Warranty Claims Fraud Prediction

The aim of this project is to analyze the warranty claims based on their region, product, claim value and other features to predict their authenticity. The dataset is taken from Kaggle. The dataset contains 358 rows and 21 columns.

Data Dictionary

Column Name	Description
Unnamed: 0	Index
Region	Region of the claim
State	State of the claim
Area	Area of the claim
City	City of the claim
Consumer_profile	Consumer profile Business/Personal
Product_category	Product category Household/Entertainment
Product_type	Product type AC/TV
AC_1001_Issue	1 0- No issue / No componenent, 1- repair, 2- replacement
AC_1002_Issue	1 0- No issue / No componenent, 1- repair, 2- replacement
AC_1003_Issue	1 0- No issue / No componenent, 1- repair, 2- replacement
TV_2001_Issue	1 0- No issue / No componenent, 1- repair, 2- replacement
TV_2002_Issue	1 0- No issue / No componenent, 1- repair, 2- replacement
TV_2003_Issue	1 0- No issue / No componenent, 1- repair, 2- replacement
Claim_Value	Claim value in INR
Service_Center	Service center code
Product_Age	Product age in days
Purchased_from	Purchased from - Dealer, Manufacturer, Internet
Call_details	Call duration
Purpose	Purpose of the call
Fraud	Fraudulent (1) or Genuine (0)

```
# Importing the libraries
import numpy as np
import pandas as pd
```

```python
import seaborn as sns
import matplotlib.pyplot as plt
sns.set()
import warnings
warnings.filterwarnings('ignore')

# Loading the dataset
df = pd.read_csv('df_Clean.csv')
df.head()
```

```
   Unnamed: 0      Region       State   Area        City  
Consumer_profile  \
0           0       South   Karnataka  Urban   Bangalore  
Business   
1           1       South   Karnataka  Rural   Bangalore  
Business   
2           2       North     Haryana  Urban  Chandigarh  
Personal   
3           3       South  Tamil Nadu  Urban     Chennai  
Business   
4           4  North East   Jharkhand  Rural      Ranchi  
Personal   

  Product_category Product_type  AC_1001_Issue  AC_1002_Issue  ...  \
0    Entertainment           TV              0              0  ...   
1        Household           AC              1              1  ...   
2        Household           AC              0              1  ...   
3    Entertainment           TV              0              0  ...   
4    Entertainment           TV              0              0  ...   

   TV_2001_Issue  TV_2002_Issue  TV_2003_Issue  Claim_Value  
Service_Centre  \
0              1              2              0      15000.0  
10   
1              0              0              0      20000.0  
12   
2              0              0              0      18000.0  
14   
3              1              1              0      12000.0  
16   
4              0              1              2      25000.0  
15   

   Product_Age  Purchased_from Call_details    Purpose Fraud  
0           60    Manufacturer          0.5  Complaint     1  
1           10          Dealer          1.0  Complaint     0  
2           10          Dealer          1.4      Claim     0  
3           20    Manufacturer          2.0  Complaint     0  
4            6          Dealer          1.3      Claim     0  
```

```
[5 rows x 21 columns]
```

Some Numerical Information about the Data

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 358 entries, 0 to 357
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Unnamed: 0        358 non-null    int64  
 1   Region            358 non-null    object 
 2   State             358 non-null    object 
 3   Area              358 non-null    object 
 4   City              358 non-null    object 
 5   Consumer_profile  358 non-null    object 
 6   Product_category  358 non-null    object 
 7   Product_type      358 non-null    object 
 8   AC_1001_Issue     358 non-null    int64  
 9   AC_1002_Issue     358 non-null    int64  
 10  AC_1003_Issue     358 non-null    int64  
 11  TV_2001_Issue     358 non-null    int64  
 12  TV_2002_Issue     358 non-null    int64  
 13  TV_2003_Issue     358 non-null    int64  
 14  Claim_Value       358 non-null    float64
 15  Service_Centre    358 non-null    int64  
 16  Product_Age       358 non-null    int64  
 17  Purchased_from    358 non-null    object 
 18  Call_details      358 non-null    float64
 19  Purpose           358 non-null    object 
 20  Fraud             358 non-null    int64  
dtypes: float64(2), int64(10), object(9)
memory usage: 58.9+ KB
```

```
df.nunique()
```

```
Unnamed: 0          358
Region                8
State                20
Area                  2
City                 27
Consumer_profile      2
Product_category      2
Product_type          2
AC_1001_Issue         3
AC_1002_Issue         3
AC_1003_Issue         3
TV_2001_Issue         3
```

