IMPORT LIBRARIES

INSTALL OPENDATASETS MODULE TO FETCH KAGGLE DATASET

```
pip install opendatasets -q
```

```
import opendatasets as od
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
pd.set_option('display.max_columns', None)

#MODEL SELECTIONS
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, accu
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
#Thresholds
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
```

LOAD DATA

Retrieving Dataset from Kaggle Portal

- The dataset is 150 MB, making it infeasible to upload on GitHub or access locally.
- To overcome this, we are fetching the dataset from the Kaggle portal.
- Initially, the `opendatasets` library was not installed.
- Installed the `opendatasets` library using the following pip command:

```
od.version()
```

```
'0.1.22'
```

```
dataset_url="https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud/data
```

od.download(dataset_url)

- this will ask you kaggle username and kaggle unique key
- to get that goto kaggle portal and sign in
- then click on your kaggle profile photo and go to settings
- there see API and click on Create new token
- one JSON file will download with your username and tokan number
- insert that one by one after executing od.download

```
od.download(dataset_url)
```

```
Please provide your Kaggle credentials to download this dataset. Learn more: http://bit.ly/kagg
Your Kaggle username: prashantkumarsundge
Your Kaggle Key: ··········
Downloading creditcardfraud.zip to ./creditcardfraud
100%|██████████| 66.0M/66.0M [00:00<00:00, 121MB/s]
```

```
data_dir="creditcardfraud"
```

```
os.listdir(data_dir)
```

```
['creditcard.csv']
```

```
creditcard=data_dir + '/creditcard.csv'
data=pd.read_csv(creditcard)
```

```
data.head()
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817

About the Dataset

Context

Credit card companies aim to detect fraudulent transactions to prevent customers from being charged for unauthorized purchases.

Content

The dataset comprises credit card transactions made by European cardholders in September 2013. It covers two days, featuring 492 frauds out of 284,807 transactions. Notably, the dataset is highly unbalanced, with fraudulent transactions accounting for only 0.172% of all transactions.

This dataset exclusively includes numerical input variables resulting from a PCA transformation. Due to confidentiality constraints, the original features and additional background information aren't provided. The features V1 through V28 represent principal components obtained via PCA. However, 'Time' and 'Amount' are the only features not subjected to PCA.

- 'Time' indicates the seconds elapsed between each transaction and the first recorded transaction.
- 'Amount' signifies the transaction amount, potentially useful for example-dependent cost-sensitive learning.
- 'Class' represents the response variable, assuming a value of 1 for fraud and 0 otherwise.

Considering the class imbalance ratio, it's advisable to evaluate accuracy using the Area Under the Precision-Recall Curve (AUPRC). Note that accuracy metrics derived from a confusion matrix may not hold significance for unbalanced classification problems.

Rough Notes

- Time, Amount and Class data are in normal format
- remain data is in v1 v2 like variable names given for columns to hide the identity
- from the observation and given context about dataset are mentioned that dataset is applied PCA transformation

  ## Understanding from dataset

- It covers two days, featuring **492 frauds out of 284,807 transactions**. Notably, the dataset is highly **unbalanced**
- This dataset exclusively includes numerical input variables resulting from a PCA transformation. Due to confidentiality constraints
- 'Class' represents the response variable, assuming a value of 1 for fraud and 0 otherwise.
- will google it, potentially useful for example-dependent cost-sensitive learning
- Considering the class imbalance ratio, it's advisable to evaluate accuracy using the Area Under the Precision-Recall Curve (AUPRC)

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64  
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

- Data is clean no duplicated no missingvalues etc

