```python
# Importing the libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
sns.set()
import warnings
warnings.filterwarnings('ignore')
```

```python
# Loading the dataset
df = pd.read_csv('WA_Fn-UseC_-Telco-Customer-Churn.csv')
df.head()
```

```
   customerID  gender  SeniorCitizen Partner Dependents  tenure
PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1
No
1  5575-GNVDE    Male              0      No         No      34
Yes
2  3668-QPYBK    Male              0      No         No       2
Yes
3  7795-CFOCW    Male              0      No         No      45
No
4  9237-HQITU  Female              0      No         No       2
Yes

      MultipleLines InternetService OnlineSecurity  ...
DeviceProtection  \
0  No phone service             DSL             No  ...
No
1                No             DSL            Yes  ...
Yes
2                No             DSL            Yes  ...
No
3  No phone service             DSL            Yes  ...
Yes
4                No     Fiber optic             No  ...
No

  TechSupport StreamingTV StreamingMovies        Contract
PaperlessBilling  \
0          No          No              No  Month-to-month
Yes
1          No          No              No        One year
No
2          No          No              No  Month-to-month
Yes
3         Yes          No              No        One year
No
4          No          No              No  Month-to-month
```

```
Yes

                PaymentMethod MonthlyCharges  TotalCharges Churn
0           Electronic check          29.85         29.85    No
1               Mailed check          56.95        1889.5    No
2               Mailed check          53.85        108.15   Yes
3  Bank transfer (automatic)          42.30       1840.75    No
4           Electronic check          70.70        151.65   Yes

[5 rows x 21 columns]
```

Some Numerical Information about the Data

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB

df.nunique()

customerID          7043
gender                 2
SeniorCitizen          2
Partner                2
```

```
Dependents                2
tenure                   73
PhoneService              2
MultipleLines             3
InternetService           3
OnlineSecurity            3
OnlineBackup              3
DeviceProtection          3
TechSupport               3
StreamingTV               3
StreamingMovies           3
Contract                  3
PaperlessBilling          2
PaymentMethod             4
MonthlyCharges         1585
TotalCharges           6531
Churn                     2
dtype: int64
```

Data Cleaning

```
df.drop_duplicates(inplace=True)

# Reduce unique values of PaymentMethid Columns
df['PaymentMethod'] = df['PaymentMethod'].apply(lambda x : 'Automatic'
if x in ['Bank transfer (automatic)', 'Credit card (automatic)'] else
x)
df['PaymentMethod'].value_counts()
```

```
PaymentMethod
Automatic           3066
Electronic check    2365
Mailed check        1612
Name: count, dtype: int64
```

```
# Replace ' '  with Average Value
df['TotalCharges'] = df['TotalCharges'].apply(lambda x : 0 if x == ' '
else x).astype(float)
mean = df['TotalCharges'].mean()
df['TotalCharges'] = df['TotalCharges'].apply(lambda x : mean if x ==
0 else x)
df['TotalCharges'].value_counts()
```

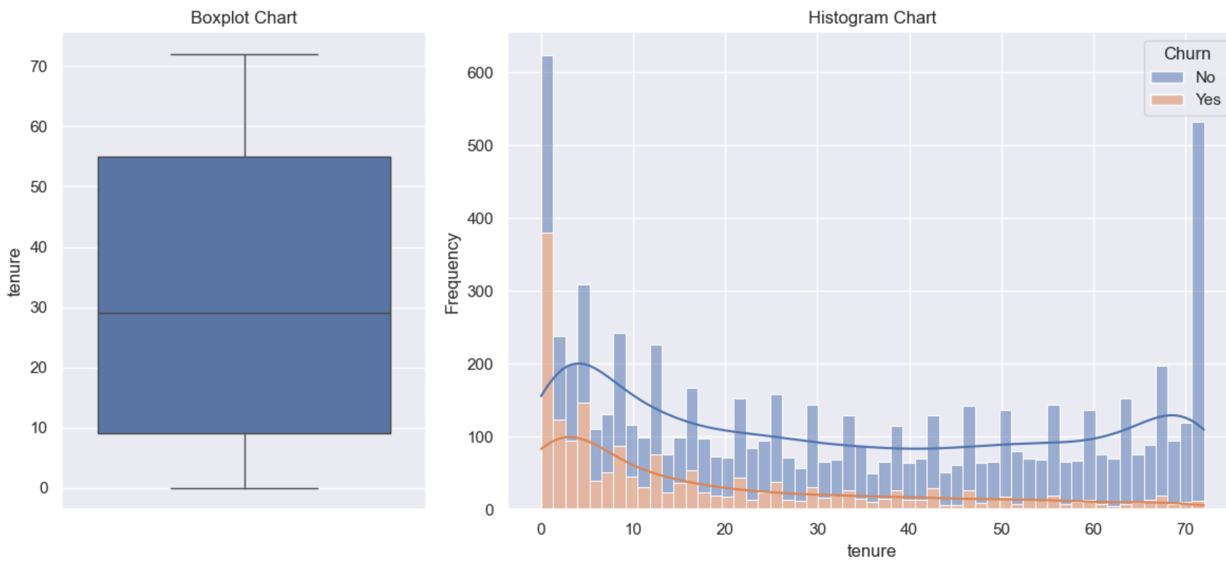
```
TotalCharges
2279.734304    11
20.200000      11
19.750000       9
20.050000       8
19.900000       8
               ..
```

