CUSTOMER CHURN PREDICTION

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1. Business Understanding

The telecomminicatons field is an important sector in our lives though we may not be aware of this. Telecommunications companies are responsible for critical tasks that we may be taking for granted such as facilitating of phone calls and providing internet connectivity. Different companies in this industry offer different packages and services, hence a customer may choose to switch to a different company due to reasons such as budget, preference, or poor customer service.

Problem statement

SyriaTel, is a telcommunications company facing churn; as is common in businesses, and are interested in reducing how much money is lost because of customers who do not stick around very long. To address this, they are interested in a machine learning model that can predict the likelihood of customer churn based on various customer characteristics and usage patterns.

Objectives

- Identify factors that are likely to lead to customer churn
- Build a classifier to predict whether a customer will stop doing business with SyriaTel
- Provide actionable insights to retain customers who are more likely to Leave SyriaTel

2. Data Understanding

The dataset is from Kaggle, [Churn in Telecom's dataset (https://www.kaggle.com/datasets/becksddf/churn-in-telecoms-dataset?resource=download)](https://www.kaggle.com/datasets/becksddf/churn-in-telecoms-dataset?resource=download)

The dataset contains various attributes of a customer such as their phone number, state, type of plan, charges for specific plans, and whether they have churned, among other details. The churn column is our target and we would like to predict it based on other relevant attributes in the dataset

> ### 2.1 LOAD THE DATASET
>
> We read in the dataset to analyse it further and get a feel of it using some EDA

In [1]:
```
#import relevant libraries
import pandas as pd
df = pd.read_csv("SyriaTel Dataset.csv")

#view first few rows of dataset
df.head()
```

Out[1]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...	tot ev cal
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	9
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	10
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	11
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	8
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	12

5 rows × 21 columns

2.2 EXPLORATORY DATA ANALYSIS

Explore the dataset further to uncover patterns, identify outliers, identify relationships between the variables and get a better data understanding before applying modeling

In [2]:
```
#shape of dataframe
print(f"Rows : {df.shape[0]} ")
print(f"Columns : {df.shape[1]}")
```

```
Rows : 3333
Columns : 21
```

In [3]:
```
#general staistics of numerical colummns
df.describe()
```

Out[3]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total ev minute
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.0000(
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	200.9803
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50.7138
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0.0000(
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166.6000(
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201.4000(
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235.3000(
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363.7000(

In [4]:
```
#general overview of the dataframe
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 [5]:
```
#identify numeical columns and categorical columns

#numerical features
numerical_features = df.select_dtypes('number').columns
print(f"""Numerical Features :

{numerical_features}\n""")

#categircal features

categorical_features = df.select_dtypes('object').columns
print(f"""Categorical Features :

{categorical_features}""")
```

```
Numerical Features :

Index(['account length', 'area code', 'number vmail messages',
       'total day minutes', 'total day calls', 'total day charge',
       'total eve minutes', 'total eve calls', 'total eve charge',
       'total night minutes', 'total night calls', 'total night charge',
       'total intl minutes', 'total intl calls', 'total intl charge',
       'customer service calls'],
      dtype='object')

Categorical Features :

Index(['state', 'phone number', 'international plan', 'voice mail plan'], dty
pe='object')
```

Numeric Features:

- account length - How long a customer has had an account in terms of days.
- area code - The area code associated with the customer's phone number.
- number vmail messages - Number of voice mail messages recieved by customer
- total day minutes - total minutes a customer used during the day
- total day calls - total calls a customer made during the day
- total day charge - total charges a customer incurred during the day
- total eve minutes - total minutes a customer used during the evening
- total eve calls - total calls a customer made during the evening
- total eve charge - total charges a customer incurred during the evening
- total intl minutes - total minutes used for international calls by the customer
- total intl calls - total international calls made by the customer
- total intl charge - total charges incurred by a customer for international calls
- customer service calls - The number of customer service calls made by the customer

Categorical Features:

- state - State where the customer resides
- phone number - The phone number associated with the customer
- international plan - Does the customer have an international plan? (Yes or No)
- voice mail plan - Does the customer have a voice mail plan? (Yes or No)
- churn - is the customer loyal? (True or False)

** The churn column has boolean values but can be included as a categorical feature

2.3 Data Cleaning

Check for missing values and duplicates

In [6]:
```
#check for missing values
print(f"The dataset contains {df.isnull().sum().sum()} missing values")

#check for duplocates
print(f"We have duplicates : {df.duplicated().any()}")
```

```
The dataset contains 0 missing values
We have duplicates : False
```

2.4 Data visualization

Generate multiple visualizations for the dataset using:

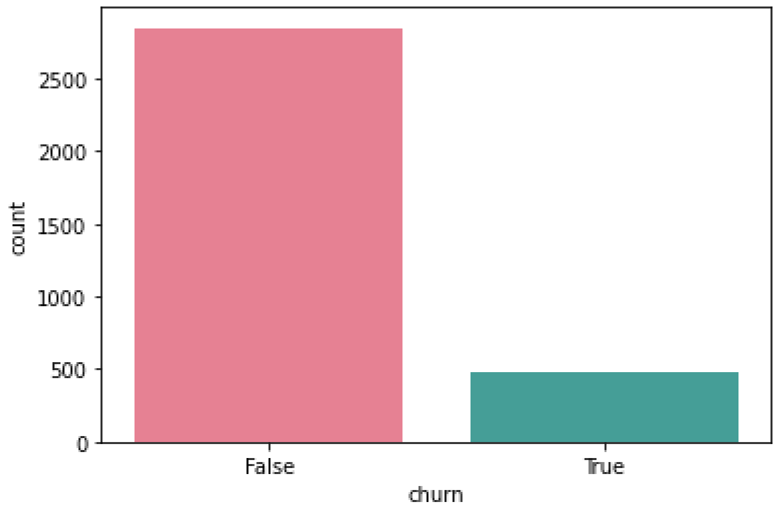
- Univariate analysis
- Bivariate analysis
- Multivariate analysis

Univariate analysis

Explore columns in the dataset to evaluate distributions and spread of the columns.

(i)Target (Churn) Distribution

In [7]:
```
#import relevant library
import seaborn as sns

#generate a plot for churn counts
sns.countplot(data = df, palette = "husl", x = "churn", legend = False, hue =
```



In [8]:
```
#evaluate counts for target variable
df["churn"].value_counts()
```

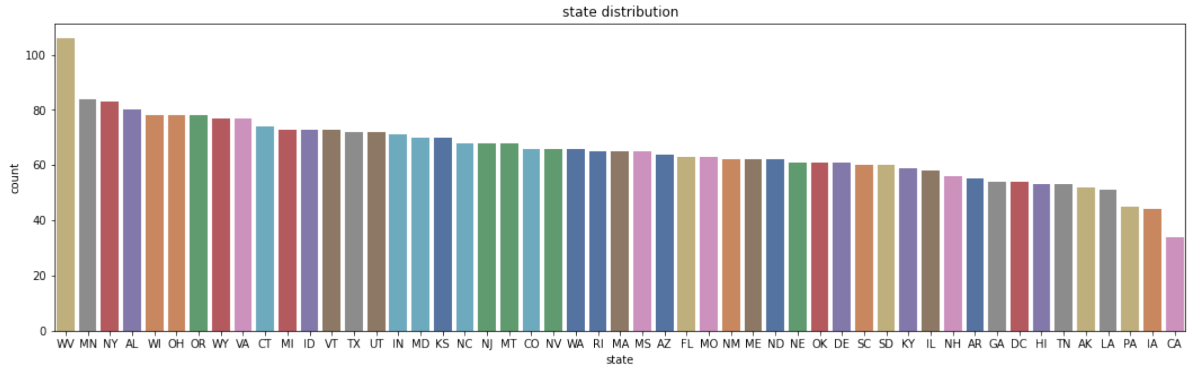
Out[8]:
```
False    2850
True      483
Name: churn, dtype: int64
```

It is evident that the we have a larger count one class that the other and the difference is huge indicating data imbalance hence we need to choose a good metric for evaluating perfomance of the model.

> ***(ii) Various categorical distributions : State, International plan and Voice mail plan***
>
> Create a function to plot various categorical features with respect to their value counts

In [9]:
```
import matplotlib.pyplot as plt
def categorical_distribution_plot(data, feature):
    plt.figure(figsize = (18,5))
    sorted_categories = data[feature].value_counts().index
    sns.countplot(x = feature, data = data, palette = "deep", hue = feature,
                  order = sorted_categories)
    plt.title(f"{feature} distribution")
    plt.show
```

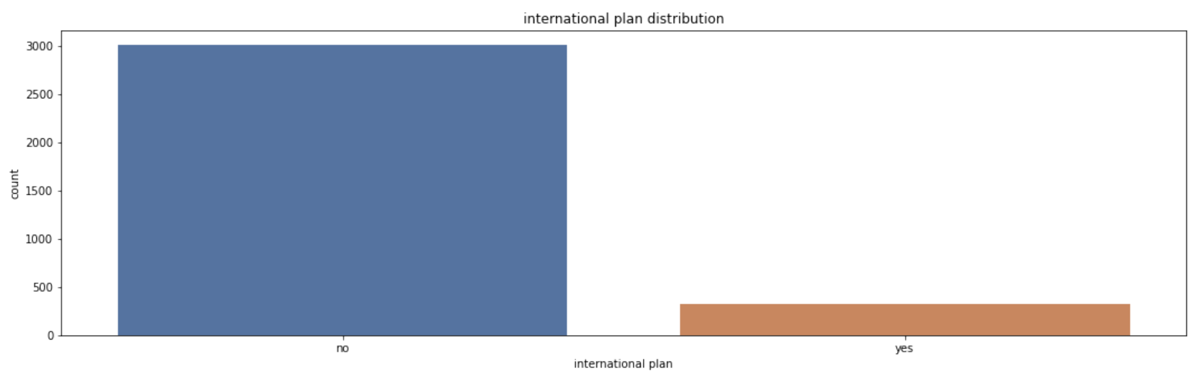
In [10]:
```
categorical_distribution_plot(df, "state")
```



It is evident that most customers are from West Virginia, Minesota, New York, Alabama and Wisconsin

In [11]:
```
print(df["international plan"].value_counts())
categorical_distribution_plot(df, "international plan")
```

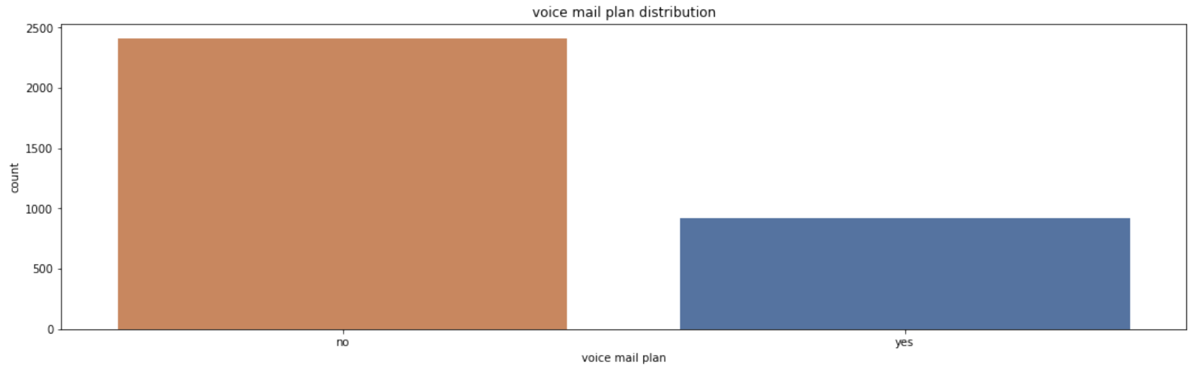
```
no     3010
yes     323
Name: international plan, dtype: int64
```



It is evident that most of the customers do not have the international plan.
Only 323 customers are in the international plan out of 3333 customers indicating 3010 customers are NOT on the international plan

In [12]:
```
print(df["voice mail plan"].value_counts())
categorical_distribution_plot(df, "voice mail plan")
```