```
data['Class'].value_counts()
```

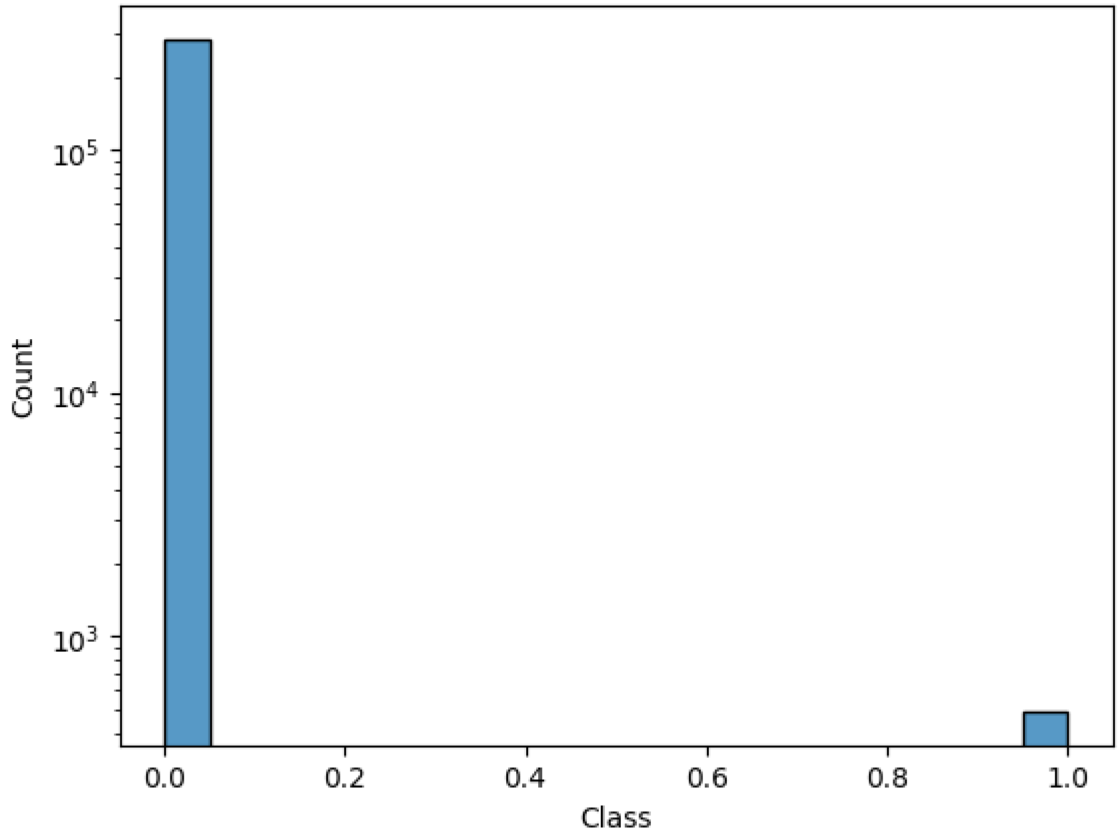
```
0    284315
1       492
Name: Class, dtype: int64
```

- as mentioned in the context data is imbalanced
- if you see the data is in PCA transformed format so no EDA is required
- we will directly load the model and check the score and yes as we know the data is imbalanced so will work after that so understand the differance between before working on Imbalance data and after

DATA IS IMBALANCE

AS IF THE DATA IS IMBALANCE WE CAN USE 2 MOTHEDS EITHER YOU CAN ADD THE THRESHOLD OR YOU CAN RASAMPLING TECHNIQUE

```
sns.histplot(data['Class'])
plt.yscale('log')
plt.show()
```



- Will understand if legit transaction and fraud transaction how much the amount used

```
data.groupby('Class')['Amount'].sum()
```

```
Class
0    25102462.04
1       60127.97
Name: Amount, dtype: float64
```

- We can see fraud AMount is around 60127

```
data.head()
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387

```
x_dummy=data.drop(columns='Class', axis=1)
y=data['Class']
```

STANDARD SCALER

```
scaler=StandardScaler()
x=scaler.fit_transform(x_dummy)
```

```
x_train, x_test, y_train, y_test=train_test_split(x,y, test_size=0.20, ra
print(f'x_train{x_train.shape}\n, x_test{x_test.shape}\n, y_train{y_trair
```

```
x_train(227845, 30)
, x_test(56962, 30)
, y_train(227845,)
, y_test(56962,)
```