```
6849.400000     1
692.350000      1
130.150000      1
3211.900000     1
6844.500000     1
Name: count, Length: 6531, dtype: int64
```

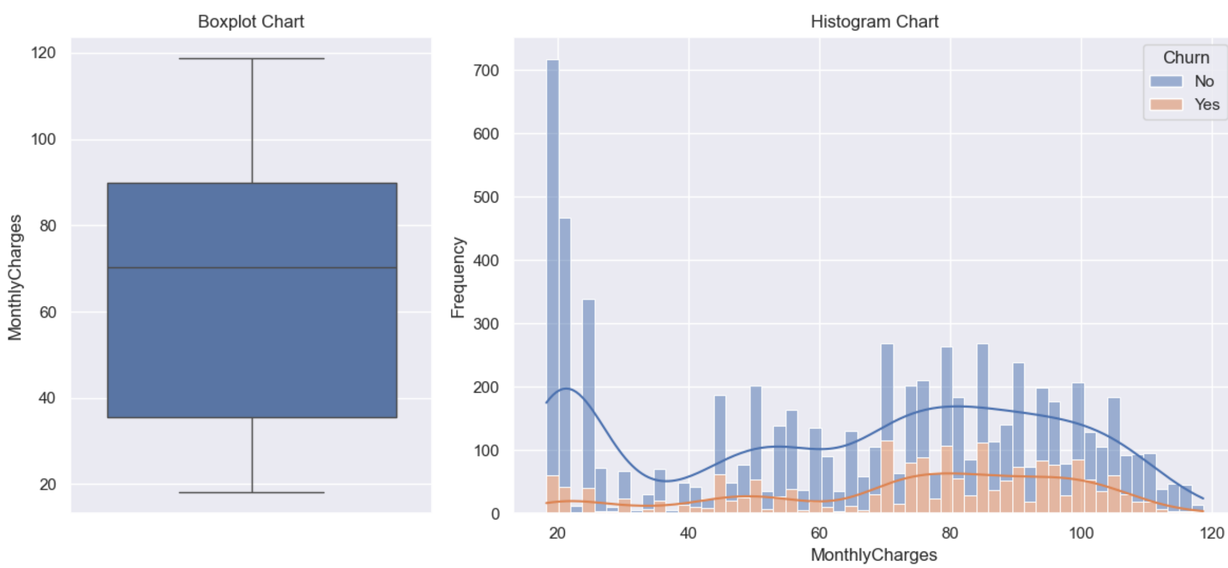
Data Visualization

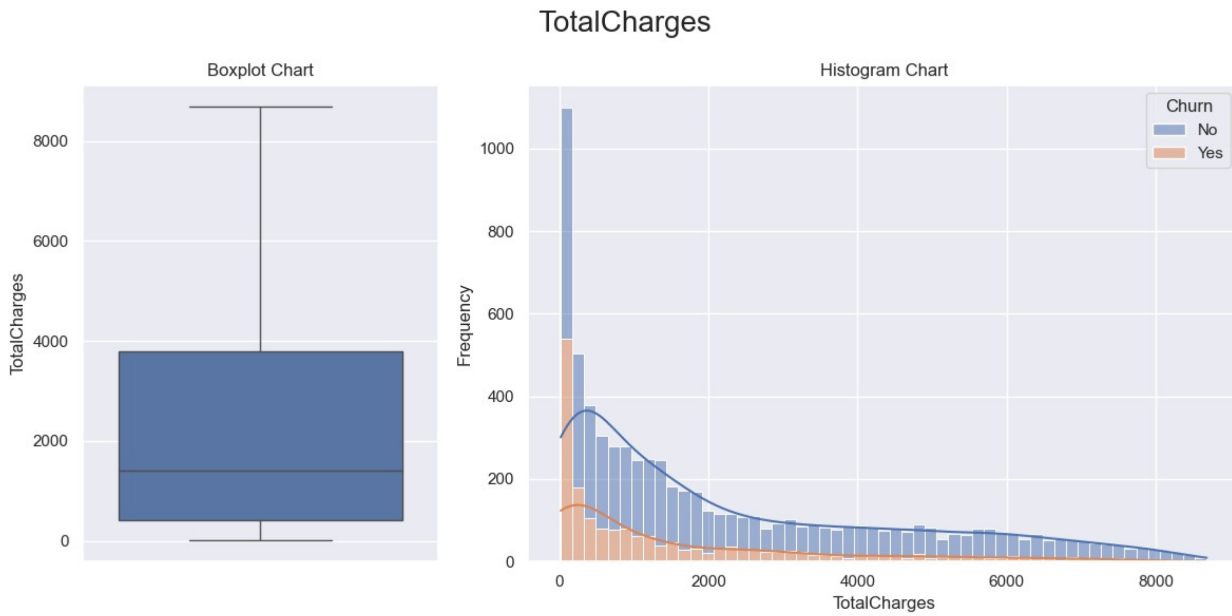
```
# Define list of Continuous columns Names
continuous = ['tenure', 'MonthlyCharges', 'TotalCharges']

# Distribution of Categorical Features
def plot_continious_distribution(df, column, hue):

    width_ratios = [2, 4]
    gridspec_kw = {'width_ratios':width_ratios}
    fig, ax = plt.subplots(1, 2, figsize=(12, 6), gridspec_kw =
gridspec_kw)
    fig.suptitle(f' {column} ', fontsize=20)

    sns.boxplot(df[column], ax=ax[0])
    ax[0].set_title('Boxplot Chart')
    ax[0].set_ylabel(column)

    sns.histplot(x = df[column], kde=True, ax=ax[1], hue=df[hue],
multiple = 'stack', bins=55)
    ax[1].set_title('Histogram Chart')
    ax[1].set_ylabel('Frequency')
    ax[1].set_xlabel(column)