```
TV_2002_Issue          3
TV_2003_Issue          3
Claim_Value          107
Service_Centre         7
Product_Age          188
Purchased_from         3
Call_details          37
Purpose                3
Fraud                  2
dtype: int64
```

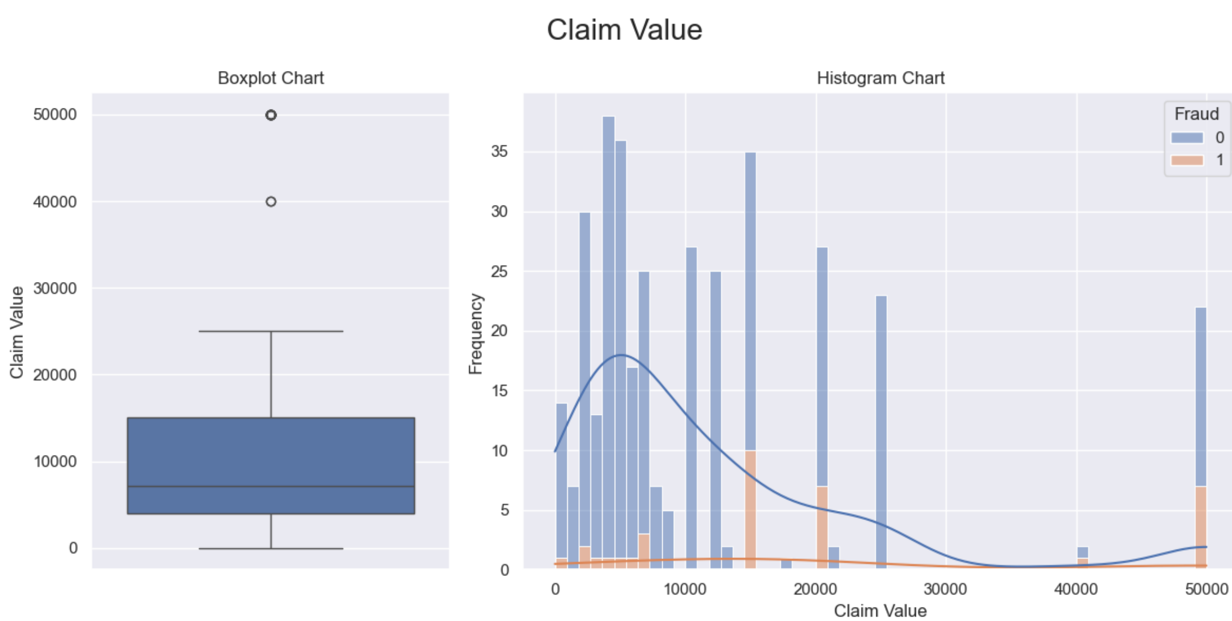
Data Cleaning

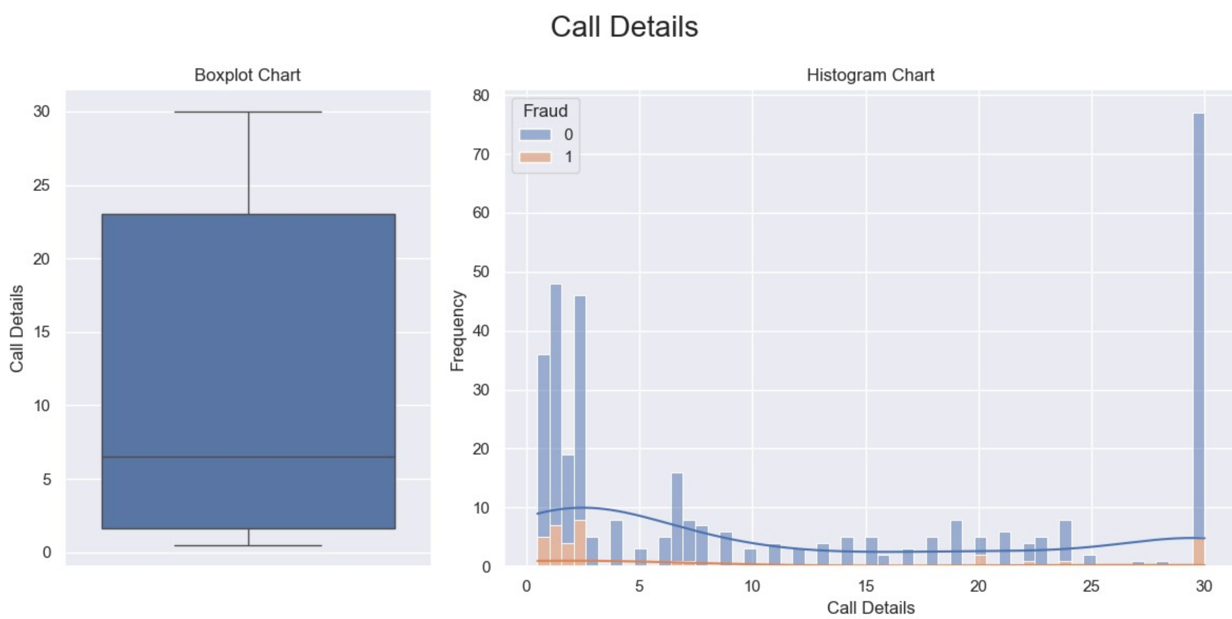
```
# Define a function for reduce uniques in categorical columns (State,
City)
def category(x, dic):
    if x in dic.keys():
        return x
    else :
        return 'Others'


state_dic = df['State'].value_counts().head(8)
df['State'] = df['State'].apply(lambda x : category(x, state_dic))

city_dic = df['City'].value_counts().head(8)
df['City'] = df['City'].apply(lambda x : category(x, city_dic))

# Apply lambda to change value 16 to 11 because of their same
correlation with Fraud column
df['Service_Centre'] = df['Service_Centre'].apply(lambda x : 11 if x
== 16 else x)
```

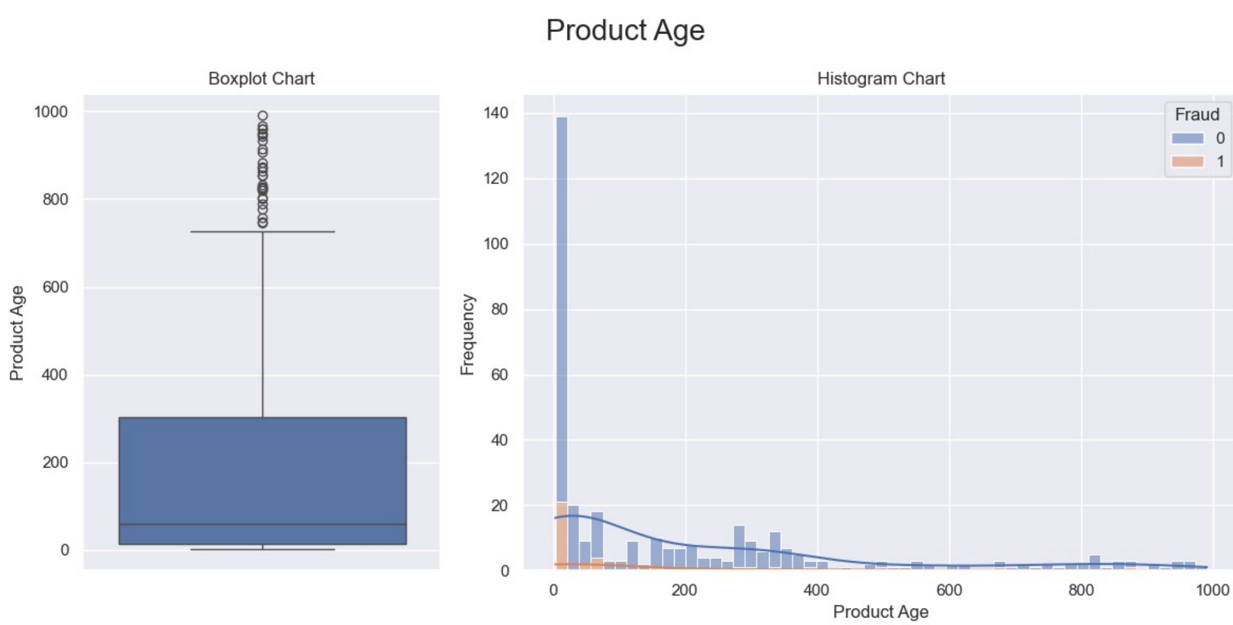
Data Visualization

```
# Define list of Continuous columns Names
continuous = ['Claim_Value', 'Call_details', 'Product_Age']

# Define a function to Capitalize the first element of string and
remove '_' character
def title(name):
    return (' '.join(word.capitalize()for word in name.split('_')))