TRAIN AND TEST MODEL

LOGISTIC REGRESSION

```
def logic_regression(x_train, y_train, x_test):
  lr=LogisticRegression()
  lr.fit(x_train, y_train)
  y_train_pred=lr.predict(x_train)
  y_train_cl_report=classification_report(y_train, y_train_pred, target_r
  print("_"*100)
  print("TRAIN MODEL CLASSIFICATION REPORT")
  print("_"*100)
  print(y_train_cl_report)
  y_test_pred=lr.predict(x_test)
  y_test_cl_report=classification_report(y_test, y_test_pred, target_name
  print("_"*100)
  print("TEST MODEL CLASSIFICATION REPORT")
  print("_"*100)
  print(y_test_cl_report)
  print("_"*100)
  return y_test_pred, lr
```

```
y_test_pred, lr= logic_regression(x_train, y_train, x_test)
```

```
____________________________________________________________________________________________________
TRAIN MODEL CLASSIFICATION REPORT
____________________________________________________________________________________________________
              precision    recall  f1-score   support

    No Fraud       1.00      1.00      1.00    227468
       Fraud       0.89      0.63      0.74       377

    accuracy                           1.00    227845
   macro avg       0.94      0.81      0.87    227845
weighted avg       1.00      1.00      1.00    227845

____________________________________________________________________________________________________
TEST MODEL CLASSIFICATION REPORT
____________________________________________________________________________________________________
              precision    recall  f1-score   support

    No Fraud       1.00      1.00      1.00     56847
       Fraud       0.83      0.61      0.70       115

    accuracy                           1.00     56962
   macro avg       0.92      0.80      0.85     56962
weighted avg       1.00      1.00      1.00     56962

____________________________________________________________________________________________________
```

- From the Above precision Recall and F1-Score we are confirmed that our data is not overfit or underfit
- Accuracy is getting 1 that we can uderstand because of large legit transations the results are showing as 1
- we are consantrating on Fraud Transactions

1. **Precision:**
   - Precision is the ratio of correctly predicted positive observations to the total predicted positives.
   - It measures the accuracy of the positive predictions.
   - Precision is calculated as: $\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$
   - Precision is high when the false positive rate is low.
2. **Recall (Sensitivity or True Positive Rate):**
   - Recall is the ratio of correctly predicted positive observations to all actual positives.
   - It measures the ability of the model to capture all the relevant cases.
   - Recall is calculated as: $\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$
   - Recall is high when the false negative rate is low.
3. **F1-score:**
   - The F1-score is the harmonic mean of precision and recall.
   - It provides a balance between precision and recall, making it useful when you want to consider both false positives and false negatives.
   - F1-score is calculated as: $\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$
   - F1-score ranges from 0 to 1, where 1 indicates perfect precision and recall.

```
def conf_mat(y_test, y_test_pred):
  con_mat=confusion_matrix(y_test, y_test_pred)
  labels = ['No Fraud', 'Fraud']
  sns.heatmap(con_mat, annot=True, fmt='d', xticklabels=labels, yticklabe
  plt.xlabel('Predicted')
  plt.ylabel('Actual')
  plt.show()


conf_mat(y_test, y_test_pred)
```

KNEIGHBORS CLASSIFICATION MODEL

```
def KNeighbors(x_train, y_train, x_test):
  Kneib=KNeighborsClassifier(n_neighbors=4)
  Kneib.fit(x_train, y_train)
  y_train_pred=Kneib.predict(x_train)
  y_train_cl_report=classification_report(y_train, y_train_pred, target_r
  print("_"*50)
  print("TRAIN MODEL CLASSIFICATION REPORT")
  print("_"*50)
  print(y_train_cl_report)
  y_test_pred=Kneib.predict(x_test)
  y_test_cl_report=classification_report(y_test, y_test_pred, target_name
  print("_"*50)
  print("TEST MODEL CLASSIFICATION REPORT")
  print("_"*50)
  print(y_test_cl_report)
  print("_"*50)
  return y_test_pred,Kneib

y_test_pred, Kneib=KNeighbors(x_train, y_train, x_test)
```

```
__________________________________________________
TRAIN MODEL CLASSIFICATION REPORT
__________________________________________________
              precision    recall  f1-score   support

    No Fraud       1.00      1.00      1.00    227468
       Fraud       0.97      0.79      0.87       377

    accuracy                           1.00    227845
   macro avg       0.99      0.89      0.93    227845
weighted avg       1.00      1.00      1.00    227845

__________________________________________________
TEST MODEL CLASSIFICATION REPORT
__________________________________________________
              precision    recall  f1-score   support
```

```
   No Fraud       1.00      1.00      1.00     56847
      Fraud       0.95      0.78      0.86       115

   accuracy                           1.00     56962
  macro avg       0.97      0.89      0.93     56962
weighted avg       1.00      1.00      1.00     56962
```

the model performs exceptionally well in identifying "No Fraud" instances,achieving perfect precision and recall. However, for the "Fraud" class, there is room for improvement, especially in terms of recall, as it correctly identifies only 78% of actual fraud cases.