    plt.tight_layout()
    plt.show()
for conti in continuous :
    plot_continious_distribution(df, conti, 'Churn')
```

tenure

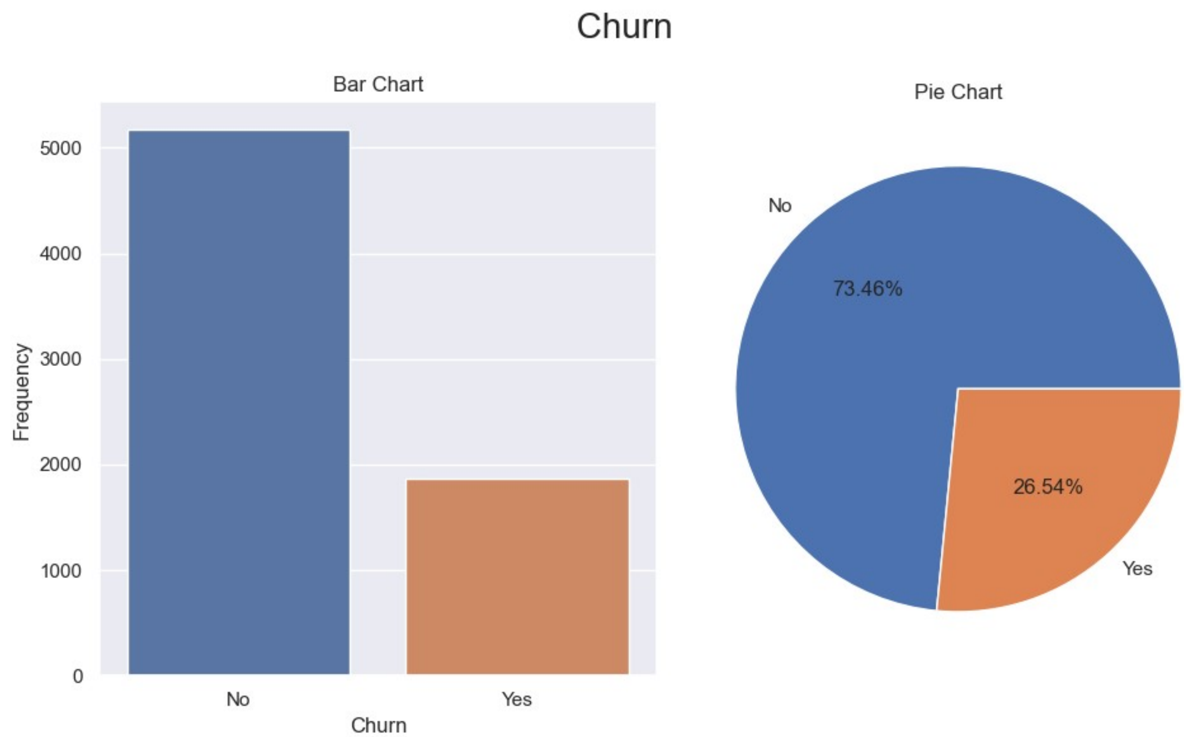