```
no     2411
yes     922
Name: voice mail plan, dtype: int64
```



From the above plot it is evident that a majority of the customers are NOT on the voice mail plan.
922 customers are on the voice mail plan and 2411 customers are NOT on the voice mail plan

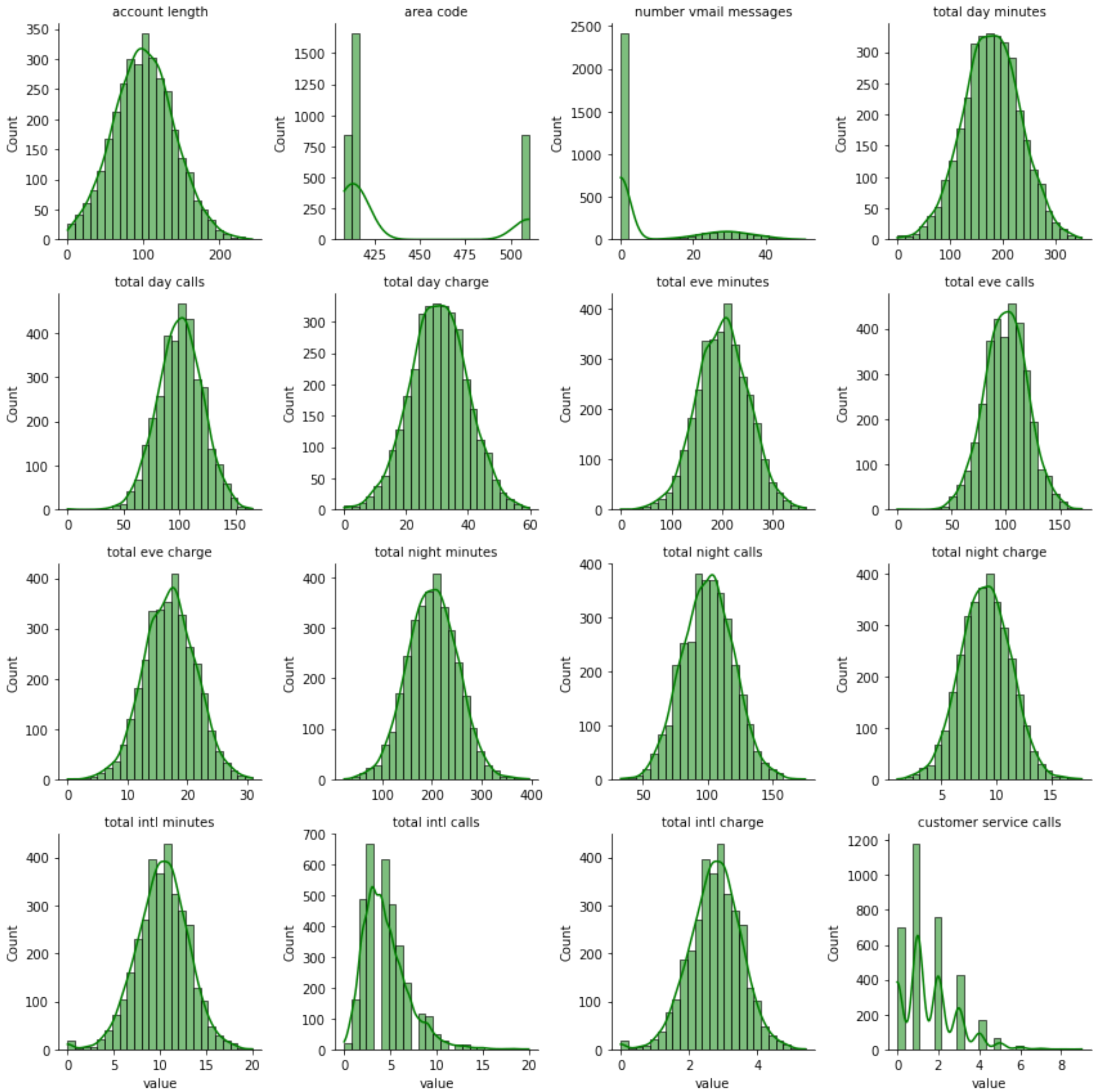
(iii). Numerical distributions

Plot numerical features to evaluate thier distributions.

A FacetGrid from the Seaborn library was used to create figures for each numerical feature.
The dataset was first converted from a wide format to a long format using melting in order for the FacetGrid to be applied on the dataset.
KDE plots and histograms were used together and both mapped to each generated figure for the numerical fearures

In [13]:
```
#melt dataframe for FacetGrid
#this sets the dataset from a wide format to a long format
#all columns are sorted into a column variable and all rows are sorted into a c
#each column name and single row value respectively
numerical_features_melted = df[numerical_features].melt()

#define a color palette
colors = sns.color_palette("husl", len(numerical_features))

#create a FacetGrid
#col = "variable" creates seperate plots each unique value in variable column t
g = sns.FacetGrid(numerical_features_melted, col = "variable", col_wrap = 4, sh
                  sharex = False)

#map histplot and kdeplot
g.map(sns.histplot, "value", kde = True, bins = 25, color = "green")

#assign titles appropriately
g.set_titles("{col_name}")
```

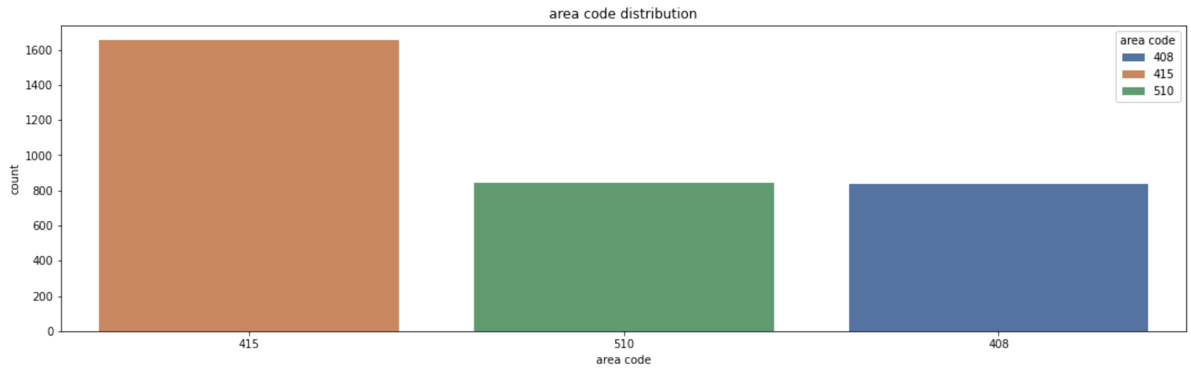
Out[13]: <seaborn.axisgrid.FacetGrid at 0x159ddfdeca0>



Based on the above plots, all numerical features have Normal Distributions apart from: customer service calls and number of voice mail messages

In [14]:
```
print(df["area code"].value_counts())
categorical_distribution_plot(df, "area code")
```

