

```

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_score

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

dataset = pd.read_csv("creditcard.csv")

#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())

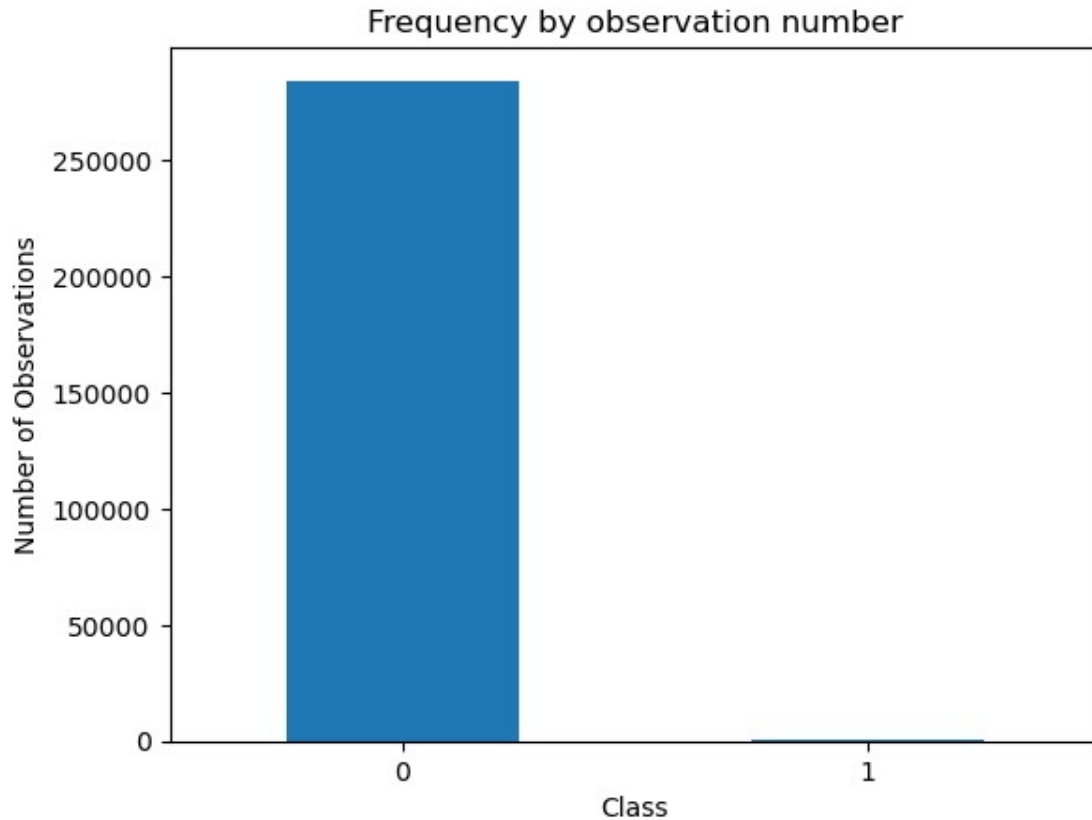
#0 is for normal credit card transcation
#1 is for fraudulent credit card transcation
print('-----')
print("Break down of Normal and Fraud Transcations")
print(pd.value_counts(dataset['Class'], sort=True))

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

#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")

Text(0, 0.5, 'Number of Observations')

```



#Save the normal and fraudulent transactions in separate dataframe

```
normal_dataset = dataset[dataset.Class == 0]
```

```
fraud_dataset = dataset[dataset.Class == 1]
```

#Visualize transaction amounts for normal and fraudulent transactions

```
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')
```