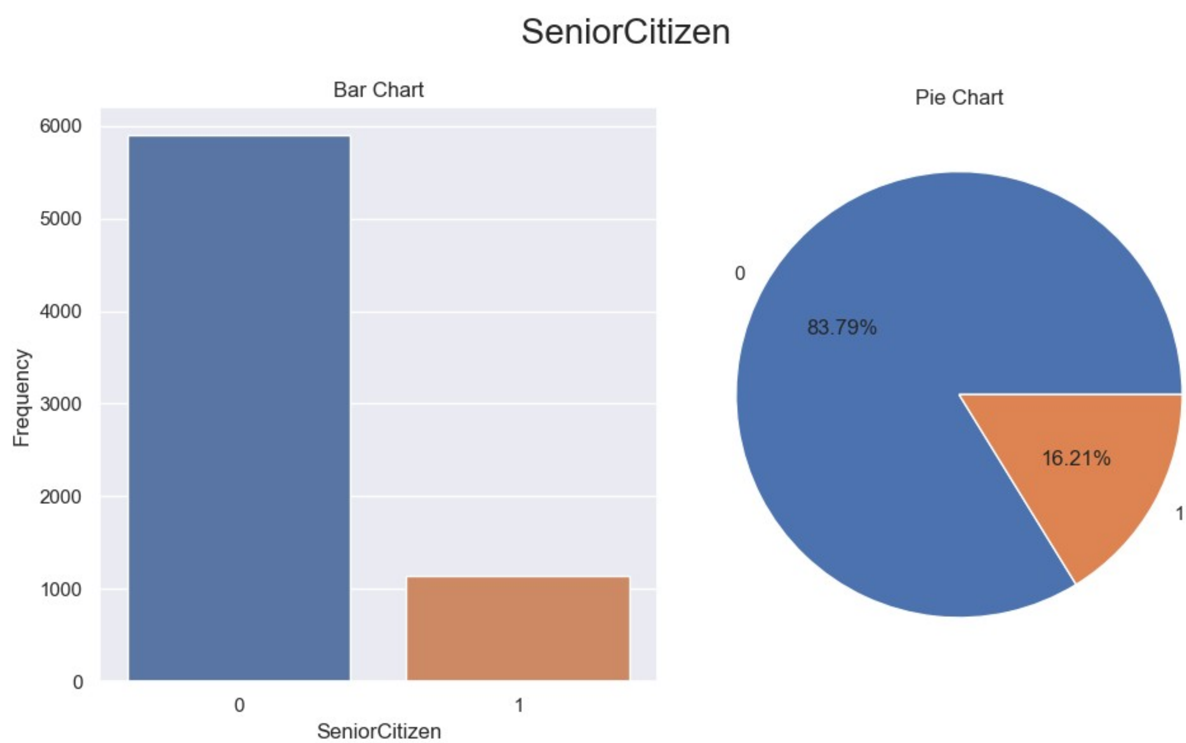
MonthlyCharges

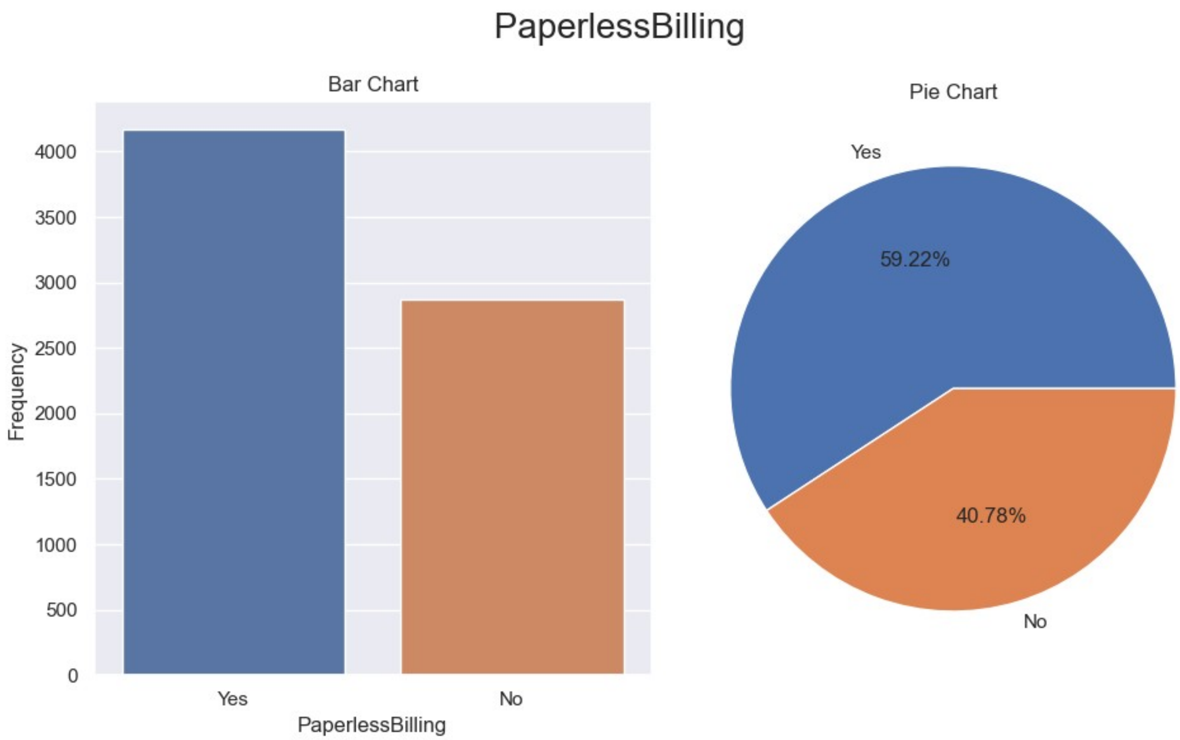


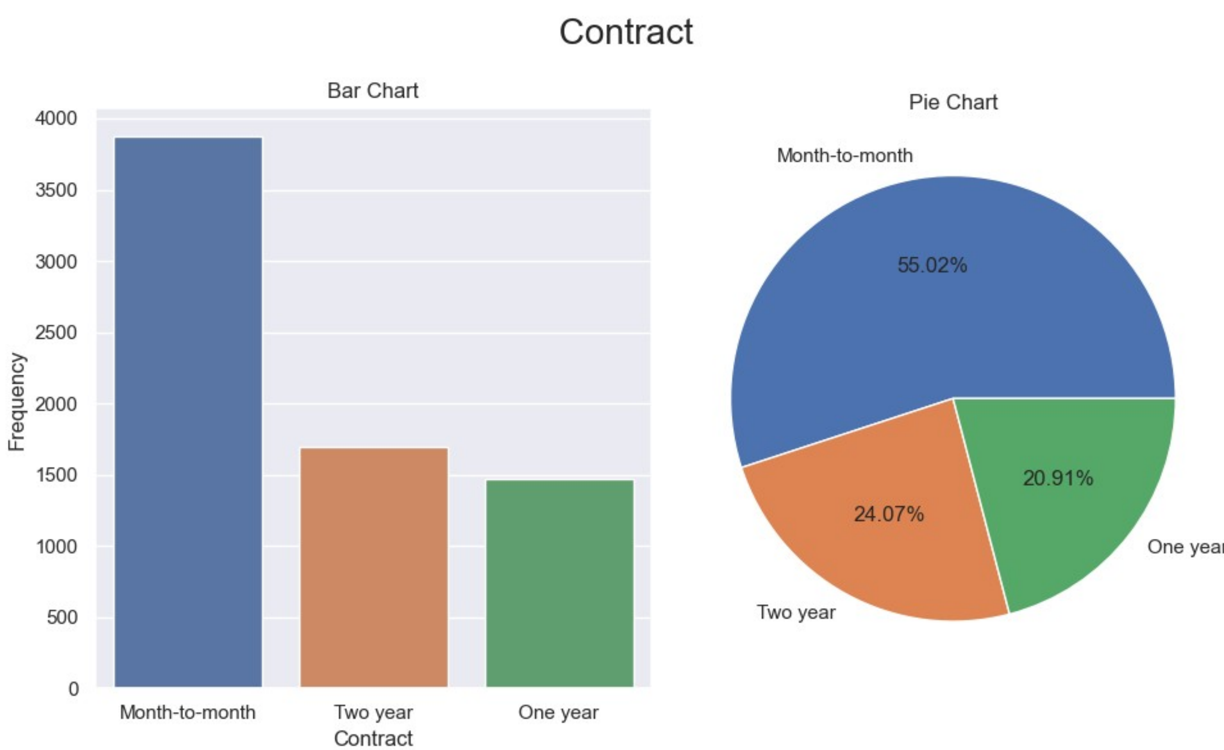


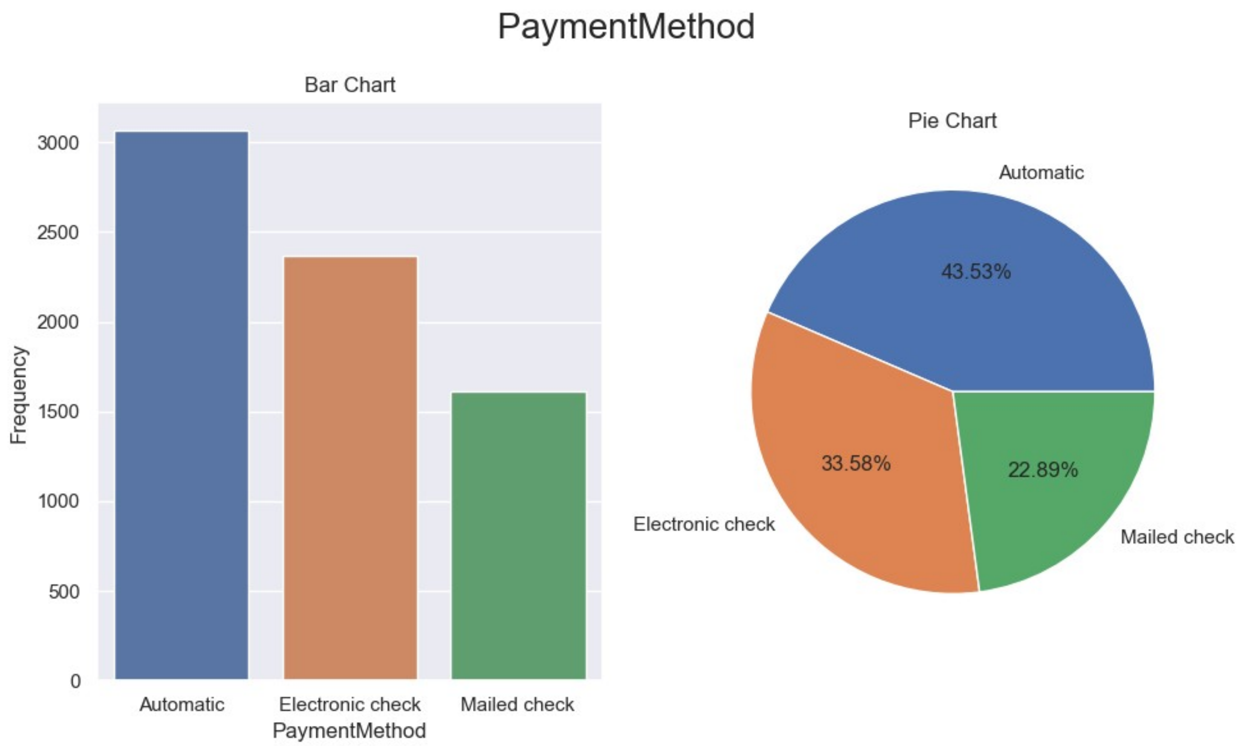