```
415    1655
510     840
408     838
Name: area code, dtype: int64
```



The Area code 415 has the most customers (1655 customers) while the Area Code 408 has the least amount of customers (838 customers).

Bivariate analysis

Explore relationships between two features/variables in the dataset to evaluate how changes in one variable may cause changes in another variable.

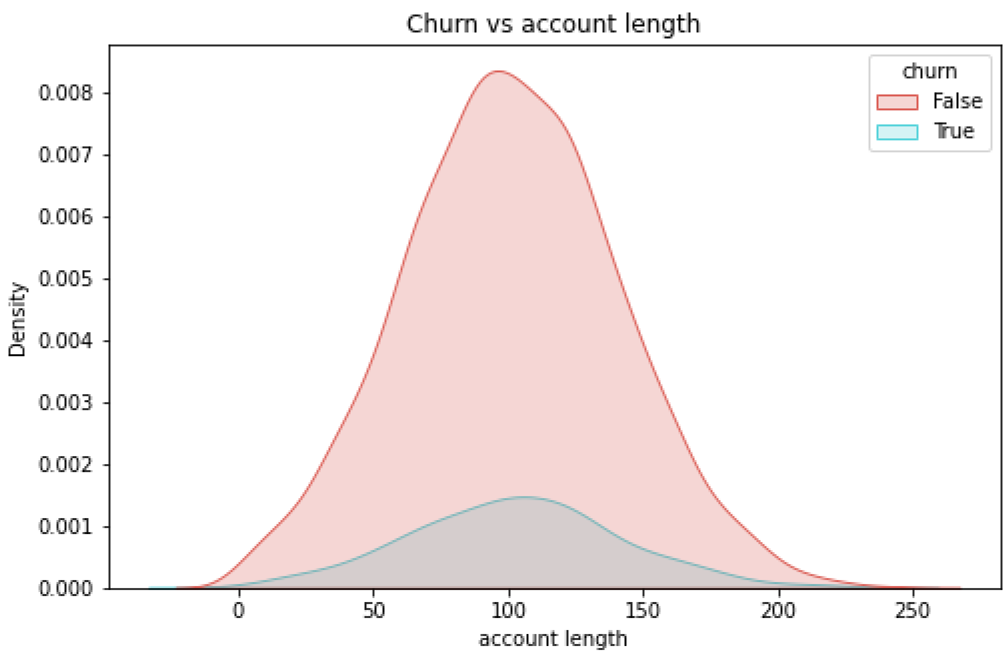
> ***Churn vs Multiple Numerical Features***
>
> Define a function to plot kdeplots to observe the distribution of Churn against various numerical features such as charges

In [15]:
```
numerical_features
```

Out[15]:
```
Index(['account length', 'area code', 'number vmail messages',
       'total day minutes', 'total day calls', 'total day charge',
       'total eve minutes', 'total eve calls', 'total eve charge',
       'total night minutes', 'total night calls', 'total night charge',
       'total intl minutes', 'total intl calls', 'total intl charge',
       'customer service calls'],
      dtype='object')
```

In [16]:
```
#function to plot a kde plot
def churn_vs_numerical(data, numerical):
    plt.figure(figsize = (8,5))
    sns.kdeplot(x = numerical, data = data, palette ="hls", hue = "churn",
                warn_singular = False, fill = True)
    plt.xlabel(f"{numerical}")
    plt.title(f"Churn vs {numerical}")
    plt.show()
```

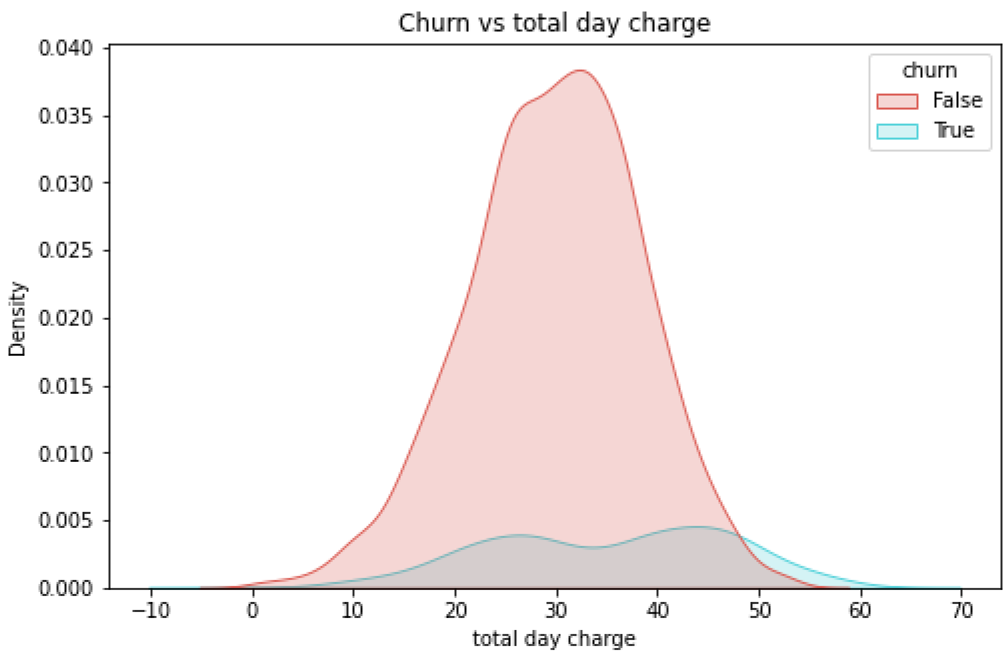
In [17]:
```
churn_vs_numerical(df, "account length")
```



CHURN VS ACCOUNT LENGTH

> ***Account Length does not appear to be a stron predictor of churn***
>
> There is NO CLEAR PATTERN.
> The peak account length for both groups is around 100 days.
> Churners(BLUE) have a slightly spread out distribution, but no significant deviation from non-churners(RED)

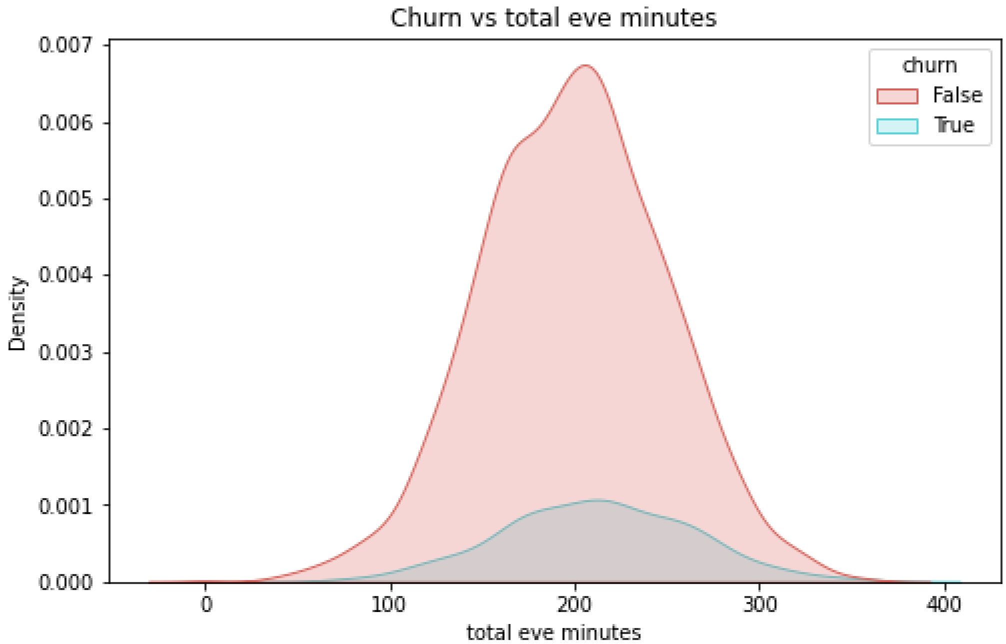
In [18]:
```
churn_vs_numerical(df, "total day charge")
```



CHURN VS TOTAL DAY CHARGE

> ***Customers with HIGHER TOTAL DAY CHARGES ARE MORE LIKELY TO CHURN***
>
> Non-Churned customers have a peak around 30 to 40 total day charge indicating most non-churners have this range of charges. Churned customers are more spread out and have a higher propotion of total day charge values above 40.

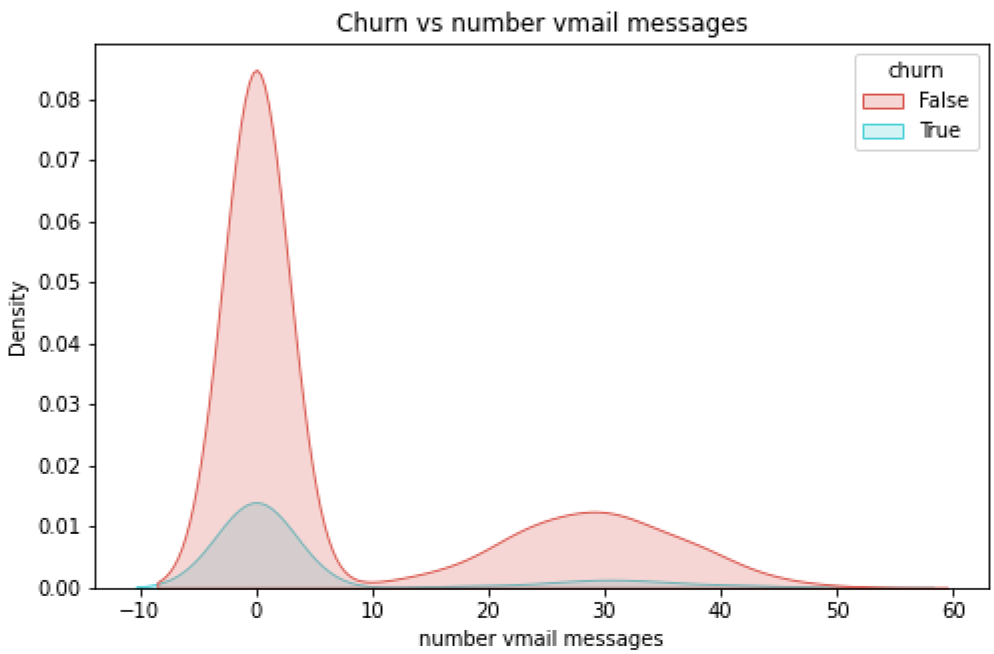
In [19]:
```
churn_vs_numerical(df, "total eve minutes")
```



CHURN VS TOTAL EVENING MINUTES

> ***Total evening minutes is NOT a significant churn indicator***
>
> Distribution shapes are similar as they both have peeks at around 200.
> Both churners and non-churners have a broadly overlappung distribution

In [20]:
```
churn_vs_numerical(df, "number vmail messages")
```

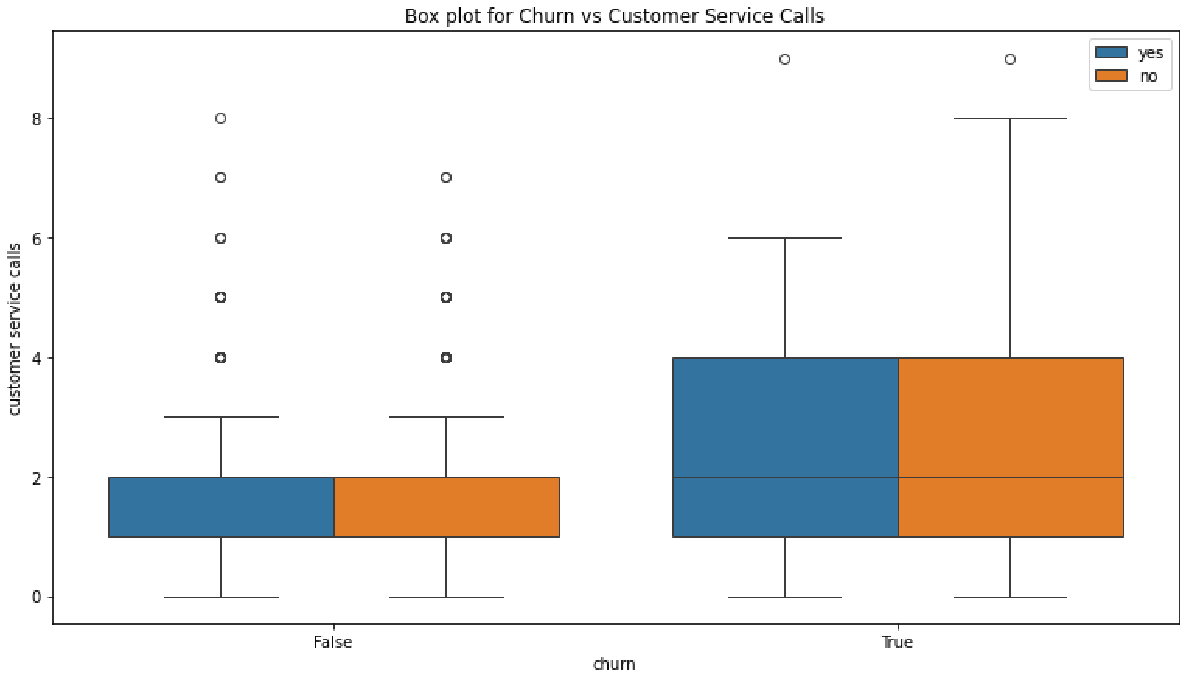


CHURN VS NUMBER OF VOICEMAIL MESSAGES

> ***Frequent use of voicemail messages indicates LESS likelihood of churning***
>
> Churners have a much lower overall distribution than for non-churners.
> Majority of customers have 0 or very few voicemail messages.
> Non churners have a secondary peak at around 25 while churners do not.
> Churners tend to have fewer or no voicemail messages.

In [21]:
```
plt.figure(figsize = (13, 7))
sns.boxplot(data = df, x = "churn", y = "customer service calls", hue = "voice
plt.legend(loc = "upper right")
plt.title("Box plot for Churn vs Customer Service Calls")
```

Out[21]: Text(0.5, 1.0, 'Box plot for Churn vs Customer Service Calls')



CHURN VS CUSTOMER SERVICE CALLS

More customer service calls indicates higher risk of churning

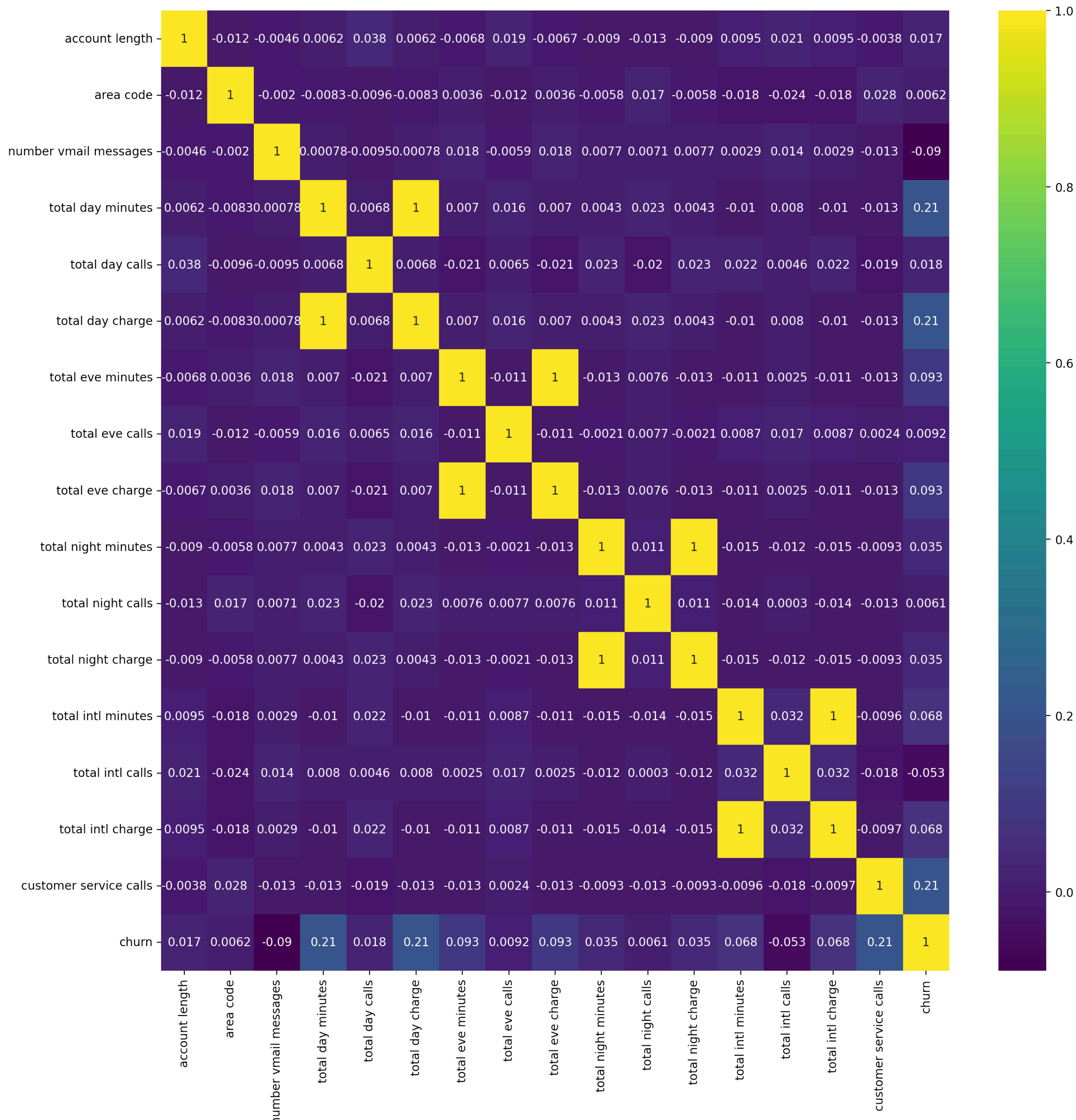
Most Non-Churners have very few customer service calls i.e less than 3 Churners have a THICKER distribution with more customer service calls and are more likely to churn. A high call frequency for customer service may indicate dissatisfaction

Multivariate analysis

Create a heatmap to evaluate correlation between different variablles in the dataset

Heatmap to show feature correlation

In [22]:
```
plt.figure(figsize = (15, 15), dpi = 200)
sns.heatmap(df.corr(),annot = True, cmap = "viridis");
```



Some features share a perfect correlation

- Total day charge and total day minutes are fully positively correlated.
- Total eve charge and total eve minutes are fully positively correlated.
- Total night charge and total night minutes are fully positively correlated.
- Total international minutes and total international charges are fully positively correlated.

Multicollinearity

In [23]:
```
import numpy as np
corr_matrix = df.corr().abs()
mask = np.triu(np.ones_like(corr_matrix, dtype = bool))
triangle_df = corr_matrix.mask(mask)

