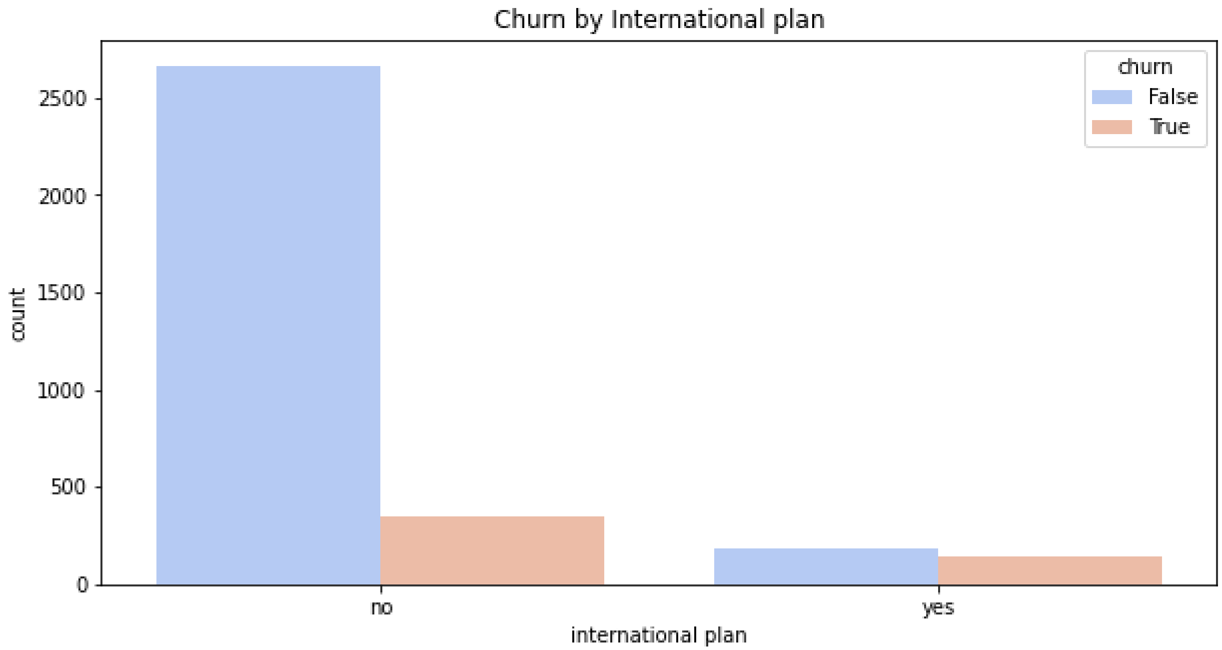
```
#Churn by Total evening minutes
barplot('total eve minutes')
```



slighly hire churn on total evening minutes

In [27]:

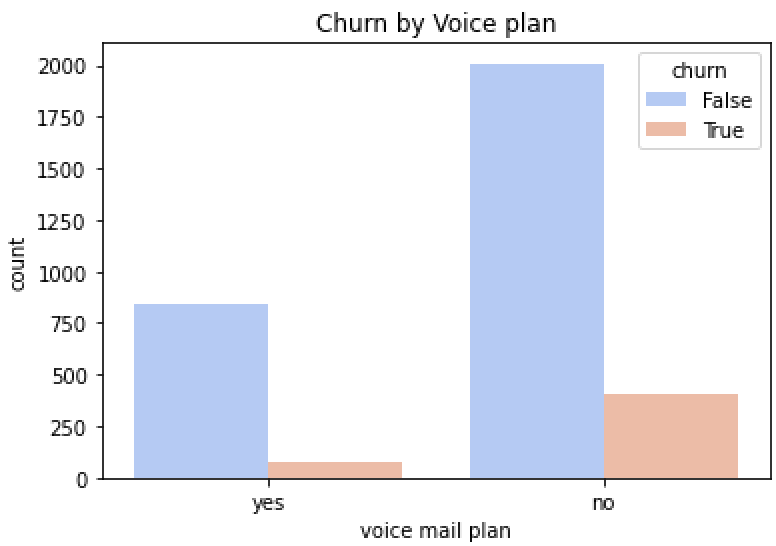
```
#Churn by International plan
plt.figure(figsize=(10, 5))
sns.countplot(data=df, x='international plan', hue='churn', palette='coolwarm')
plt.title("Churn by International plan");
```



Most customers did not have an international plan and most of them did not churn. Those with international plan have the same rate of churn, meaning higher churn rate in this group