```python
# Define list Name of Categorical columns
categorical = [ 'Churn', 'SeniorCitizen', 'PaperlessBilling',
'Contract', 'PaymentMethod', 'InternetService']

# distribution of categorical features

def plot_categorical_distribution(df, column):
    fig, ax = plt.subplots(1, 2, figsize=(10, 6))
    fig.suptitle(f' {column} ', fontsize=20)

    sns.barplot(df[column].value_counts(), ax=ax[0], palette='deep')
    ax[0].set_title('Bar Chart')
    ax[0].set_xlabel(column)
    ax[0].set_ylabel('Frequency')


    df[column].value_counts().plot(kind='pie', autopct="%.2f%%",
ax=ax[1])
    ax[1].set_title('Pie Chart')
    ax[1].set_ylabel(None)

    plt.tight_layout()
    plt.show()

for cat in categorical:
    plot_categorical_distribution(df, cat)
```

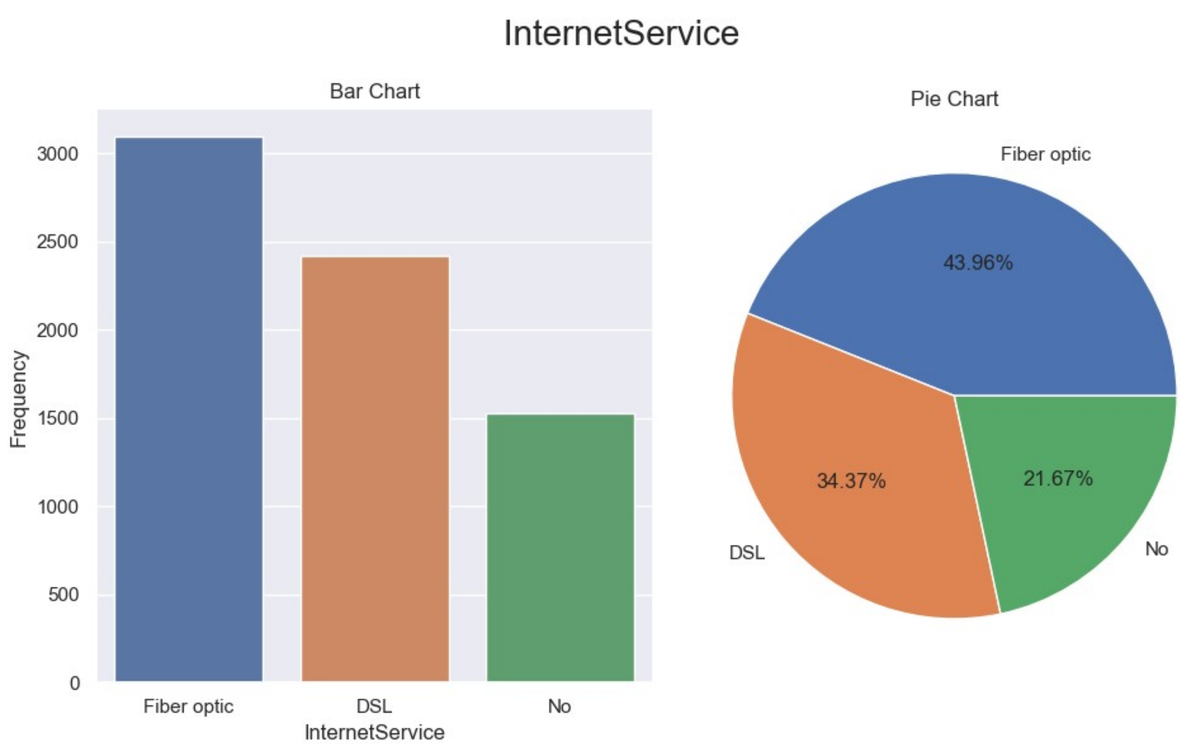

Churn
Bar Chart
Frequency
5000
4000
3000
2000
1000
0
No
Yes
Churn
Pie Chart
No
73.46%
26.54%
Yes


SeniorCitizen
Bar Chart
Frequency
6000
5000
4000
3000
2000
1000
0
0
1
SeniorCitizen
Pie Chart
0
83.79%
16.21%
1


PaperlessBilling
Bar Chart
Pie Chart
Frequency
4000
3500
3000
2500
2000
1500
1000
500
0
Yes
No
PaperlessBilling
Yes
59.22%
40.78%
No

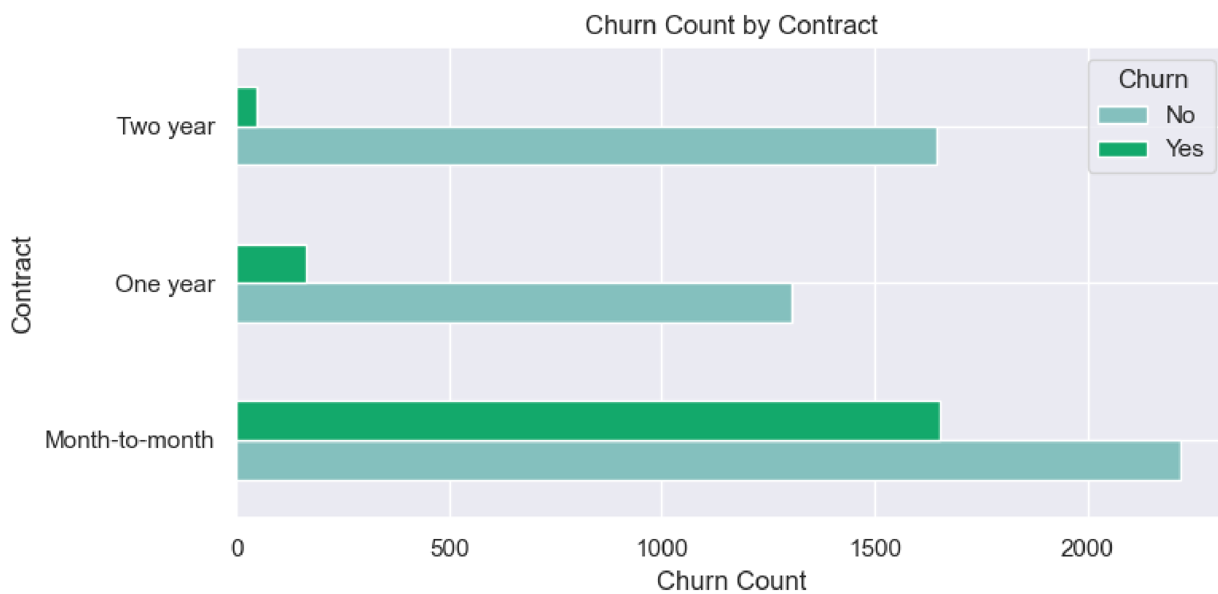

Contract
Bar Chart
Pie Chart
Frequency
4000
3500
3000
2500
2000
1500
1000
500
0
Month-to-month
Two year
One year
Contract
Month-to-month
55.02%
24.07%
20.91%
Two year
One year

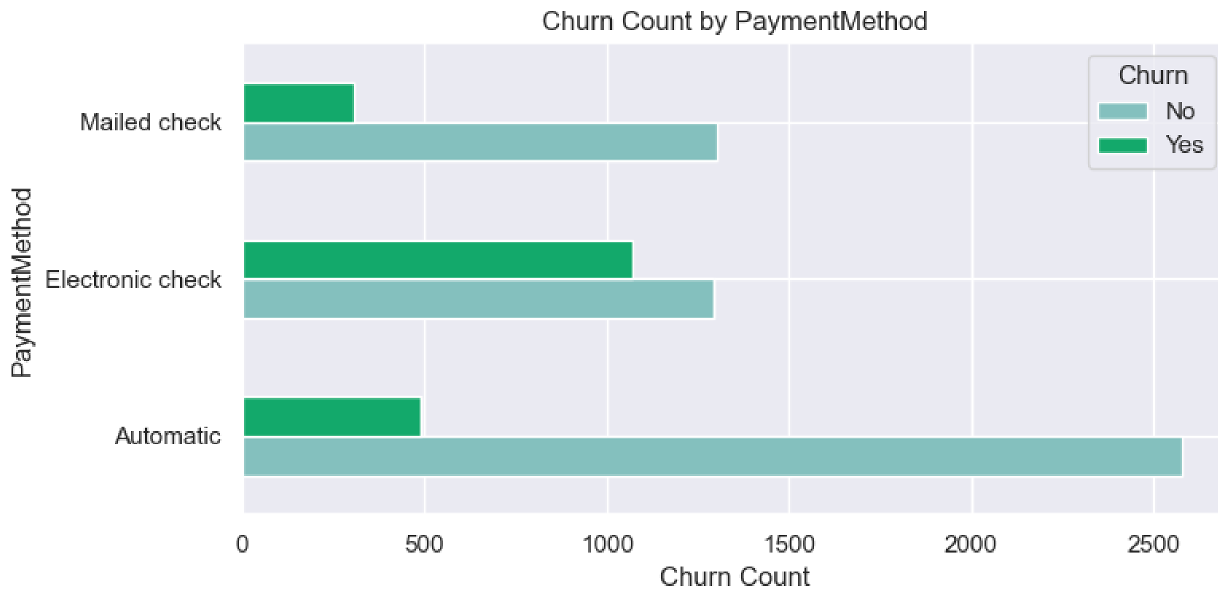




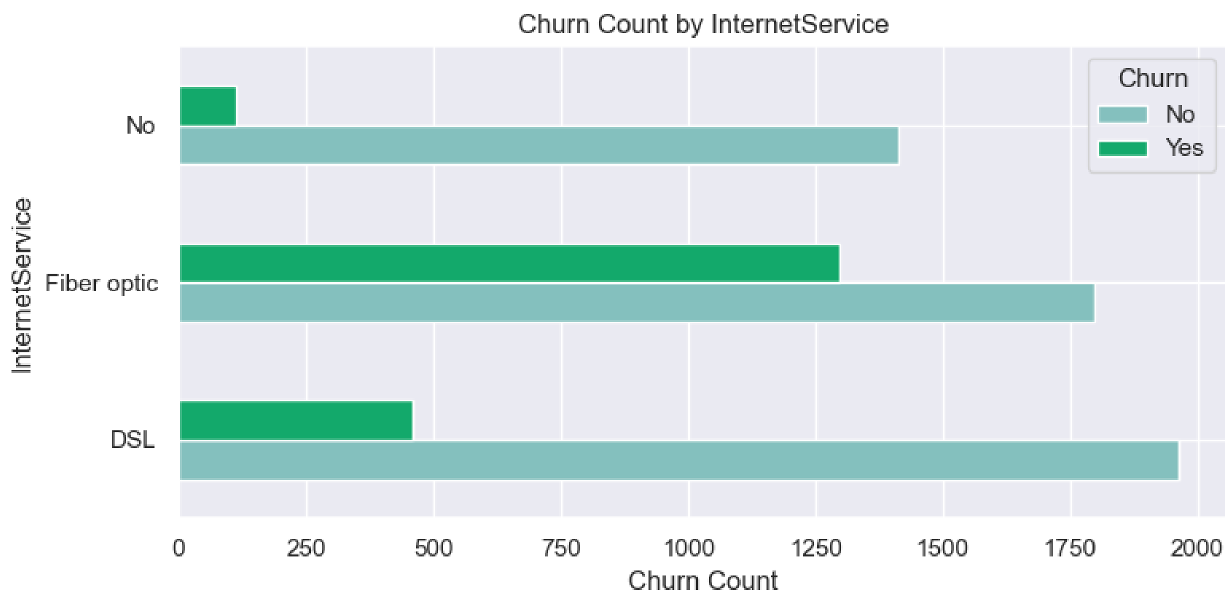