features_to_drop = [col for col in triangle_df.columns if any(triangle_df[col]

df = df.drop(features_to_drop, axis = 1)
```

3. Data Preporcessing

We now prepare the data for modelling. This will include steps such as One Hot encoding or Ordinal Encoding on relevant columns. Scaling will also be carried out to have improved model accuracy.
We will also define X and y which will be used for training and modelling.
X and y will also be split into relevant groups i.e Train data and Test data Irrelevant columns for our prediction such as phone number are also dropped from the dataframe

> ### Ordinal Encoding
>
> Ordinal Encoding can be used to encode categorical features to binary values of 0 and 1.
> We will ordinal encode the following features: international plan, voice mail plan and churn

In [24]:
```
#drop irrelevant columns for model bulding
irrelevant_cols = ["phone number", "area code", "state"]
df = df.drop(columns = irrelevant_cols)

#ordinal encode relevant categorical columns

#import relevant libraries
from sklearn.preprocessing import OrdinalEncoder

#data to be transfromed
to_ordinal_encode = df[["international plan", "voice mail plan", "churn"]]

#instantiate transformer object
ordinal_encoder = OrdinalEncoder()

#fit object on relevant data
ordinal_encoder.fit(to_ordinal_encode)

#tranform on relevant data
ordinal_encoded = ordinal_encoder.transform(to_ordinal_encode)
df[["international plan", "voice mail plan", "churn"]] = ordinal_encoded

#evaluate encoded columns
df[["international plan", "voice mail plan", "churn"]]
```

Out[24]:

	international plan	voice mail plan	churn
0	0.0	1.0	0.0
1	0.0	1.0	0.0
2	0.0	0.0	0.0
3	1.0	0.0	0.0
4	1.0	0.0	0.0
...	...	...	...
3328	0.0	1.0	0.0
3329	0.0	0.0	0.0
3330	0.0	0.0	0.0
3331	1.0	0.0	0.0
3332	0.0	1.0	0.0

3333 rows × 3 columns

Define X and y.

We seperate the features from the labels into 2 objects, X and y

In [25]:
```
y = df["churn"]
X = df.drop("churn", axis = 1)
```

Split the data

We perform train test split to split the dataset into 2, with a test size of 15% and random state of 107

In [26]:
```
print(df.dtypes)
```

```
account length              int64
international plan        float64
voice mail plan           float64
number vmail messages       int64
total day calls             int64
total day charge          float64
total eve calls             int64
total eve charge          float64
total night calls           int64
total night charge        float64
total intl calls            int64
total intl charge         float64
customer service calls      int64
churn                     float64
dtype: object
```

In [27]:
```
df.head()
```

Out[27]:

	account length	international plan	voice mail plan	number vmail messages	total day calls	total day charge	total eve calls	total eve charge	total night calls	total night charge	total intl calls	ch
0	128	0.0	1.0	25	110	45.07	99	16.78	91	11.01	3	
1	107	0.0	1.0	26	123	27.47	103	16.62	103	11.45	3	
2	137	0.0	0.0	0	114	41.38	110	10.30	104	7.32	5	
3	84	1.0	0.0	0	71	50.90	88	5.26	89	8.86	7	
4	75	1.0	0.0	0	113	28.34	122	12.61	121	8.41	3	

In [28]:
```
print(X.dtypes.value_counts())  # Should NOT include 'object'
```

```
int64      7
float64    6
dtype: int64
```

In [29]:
```
#import relevant library
from sklearn.model_selection import train_test_split

#split the data
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.15, ran

#evaluate splits
len(X_train), len(X_test)
```

Out[29]:
```
(2833, 500)
```

In [30]:
```
print(X_train.dtypes)
```

```
account length              int64
international plan        float64
voice mail plan           float64
number vmail messages       int64
total day calls             int64
total day charge          float64
total eve calls             int64
total eve charge          float64
total night calls           int64
total night charge        float64
total intl calls            int64
total intl charge         float64
customer service calls      int64
dtype: object
```

Scale the Data

Scaling the data is necessary to transform numerical features to a reasonable range by helping reduce effects of outliers and standardizing the variable.
A common method of scaling is Min-Max Normalization, which scales the variables to a specific range.
Min-Max normalization scales the minimum variable to 0 and the maximum variable is transformed to 1.
The rest of the variables are scaled in between the range 0 and 1 appropriately

In [31]:
```
#import relevant library
from sklearn.preprocessing import MinMaxScaler

#select numerical columns only
numeric_features_to_scale = df.select_dtypes(include = ["float64", "int64"]).c

#instantiate transformer object
scaler = MinMaxScaler()