# 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' {title(column)} ', fontsize=20)

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

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

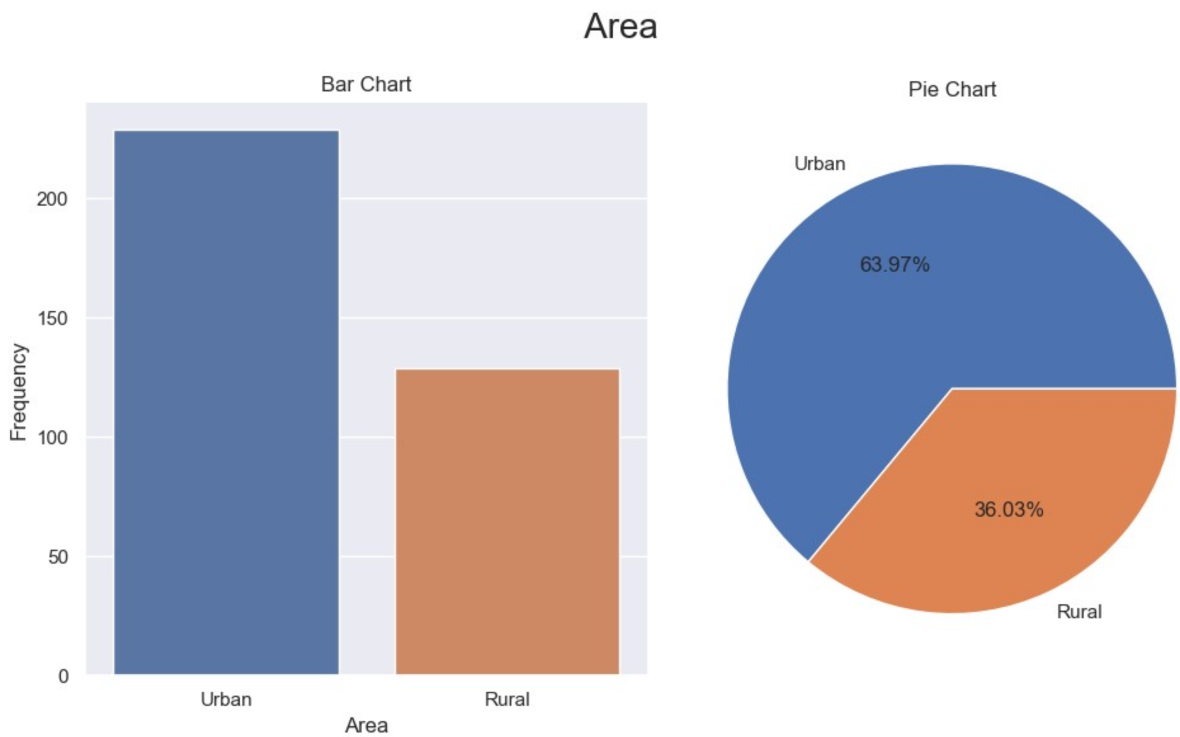


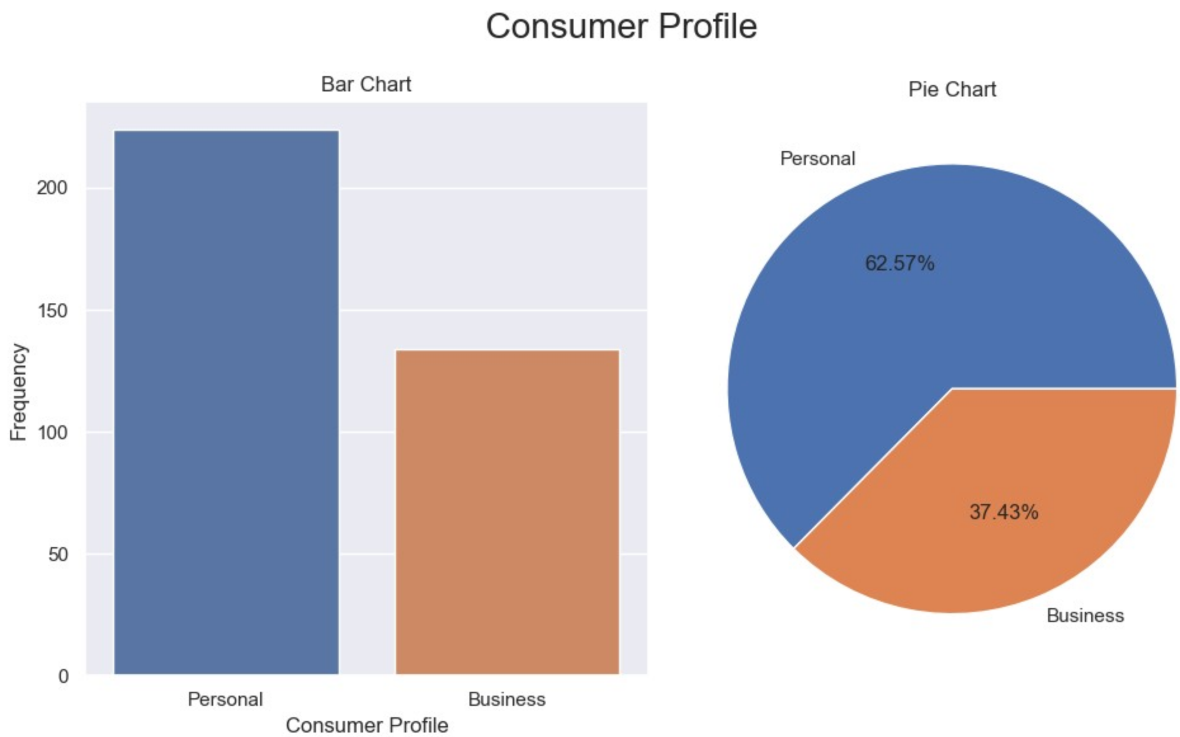


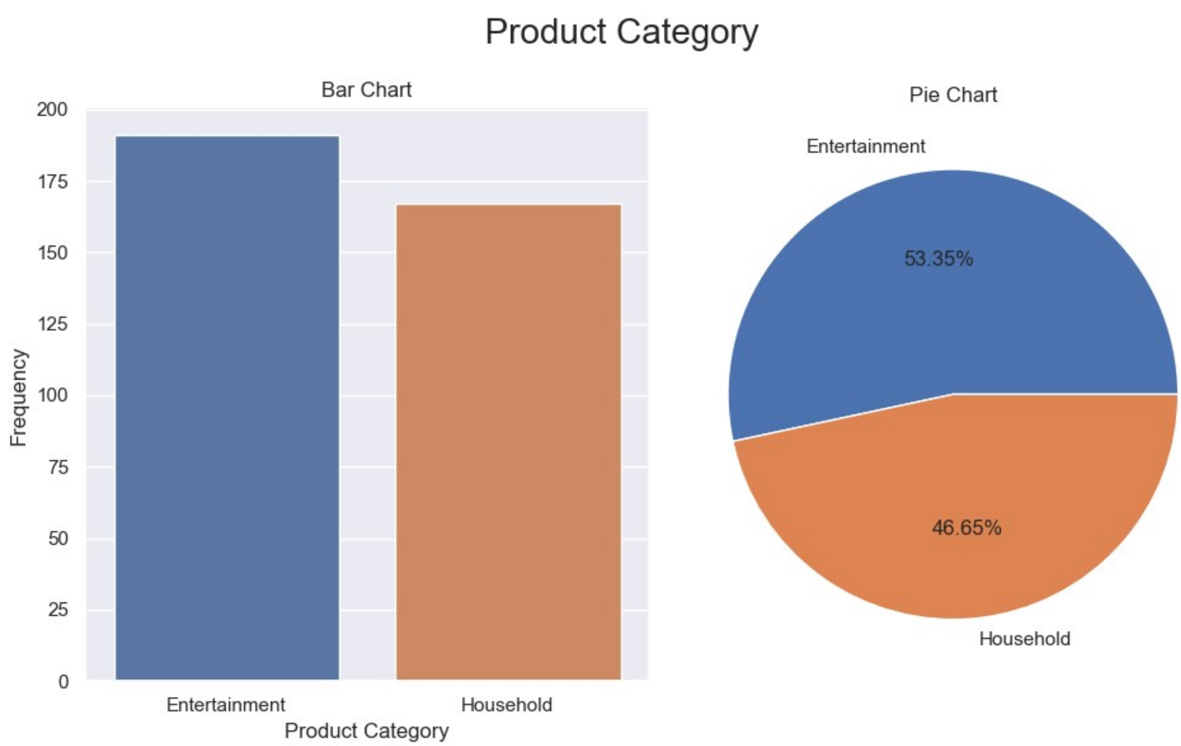


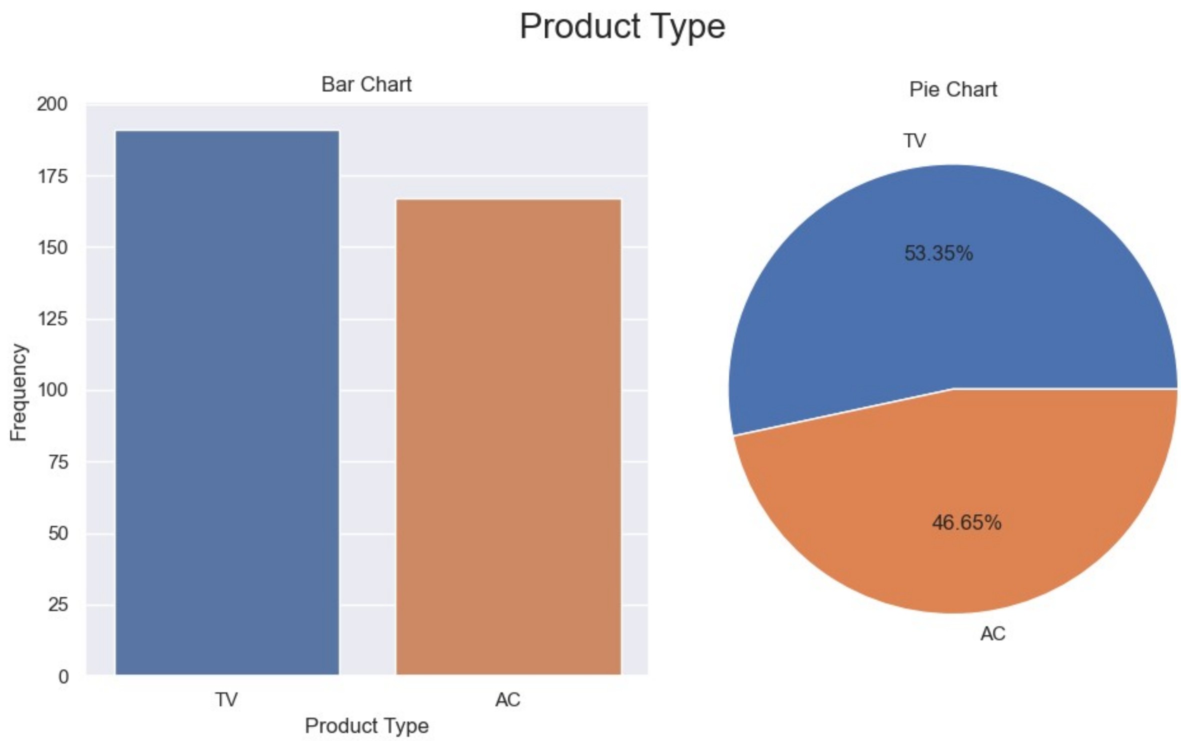