ROC Curve and Optimal Thresholds for Logistic Regression and K-Neighbors Models

```
lr_prob=lr.predict_proba(x_test)
KNeib_prob=Kneib.predict_proba(x_test)
fpr1, tpr1, thresh1=roc_curve(y_test, lr_prob[:,1], pos_label=1)
fpr2, tpr2, thresh2=roc_curve(y_test, KNeib_prob[:,1], pos_label=1)

optimal_thres_lr=thresh1[np.argmax(tpr1 - fpr1)]
optimal_thres_KNeib=thresh2[np.argmax(tpr2 - fpr2)]
# roc curve for tpr = fpr
random_probs = [0 for i in range(len(y_test))]
p_fpr, p_tpr, _ = roc_curve(y_test, random_probs, pos_label=1)
print(f" optimal_thres_lr\t {optimal_thres_lr} \n optimal_thres_KNeib\t{o
```

```
 optimal_thres_lr        0.007890862084915292
 optimal_thres_KNeib    0.25
```

```
opt={'Logistic Regression':optimal_thres_lr,'KNeighbors Classification':c
for model, thresh in opt.items():
  if model == 'Logistic Regression':
    y_test_pred_adj=lr.predict_proba(x_test)[:,1]
  elif model =='KNeighbors Classification':
    y_test_pred_adj=Kneib.predict_proba(x_test)[:,1]

  y_test_pred_adj1 = (y_test_pred_adj >= thresh).astype(int)
  ac_score = accuracy_score(y_test, y_test_pred_adj1)
  ROC_AC=roc_auc_score(y_test, y_test_pred_adj1)

  print("_" * 50)
  print(f"Model: {model}")
  print(f"Threshold: {thresh}")
  print(f"Accuracy Score: {ac_score}")
  print(f"ROC Accuracy Score: {ROC_AC}")
  print("_" * 50)

  y_test_cl_report_adj = classification_report(y_test, y_test_pred_adj1,
  print("_" * 50)
  print("Classification Report:")
  print(y_test_cl_report_adj)
  print("_" * 50)
```

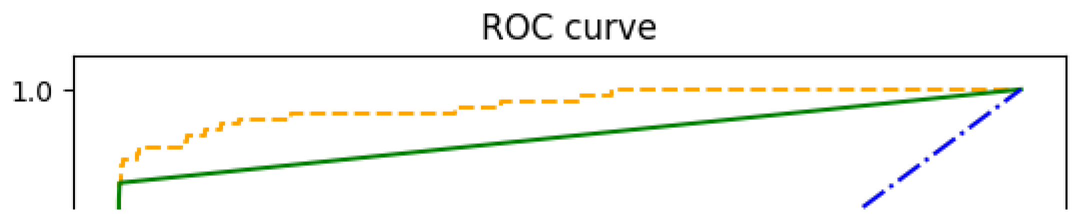
```
__________________________________________________
Model: Logistic Regression
Threshold: 0.007890862084915292
Accuracy Score: 0.9960675538078017
ROC Accuracy Score: 0.945961432709156

__________________________________________________
__________________________________________________
Classification Report:
              precision    recall  f1-score   support

    No Fraud       1.00      1.00      1.00     56847
       Fraud       0.33      0.90      0.48       115

    accuracy                           1.00     56962
   macro avg       0.66      0.95      0.74     56962
weighted avg       1.00      1.00      1.00     56962


__________________________________________________
__________________________________________________
Model: KNeighbors Classification
Threshold: 0.25
Accuracy Score: 0.9985955549313578
ROC Accuracy Score: 0.9298718681189247
__________________________________________________
__________________________________________________
Classification Report:
              precision    recall  f1-score   support

    No Fraud       1.00      1.00      1.00     56847
```

```
       Fraud       0.61      0.86      0.71       115

    accuracy                           1.00     56962
   macro avg       0.80      0.93      0.86     56962
weighted avg       1.00      1.00      1.00     56962
```

RESULT UNDERSTANDING

- The model is highly accurate overall but has room for improvement in precision for the "Fraud" class.
- The chosen threshold of 0.25 results in a trade-off between precision and recall.
- Depending on the specific requirements and priorities, you might want to adjust the threshold to optimize for precision, recall, or another metric.

```
# plot roc curves
plt.plot(fpr1, tpr1, linestyle='--',color='orange', label='Logistic Regre
plt.plot(fpr2, tpr2, linestyle='-',color='green', label='KNN')
plt.plot(p_fpr, p_tpr, linestyle='dashdot',color='blue', label='RANDOM')
# title
plt.title('ROC curve')
# x label
plt.xlabel('False Positive Rate')
# y label
plt.ylabel('True Positive rate')

plt.legend(loc='best')
plt.savefig('ROC',dpi=300)
plt.show();
```



- The ROC curves compare the performance of Logistic Regression, K-Neighbors (KNN), and a Random Classifier.
- Logistic Regression and K-Neighbors outperform the random classifier in distinguishing between classes.
- The area under the ROC curve (AUC) provides a quantitative measure of the model's discriminative ability.
- Consider the trade-off between false positives and true positives when selecting a model or threshold.