#fit and transform applying back to the same numerical column names
df[numeric_features_to_scale] = scaler.fit_transform(df[numeric_features_to_sc
df.head()
```

Out[31]:

	account length	international plan	voice mail plan	number vmail messages	total day calls	total day charge	total eve calls	total eve charge	total night calls	
0	0.524793	0.0	1.0	0.490196	0.666667	0.755701	0.582353	0.542866	0.408451	0.
1	0.438017	0.0	1.0	0.509804	0.745455	0.460597	0.605882	0.537690	0.492958	0.
2	0.561983	0.0	0.0	0.000000	0.690909	0.693830	0.647059	0.333225	0.500000	0.
3	0.342975	1.0	0.0	0.000000	0.430303	0.853454	0.517647	0.170171	0.394366	0.
4	0.305785	1.0	0.0	0.000000	0.684848	0.475184	0.717647	0.407959	0.619718	0.

Recall: Univariate analysis - Churn Distribution

We evaluated the target's distribution with respect to its value counts.
Applying .value_counts() on the target variable revealed that there is a class imbalance.
In order to deal with class imbalance, we use Class Weights to solve the class imbalance issue.

> **Adjust Class weights**
>
> Solve class imbalance problems using Class Weights

4. Modelling

Our task is to build a model that will predict churn, our target variable.
We use different classification algorithms to build a model that best predicts customer churn using the rest of the features in out dataset.
We will use various classification algorithms such as:

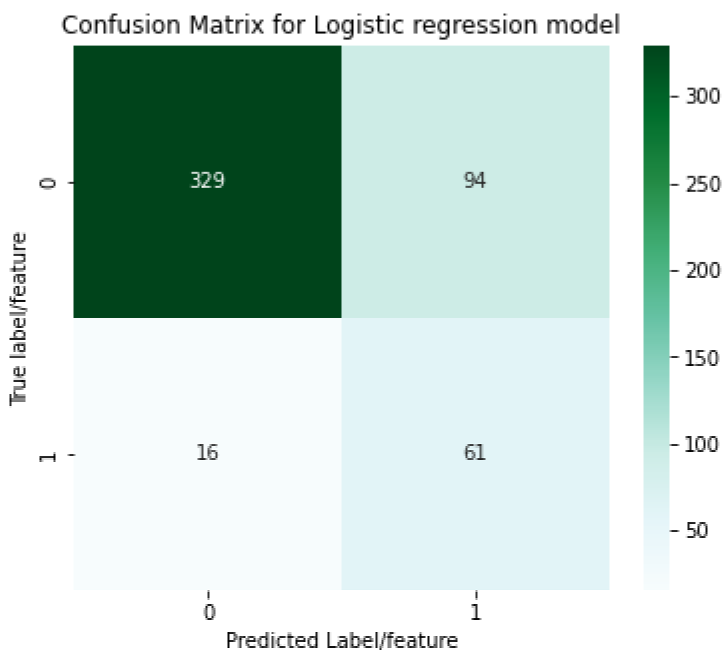
- Logistic Regression.
- Decision Tree.
- Random Forest.
- XGBoost

Logistic Regression

We first buld a baseline model using Logistic Regression.
Logistic regression is a statistical model useful for binary classification.
The target/dependant variable should be binary, just as is our case for churn

In [32]:
```
#import  relevant library
from sklearn.linear_model import LogisticRegression

#Instatiate baseline model
baseline_logmodel = LogisticRegression(random_state = 42, class_weight = "bala

#fit baseline model on training data
baseline_logmodel.fit(X_train, y_train)

#predict on test set
y_pred_baseline_logmodel = baseline_logmodel.predict(X_test)
```

In [33]:
```
#import relevant library
from sklearn.metrics import confusion_matrix, classification_report

#compute a confusion matrix with (y true values, y predicted values)
cm = confusion_matrix(y_test, y_pred_baseline_logmodel)

#plot a confusion matrix
plt.figure(figsize = (6,5))
sns.heatmap(cm, annot = True, fmt = 'd', cmap = "BuGn")

#labels and title
plt.xlabel("Predicted Label/feature")
plt.ylabel("True label/feature")
plt.title("Confusion Matrix for Logistic regression model")

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



In [34]:
```
#Evaluate accuracy score for Baseline model

#import relevant library
from sklearn.metrics import accuracy_score

#obtain accuracy score
baseline_logmodel_accuracy = accuracy_score(y_pred_baseline_logmodel, y_test)
print(f"Accuracy of Baseline Logistic regression : {baseline_logmodel_accuracy
```

```
Accuracy of Baseline Logistic regression : 78.0%
```

In [35]:
```
#print classification report
print(classification_report(y_test, y_pred_baseline_logmodel))
```

```
              precision    recall  f1-score   support

         0.0       0.95      0.78      0.86       423
         1.0       0.39      0.79      0.53        77

    accuracy                           0.78       500
   macro avg       0.67      0.78      0.69       500
weighted avg       0.87      0.78      0.81       500
```

Interpretation

- A precision of 0.95 for non-churners indicates the model is correct 95% of the time detecting class 0, hence quite efficient for class 0
- The model is not efficent at detecting churners(class 1) due to a 0.39 precision indicating it is correct 39% of the time detecting class 1
- The model correctly identifies 78% of class 0 since recall is 0.78
- The model correctly identifies 79% of class 1 since recall is 0.79. This also indicates that it captures most churners but has a low precision indicating many false values
- The model accurately predicts the class in 78% of all cases since accuracy is 0.78 which is equivalent to 78%
- The model is good at detecting non-churners(class 0) but poor at correctly predicting churners(class 1)

Based on this we can improve the model or try a different model such as Decision Trees followed by Random Forest

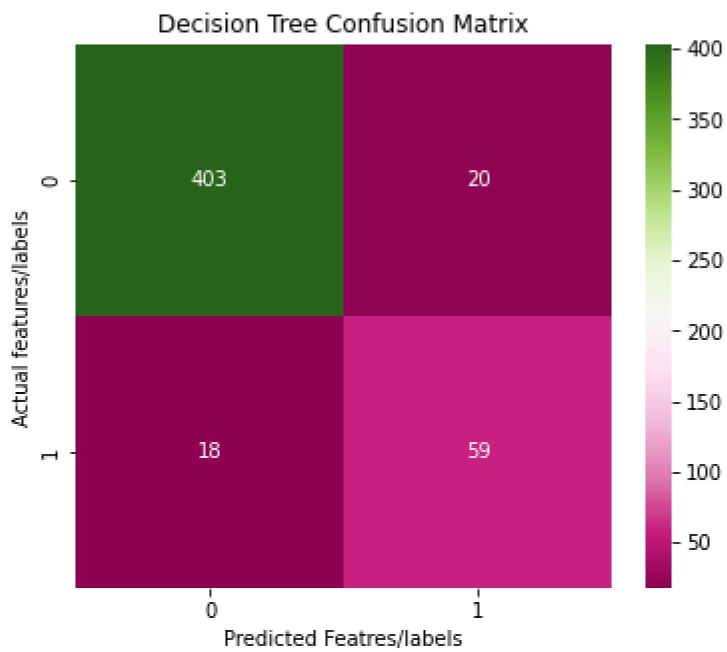
Decision Tree

A supervised M.L algorithm used for classification and regression tasks. It splits the dataset into branches based on feature values such as high phone charges or high number of minutes used on the device.
This algorithm will split the data into such nodes based on the features present and make appropriate decisions similar to how a pseudo code opertates

In [36]:
```
#import relevant library
from sklearn.tree import DecisionTreeClassifier

#initialize and train the Decision Tree
decision_tree = DecisionTreeClassifier(criterion = 'gini', max_depth = 7, rand
decision_tree.fit(X_train, y_train)
```

Out[36]:
```
DecisionTreeClassifier

DecisionTreeClassifier(class_weight='balanced', max_depth=7, random_state=4
2)
```

In [37]:
```
#make predictions
y_decision_tree_pred = decision_tree.predict(X_test)

#evaluate the Decision Tree model using a confusion matrix
decision_tree_cm = confusion_matrix(y_test, y_decision_tree_pred)
plt.figure(figsize = (6,5))
sns.heatmap(decision_tree_cm, annot = True, fmt = "d", cmap = "PiYG")
plt.xlabel("Predicted Featres/labels")
plt.ylabel("Actual features/labels")
plt.title("Decision Tree Confusion Matrix")
plt.show()
```



In [38]:
```
#Evaluate accuracy score for Decision Tree model

#obtain accuracy score
decision_tree_model_accuracy = accuracy_score(y_decision_tree_pred, y_test)
print(f"Accuracy of Decision Tree :{decision_tree_model_accuracy * 100}%")
```

```
Accuracy of Decision Tree :92.4%
```

In [39]:
```
print(classification_report(y_test, y_decision_tree_pred))
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.95      0.95       423
         1.0       0.75      0.77      0.76        77

    accuracy                           0.92       500
   macro avg       0.85      0.86      0.86       500
weighted avg       0.92      0.92      0.92       500
```

Interpretation

- With a precision of 0.96 for class 0 the model detects non-churners correctly 96% of the time
- A precision of 0.75 for churners(class 1) shows that the model detects class 1 correctly 75% of the time.
- The model correctly identifies 95% of class 0 since recall is 0.95
- The model correctly identifies 77% of class 1 since recall is 0.77.
- The model correctly predicts the class in 92% of all cases since accuracy is 0.92 which is equivalent to 92%
- The model seems good generally bt we can improve the recall for class 1

Based on this we can improve the model or try a different model such as Random Forest and see if we can improve our classs 1 recall value

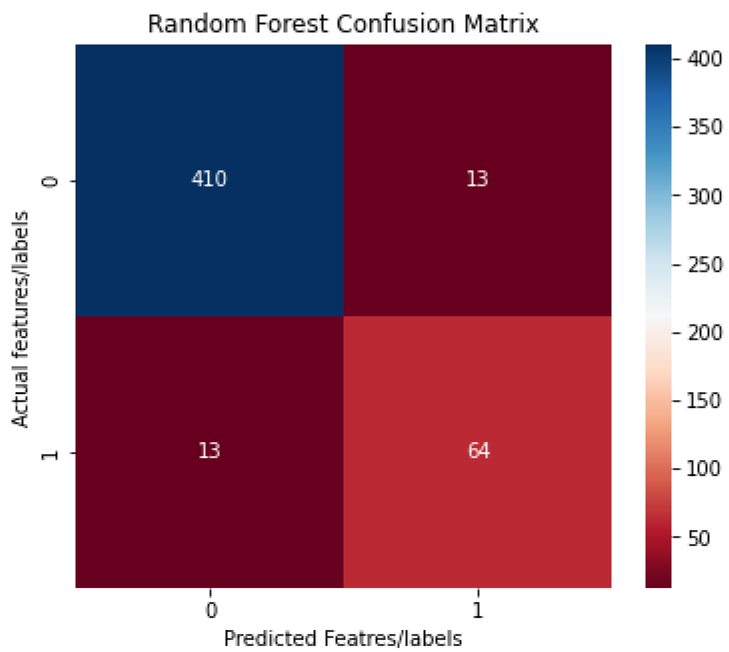
Random Forest

These are basically multiple decision trees where samples are collected with replacement for training each decision tree. Each decision tree predicts an output and the most popular output is voted as the final prediction.
This imporves accuracy, redices overfitting and created a better model than a single Decision Tree