```
categorical = ['Area', 'Consumer_profile', 'Product_category',
'Product_type', 'Purchased_from', 'Purpose']

# distribution of categorical features

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

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

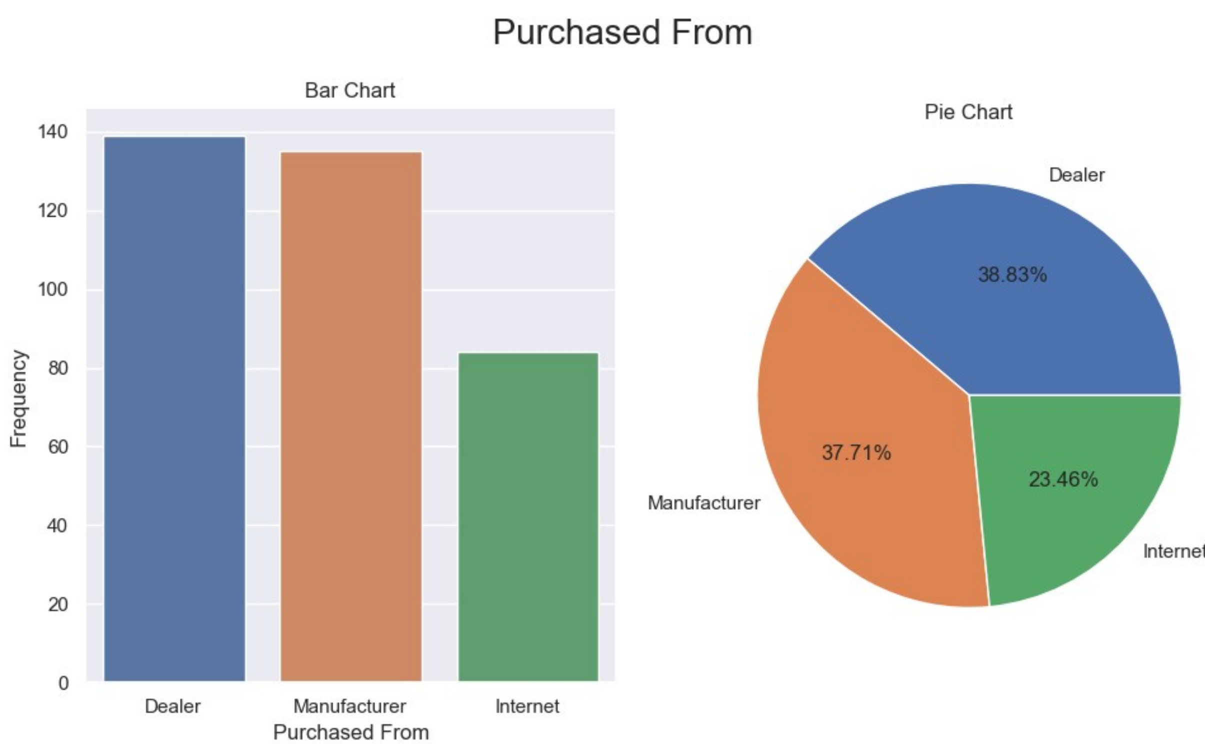
```
    ax[0].set_ylabel('Frequency')


