

```
In [1]: import pandas as pd
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, recall_score, accuracy_score, precision_

RANDOM_SEED = 2021
TEST_PCT = 0.3
LABELS = ["Normal", "Fraud"]
```

```
In [2]: dataset = pd.read_csv("creditcard.csv")
```

```
In [3]: #check for any null values
print("Any nulls in the dataset",dataset.isnull().values.any())
print('-----')
print("No. of unique labels",len(dataset['Class'].unique()))
print("Label values",dataset.Class.unique())

#0 is for normal credit card transcation
#1 is for fraudulent credit card transcation
print('-----')
print("Break down of Normal and Fraud Transcations")
print(pd.value_counts(dataset['Class'],sort=True))
```

Any nulls in the dataset False

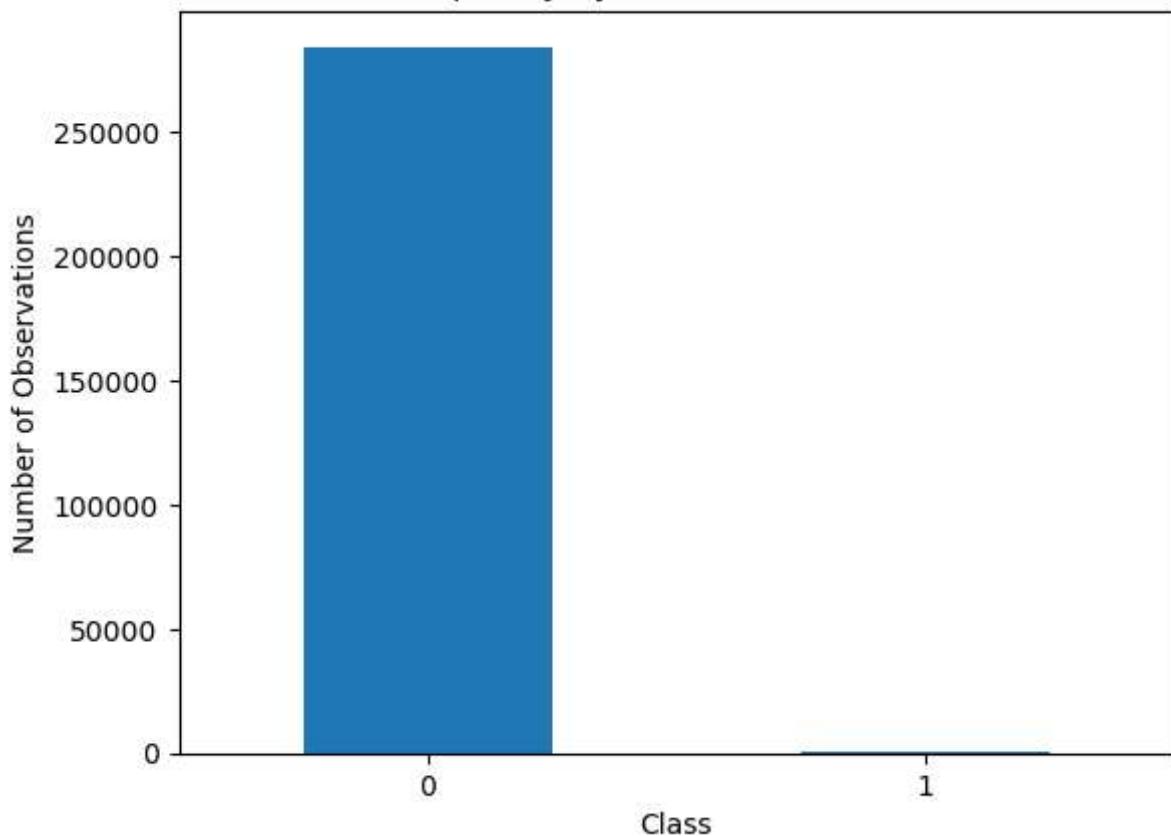
No. of unique labels 2
Label values [0 1]

Break down of Normal and Fraud Transcations
0 284315
1 492
Name: Class, dtype: int64