```
# Define a Function for Barh Plot
def bar_plot(x, y, df):
    barh = df.groupby([x, y]).size().unstack()
    barh.plot(kind='barh',  color = ['#84c0be', '#13a96b'],
```

```
figsize=(8,4))
    plt.title(f'{y} Count by {x}')
    plt.xlabel(f'{y} Count')
    plt.ylabel(x)

    plt.tight_layout()
    plt.show()

bar_plot('Contract', 'Churn', df)
bar_plot('PaymentMethod', 'Churn', df)
bar_plot('InternetService', 'Churn', df)
bar_plot('SeniorCitizen', 'Churn', df)
bar_plot('PaperlessBilling', 'Churn', df)
```

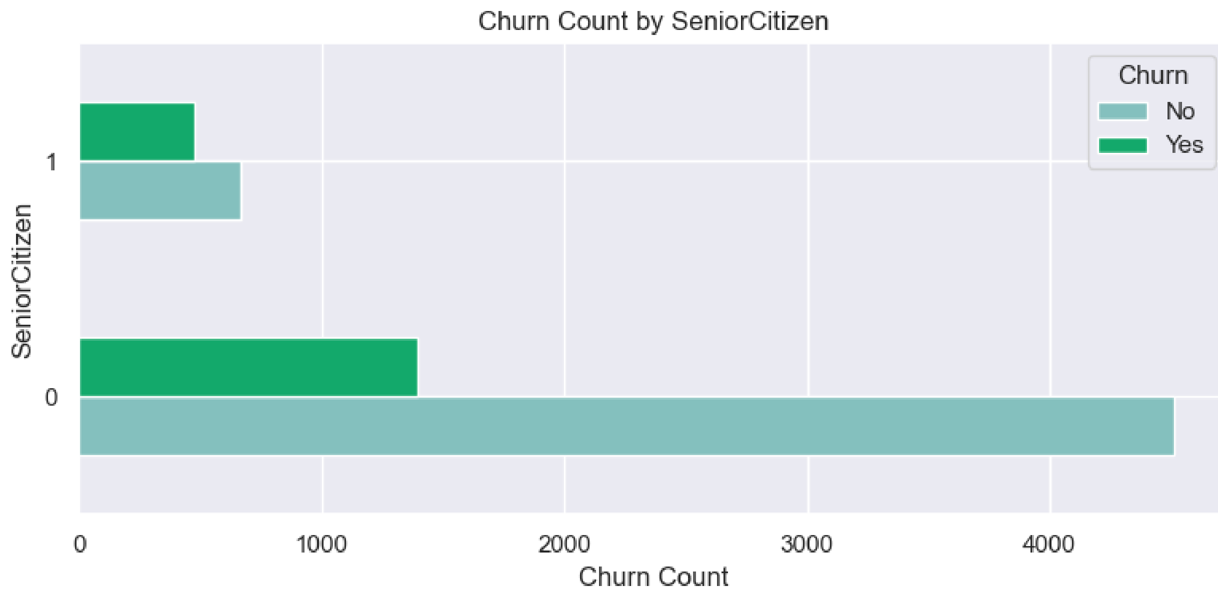


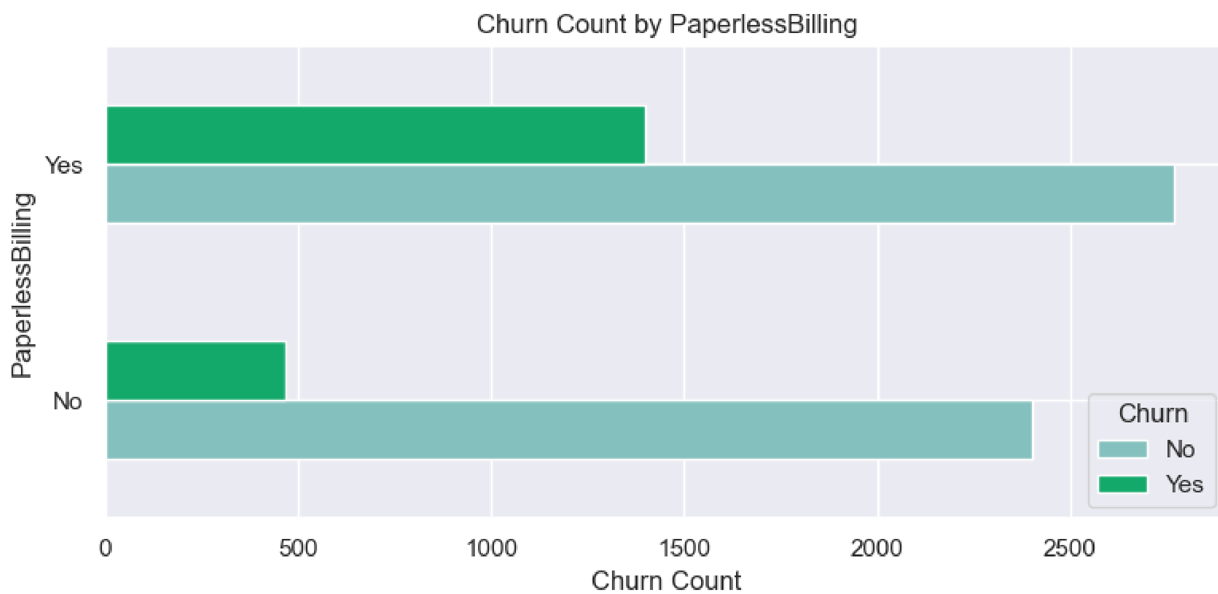


Churn Count by PaymentMethod
Churn
No
Yes
Mailed check
Electronic check
Automatic
PaymentMethod
0
500
1000
1500
2000
2500
Churn Count



Churn Count by InternetService
Churn
No
Yes
No
Fiber optic
DSL
InternetService
0
250
500
750
1000
1250
1500
1750
2000
Churn Count





Data Preprocessing

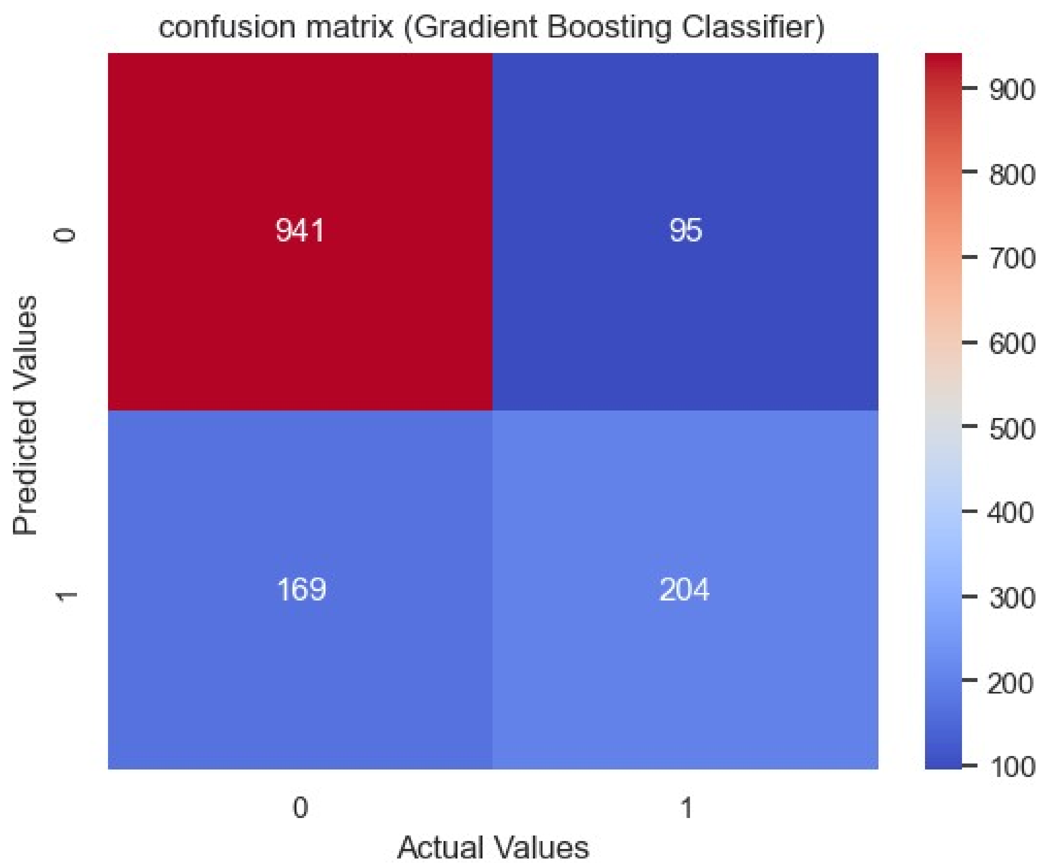
```
from sklearn.preprocessing import StandardScaler, LabelEncoder