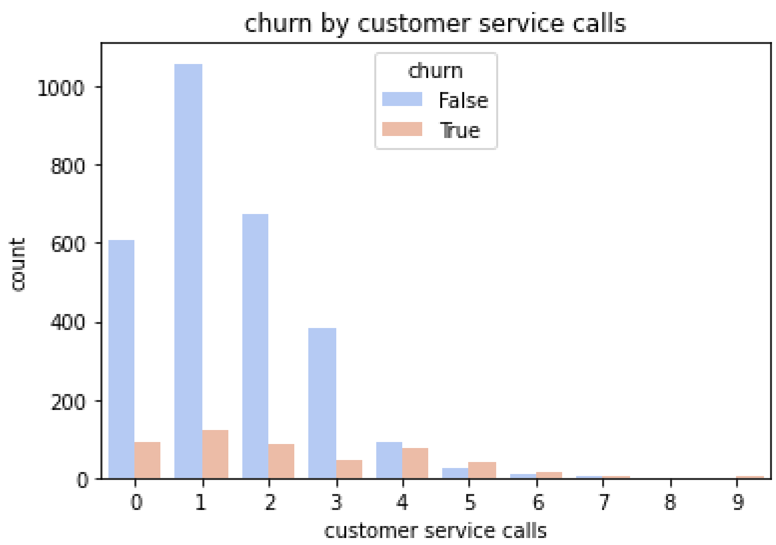
In [28]:

```
#Churn by Voice plan
sns.countplot(data=df, x='voice mail plan', hue='churn', palette='coolwarm')
plt.title("Churn by Voice plan");
```



Many customers have no voice plan and many and majority did not churn. Those with voice mail plan many of them did not churn

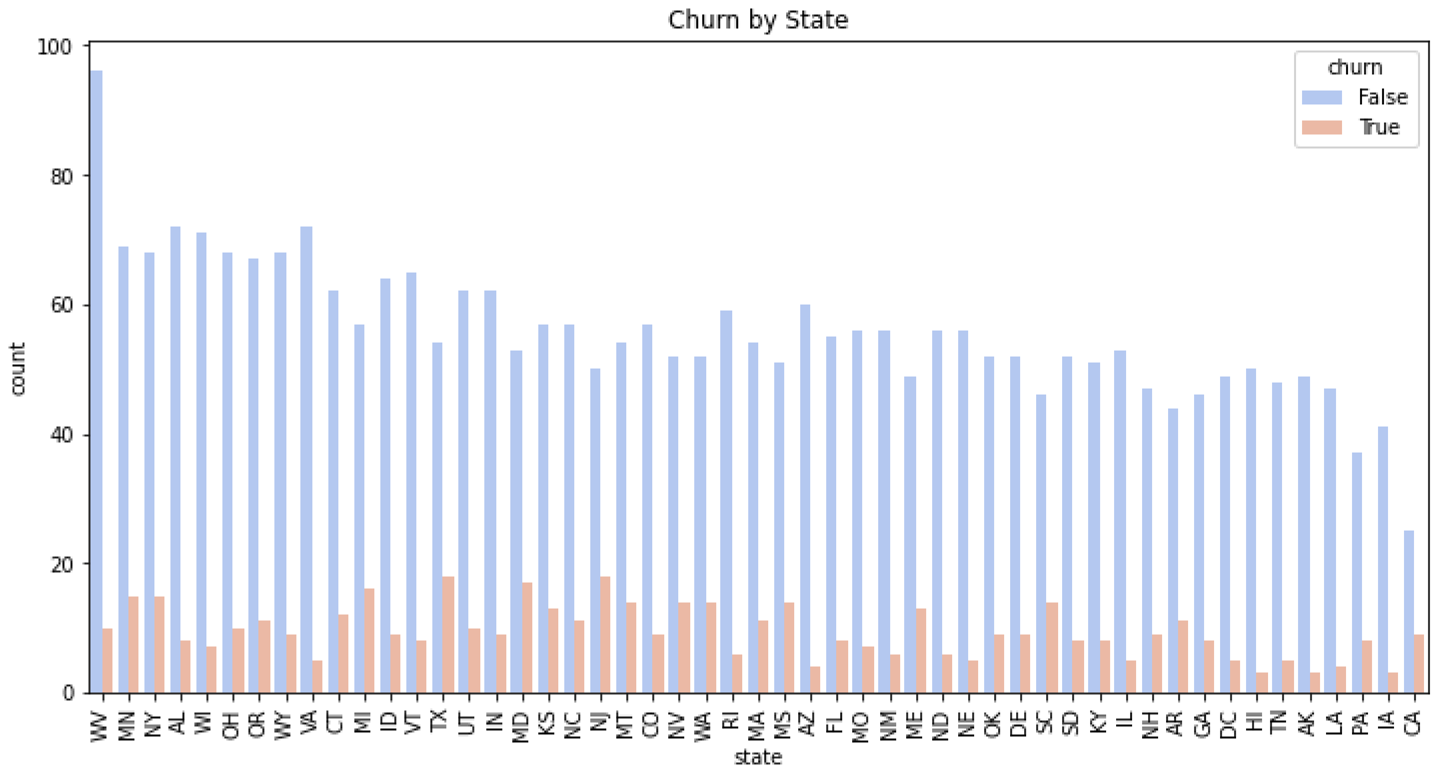
In [29]:
```python
#churn by customer service calls
sns.countplot(data=df, x='customer service calls', hue='churn', palette='coolwarm')
plt.title("churn by customer service calls");
```