In [40]:
```
#import the necessary library
from sklearn.ensemble import RandomForestClassifier

#initialize and train the model
random_forest = RandomForestClassifier(n_estimators = 100, random_state = 42,
                        class_weight = "balanced", max_depth = 10, min_samples_
random_forest.fit(X_train, y_train)
```

Out[40]:
```
                    RandomForestClassifier
RandomForestClassifier(class_weight='balanced', max_depth=10,
                       min_samples_split=10, random_state=42)
```

In [41]:
```
#make predicitons and generate a confusion matrix
y_random_forest_pred = random_forest.predict(X_test)

#confusion matrix
random_forest_cm = confusion_matrix(y_test, y_random_forest_pred)
plt.figure(figsize = (6,5))
sns.heatmap(random_forest_cm, annot = True, fmt = "d", cmap = "RdBu")
plt.xlabel("Predicted Featres/labels")
plt.ylabel("Actual features/labels")
plt.title("Random Forest Confusion Matrix")
plt.show()
```



In [42]:
```
#Evaluate accuracy score for Decision Tree model

#obtain accuracy score
random_forest_model_accuracy = accuracy_score(y_random_forest_pred, y_test)
print(f"Accuracy of Random Forest model :{random_forest_model_accuracy * 100}%
```

```
Accuracy of Random Forest model :94.8%
```

In [43]:
```
print(classification_report(y_test, y_random_forest_pred))
```

```
              precision    recall  f1-score   support

         0.0       0.97      0.97      0.97       423
         1.0       0.83      0.83      0.83        77

    accuracy                           0.95       500
   macro avg       0.90      0.90      0.90       500
weighted avg       0.95      0.95      0.95       500
```

Interpretaion

- The model is efficient at detecting class 0 since we have 97% precision, indicating it is correct 97% of the time detecting class 0
- The model is better at detecting churners(class 1) compared to the Decision Tree model. We have an improved precision rate of 83% from 75% precision
- The model correctly identifies 97% of class 0 since recall is 0.97
- The model correctly identifies 83% of class 1 since recall is 0.83. This is higher as compared to Decision tree model which had a recall of 0.77
- The model correctly predicts the class on 95% of all cases since accuracy is 0.95 equivalent to 95%

We can improve the model further or try a different model such as XGBoost

XGboost (Extreme gradient Boosting)

A M.L algorithm based on gradient boosting which builds multiple weak decision trees sequentially, where each new tree corrects the errors of the previous trees.
Includes regularization like Liasso and Ridge to prevent overfitting

In [44]:
```
#Import relevant libraries
import xgboost as xgb

#ignore warnings
import warnings
warnings.filterwarnings("ignore")

#instantiate and train the model
xgboost_model = xgb.XGBClassifier(random_state = 42,
                                  scale_pos_weight = len(y_train[y_train == 0]
xgboost_model.fit(X_train, y_train)
```

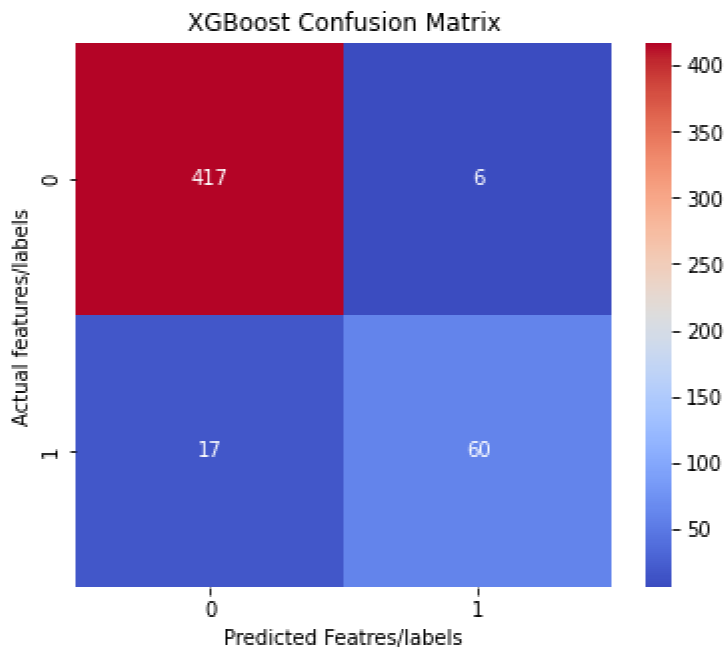
```
C:\Users\user\anaconda3\envs\learn-env\lib\site-packages\xgboost\compat.py:9
3: FutureWarning: pandas.Int64Index is deprecated and will be removed from pa
ndas in a future version. Use pandas.Index with the appropriate dtype instea
d.
  from pandas import MultiIndex, Int64Index
```

Out[44]:

XGBClassifier

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=0, num_parallel_tree=1, random_stat
e=42,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=5.97783251231527
1,
              subsample=1, tree_method='exact', validate_parameters=1,
```

In [45]:
```
#make predictions and generate a confusion matrix
xgboost_model_pred = xgboost_model.predict(X_test)

#confusion matrix
xgboost_cm = confusion_matrix(y_test, xgboost_model_pred)
plt.figure(figsize = (6,5))
sns.heatmap(xgboost_cm, annot = True, fmt = "d", cmap = "coolwarm")
plt.xlabel("Predicted Featres/labels")
plt.ylabel("Actual features/labels")
plt.title("XGBoost Confusion Matrix")
plt.show()
```



In [46]:
```
#Evaluate accuracy score for Decision Tree model

#obtain accuracy score
xgboost_model_accuracy = accuracy_score(xgboost_model_pred, y_test)
print(f"Accuracy of XGBoost model :{xgboost_model_accuracy * 100}%")
```

```
Accuracy of XGBoost model :95.39999999999999%
```

In [47]:
```
print(classification_report(y_test, xgboost_model_pred))
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.99      0.97       423
         1.0       0.91      0.78      0.84        77

    accuracy                           0.95       500
   macro avg       0.93      0.88      0.91       500
weighted avg       0.95      0.95      0.95       500
```

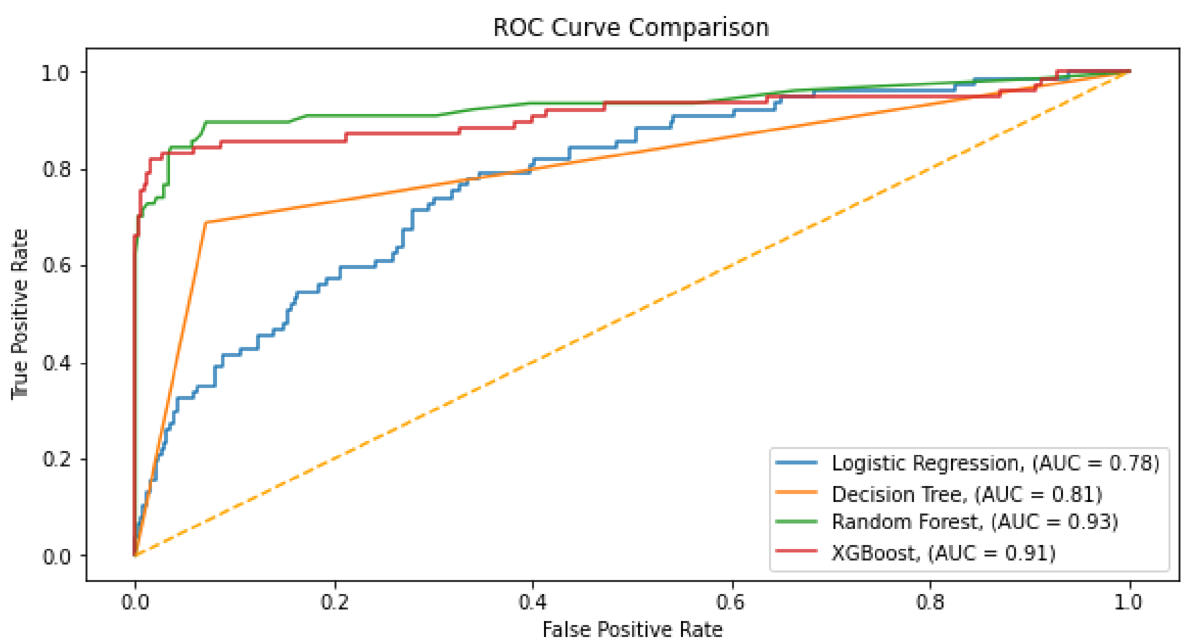
Interpretaion

- The model is better at detecting class 0 since we have 96% precision, indicating it is correct 96% of the time detecting class.
- This model is the best at detecting churners(class 1) compared to the rest of the models. We have the best precision rate at 91%
- The model correctly identifies 99% of class 0 since recall is 0.99.(Best so far)
- The model correctly identifies 78% of class 0 since recall is 0.78. This is LOWER as compared to the random forest which had a recall of 0.83
- The model correctly predicts the class on 95% of all cases since accuracy is 0.95

5.Model Evaluation

We evaluate the model's performance using the ROC and AUC curves.
ROC Curve(Receiver-operating Characteristic curve) is a visual representation of model performance across all threshholds AUC Curve(Area under the ROC curve) represents the probability that the model will rank the positive higher than the negative if given a randomly chosen posititve and negative example.
A perfect model has an AUC of 1.0
We will plot an ROC of all our models. The Baseline model will still be Logistic Regression

In [48]:
```
#import relevant libraries
from sklearn.metrics import roc_curve, roc_auc_score

#define classifiers
classifiers = {"Logistic Regression" : LogisticRegression(),
              "Decision Tree" : DecisionTreeClassifier(),
              "Random Forest" : RandomForestClassifier(),
              "XGBoost" : xgb.XGBClassifier()
              }


#define your figure to plot in trained models
plt.figure(figsize = (10,5))

#train models
for name, classifier in classifiers.items():
    #fit each classifier and generate predicted values
    classifier.fit(X_train, y_train)

    #compute ROC curve
    fpr, tpr, _ = roc_curve(y_test, classifier.predict_proba(X_test)[:, 1])
    auc = roc_auc_score(y_test, classifier.predict_proba(X_test)[:, 1])
    plt.plot(fpr, tpr, label = f"{name}, (AUC = {auc:.2f})")
#plot reference line(Baseline Model)
plt.plot([0,1], [0,1], linestyle = "--", color = "orange")

#titles and labels
plt.title("ROC Curve Comparison")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend(loc = "lower right")