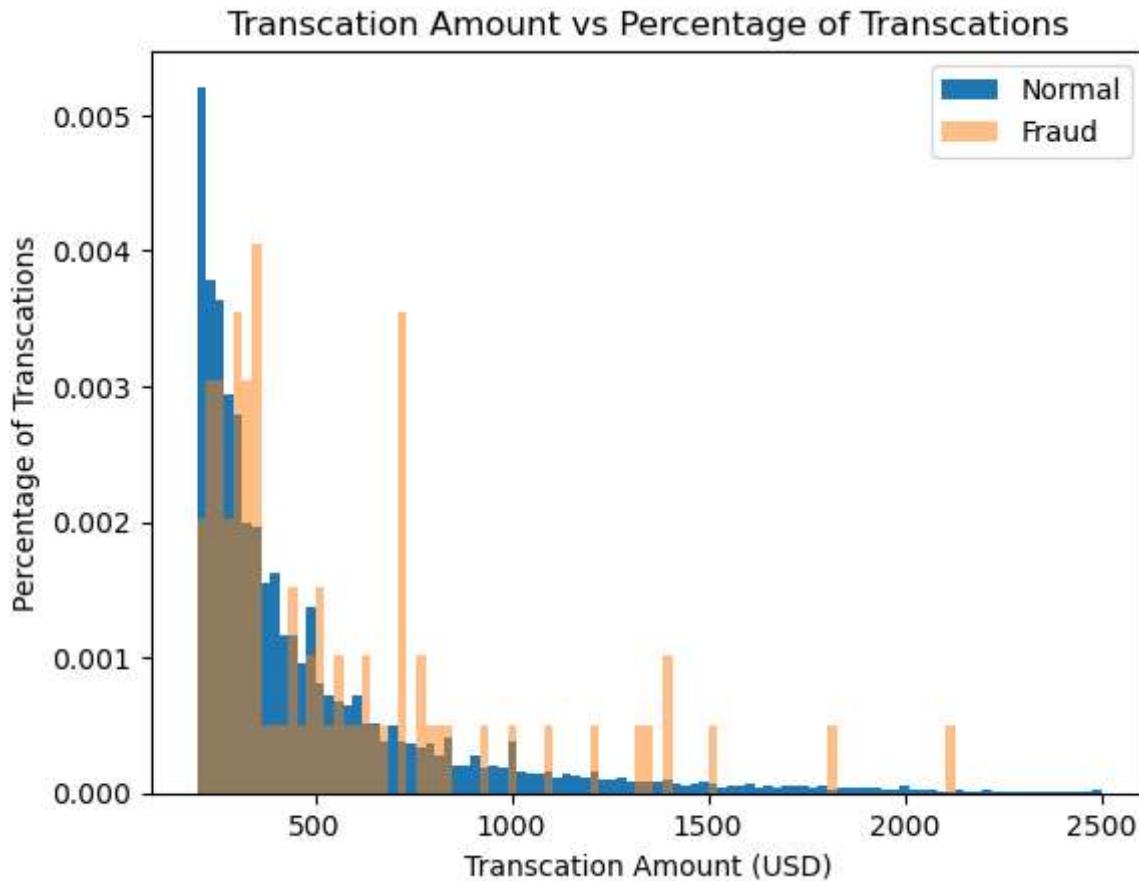
```
In [4]: #visualizing the imbalanced dataset
count_classes = pd.value_counts(dataset['Class'],sort=True)
count_classes.plot(kind='bar',rot=0)
plt.xticks(range(len(dataset['Class'].unique()))),dataset.Class.unique())
plt.title("Frequency by observation number")
plt.xlabel("Class")
plt.ylabel("Number of Observations")
```

```
Out[4]: Text(0, 0.5, 'Number of Observations')
```

Frequency by observation number



```
In [5]: #Save the normal and fraudulent transctions in seperate dataframes  
normal_dataset = dataset[dataset.Class == 0]  
fraud_dataset = dataset[dataset.Class == 1]  
  
#Visualize transcation amounts for normal and fraudulent transctions  
bins = np.linspace(200,2500,100)  
plt.hist(normal_dataset.Amount,bins=bins,alpha=1,density=True,label='Normal')  
plt.hist(fraud_dataset.Amount,bins=bins,alpha=0.5,density=True,label='Fraud')  
plt.legend(loc='upper right')  
plt.title("Transcation Amount vs Percentage of Transcations")  
plt.xlabel("Transcation Amount (USD)")  
plt.ylabel("Percentage of Transcations")  
plt.show()
```