Majority of customers have made 0,1 0r 2 calls to customer service. Most of these customers did not churn.As the number of calls increased the proportion of churned customers increased

In [30]:

```python
#churn  by state
plt.figure(figsize=(12, 6))
sns.countplot(data=df, x='state', hue='churn', palette='coolwarm', order=df['state'].value_counts().ind
plt.xticks(rotation=90)
plt.title("Churn by State")
plt.show()
```



Churn is spread across all states. No state has zero churn, meaning churn is a universal issues accross locations.Some Sates have higher churn rates

5.0 Modelling

In [31]:

```
#define feature columns
X = df.drop(columns='churn')
y = df['churn']

#split data into training and test sets
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,shuffle=True,stratify = y)
```

In [32]:

```
#use column transformers to perform processing for different columns
categorical_features = X.select_dtypes(include='O').columns
numerical_features = X.select_dtypes(include=['int','float']).columns

#define log transformer
log_transformer = FunctionTransformer(np.log1p)
#define transformer
transformer = ColumnTransformer([
    ('ohe',OneHotEncoder(handle_unknown='ignore'),categorical_features), #Encode categorical variables
    ('log_transform',log_transformer,['total intl calls','customer service calls']), #log transformatio
    ('scaler',StandardScaler(),numerical_features) #scale numerical features
])
```

In [33]:

```
pipe = ImbPipeline([
    ('preprocessor',transformer),
    ('smote',SMOTE(sampling_strategy='auto',random_state=42)),
    ('model',LogisticRegression(solver='liblinear'))
])
pipe.fit(X_train,y_train)
y_pred = pipe.predict(X_test)
print(classification_report(y_true = y_test,y_pred=y_pred))
```

```
              precision    recall  f1-score   support

       False       0.96      0.83      0.89       570
        True       0.44      0.78      0.56        97

    accuracy                           0.82       667
   macro avg       0.70      0.81      0.73       667
weighted avg       0.88      0.82      0.84       667
```

We have defined churn as our target variable, with all other columns serving as feature variables. After performing a train-test split, we divided the dataset into training and testing sets.

To ensure proper preprocessing, we used a ColumnTransformer to apply different transformations based on data types:

One-hot encoding for categorical features Log transformation for right-skewed numerical features Scaling for numerical features, as they have different scales To streamline both data transformation and modeling, we implemented an ImbalancedPipeline (ImbPipeline). This allows us to handle imbalanced data using resampling techniques such as SMOTE, ensuring better model performance on minority classes.

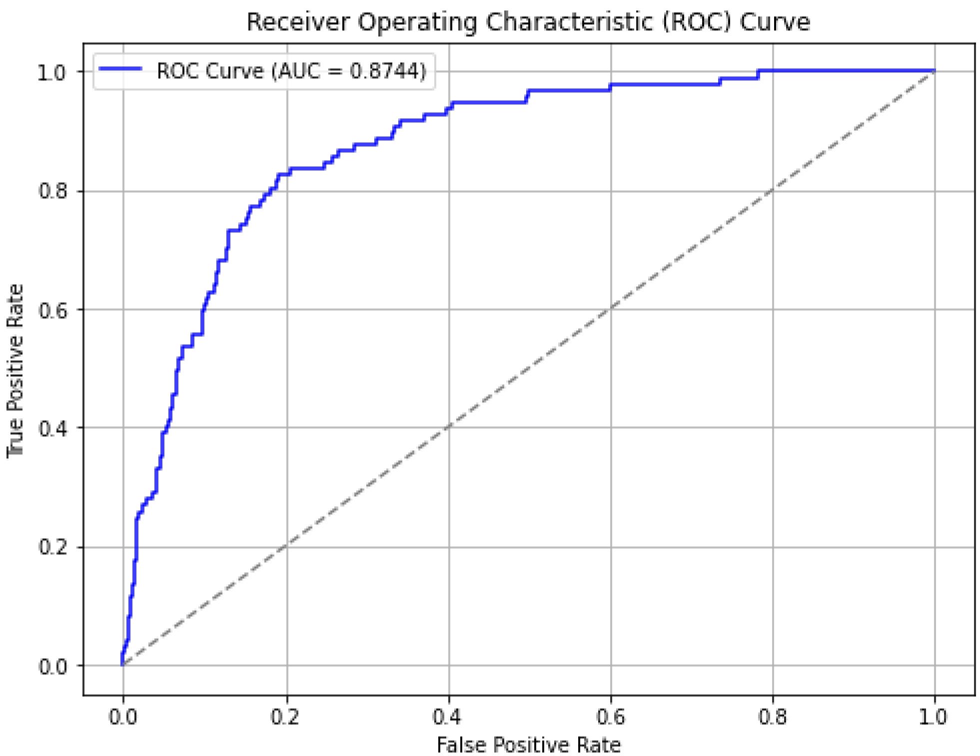
In [34]:

```python
#function to fit, predict and evaluate
def modelling(pipe):
    pipe.fit(X_train, y_train)

    # Predict train and test data
    y_hat_train = pipe.predict(X_train)
    y_hat_test = pipe.predict(X_test)

    # Get accuracy, precision, recall, and F1-score
    train_accuracy = accuracy_score(y_train, y_hat_train)
    test_accuracy = accuracy_score(y_test, y_hat_test)
    train_precision = precision_score(y_train, y_hat_train, average='weighted')
    test_precision = precision_score(y_test, y_hat_test, average='weighted')
    train_recall = recall_score(y_train, y_hat_train, average='weighted')
    test_recall = recall_score(y_test, y_hat_test, average='weighted')
    train_f1 = f1_score(y_train, y_hat_train, average='weighted')
    test_f1 = f1_score(y_test, y_hat_test, average='weighted')

    # Get prediction probabilities for AUC score
    y_pred_proba = pipe.predict_proba(X_test)[:, 1]
    test_roc_auc = roc_auc_score(y_test, y_pred_proba)

     # Compute ROC curve
    fpr, tpr, _ = roc_curve(y_test, y_pred_proba)

    # Plot ROC Curve
    plt.figure(figsize=(8, 6))
    plt.plot(fpr, tpr, color='blue', label=f'ROC Curve (AUC = {test_roc_auc:.4f})')
    plt.plot([0, 1], [0, 1], color='gray', linestyle='--')  # Diagonal reference line
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve')
    plt.legend()
    plt.grid();

    return {
        'Training Accuracy': train_accuracy,
        'Test Accuracy': test_accuracy,
#         'Training precision': base_train_precision,
        'Test precision': test_precision,
#         'Training recall': base_train_recall,
        'Test recall': test_recall,
#         'Training f1_score': base_train_f1,
```

```
        'Test f1_score': test_f1,
        'Test AUC': test_roc_auc
    }
```