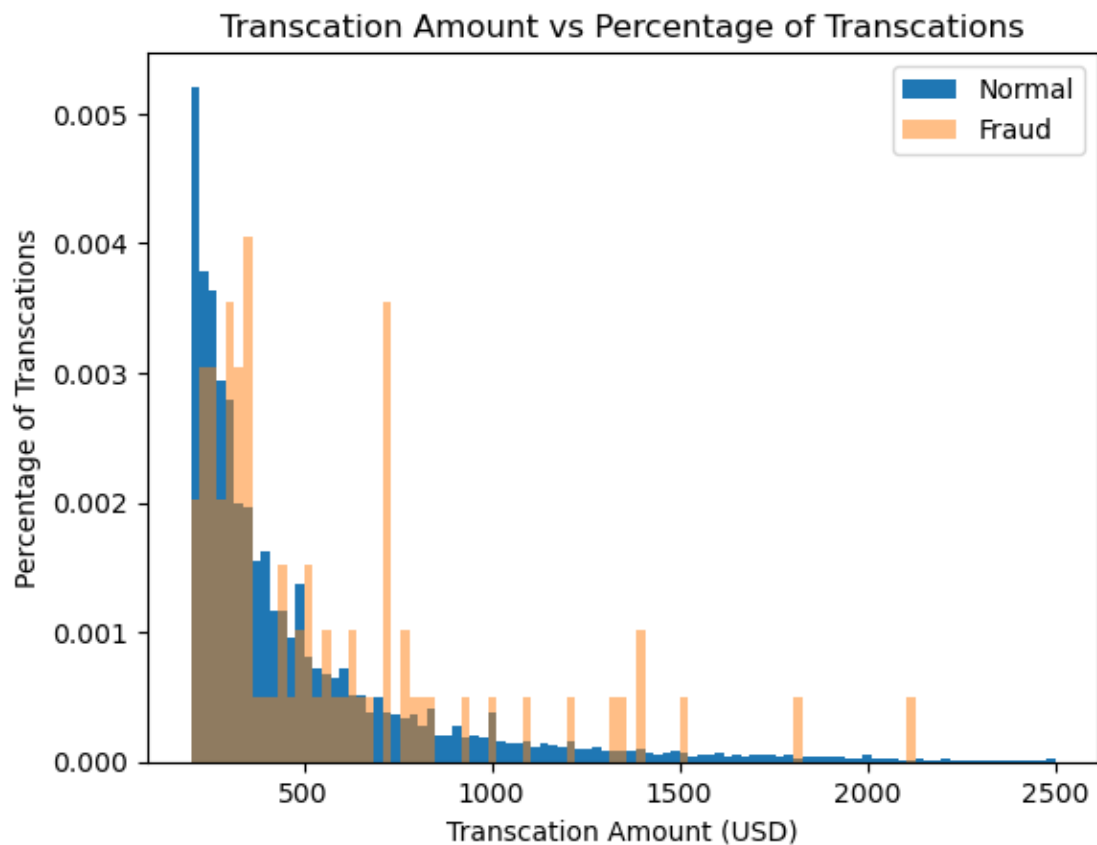
```
plt.legend(loc='upper right')
```

```
plt.title("Transaction Amount vs Percentage of Transactions")
```

```
plt.xlabel("Transaction Amount (USD)")
```

```
plt.ylabel("Percentage of Transactions")
```

```
plt.show()
```



dataset

	Time	V1	V2	V3	V4	
V5 \						
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193
...
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961

284806 172792.0 -0.533413 -0.189733 0.703337 -0.506271 -0.012546

	V6	V7	V8	V9	...	V21
V22 \						
0	0.462388	0.239599	0.098698	0.363787	...	-0.018307
0.277838						
1	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775
0.638672						
2	1.800499	0.791461	0.247676	-1.514654	...	0.247998
0.771679						
3	1.247203	0.237609	0.377436	-1.387024	...	-0.108300
0.005274						
4	0.095921	0.592941	-0.270533	0.817739	...	-0.009431
0.798278						
...
.						
284802	-2.606837	-4.918215	7.305334	1.914428	...	0.213454
0.111864						
284803	1.058415	0.024330	0.294869	0.584800	...	0.214205
0.924384						
284804	3.031260	-0.296827	0.708417	0.432454	...	0.232045
0.578229						
284805	0.623708	-0.686180	0.679145	0.392087	...	0.265245
0.800049						
284806	-0.649617	1.577006	-0.414650	0.486180	...	0.261057
0.643078						

	V23	V24	V25	V26	V27	V28
Amount \						
0	-0.110474	0.066928	0.128539	-0.189115	0.133558	-0.021053
149.62						
1	0.101288	-0.339846	0.167170	0.125895	-0.008983	0.014724
2.69						
2	0.909412	-0.689281	-0.327642	-0.139097	-0.055353	-0.059752
378.66						
3	-0.190321	-1.175575	0.647376	-0.221929	0.062723	0.061458
123.50						
4	-0.137458	0.141267	-0.206010	0.502292	0.219422	0.215153
69.99						
...
...						
284802	1.014480	-0.509348	1.436807	0.250034	0.943651	0.823731
0.77						
284803	0.012463	-1.016226	-0.606624	-0.395255	0.068472	-0.053527
24.79						
284804	-0.037501	0.640134	0.265745	-0.087371	0.004455	-0.026561
67.88						
284805	-0.163298	0.123205	-0.569159	0.546668	0.108821	0.104533

```
10.00
284806  0.376777  0.008797 -0.473649 -0.818267 -0.002415  0.013649
217.00
```

```
      Class
0         0
1         0
2         0
3         0
4         0
...      ...
284802     0
284803     0
284804     0
284805     0
284806     0
```

```
[284807 rows x 31 columns]
```