In [6]: dataset

Out[6]:

| | Time | V1 | V2 | V3 | V4 | V5 | V6 | V7 |
|--------|----------|------------|-----------|-----------|-----------|-----------|-----------|-----------|
| 0 | 0.0 | -1.359807 | -0.072781 | 2.536347 | 1.378155 | -0.338321 | 0.462388 | 0.239599 |
| 1 | 0.0 | 1.191857 | 0.266151 | 0.166480 | 0.448154 | 0.060018 | -0.082361 | -0.078803 |
| 2 | 1.0 | -1.358354 | -1.340163 | 1.773209 | 0.379780 | -0.503198 | 1.800499 | 0.791461 |
| 3 | 1.0 | -0.966272 | -0.185226 | 1.792993 | -0.863291 | -0.010309 | 1.247203 | 0.237609 |
| 4 | 2.0 | -1.158233 | 0.877737 | 1.548718 | 0.403034 | -0.407193 | 0.095921 | 0.592941 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 284802 | 172786.0 | -11.881118 | 10.071785 | -9.834783 | -2.066656 | -5.364473 | -2.606837 | -4.918215 |
| 284803 | 172787.0 | -0.732789 | -0.055080 | 2.035030 | -0.738589 | 0.868229 | 1.058415 | 0.024330 |
| 284804 | 172788.0 | 1.919565 | -0.301254 | -3.249640 | -0.557828 | 2.630515 | 3.031260 | -0.296827 |
| 284805 | 172788.0 | -0.240440 | 0.530483 | 0.702510 | 0.689799 | -0.377961 | 0.623708 | -0.686180 |
| 284806 | 172792.0 | -0.533413 | -0.189733 | 0.703337 | -0.506271 | -0.012546 | -0.649617 | 1.577006 |

284807 rows × 31 columns

```
In [7]: sc = StandardScaler()
dataset['Time'] = sc.fit_transform(dataset['Time'].values.reshape(-1,1))
dataset['Amount'] = sc.fit_transform(dataset['Amount'].values.reshape(-1,1))
```

```
In [8]: raw_data = dataset.values
#The last element contains if the transaction is normal which is represented by 0 and
labels = raw_data[:, -1]

#The other data points are the electrocardiogram data
data = raw_data[:, 0:-1]

train_data, test_data, train_labels, test_labels = train_test_split(data, labels, test_size=
```

```
In [9]: min_val = tf.reduce_min(train_data)
max_val = tf.reduce_max(train_data)

train_data = (train_data - min_val) / (max_val - min_val)
test_data = (test_data - min_val) / (max_val - min_val)

train_data = tf.cast(train_data, tf.float32)
test_data = tf.cast(test_data, tf.float32)
```

```
In [10]: train_labels = train_labels.astype(bool)
test_labels = test_labels.astype(bool)

#Creating normal and fraud datasets
normal_train_data = train_data[~train_labels]
normal_test_data = test_data[~test_labels]

fraud_train_data = train_data[train_labels]
fraud_test_data = test_data[test_labels]
print("No. of records in Fraud Train Data=", len(fraud_train_data))
print("No. of records in Normal Train Data=", len(normal_train_data))
print("No. of records in Fraud Test Data=", len(fraud_test_data))
print("No. of records in Normal Test Data=", len(normal_test_data))
```

No. of records in Fraud Train Data= 389
 No. of records in Normal Train Data= 227456
 No. of records in Fraud Test Data= 103
 No. of records in Normal Test Data= 56859

```
In [11]: nb_epoch = 50
batch_size = 64
input_dim = normal_train_data.shape[1]
#num of columns, 30
encoding_dim = 14
hidden_dim1 = int(encoding_dim / 2)
hidden_dim2 = 4
learning_rate = 1e-7
```

```
In [12]: #input Layer
input_layer = tf.keras.layers.Input(shape=(input_dim,))

#Encoder
encoder = tf.keras.layers.Dense(encoding_dim, activation="tanh", activity_regularizer =
encoder = tf.keras.layers.Dropout(0.2)(encoder)
encoder = tf.keras.layers.Dense(hidden_dim1, activation='relu')(encoder)
encoder = tf.keras.layers.Dense(hidden_dim2, activation=tf.nn.leaky_relu)(encoder)
```

```
#Decoder
decoder = tf.keras.layers.Dense(hidden_dim1, activation='relu')(encoder)
decoder = tf.keras.layers.Dropout(0.2)(decoder)
decoder = tf.keras.layers.Dense(encoding_dim, activation='relu')(decoder)
decoder = tf.keras.layers.Dense(input_dim, activation='tanh')(decoder)

#Autoencoder
autoencoder = tf.keras.Model(inputs = input_layer,outputs = decoder)
autoencoder.summary()
```