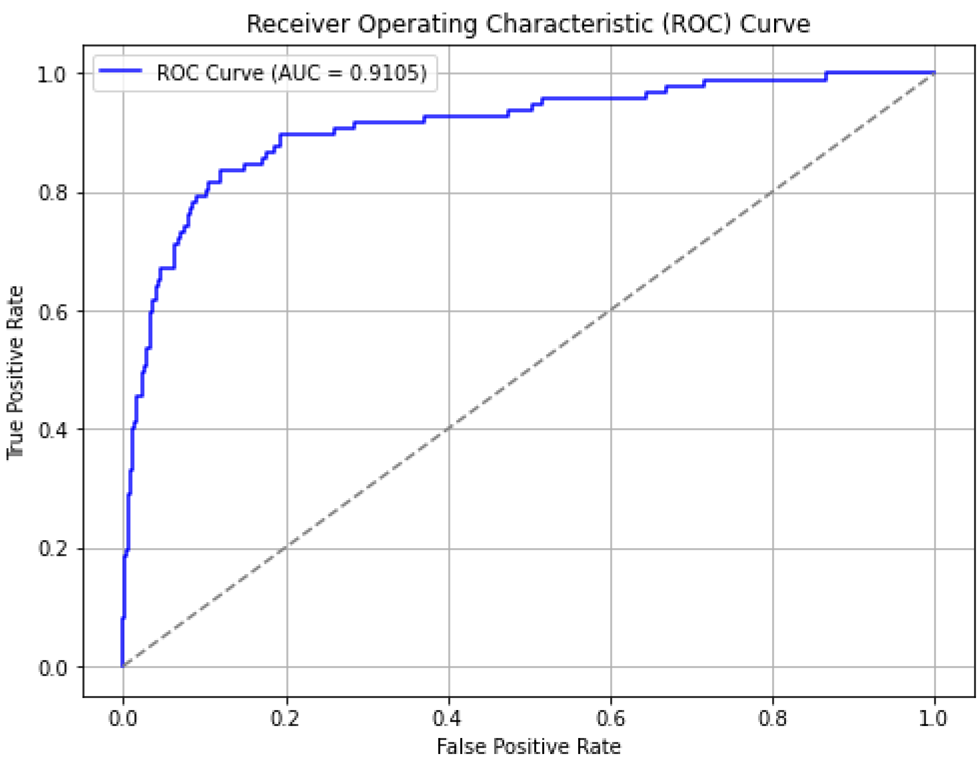
In [35]:
```
#Logistic Regression(basemodel)
logreg = modelling(pipe)
logreg
```

Out[35]:
```
{'Training Accuracy': 0.7955738934733684,
 'Test Accuracy': 0.823088455772114,
 'Test precision': 0.8821318553706694,
 'Test recall': 0.823088455772114,
 'Test f1_score': 0.8416688481156247,
 'Test AUC': 0.874425755109423}
```