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

```
raw_data = dataset.values
#The last element contains if the transaction is normal which is
represented by 0 and if fraud then 1
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 = 0.2, random_state = 2021)
```

```
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)
```

```
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

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

#input layer
input_layer = tf.keras.layers.Input(shape=(input_dim,))

#Encoder
encoder =
tf.keras.layers.Dense(encoding_dim,activation="tanh",activity_regularizer = tf.keras.regularizers.l2(learning_rate))(input_layer)
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 #
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
Total params: 1,168		
Trainable params: 1,168		
Non-trainable params: 0		

```

cp =
tf.keras.callbacks.ModelCheckpoint(filepath="autoencoder_fraud.h5",mod
e='min',monitor='val_loss',verbose=2,save_best_only=True)
#Define our early stopping
early_stop = tf.keras.callbacks.EarlyStopping(
    monitor='val_loss',
    min_delta=0.0001,
    patience=10,
    verbose=11,
    mode='min',
    restore_best_weights=True
)

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

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: 0.0312WARNING: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: 0.0561
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

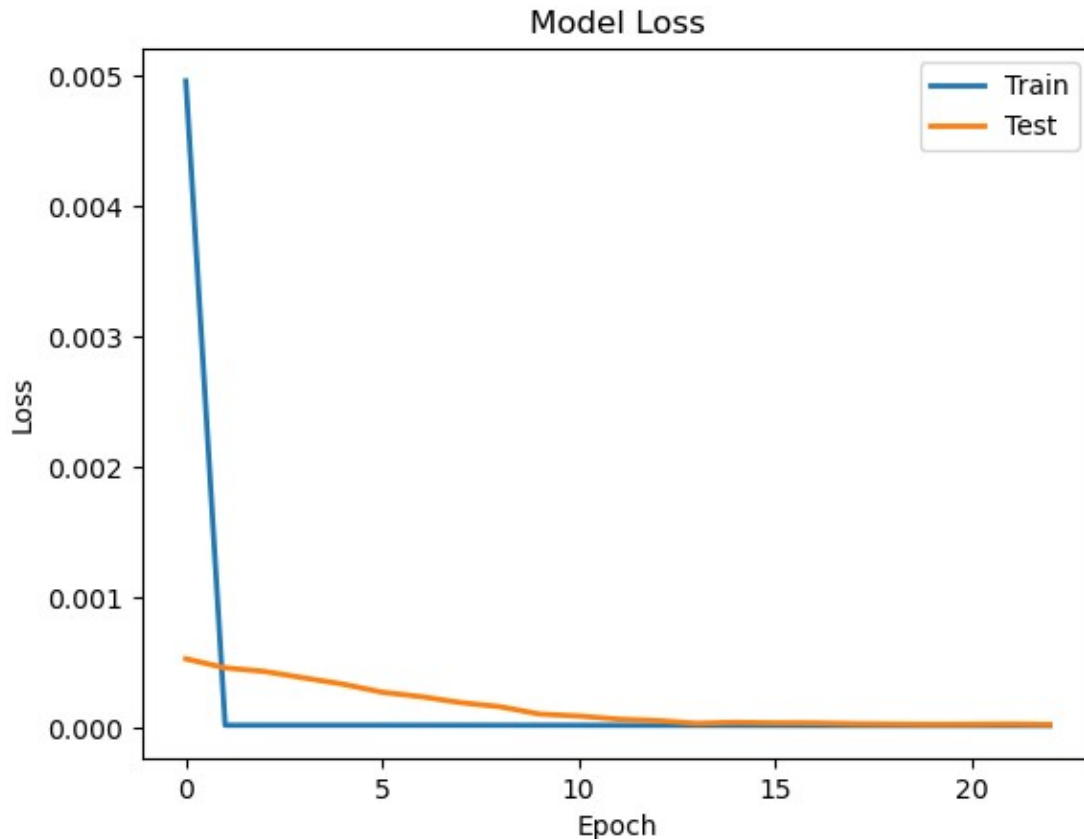
Epoch 00013: val_loss improved from 0.00007 to 0.00005, saving model to autoencoder_fraud.h5
3554/3554 [=====] - 2s 599us/step - loss: 1.8576e-05 - accuracy: 0.0855 - val_loss: 5.4927e-05 - val_accuracy: 0.0253
Epoch 14/50
3500/3554 [=====>.] - ETA: 0s - loss: 1.8386e-05 - accuracy: 0.0892
Epoch 00014: 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

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)