Model: "functional_1"

| Layer (type) | Output Shape | Param # |
|-------------------------|--------------|---------|
| <hr/> | | |
| input_1 (InputLayer) | [None, 30] | 0 |
| dense (Dense) | (None, 14) | 434 |
| dropout (Dropout) | (None, 14) | 0 |
| dense_1 (Dense) | (None, 7) | 105 |
| dense_2 (Dense) | (None, 4) | 32 |
| dense_3 (Dense) | (None, 7) | 35 |
| dropout_1 (Dropout) | (None, 7) | 0 |
| dense_4 (Dense) | (None, 14) | 112 |
| dense_5 (Dense) | (None, 30) | 450 |
| <hr/> | | |
| Total params: 1,168 | | |
| Trainable params: 1,168 | | |
| Non-trainable params: 0 | | |

In [13]:

```
cp = tf.keras.callbacks.ModelCheckpoint(filepath="autoencoder_fraud.h5",mode='min',monitor='val_loss')
#define our early stopping
early_stop = tf.keras.callbacks.EarlyStopping(
    monitor='val_loss',
    min_delta=0.0001,
    patience=10,
    verbose=1,
    mode='min',
    restore_best_weights=True
)
```

In [14]:

```
autoencoder.compile(metrics=['accuracy'], loss= 'mean_squared_error', optimizer='adam')
```