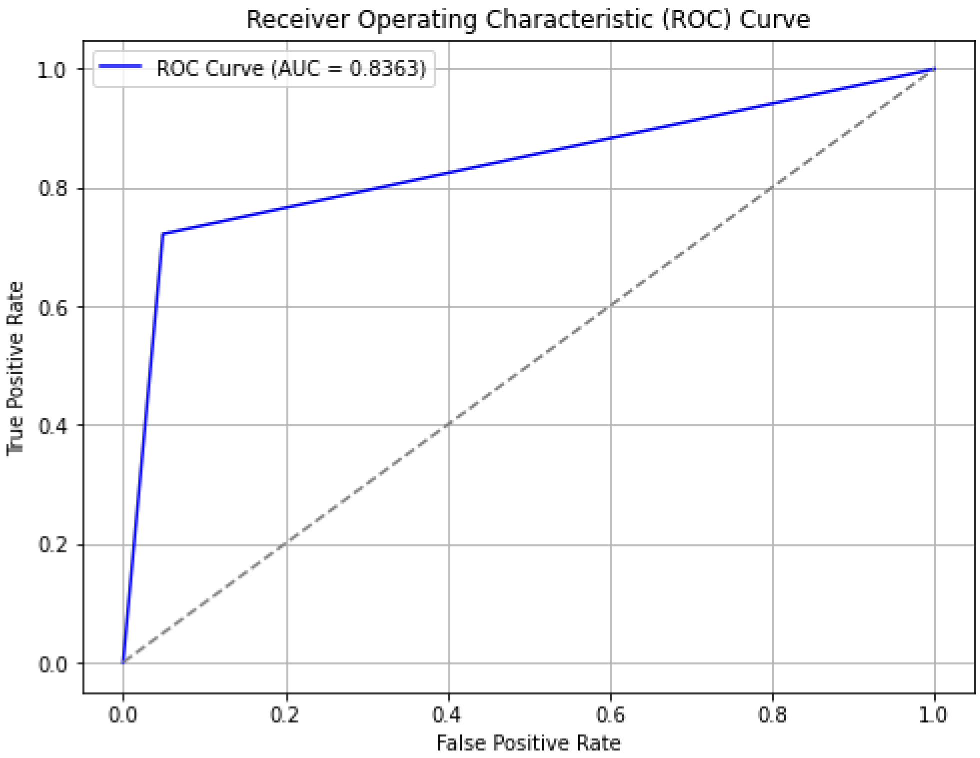
In [36]:
```python
#Support Vector Machine
pipe.set_params(model=svm.SVC(probability=True))
svm = modelling(pipe)
svm
```

Out[36]:
```
{'Training Accuracy': 0.9456114028507127,
 'Test Accuracy': 0.8980509745127436,
 'Test precision': 0.9058410796518612,
 'Test recall': 0.8980509745127436,
 'Test f1_score': 0.9012091310724913,
 'Test AUC': 0.9104901428829806}
```



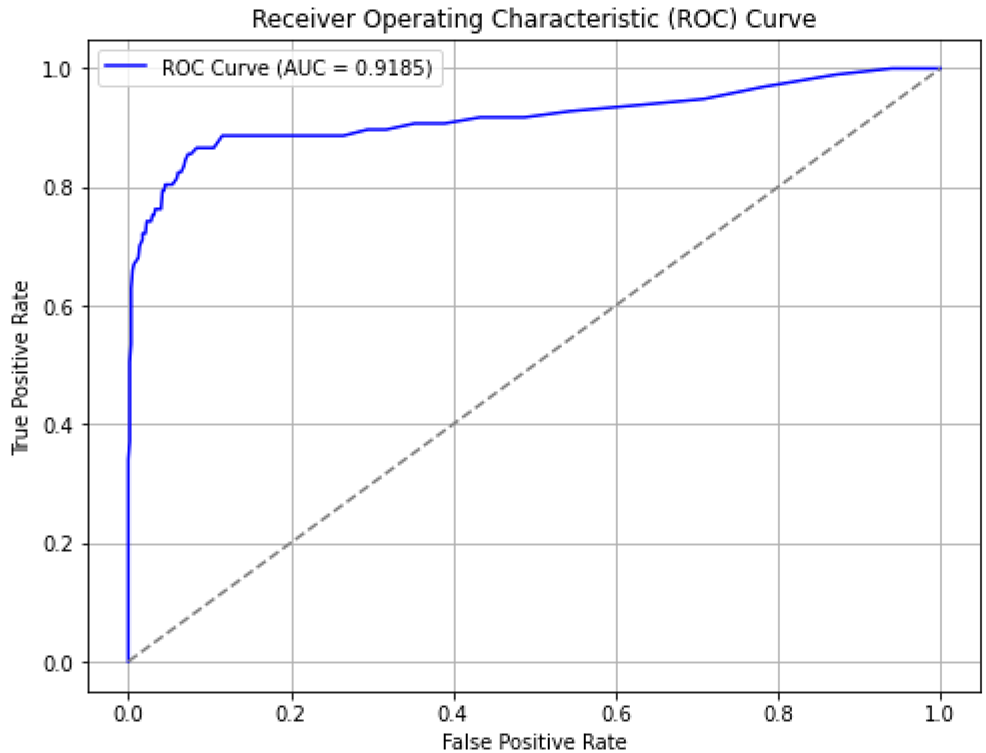
In [37]:
```python
#Decision Tree
from sklearn.tree import DecisionTreeClassifier
pipe.set_params(model=DecisionTreeClassifier())
dt = modelling(pipe)
dt
```