#show plot
plt.show()
```



ROC-AUC Curve Interpretation

The closer the curve hugs the y-axis/the closer the curve is to the top_left corner , the better the model is at distinguishing between the classes.

- XGBoost(AUC = 0.91)
  - Best overall classification ability indicating that in 91% of the cases, the model will rank a randomly chosen positive instance hiogher than a randomly chosen negative instance
- Logistic Regression(AUC = 0.78)
  - Close but lower than XGBoost. An AUC of 0.91 indicates it is a strong classifer but less effective than XGboost
- Random Forest(AUC = 0.93)
  - Captures patterns but not as effectively as XGBoost and is better than Logistic and Decision Tree
- Decision Tree(AUC = 0.82)
  - Least overall classification among our 4 models ability indicating that in 82% of the cases, it has a higher false positive rate and is lss reliable than others
- Baseline(Orange Dashed Line)
  - Represents a random clasiffier with AUC = 0.50 and any model performing below this line is worse than random guessing

Hyperparameter tuning

Involves evaluating the models further by exploring various hyperparameters that influence model performance and tuning various parameters for enhanced accuracy and reliability.
I decided to tune 3 models i.e Logistic Regression, Random Forest and XGBoost

> ## Logistic Regression
>
> We use GridSearchCV for optimizing the model.
> This is a Method provided by the scikit learn Library where we pass in various parameter tunes and the method finds the best combination of hyperparamters that optimize the model BEST.
> It also uses Cross-Validation to evaluate perfomance of each combination and selects the set of hyperparameters that provide the best Cross-Validation performance.

In [49]:
```
#baseline_logmodel's accuracy
print(f"The Accuracy of baseline logistic regression without hyperparameter : 
```

```
The Accuracy of baseline logistic regression without hyperparameter : 78.0%
```

In [50]:
```
#define various hyperparameters to be used in logistic regression
baseline_logmodel_parameters = [{
    "penalty" : ["l1", "l2", "elasticnet", "None"],
    "C" : [0.01, 0.1, 1, 10],
    "solver" : ["lbfgs", "liblinear","sag and saga"],
    "max_iter" : [1000, 2000, 3000, 4000, 5000]
    }]

#import relevant library : GridSearchCV
from sklearn.model_selection import GridSearchCV

#total hyperparameters to be chosen
logisitc_parameters = GridSearchCV(baseline_logmodel, param_grid = baseline_lo
                                   cv = 5, n_jobs = 1)
logisitc_parameters
```

Out[50]:
```
▸ GridSearchCV
▸ estimator: LogisticRegression
    ▸ LogisticRegression
```

In [51]:
```
#apply best Hyperparameters to Logistic Regression
logisitc_best_parameters = logisitc_parameters.fit(X, y)
#logisitc_best_parameters.best_estimator_

#evaluate best parameters chosen
logisitc_best_parameters.best_params_
```

Out[51]: {'C': 10, 'max_iter': 1000, 'penalty': 'l2', 'solver': 'lbfgs'}

In [52]:
```
#evaluate tuned model's score
logisitc_best_parameters.best_score_
```

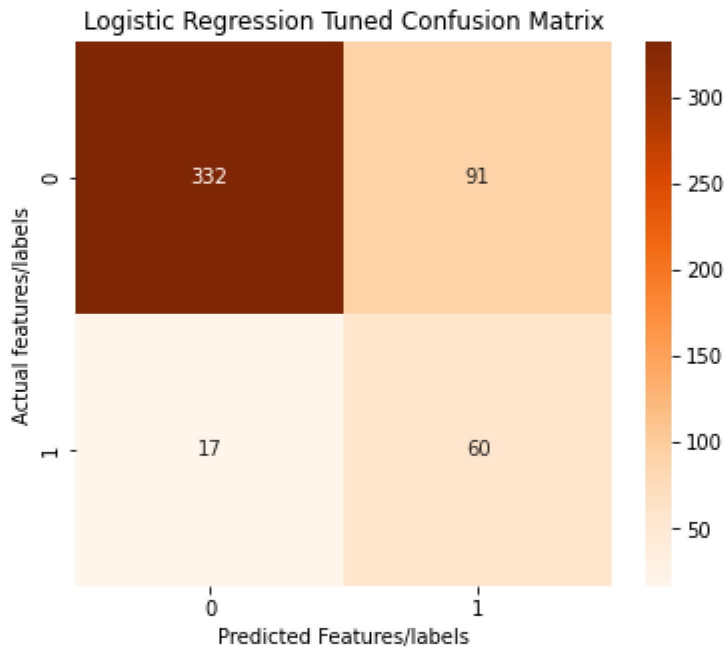
Out[52]: 0.77168082625354

Evaluate tuned Logistic model

In [53]:
```
#baseline_logmodel's accuracy
print(f"The Accuracy of baselne logistic regression WITHOUT hyperparameter tun

#tuned baseline_logmodel's accuracy
print(f"The Accuracy of baselne logistic regression WITH hyperparameter tuning
```

```
The Accuracy of baselne logistic regression WITHOUT hyperparameter tuning : 7
8.0%
The Accuracy of baselne logistic regression WITH hyperparameter tuning :78.4%
```

In [54]:
```
#make predictions for tuned Logistic Regression model
y_pred_logisitc_best_parameters = logisitc_best_parameters.predict(X_test)

#confusion matrix for tuned Logistic Regression model
logistic_tuned_cm = confusion_matrix(y_test, y_pred_logisitc_best_parameters)
plt.figure(figsize = (6,5))
sns.heatmap(logistic_tuned_cm, annot = True, fmt = "d", cmap = "Oranges")
plt.xlabel("Predicted Features/labels")
plt.ylabel("Actual features/labels")
plt.title("Logistic Regression Tuned Confusion Matrix")
plt.show()
```



In [55]:
```
print(classification_report(y_test, y_pred_logisitc_best_parameters ))
```

```
              precision    recall  f1-score   support

         0.0       0.95      0.78      0.86       423
         1.0       0.40      0.78      0.53        77

    accuracy                           0.78       500
   macro avg       0.67      0.78      0.69       500
weighted avg       0.87      0.78      0.81       500
```

Random Forest

In [56]:
```
#Original Random Forest Model accuracy
print(f"The Accuracy of original Random Forest model WITHOUT hyperparameter :
```

```
The Accuracy of original Random Forest model WITHOUT hyperparameter : 94.8%
```

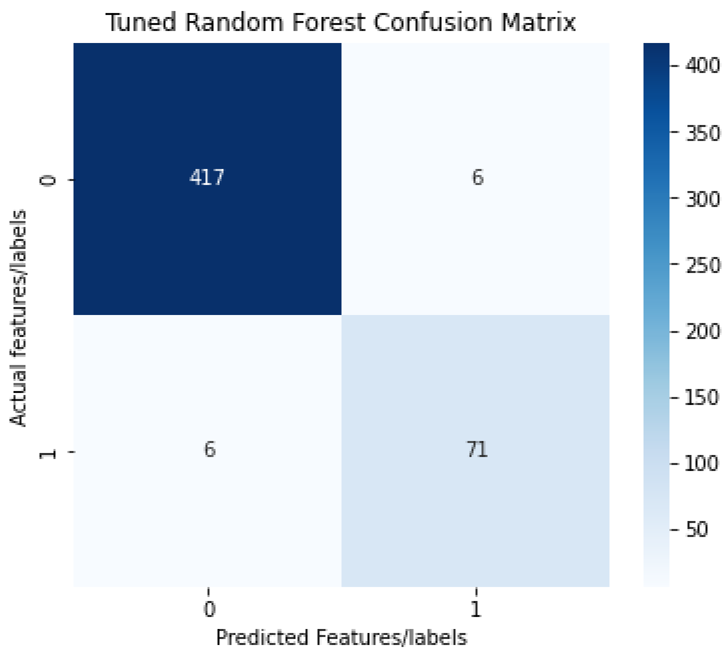
In [57]:
```
#import relevant libraries
from sklearn.model_selection import RandomizedSearchCV

#define various hyperparameters to be used in tuning of random forest model
random_forest_parameters = {
    "n_estimators" : [100, 150, 200],
    "max_features" : ["sqrt", "log2", None],
    "max_depth" : [10, 15, None],
    "min_samples_split" : [5, 10, 20],
    "min_samples_leaf" : [2, 5, 7],
    "class_weight" : ["balanced", None]
    }

#total hyperparameters to be chosen
random_forest_parameters = RandomizedSearchCV(random_forest, random_forest_para
                                              cv = 3, n_jobs = 1)
random_forest_parameters
```

Out[57]:
```
▸ RandomizedSearchCV
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier
```

In [58]:
```
#apply best Hyperparameters to Random Forest
random_forest_best_parameters = random_forest_parameters.fit(X, y)
#random_forest_best_parameters.best_estimator_

#evaluate best parameters chosen
random_forest_best_parameters.best_params_
```

Out[58]:
```
{'n_estimators': 100,
 'min_samples_split': 5,
 'min_samples_leaf': 5,
 'max_features': None,
 'max_depth': None,
 'class_weight': 'balanced'}
```

In [59]:
```
#make predictions for tuned Logistic Regression model
y_pred_random_forest_best_parameters = random_forest_best_parameters.predict(X_

#confusion matrix for tuned Logistic Regression model
random_forest_tuned_cm = confusion_matrix(y_test, y_pred_random_forest_best_pa
plt.figure(figsize = (6,5))
sns.heatmap(random_forest_tuned_cm, annot = True, fmt = "d", cmap = "Blues")
plt.xlabel("Predicted Features/labels")
plt.ylabel("Actual features/labels")
plt.title("Tuned Random Forest Confusion Matrix")
plt.show()
```



In [60]:
```
print(classification_report(y_test, y_pred_random_forest_best_parameters))
```

```
              precision    recall  f1-score   support

         0.0       0.99      0.99      0.99       423
         1.0       0.92      0.92      0.92        77

    accuracy                           0.98       500
   macro avg       0.95      0.95      0.95       500
weighted avg       0.98      0.98      0.98       500
```

Could we be Overfitting?

Perform the following tests below to check for overfitting:

- Train vs test Perfomance
- Cross-Validation Score

In [61]:
```
#Train vs test Perfomance
from sklearn.metrics import roc_auc_score

train_auc = roc_auc_score(y_train, random_forest_best_parameters.predict_proba
test_auc = roc_auc_score(y_test, random_forest_best_parameters.predict_proba(X_

print(f"Train AUC: {train_auc:.4f}")
print(f"Test AUC: {test_auc:.4f}")
```

```
Train AUC: 0.9972
Test AUC: 0.9979
```

The train-test AUC is very close which is a good indicator however, we also check for CV AUC

In [62]:
```
#Cross-Validation Score
from sklearn.model_selection import cross_val_score

cv_scores = cross_val_score(random_forest_best_parameters, X_train, y_train, c
print(f"Cross-validation AUC: {cv_scores.mean():.4f} ± {cv_scores.std():.4f}")
```

```
Cross-validation AUC: 0.9083 ± 0.0154
```

The CV AUC is lower than the train-test AUC indicating SLIGHT OVERFITTING

CONCLUSION

The model is highly accurate but SLIGHTLY OVERFITTING.
Test AUC and CV AUC need to be closer in order for the model to be more generalizable.

XGBoost

Apply GridSearchCV to obtain best parameters

In [63]:
```
#Original XGBoost accuracy
print(f"The Accuracy of original XGBoost model WITHOUT hyperparameter : {xgboo
```

```
The Accuracy of original XGBoost model WITHOUT hyperparameter : 95.3999999999
9999%
```

In [64]:
```
xgboost_model_parameters = {
    "max_depth" : [3, 5, 7, 9, 10],
    "learning_rate" : [0.1, 0.01, 0.001],
    "subsampe" : [0.5, 0.7, 0.9, 1]
}

xgboost_parameters = GridSearchCV(xgboost_model, param_grid = xgboost_model_pa
                                  cv = 5, scoring = 'roc_auc')
xgboost_parameters
```

Out[64]:
```
▸ GridSearchCV
▸ estimator: XGBClassifier
    ▸ XGBClassifier
```

In [65]:
```
xgboost_best_parameters = xgboost_parameters.fit(X, y)
#xgboost_best_parameters.best_estimator_
#xgboost_best_parameters.best_params_
```

```
[21:13:22] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_
1.2.0\src\learner.cc:516:
Parameters: { subsampe } might not be used.