In [15]:

```
history = autoencoder.fit(normal_train_data,normal_train_data,epochs = nb_epoch,
                           batch_size = batch_size,shuffle = True,
                           validation_data = (test_data,test_data),
                           verbose=1,
                           callbacks = [cp,early_stop]).history
```

```
Epoch 1/50
1/3554 [...........................] - ETA: 0s - loss: 0.2476 - accuracy: 0.031
2WARNING:tensorflow:Callbacks method `on_train_batch_end` is slow compared to the batch time (batch time: 0.0000s vs `on_train_batch_end` time: 0.0010s). Check your callbacks.
3535/3554 [=====>.] - ETA: 0s - loss: 0.0050 - accuracy: 0.056
1
Epoch 00001: val_loss improved from inf to 0.00053, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 642us/step - loss: 0.0050 - accuracy: 0.0562 - val_loss: 5.2896e-04 - val_accuracy: 0.0236
Epoch 2/50
3469/3554 [=====>.] - ETA: 0s - loss: 1.9377e-05 - accuracy: 0.0736
Epoch 00002: val_loss improved from 0.00053 to 0.00046, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 566us/step - loss: 1.9396e-05 - accuracy: 0.0737 - val_loss: 4.5975e-04 - val_accuracy: 0.0236
Epoch 3/50
3495/3554 [=====>.] - ETA: 0s - loss: 1.9433e-05 - accuracy: 0.0639
Epoch 00003: val_loss improved from 0.00046 to 0.00043, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 592us/step - loss: 1.9440e-05 - accuracy: 0.0636 - val_loss: 4.3223e-04 - val_accuracy: 0.0236
Epoch 4/50
3508/3554 [=====>.] - ETA: 0s - loss: 1.9483e-05 - accuracy: 0.0640
Epoch 00004: val_loss improved from 0.00043 to 0.00038, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 693us/step - loss: 1.9526e-05 - accuracy: 0.0641 - val_loss: 3.8281e-04 - val_accuracy: 0.0236
Epoch 5/50
3516/3554 [=====>.] - ETA: 0s - loss: 1.9479e-05 - accuracy: 0.0620
Epoch 00005: val_loss improved from 0.00038 to 0.00033, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 576us/step - loss: 1.9505e-05 - accuracy: 0.0621 - val_loss: 3.3468e-04 - val_accuracy: 0.1279
Epoch 6/50
3501/3554 [=====>.] - ETA: 0s - loss: 1.9459e-05 - accuracy: 0.0663
Epoch 00006: val_loss improved from 0.00033 to 0.00027, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 579us/step - loss: 1.9461e-05 - accuracy: 0.0664 - val_loss: 2.7270e-04 - val_accuracy: 0.1279
Epoch 7/50
3451/3554 [=====>.] - ETA: 0s - loss: 1.9352e-05 - accuracy: 0.0638
Epoch 00007: val_loss improved from 0.00027 to 0.00024, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 600us/step - loss: 1.9421e-05 - accuracy: 0.0643 - val_loss: 2.3810e-04 - val_accuracy: 0.0251
Epoch 8/50
3503/3554 [=====>.] - ETA: 0s - loss: 1.9365e-05 - accuracy: 0.0710
Epoch 00008: val_loss improved from 0.00024 to 0.00019, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 566us/step - loss: 1.9355e-05 - accuracy: 0.0708 - val_loss: 1.9277e-04 - val_accuracy: 0.0251
```

```
Epoch 9/50
3536/3554 [=====>.] - ETA: 0s - loss: 1.9274e-05 - accuracy: 0.0710
Epoch 00009: val_loss improved from 0.00019 to 0.00016, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 575us/step - loss: 1.9277e-05 - accuracy: 0.0711 - val_loss: 1.6159e-04 - val_accuracy: 0.0251
Epoch 10/50
3470/3554 [=====>.] - ETA: 0s - loss: 1.9170e-05 - accuracy: 0.0754
Epoch 00010: val_loss improved from 0.00016 to 0.00011, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 598us/step - loss: 1.9138e-05 - accuracy: 0.0758 - val_loss: 1.0516e-04 - val_accuracy: 0.0251
Epoch 11/50
3511/3554 [=====>.] - ETA: 0s - loss: 1.8960e-05 - accuracy: 0.0844