Out[37]:
```
{'Training Accuracy': 1.0,
 'Test Accuracy': 0.9175412293853074,
 'Test precision': 0.9178984447018268,
 'Test recall': 0.9175412293853074,
 'Test f1_score': 0.9177164642504845,
 'Test AUC': 0.8362633387592693}
```



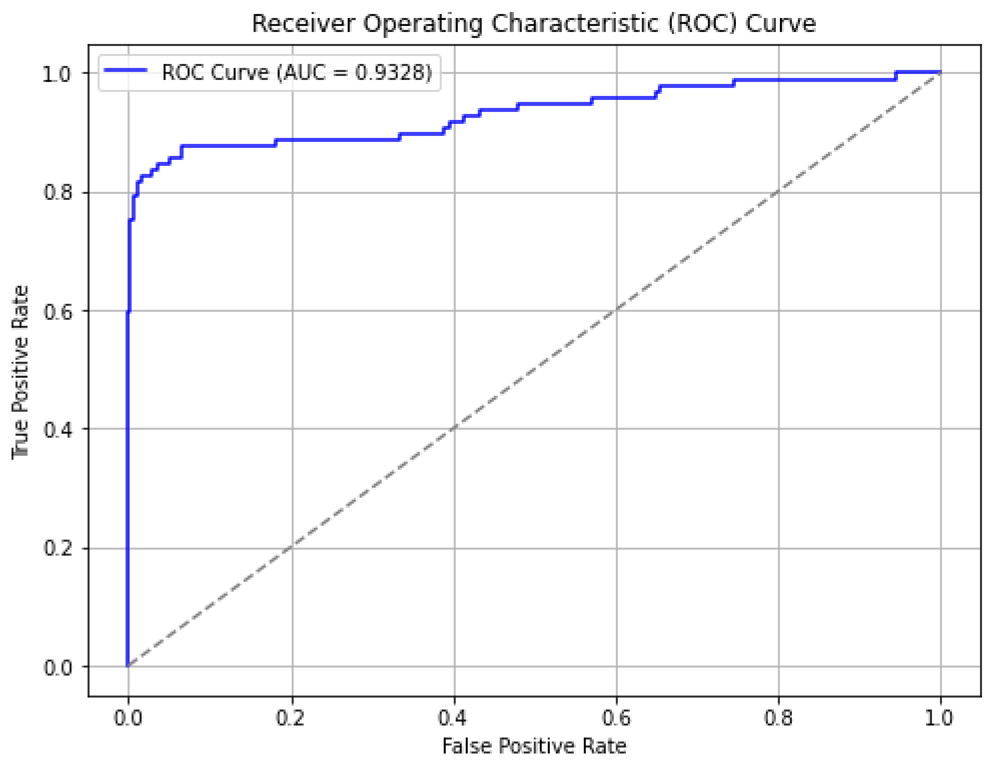
In [38]:
```
#Random Forest
pipe.set_params(model=RandomForestClassifier())
rf =modelling(pipe)
rf
```

Out[38]:
```
{'Training Accuracy': 1.0,
 'Test Accuracy': 0.9370314842578711,
 'Test precision': 0.9360465883726676,
 'Test recall': 0.9370314842578711,
 'Test f1_score': 0.9364787425941059,
 'Test AUC': 0.918529571351058}
```



In [39]:
```
pipe.set_params(model=XGBClassifier())
xgb =modelling(pipe)
xgb
```

Out[39]:
```
{'Training Accuracy': 0.9996249062265566,
 'Test Accuracy': 0.95952023988006,
 'Test precision': 0.9585597274372707,
 'Test recall': 0.95952023988006,
 'Test f1_score': 0.9586941339858613,
 'Test AUC': 0.9327545668294447}
```



In [40]:

```
#Create a dataframe for all items
#Dictionary of model resuts
model_results = {
    "Logistic Regression": logreg,
    "Random Forest": rf,
    "Decision Tree": dt,
    "SVM": svm,
    'XGB':xgb
}

#convert dictionary to dataframe
df_results = pd.DataFrame.from_dict(model_results,orient='index')

#Display the Dataframe
df_results
```

Out[40]:

	Training Accuracy	Test Accuracy	Test precision	Test recall	Test f1_score	Test AUC
Logistic Regression	0.795574	0.823088	0.882132	0.823088	0.841669	0.874426
Random Forest	1.000000	0.937031	0.936047	0.937031	0.936479	0.918530
Decision Tree	1.000000	0.917541	0.917898	0.917541	0.917716	0.836263
SVM	0.945611	0.898051	0.905841	0.898051	0.901209	0.910490
XGB	0.999625	0.959520	0.958560	0.959520	0.958694	0.932755