# Initialize StandardScaler
stc = StandardScaler()
le = LabelEncoder()
stc_cols = ['tenure', 'MonthlyCharges', 'TotalCharges']
le_cols = ['Churn', 'PaperlessBilling', 'PhoneService', 'Dependents',
'Partner', 'SeniorCitizen', 'gender']
dum_cols = ['PaymentMethod', 'Contract', 'StreamingMovies',
'StreamingTV', 'TechSupport', 'DeviceProtection', 'OnlineBackup',
```

```
'OnlineSecurity', 'InternetService', 'MultipleLines', 'PhoneService']
# Apply Standard Scaler to the selected columns
df[stc_cols] = stc.fit_transform(df[stc_cols])

for col in le_cols :
    df[col] = le.fit_transform(df[col])

# Apply get_dummies to the selected columns
df = pd.get_dummies(df, columns=dum_cols)
```

Training and Evaluating Different Models

```
from sklearn.model_selection import train_test_split

x = df.drop(['Churn', 'customerID', 'gender'], axis=1)
y = df['Churn']  # Target Variable

x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.2, random_state=42)

#Importing the Libraries
from sklearn.ensemble import  GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from catboost import CatBoostClassifier
from lightgbm import LGBMClassifier
from xgboost import XGBClassifier

# List of Models to Try
models = [
    ('Gradient Boosting', GradientBoostingClassifier()),
    ('K-Nearest Neighbors', KNeighborsClassifier()),
    ('CatBosst Classifier', CatBoostClassifier(verbose=False)),
    ('LGBM Classifier', LGBMClassifier(verbose=-1)),
    ('Random Forest', RandomForestClassifier()),
    ('XGB Classifier', XGBClassifier()),
]

# Train and evaluate each model
for name, model in models:
    model.fit(x_train, y_train)
    y_pred = model.predict(x_test)
    print(f'Training accuracy: {name}', model.score(x_train, y_train))
    print(f'Test accuracy: {name}', accuracy_score(y_test, y_pred))
    print()
```

```
Training accuracy: Gradient Boosting 0.8262335818246361
Test accuracy: Gradient Boosting 0.8126330731014905

Training accuracy: K-Nearest Neighbors 0.8354632587859425
Test accuracy: K-Nearest Neighbors 0.7821149751596878

Training accuracy: CatBosst Classifier 0.8691870784522542
Test accuracy: CatBosst Classifier 0.8041163946061036

Training accuracy: LGBM Classifier 0.8789492367767128
Test accuracy: LGBM Classifier 0.8055358410220014

Training accuracy: Random Forest 0.9980475683351083
Test accuracy: Random Forest 0.7835344215755855

Training accuracy: XGB Classifier 0.936812211572595
Test accuracy: XGB Classifier 0.7821149751596878


gb = GradientBoostingClassifier()
gb.fit(x_train, y_train)
gb_pred = gb.predict(x_test)

print(f'Training accuracy:', gb.score(x_train, y_train))
print(f'Test accuracy:', accuracy_score(y_test, gb_pred))

Training accuracy: 0.8262335818246361
Test accuracy: 0.8126330731014905

# Visualize confusion matrix for Gradient Boosting Classifier
sns.heatmap(confusion_matrix(y_test, gb_pred),annot= True, cmap =
'coolwarm', fmt='.0f')
plt.title('confusion matrix (Gradient Boosting Classifier)')
plt.ylabel('Predicted Values')
plt.xlabel('Actual Values')
plt.show()
```