    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)
```

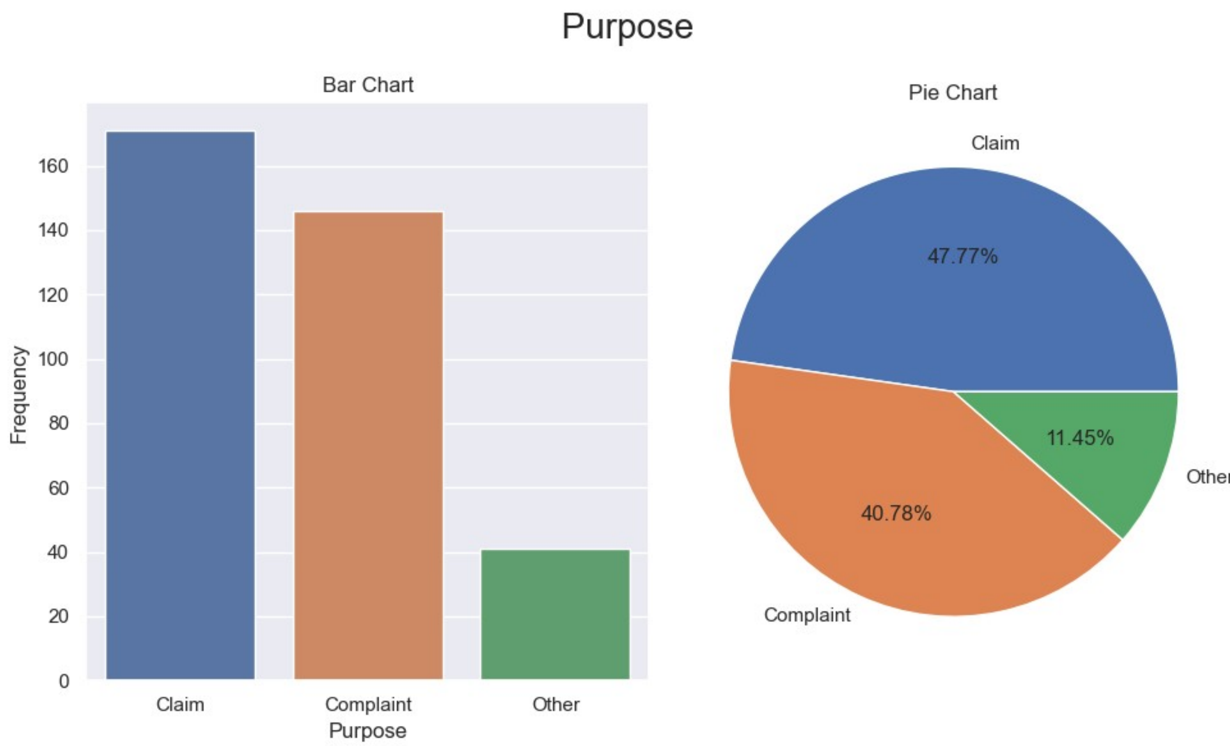



Consumer Profile
Bar Chart
Frequency
0
50
100
150
200
Personal
Business
Consumer Profile
Pie Chart
Personal
62.57%
37.43%
Business

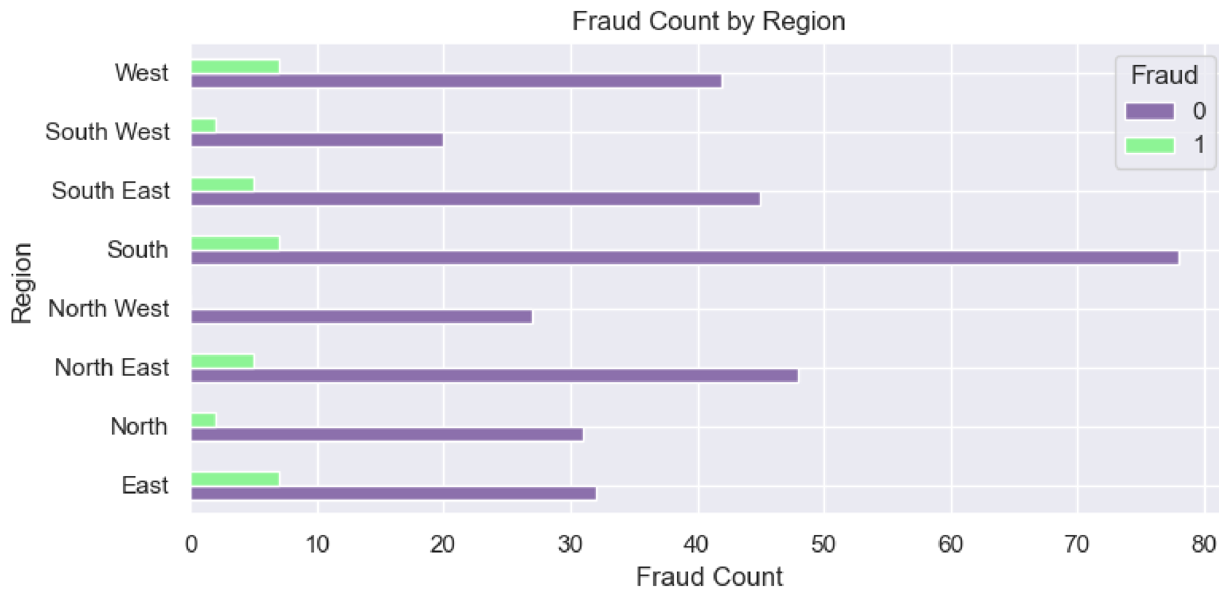

Product Category
Bar Chart
Frequency
0
25
50
75
100
125
150
175
200
Entertainment
Household
Product Category
Pie Chart
Entertainment
53.35%