RESAMPLING TECHNIQUES


```
data['Class'].value_counts()
```

```
0    284315
1       492
Name: Class, dtype: int64
```

- Data is not balanced if you see 0 legit transactions are 284315, where as fraud transations are 492
- so we are using the Resampling Technique

Under-sampling the Majority Class:

- Randomly remove instances from the majority class to balance the class distribution.
- Be cautious not to remove too much data, as it may result in information loss.
- Created the 2 dataset based on classifications with equal rows

```
df_0 = data[data['Class'] == 0].sample(n=492, random_state=42)
df_1= data[data['Class'] == 1].sample(n=492, random_state=42)
```

```
print(f' Fraud Shape{df_1.shape}\n No Fraud shape{df_0.shape}')
```

```
 Fraud Shape(492, 31)
 No Fraud shape(492, 31)
```

```
df_concat=pd.concat([df_0,df_1], ignore_index=True)
```

DATSET IS READY

```
df_concat.shape
```

```
(984, 31)
```

BALANCE DATASET TRAIN TEST SPLIT

```
x_bal_dummy=df_concat.drop('Class', axis=1)
y_bal=df_concat['Class']
print(x_bal_dummy.shape, '\n', y_bal.shape)
```

```
(984, 30)
 (984,)
```

```
x_bal=scaler.fit_transform(x_bal_dummy)
```

```
x_train_b, x_test_b, y_train_b, y_test_b=train_test_split(x_bal,y_bal, te
print(f'x_train{x_train_b.shape}\n, x_test{x_test_b.shape}\n, y_train{y_t
```

```
x_train(787, 30)
, x_test(197, 30)
, y_train(787,)
, y_test(197,)
```

BALANCE DATASET LOGISTIC REGRESSION

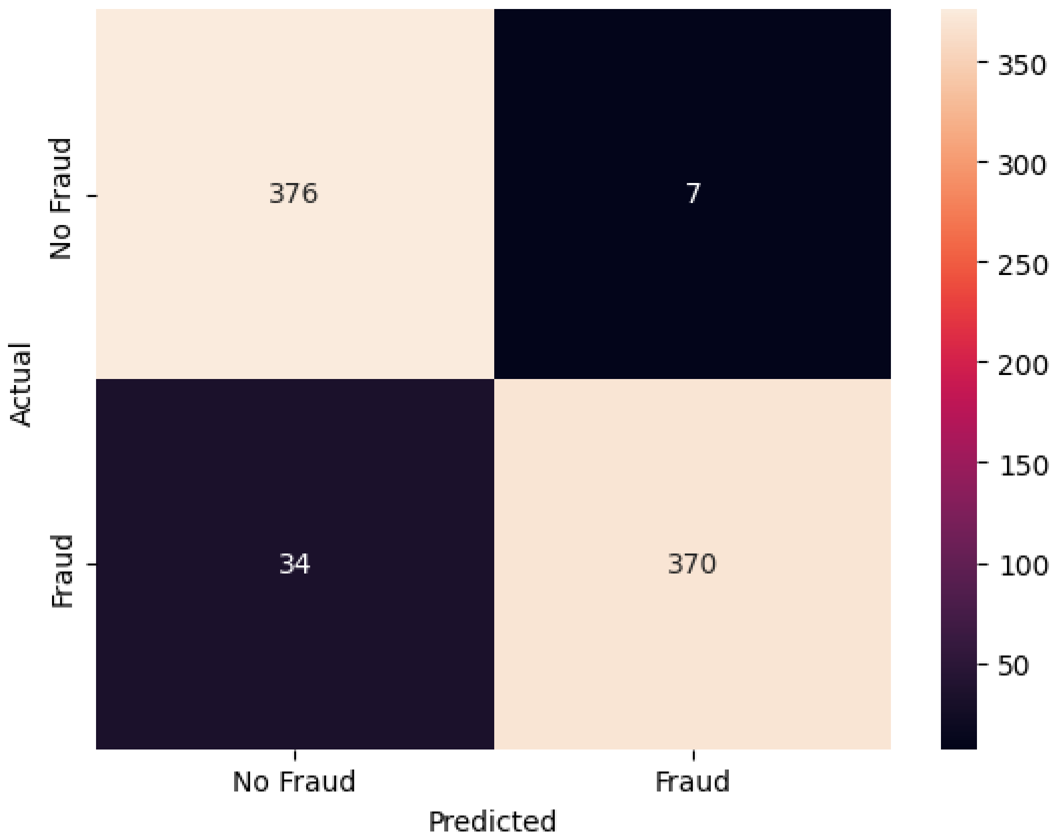
```
bal_lr=LogisticRegression()
bal_lr.fit(x_train_b,y_train_b)
bal_pred_train=bal_lr.predict(x_train_b)
bal_pred_test=bal_lr.predict(x_test_b)
```

```
bal_cl_report_train=classification_report(y_train_b,bal_pred_train)
print(bal_cl_report_train)
bal_cl_report_test=classification_report(y_test_b,bal_pred_test)
print(bal_cl_report_test)
```

```
              precision    recall  f1-score   support

           0       0.92      0.98      0.95       383
           1       0.98      0.92      0.95       404

    accuracy                           0.95       787
   macro avg       0.95      0.95      0.95       787
```

```
weighted avg       0.95      0.95      0.95       787

              precision    recall  f1-score   support

           0       0.94      0.97      0.95       109
           1       0.96      0.92      0.94        88

    accuracy                           0.95       197
   macro avg       0.95      0.95      0.95       197
weighted avg       0.95      0.95      0.95       197
```

```
conf_mat(y_train_b,bal_pred_train)
```