In [41]:

```
df_results['Training Accuracy'] - df_results['Test Accuracy']
```

Out[41]:

```
Logistic Regression   -0.027515
Random Forest          0.062969
Decision Tree          0.082459
SVM                    0.047560
XGB                    0.040105
dtype: float64
```

XGB is the best performing model.despite overfitting(Training accuracy almost 100%) it performs well on test data

XGB has a small difference between train and test acuracy

In [42]:

```
#use cross validation to check whether it improves scores than a train test split

#Define the model
model = pipe.set_params(model=XGBClassifier())
skf = StratifiedKFold(n_splits = 5, shuffle=True,random_state=42)

#perform 5-Fold Cross-Validation
cv_scores = cross_val_score(model,X_train,y_train,cv=skf,scoring='accuracy')

#print results
print(f'Cross-Validation Scores: {cv_scores}')
print(f'Mean Accuracy: {cv_scores.mean():.4f}')
```

```
Cross-Validation Scores: [0.95692884 0.93621013 0.93621013 0.96622889 0.95684803]
Mean Accuracy: 0.9505
```

No much difference between split and cross validation, train_test_split performs slighlty better on adding shuffle and stratify

6.0 Parameter tuning XGBOOST

In [43]:

```
param_grid = {
    'model__max_depth': [3, 6, 9],
    'model__learning_rate': [0.01, 0.1, 0.2],
    'model__n_estimators': [100, 500, 1000],
    'model__subsample': [0.7, 0.9, 1.0]
}

xgb_model = pipe.set_params(model = XGBClassifier())
grid_search = GridSearchCV(xgb_model, param_grid, cv=3, scoring='accuracy', n_jobs=-1)
grid_search.fit(X_train, y_train)

print("Best parameters:", grid_search.best_params_)

```

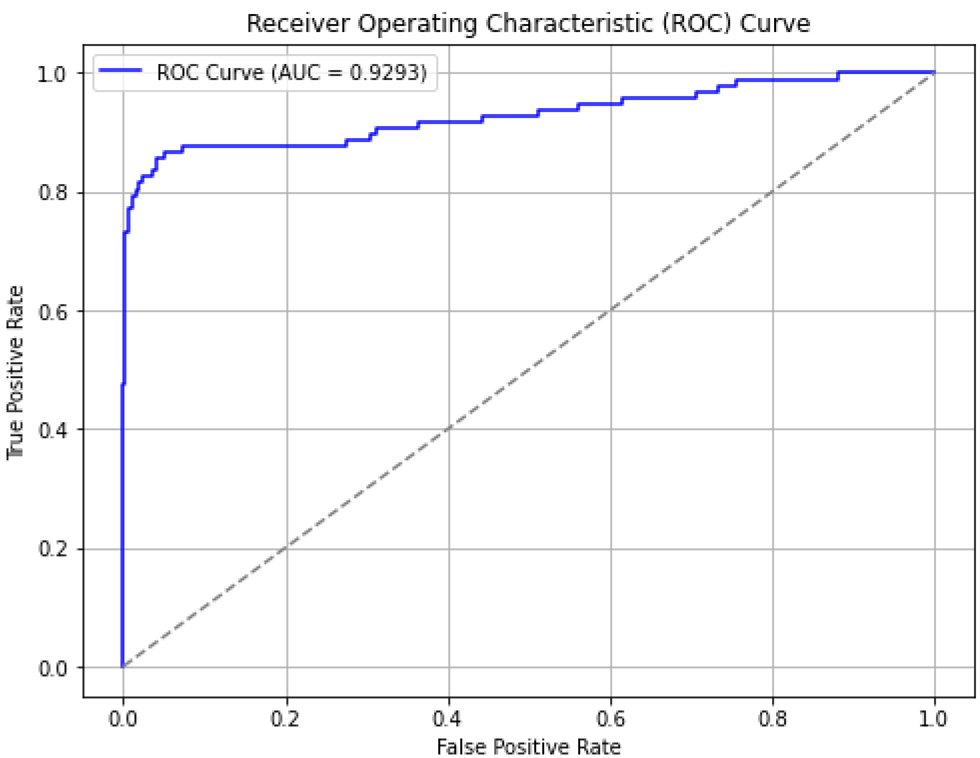
```
Best parameters: {'model__learning_rate': 0.1, 'model__max_depth': 9, 'model__n_estimators': 100, 'model__su
bsample': 1.0}
```

In [47]:

```
pipe.set_params(model = XGBClassifier(learning_rate=0.1,
                                      max_depth = 9,
                                      n_estimators = 500,
                                      subsample = 0.9
                                        ))
xgb_model_tuned = modelling(pipe)
xgb_model_tuned
```

Out[47]:

```
{'Training Accuracy': 1.0,
 'Test Accuracy': 0.9550224887556222,
 'Test precision': 0.9541173781241248,
 'Test recall': 0.9550224887556222,
 'Test f1_score': 0.9544225046883932,
 'Test AUC': 0.9293000542593598}
```