46.65%
Household

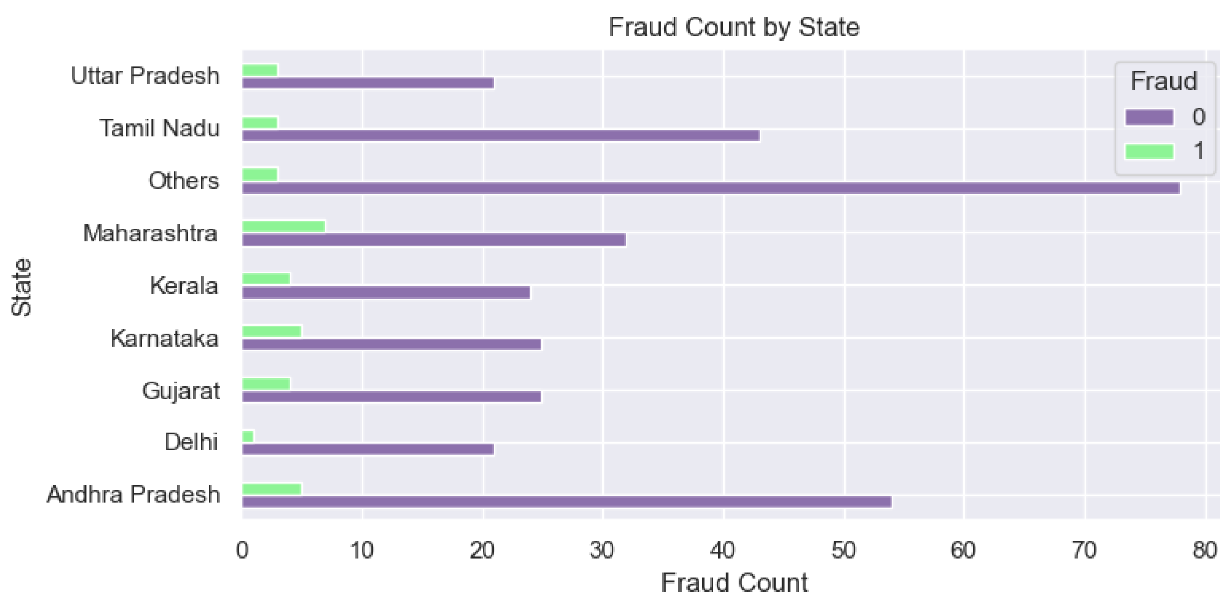

Product Type
Bar Chart
Frequency
200
175
150
125
100
75
50
25
0
TV
AC
Product Type
Pie Chart
TV
53.35%
46.65%
AC

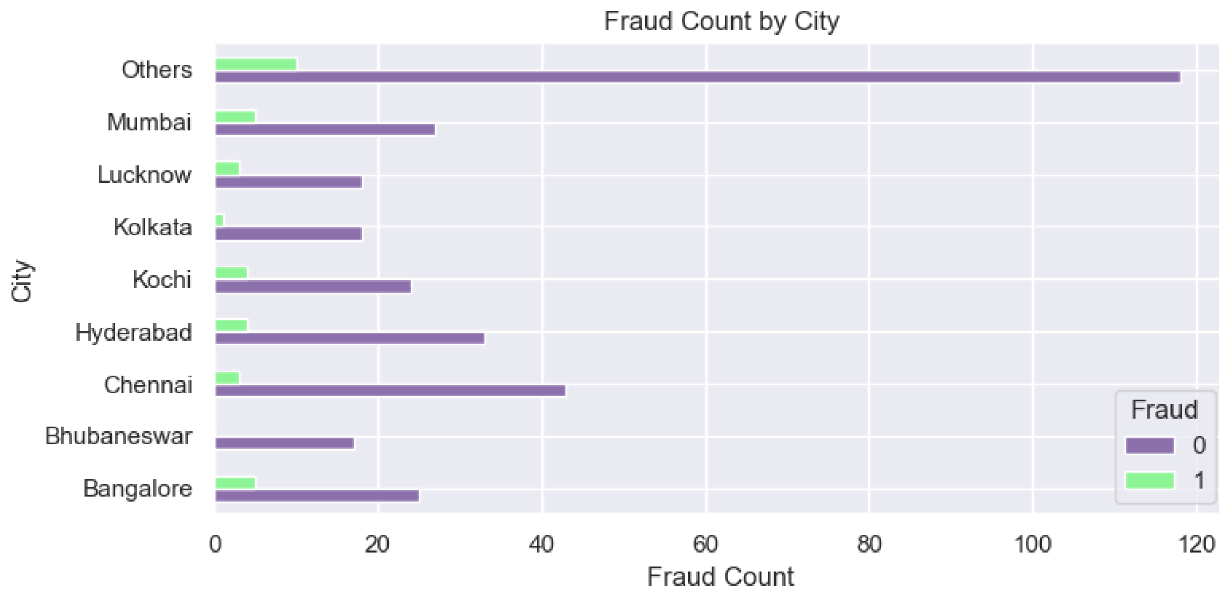

Purchased From
Bar Chart
Frequency
140
120
100
80
60
40
20
0
Dealer
Manufacturer
Internet
Purchased From
Pie Chart
Dealer
38.83%
37.71%
23.46%
Manufacturer
Internet



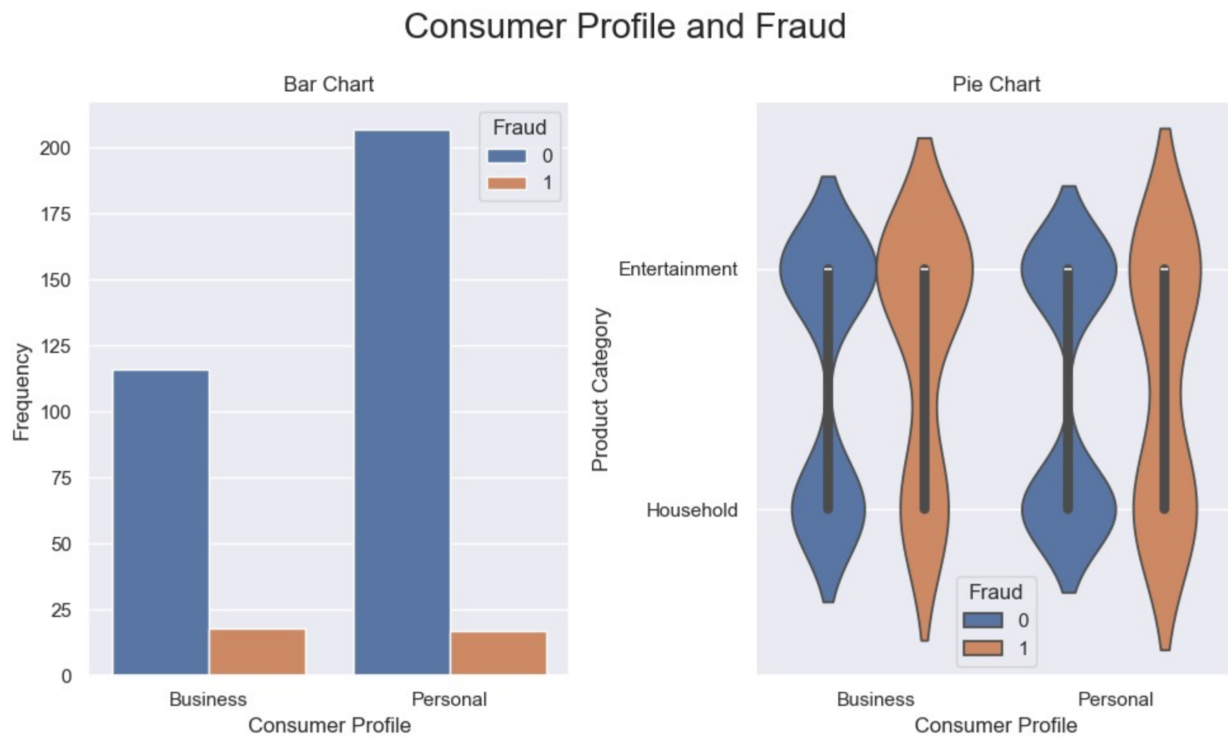