```
# Visualize Classification report for Gradient Boosting Classifier
print(classification_report(y_test,gb_pred))

              precision    recall  f1-score   support

           0       0.85      0.91      0.88      1036
           1       0.68      0.55      0.61       373

    accuracy                           0.81      1409
   macro avg       0.77      0.73      0.74      1409
weighted avg       0.80      0.81      0.81      1409
```

As we can see in the above cell , precision of our model in the '1' values of taget is too weak , so we gonna use of imblearn library for balancing values of target

```
# Redefine x and y
x = df.drop(['Churn', 'customerID', 'gender'], axis=1)
y = df['Churn']  # Target Variable

from imblearn.over_sampling import SMOTE
```

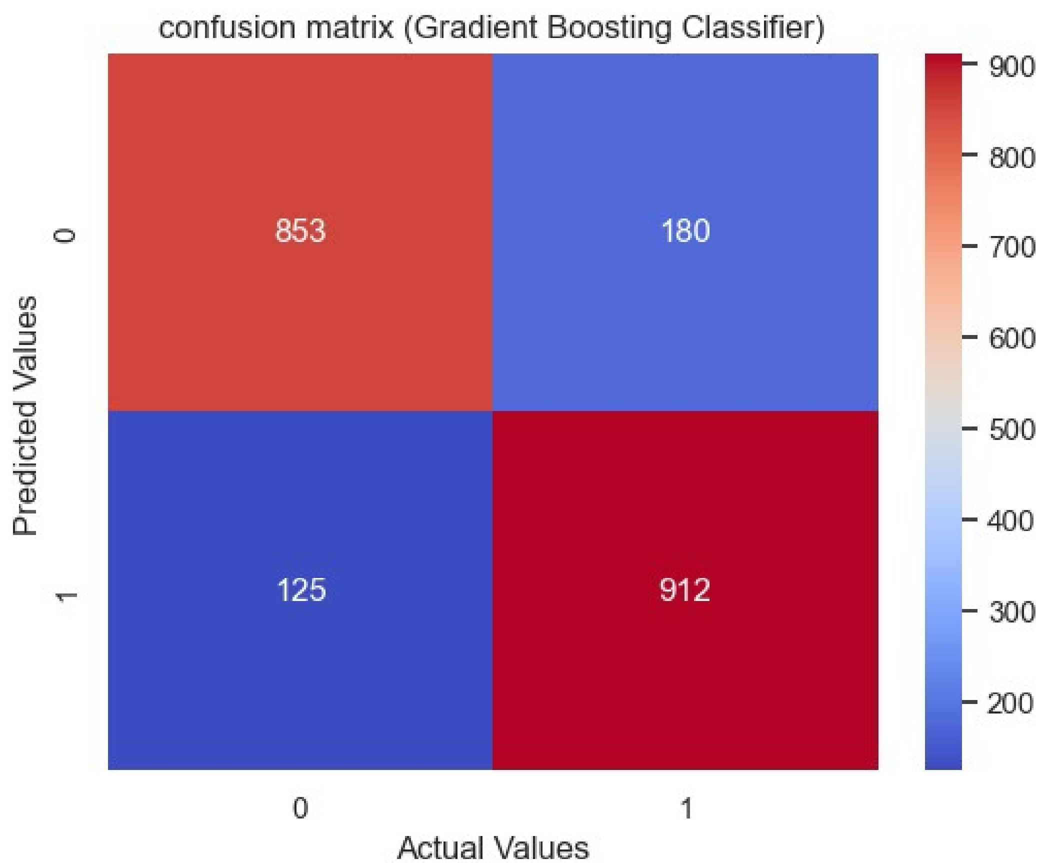
```python
# Initialize Smote
smote = SMOTE(random_state=142)

# Apply Smote to the x and y
x_resampled, y_resampled = smote.fit_resample(x, y)
x_train, x_test, y_train, y_test = train_test_split(x_resampled,
y_resampled, test_size=0.2, random_state=0)

# List of Models to Try
models = [
    ('Gradient Boosting', GradientBoostingClassifier()),
    ('K-Nearest Neighbors', KNeighborsClassifier()),
    ('CatBosst Classifier', CatBoostClassifier(verbose=False)),
    ('LGBM Classifier', LGBMClassifier(verbose=-1)),
    ('Random Forest', RandomForestClassifier()),
    ('XGB Classifier', XGBClassifier()),
]

# Train and evaluate each model
for name, model in models:
    model.fit(x_train, y_train)
    y_pred = model.predict(x_test)
    print(f'Training accuracy: {name}', model.score(x_train, y_train))
    print(f'Test accuracy: {name}', accuracy_score(y_test, y_pred))
    print()
```

```
Training accuracy: Gradient Boosting 0.8357091084803092
Test accuracy: Gradient Boosting 0.8217391304347826

Training accuracy: K-Nearest Neighbors 0.8765402271079971
Test accuracy: K-Nearest Neighbors 0.8101449275362319

Training accuracy: CatBosst Classifier 0.8878956269630346
Test accuracy: CatBosst Classifier 0.8526570048309179

Training accuracy: LGBM Classifier 0.8912780864943223
Test accuracy: LGBM Classifier 0.8487922705314009

Training accuracy: Random Forest 0.9979463638560039
Test accuracy: Random Forest 0.8454106280193237

Training accuracy: XGB Classifier 0.9347668518965934
Test accuracy: XGB Classifier 0.840096618357488
```

```python
cb = CatBoostClassifier(verbose=False)
cb.fit(x_train, y_train)
cb_pred = cb.predict(x_test)

print(f'Training accuracy:', cb.score(x_train, y_train))
print(f'Test accuracy:', accuracy_score(y_test, cb_pred))
```

```
Training accuracy: 0.8878956269630346
Test accuracy: 0.8526570048309179
```

```python
# Visualize confusion matrix for Gradient Boosting Classifier
sns.heatmap(confusion_matrix(y_test,cb_pred),annot= True, cmap =
'coolwarm', fmt='.0f')
plt.title('confusion matrix (Gradient Boosting Classifier)')
plt.ylabel('Predicted Values')
plt.xlabel('Actual Values')
plt.show()
```




```python
# Visualize Classification report for Gradient Boosting Classifier
print(classification_report(y_test,cb_pred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.83      0.85      1033
           1       0.84      0.88      0.86      1037

    accuracy                           0.85      2070
   macro avg       0.85      0.85      0.85      2070
weighted avg       0.85      0.85      0.85      2070
```

By employing the SMOTE method, the number of samples for minority classes has increased, leading to an enhancement in the predictive accuracy of the model. Rebalancing the model with new and balanced data has resulted in improved performance in predicting fraudulent warranty claims.

These findings demonstrate that utilizing class balancing techniques like SMOTE can significantly enhance the performance of fraud prediction models. Therefore, it is recommended to employ ADASYN and machine learning models trained using this method for analyzing and predicting warranty claims fraud, as it can lead to improved accuracy and predictive capability of the models.

Developed by Hosein Mohammadi

GitHub : https://github.com/Hosein541

Kaggle : https://www.kaggle.com/hoseinnnnnnn

Gmail : Huseinmohammadi83@gmail.com