Logistic Regression:

- **Precision:**
  - Class 0: 0.92 (92%)
  - Class 1: 0.98 (98%)
- **Recall (Sensitivity):**
  - Class 0: 0.98 (98%)
  - Class 1: 0.92 (92%)
- **F1-score:**
  - Class 0: 0.95 (95%)
  - Class 1: 0.95 (95%)

- **Support:**
    - Class 0: 383 instances
    - Class 1: 404 instances

```
conf_mat(y_test_b,bal_pred_test)
```

BALANCE DATASET KNEIGHBORS CLASSIFICATION

```
knn=KNeighborsClassifier()
knn.fit(x_train_b,y_train_b)
knn_bal_pred_train=bal_lr.predict(x_train_b)
knn_bal_pred_test=bal_lr.predict(x_test_b)
```

```
knn_bal_cl_report_train=classification_report(y_train_b,knn_bal_pred_trai
print(knn_bal_cl_report_train)
knn_bal_cl_report_test=classification_report(y_test_b,knn_bal_pred_test)
print(knn_bal_cl_report_test)
```

```
              precision    recall  f1-score   support

           0       0.92      0.98      0.95       383
           1       0.98      0.92      0.95       404

    accuracy                           0.95       787
```

```
   macro avg       0.95      0.95      0.95       787
weighted avg       0.95      0.95      0.95       787

              precision    recall  f1-score   support

           0       0.94      0.97      0.95       109
           1       0.96      0.92      0.94        88

    accuracy                           0.95       197
   macro avg       0.95      0.95      0.95       197
weighted avg       0.95      0.95      0.95       197
```

Confusion Matrix for Train and Test

```
conf_mat(y_train_b,knn_bal_pred_train)
conf_mat(y_test_b,knn_bal_pred_test)
```

K-Neighbors:

- **Precision:**
  - Class 0: 0.92 (92%)
  - Class 1: 0.98 (98%)
- **Recall (Sensitivity):**
  - Class 0: 0.98 (98%)
  - Class 1: 0.92 (92%)
- **F1-score:**
  - Class 0: 0.95 (95%)
  - Class 1: 0.95 (95%)
- **Support:**
  - Class 0: 383 instances
  - Class 1: 404 instances

Summary:

1. Both models (Logistic Regression and K-Neighbors) perform exceptionally well, achieving high precision, recall, and F1-scores for both classes.
2. The models show balanced performance in correctly identifying instances of both classes (0 and 1), as indicated by the similarity in precision and recall values.
3. The F1-scores for both classes are also high, suggesting a good balance between precision and recall.

Conclusion:

- Both models are effective in handling the classification task with high accuracy and balanced