```
# Define a Function for Barh Plot
def bar_plot(x, y, df):
    barh = df.groupby([x, y]).size().unstack()
    barh.plot(kind='barh',  color = ['#8c70ac', '#8df495'],
figsize=(8,4))
    plt.title(f'{y} Count by {x}')
    plt.xlabel(f'{y} Count')
    plt.ylabel(x)

    plt.tight_layout()
    plt.show()

bar_plot('Region', 'Fraud', df)
bar_plot('State', 'Fraud', df)
bar_plot('City', 'Fraud', df)
```


Fraud Count by Region
Region
West
South West
South East
South
North West
North East
North
East
Fraud
0
1
0
10
20
30
40
50
60
70
80
Fraud Count


Fraud Count by State
State
Uttar Pradesh
Tamil Nadu
Others
Maharashtra
Kerala
Karnataka
Gujarat
Delhi
Andhra Pradesh
Fraud
0
1
0
10
20
30
40
50
60
70
80
Fraud Count




```
# distribution of categorical features

def plot_categorical(data, x, y, hue):
    fig, ax = plt.subplots(1, 2, figsize=(10, 6))
    fig.suptitle(f' {title(x)} and {title(hue)} ', fontsize=20)

    sns.countplot(x=x, hue=hue, data=data, ax=ax[0])
    ax[0].set_title('Bar Chart')
    ax[0].set_ylabel('Frequency')
    ax[0].set_xlabel(title(x))

    sns.violinplot(x=x, y=y, hue=hue, data=data, ax=ax[1])
    ax[1].set_title('Pie Chart')
    ax[1].set_xlabel(title(x))
    ax[1].set_ylabel(title(y))
    ax[1].legend(loc='lower center', title=hue)

    plt.tight_layout()
    plt.show()

plot_categorical(x='Consumer_profile', y='Product_category',
hue='Fraud', data=df)
plot_categorical(x='Purchased_from', y='Purpose', hue='Fraud',
data=df)
```



Data Preprocessing

```
from sklearn.preprocessing import StandardScaler, LabelEncoder
```

```python
# Initialize StandardScaler
stc = StandardScaler()
# Initialize LabelEncoder
le = LabelEncoder()

stc_cols = ['Call_details', 'Product_Age', 'Claim_Value']
le_cols = ['Product_type', 'Product_category', 'Consumer_profile',
'Area']
dum_cols = ['Purchased_from', 'Purpose', 'Service_Centre',
'TV_2003_Issue', 'TV_2002_Issue', 'TV_2001_Issue', 'AC_1003_Issue',
'AC_1002_Issue', 'AC_1001_Issue', 'City', 'State', 'Region']

# Apply Standard Scaler to the selected columns
df[stc_cols] = stc.fit_transform(df[stc_cols])

# Apply Label Encoder to the selected columns
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

```python
from sklearn.model_selection import train_test_split

x = df.drop(['Fraud', 'Unnamed: 0'], axis=1)
y = df['Fraud']  # Target Variable

x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.2, random_state=0)

#Importing the Libraries
from sklearn.ensemble import  GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LinearRegression
from sklearn.metrics import classification_report
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from xgboost import XGBClassifier

# List of Models to Try
models = [
    ('Gradient Boosting', GradientBoostingClassifier()),
    ('K-Nearest Neighbors', KNeighborsClassifier()),
```

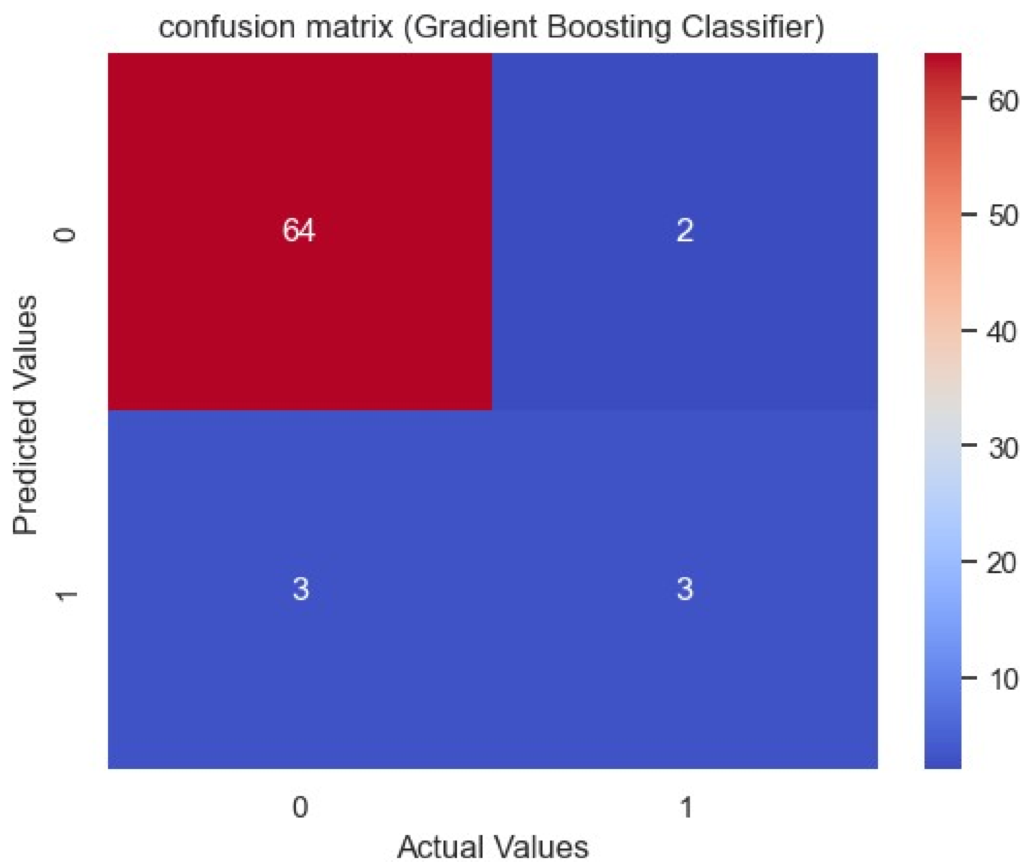
```python
    ('Random Forest', RandomForestClassifier()),
    ('Decision Tree', DecisionTreeClassifier()),
    ('XGB Classifier', XGBClassifier())
]

# 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 0.972027972027972
Test accuracy: Gradient Boosting 0.9305555555555556

Training accuracy: K-Nearest Neighbors 0.9125874125874126
Test accuracy: K-Nearest Neighbors 0.9027777777777778

Training accuracy: Random Forest 0.972027972027972
Test accuracy: Random Forest 0.9027777777777778

Training accuracy: Decision Tree 0.972027972027972
Test accuracy: Decision Tree 0.8055555555555556

Training accuracy: XGB Classifier 0.972027972027972
Test accuracy: XGB Classifier 0.9166666666666666
```

```python
#Craete a Object of Gradient Boosting Classifier
gb = GradientBoostingClassifier()

# Train and Evaluate the Model
gb.fit(x_train, y_train)
gb_pred = gb.predict(x_test)

accuracy = accuracy_score(y_test, gb_pred)
print(f'R-squared (Gradien Boosting Classifier): {round(accuracy, 
3)}')
```

```
R-squared (Gradien Boosting Classifier): 0.931
```

```python
# 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()
```