  This may not be accurate due to some parameters are only used in language
bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip th
rough this
  verification. Please open an issue if you find above cases.


[21:13:22] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_
1.2.0\src\learner.cc:516:
Parameters: { subsampe } might not be used.

  This may not be accurate due to some parameters are only used in language
bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip th
rough this
```

In [66]:
```
xgboost_best_parameters.best_params_
```

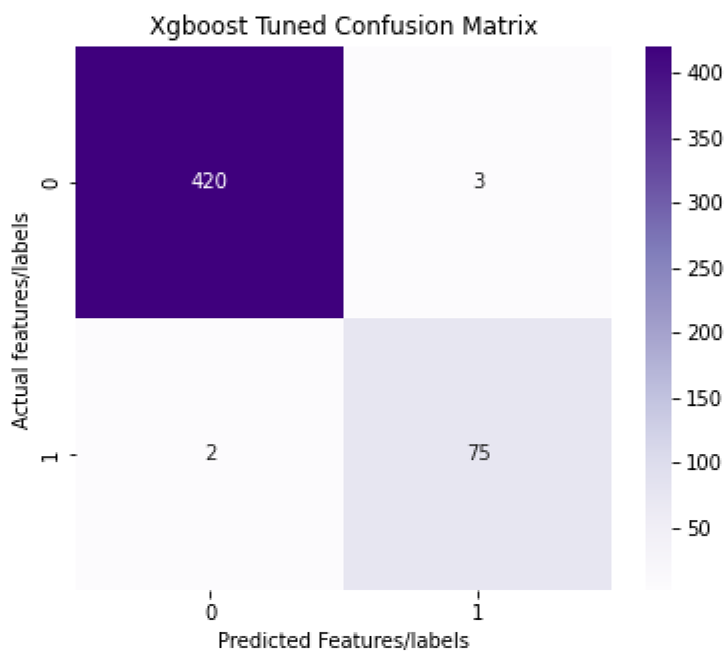
Out[66]:
```
{'learning_rate': 0.1, 'max_depth': 5, 'subsampe': 0.5}
```

Evaluate tuned model

In [67]:
```
#Original XGBoost accuracy
print(f"The Accuracy of original XGBoost model WITHOUT hyperparameter : {xgboo

#tuned XGBoost accuracy
print(f"The Accuracy of tuned XGBoost model WITH hyperparameter : {xgboost_bes
```

```
The Accuracy of original XGBoost model WITHOUT hyperparameter : 95.3999999999
9999%
The Accuracy of tuned XGBoost model WITH hyperparameter : 99.92324460409566
```

In [68]:
```
#make predictions for tuned XGBoost
y_pred_xgboost_best_parameters = xgboost_best_parameters.predict(X_test)

#confusion matrix for tuned model
xgboost_tuned_cm = confusion_matrix(y_test, y_pred_xgboost_best_parameters)
plt.figure(figsize = (6,5))
sns.heatmap(xgboost_tuned_cm, annot = True, fmt = "d", cmap = "Purples")
plt.xlabel("Predicted Features/labels")
plt.ylabel("Actual features/labels")
plt.title("Xgboost Tuned Confusion Matrix")
plt.show()
```



In [69]:
```
print(classification_report(y_test, y_pred_xgboost_best_parameters))
```

```
              precision    recall  f1-score   support

         0.0       1.00      0.99      0.99       423
         1.0       0.96      0.97      0.97        77

    accuracy                           0.99       500
   macro avg       0.98      0.98      0.98       500
weighted avg       0.99      0.99      0.99       500
```

In [70]:
```
from sklearn.metrics import roc_auc_score

train_auc = roc_auc_score(y_train, xgboost_best_parameters.predict_proba(X_tra
test_auc = roc_auc_score(y_test, xgboost_best_parameters.predict_proba(X_test)

print(f"Train AUC: {train_auc:.4f}")
print(f"Test AUC: {test_auc:.4f}")
```

```
Train AUC: 0.9983
Test AUC: 0.9992
```

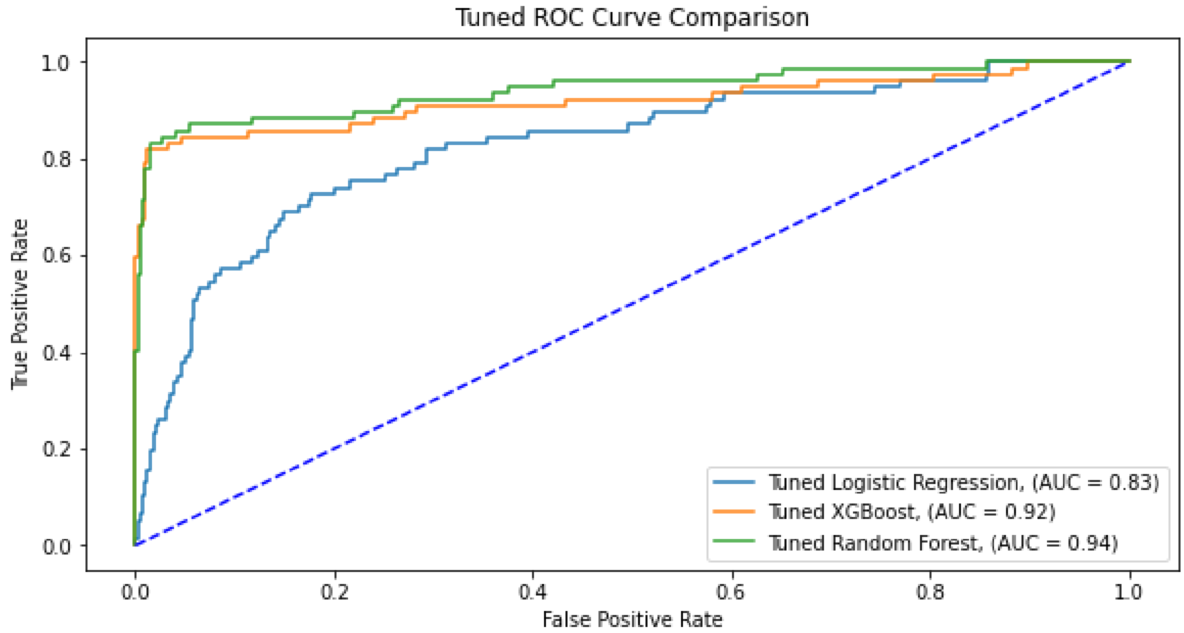
XGBoost is still the BEST model even after tuning

The tuned XGBoost model has the highest recall and F1-score compared to the tuned logistic regression model and tuned random forest

Plot ROC- AUC curves for tuned models to compare them

In [71]:
```
#use ** to unpack the dictionaries of parametrs
tuned_classifiers = {"Logistic Regression" : LogisticRegression(**logisitc_bes
              "XGBoost" : xgb.XGBClassifier(**xgboost_best_parameters.best_par
              "Random Forest" : RandomForestClassifier(**random_forest_best_pa
              }


#define your figure to plot in trained models
plt.figure(figsize = (10,5))

#train models
for name, tuned_classifier in tuned_classifiers.items():
    #fit each classifier and generate predicted values
    tuned_classifier.fit(X_train, y_train)

    #compute ROC curve
    fpr, tpr, _ = roc_curve(y_test, tuned_classifier.predict_proba(X_test)[:,
    auc = roc_auc_score(y_test, tuned_classifier.predict_proba(X_test)[:, 1])
    plt.plot(fpr, tpr, label = f"Tuned {name}, (AUC = {auc:.2f})")
#plot reference line
plt.plot([0,1], [0,1], linestyle = "--", color = "blue")

#titles and labels
plt.title("Tuned ROC Curve Comparison")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend(loc = "lower right")

#show plot
plt.show()
```

```
[21:15:05] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_1.
2.0\src\learner.cc:516:
Parameters: { subsampe } might not be used.

  This may not be accurate due to some parameters are only used in language b
indings but
  passed down to XGBoost core.  Or some parameters are not used but slip thro
ugh this
  verification. Please open an issue if you find above cases.
```



TUNED ROC-AUC Curve Interpretation

The closer the curve hugs the y-axis/the closer the curve is to the top_left corner , the better the model is at distinguishing between the classes.

- Tuned XGBoost(AUC = 0.92)
  - Good overall classification ability indicating that in 92% of the cases, the model will rank a randomly chosen positive instance higher than a randomly chosen negative instance
- Logistic Regression(AUC = 0.83)
  - Lowest AUC of the three. An AUC of 0.83 which is an improvement from 0.78
- Random Forest(AUC = 0.93)
  - Best overall classification ability of the three but not a significant difference when compared with AUC of tuned XGBoost
  - AUC also did not change significantyly after hyperparameter tuning indicating tuning did not boost performance
- Baseline(Blue Dashed Line)
  - Represents a random clasiffier with AUC = 0.50 and any model performing below this line is worse than random guessing

6.Conclusion

XGBoost Model is the best model to use to predict customer churn.
To further evaluate this model we can undertake feature engineering to boost its scores further Additionally evaluation of feature importance would also be useful to evaluate which features are the most important in predicting customer churn Random Forest Model also showed great potential but showed signs of slight overfitting

Recommendations

- Customer service quality should be improved in order to reduce the number of customer service calls. Training programs to the customer care team can be applied to have the team provide effective solutions to issues affecting customers.
- Discounts should be introduced as customers with higher charges are more likely to churn. Discount tactics such as discounting customers who have consistently high charges could help reduce churn.
- Voicemail plans should be marketed more to try and increase the adoption of voicemail plans as frequent usage of voice mail plans shows that the customer is less likely to churn.