Epoch 00011: val_loss improved from 0.00011 to 0.00009, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 689us/step - loss: 1.8965e-05 - accuracy: 0.0843 - val_loss: 9.0067e-05 - val_accuracy: 0.0252
Epoch 12/50
3502/3554 [=====>.] - ETA: 0s - loss: 1.8767e-05 - accuracy: 0.0838
Epoch 00012: val_loss improved from 0.00009 to 0.00007, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 606us/step - loss: 1.8748e-05 - accuracy: 0.0845 - val_loss: 6.6048e-05 - val_accuracy: 0.0252
Epoch 13/50
3449/3554 [=====>.] - ETA: 0s - loss: 1.8550e-05 - accuracy: 0.0849
Epoch 00013: val_loss improved from 0.00007 to 0.00005, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 599us/step - loss: 1.8576e-05 - accuracy: 0.0855 - val_loss: 5.4927e-05 - val_accuracy: 0.0253
Epoch 14/50
3500/3554 [=====>.] - ETA: 0s - loss: 1.8386e-05 - accuracy: 0.0892
Epoch 00014: val_loss improved from 0.00005 to 0.00003, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 578us/step - loss: 1.8389e-05 - accuracy: 0.0892 - val_loss: 3.3855e-05 - val_accuracy: 0.0253
Epoch 15/50
3517/3554 [=====>.] - ETA: 0s - loss: 1.8035e-05 - accuracy: 0.0925
Epoch 00015: val_loss did not improve from 0.00003
3554/3554 [=====] - 2s 560us/step - loss: 1.8029e-05 - accuracy: 0.0924 - val_loss: 4.0921e-05 - val_accuracy: 0.0253
Epoch 16/50
3535/3554 [=====>.] - ETA: 0s - loss: 1.7700e-05 - accuracy: 0.1055
Epoch 00016: val_loss did not improve from 0.00003
3554/3554 [=====] - 2s 572us/step - loss: 1.7701e-05 - accuracy: 0.1056 - val_loss: 3.6986e-05 - val_accuracy: 0.0252
Epoch 17/50
3488/3554 [=====>.] - ETA: 0s - loss: 1.7497e-05 - accuracy: 0.1210
Epoch 00017: val_loss did not improve from 0.00003
3554/3554 [=====] - 2s 562us/step - loss: 1.7491e-05 - accuracy: 0.1214 - val_loss: 3.6741e-05 - val_accuracy: 0.0252
```

```

Epoch 18/50
3494/3554 [=====>.] - ETA: 0s - loss: 1.7332e-05 - accuracy: 0.1364
Epoch 00018: val_loss improved from 0.00003 to 0.00003, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 585us/step - loss: 1.7327e-05 - accuracy: 0.1367 - val_loss: 3.0728e-05 - val_accuracy: 0.0253
Epoch 19/50
3523/3554 [=====>.] - ETA: 0s - loss: 1.7232e-05 - accuracy: 0.1513
Epoch 00019: val_loss improved from 0.00003 to 0.00003, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 691us/step - loss: 1.7230e-05 - accuracy: 0.1514 - val_loss: 2.7787e-05 - val_accuracy: 0.0253
Epoch 20/50
3499/3554 [=====>.] - ETA: 0s - loss: 1.7147e-05 - accuracy: 0.1674
Epoch 00020: val_loss improved from 0.00003 to 0.00003, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 594us/step - loss: 1.7145e-05 - accuracy: 0.1674 - val_loss: 2.5756e-05 - val_accuracy: 0.0253
Epoch 21/50
3524/3554 [=====>.] - ETA: 0s - loss: 1.7070e-05 - accuracy: 0.1872
Epoch 00021: val_loss did not improve from 0.00003
3554/3554 [=====] - 2s 559us/step - loss: 1.7076e-05 - accuracy: 0.1871 - val_loss: 2.6697e-05 - val_accuracy: 0.0252
Epoch 22/50
3489/3554 [=====>.] - ETA: 0s - loss: 1.7009e-05 - accuracy: 0.2023
Epoch 00022: val_loss did not improve from 0.00003
3554/3554 [=====] - 2s 622us/step - loss: 1.7025e-05 - accuracy: 0.2026 - val_loss: 2.8282e-05 - val_accuracy: 0.0251
Epoch 23/50
3539/3554 [=====>.] - ETA: 0s - loss: 1.6937e-05 - accuracy: 0.2238
Epoch 00023: val_loss improved from 0.00003 to 0.00002, saving model to autoencoder_fraud.h5
Restoring model weights from the end of the best epoch.
3554/3554 [=====] - 2s 625us/step - loss: 1.6938e-05 - accuracy: 0.2240 - val_loss: 2.4854e-05 - val_accuracy: 0.0251
Epoch 00023: early stopping