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

```
              precision    recall  f1-score   support

           0       0.96      0.97      0.96        66
           1       0.60      0.50      0.55         6

    accuracy                           0.93        72
   macro avg       0.78      0.73      0.75        72
weighted avg       0.93      0.93      0.93        72
```

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

```python
# redefine x and y
x = df.drop(['Fraud', 'Unnamed: 0'], axis=1)
y = df['Fraud']  # Target Variable

from imblearn.over_sampling import ADASYN
```

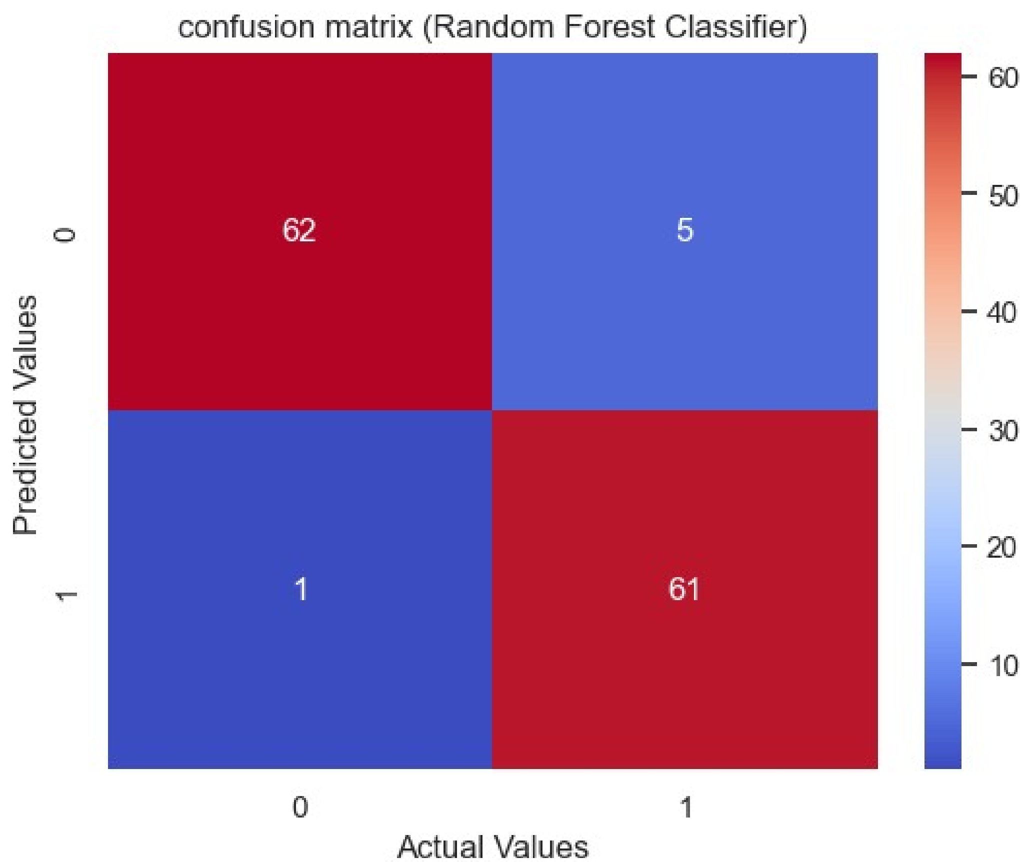
```python
# Initialize ADASYN
adasyn = ADASYN()

# Apply ADASYN to the x and y
x_resampled, y_resampled = adasyn.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()),
    ('Random Forest', RandomForestClassifier()),
    ('Decision Tree', DecisionTreeClassifier()),
    ('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 0.9825242718446602
Test accuracy: Gradient Boosting 0.9457364341085271

Training accuracy: K-Nearest Neighbors 0.9495145631067962
Test accuracy: K-Nearest Neighbors 0.9457364341085271

Training accuracy: Random Forest 0.9844660194174757
Test accuracy: Random Forest 0.9534883720930233

Training accuracy: Decision Tree 0.9844660194174757
Test accuracy: Decision Tree 0.9147286821705426

Training accuracy: XGB Classifier 0.9844660194174757
Test accuracy: XGB Classifier 0.9302325581395349
```

```python
#Craete a Object of Random Forest Classifier
rf = RandomForestClassifier()

# Train and Evaluate the Model
rf.fit(x_train, y_train)
rf_pred = rf.predict(x_test)

accuracy = accuracy_score(y_test, rf_pred)
print(f'R-squared (Random Forest Classifier): {round(accuracy, 3)}')
```

```
R-squared (Random Forest Classifier): 0.953
```

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




```python
# Visualize Classification report for Random Forest Classifier
print(classification_report(y_test,rf_pred))
```

```
              precision    recall  f1-score   support

           0       0.98      0.93      0.95        67
           1       0.92      0.98      0.95        62

    accuracy                           0.95       129
   macro avg       0.95      0.95      0.95       129
weighted avg       0.96      0.95      0.95       129
```

By employing the ADASYN 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 ADASYN 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.

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