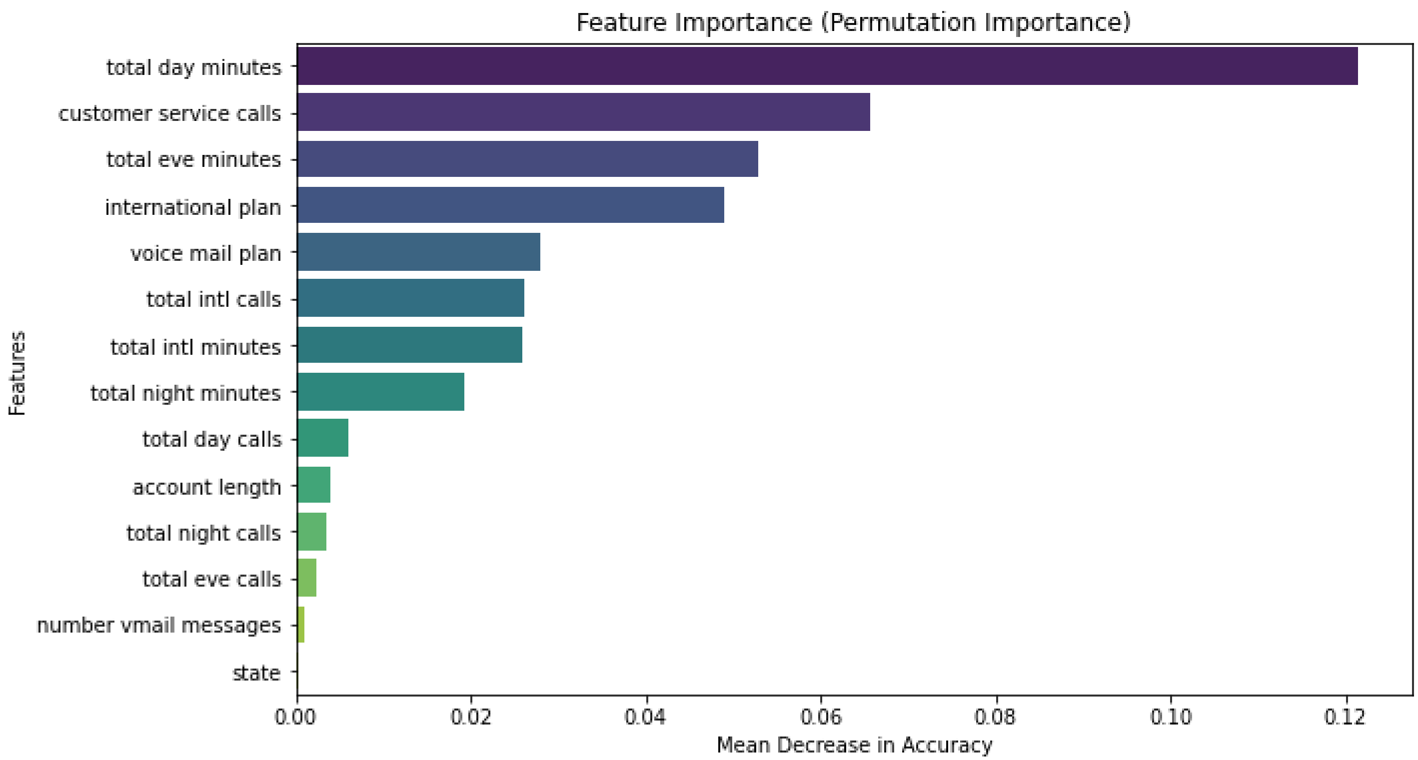


7.0 summary and recommendations

In [82]:

```
model.fit(X_train,y_train)
perm_importance = permutation_importance(model, X_train, y_train, scoring='accuracy')

# Convert to pandas series
perm_importance_df = pd.Series(perm_importance.importances_mean, index=X.columns)

# Sort feature importance values
sorted_importance = perm_importance_df.sort_values(ascending=False)
print(sorted_importance)
# Plot
plt.figure(figsize=(10, 6))
sns.barplot(x=sorted_importance, y=sorted_importance.index, palette="viridis")

# Labels and title
plt.xlabel("Mean Decrease in Accuracy")
plt.ylabel("Features")
plt.title("Feature Importance (Permutation Importance)")
plt.show()
```

```
total day minutes         0.121530
customer service calls    0.065566
total eve minutes         0.052963
international plan        0.049062
voice mail plan           0.027907
total intl calls          0.026107
total intl minutes        0.025881
total night minutes       0.019280
total day calls           0.005926
account length            0.003901
total night calls         0.003451
total eve calls           0.002251
number vmail messages     0.000900
state                     0.000375
dtype: float64
```


Feature Importance (Permutation Importance)
total day minutes
customer service calls
total eve minutes
international plan
voice mail plan
total intl calls
total intl minutes
total night minutes
total day calls
account length
total night calls
total eve calls
number vmail messages
state
Features
0.00
0.02
0.04
0.06
0.08
0.10
0.12
Mean Decrease in Accuracy

In [ ]:
```
1
```

In [ ]:
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1
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1
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