```

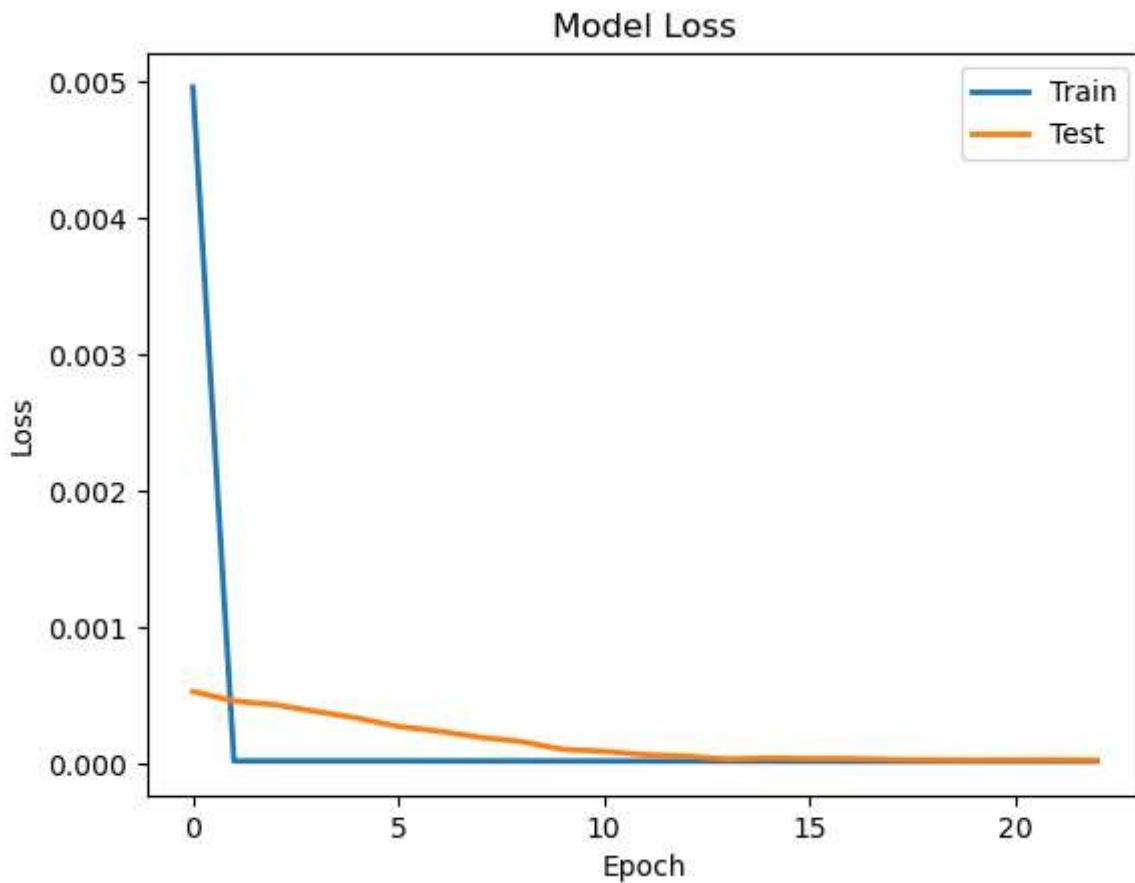
```

In [16]: plt.plot(history['loss'], linewidth = 2, label = 'Train')
plt.plot(history['val_loss'], linewidth = 2, label = 'Test')
plt.legend(loc='upper right')
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')

#plt.ylim(ymin=0.70,ymax=1)

plt.show()

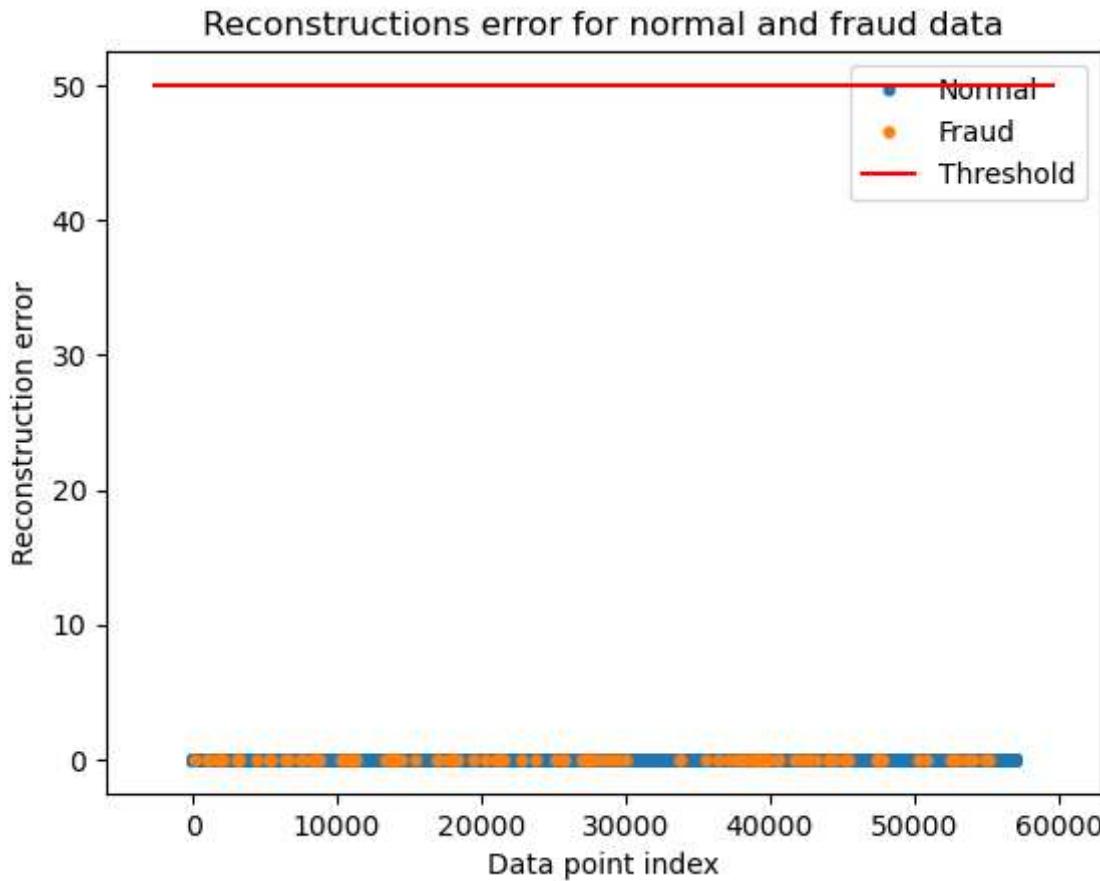
```



```
In [17]: test_x_predictions = autoencoder.predict(test_data)
mse = np.mean(np.power(test_data - test_x_predictions, 2), axis = 1)
error_df = pd.DataFrame({'Reconstruction_error':mse,
                         'True_class':test_labels})
```

```
In [18]: threshold_fixed = 50
groups = error_df.groupby('True_class')
fig,ax = plt.subplots()

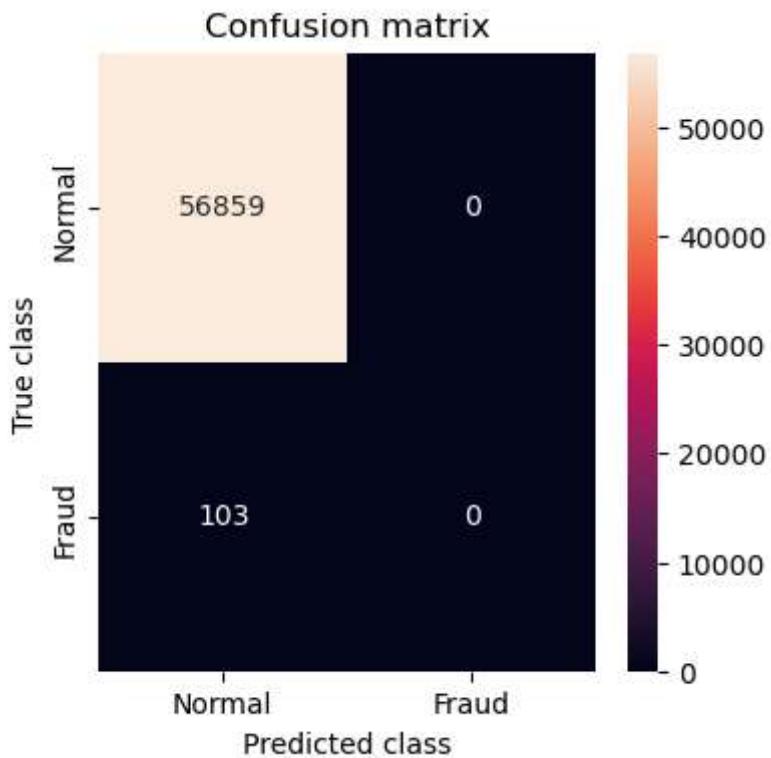
for name,group in groups:
    ax.plot(group.index,group.Reconstruction_error,marker='o',ms = 3.5,linestyle='-' 
            label = "Fraud" if name==1 else "Normal")
ax.hlines(threshold_fixed,ax.get_xlim()[0],ax.get_xlim()[1],colors="r",zorder=100,label="Threshold")
ax.legend()
plt.title("Reconstructions error for normal and fraud data")
plt.ylabel("Reconstruction error")
plt.xlabel("Data point index")
plt.show()
```



```
In [19]: threshold_fixed = 52
pred_y = [1 if e > threshold_fixed else 0
          for e in
              error_df.Reconstruction_error.values]
error_df['pred'] = pred_y
conf_matrix = confusion_matrix(error_df.True_class,pred_y)

plt.figure(figsize = (4,4))
sns.heatmap(conf_matrix,xticklabels = LABELS,yticklabels = LABELS,annot = True,fmt="d")
plt.title("Confusion matrix")
plt.ylabel("True class")
plt.xlabel("Predicted class")
plt.show()

#Print Accuracy,Precision and Recall
print("Accuracy :",accuracy_score(error_df['True_class'],error_df['pred']))
print("Recall :",recall_score(error_df['True_class'],error_df['pred']))
print("Precision :",precision_score(error_df['True_class'],error_df['pred']))
```



Accuracy : 0.9981917769741231

Recall : 0.0

Precision : 0.0

```
C:\Users\Manish\.conda\envs\tensorflow\lib\site-packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.  
_warn_prf(average, modifier, msg_start, len(result))
```