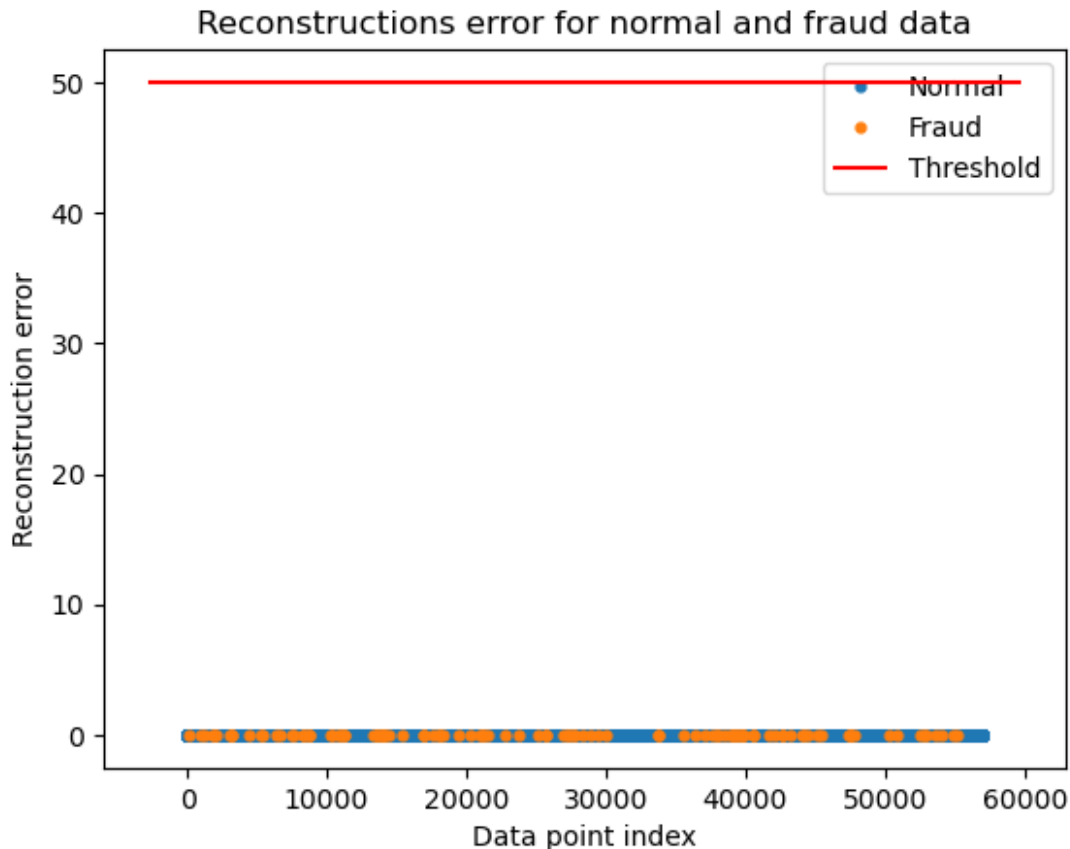
plt.show()
```



```
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})

threshold_fixed = 50
groups = error_df.groupby('True_class')
fig,ax = plt.subplots()

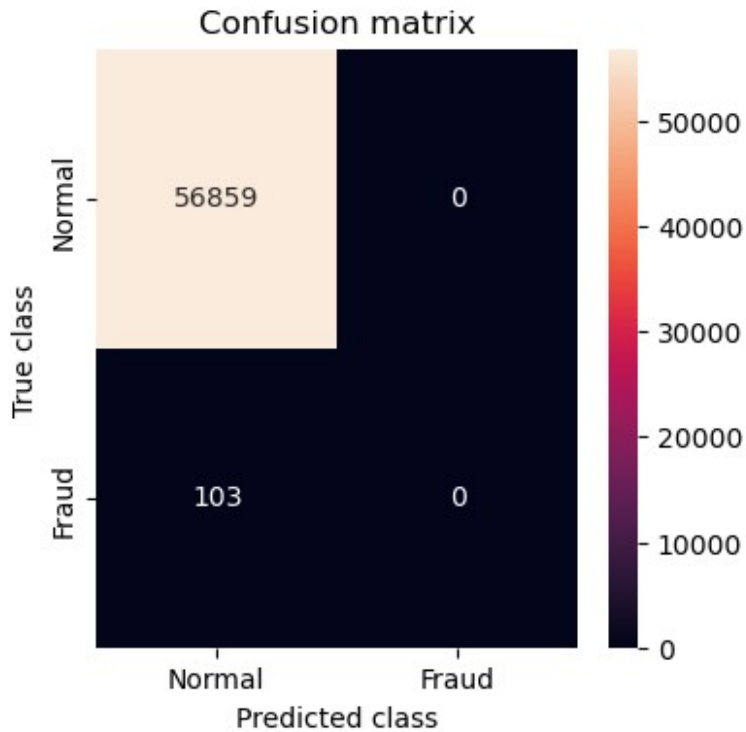
for name,group in groups:
    ax.plot(group.index,group.Reconstruction_error,marker='o',ms =
3.5,linestyle='',
            label = "Fraud" if name==1 else "Normal")
ax.hlines(threshold_fixed,ax.get_xlim()[0],ax.get_xlim()
[1],colors="r",zorder=100,label="Threshold")
ax.legend()
plt.title("Reconstructions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



```
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['pre
d']))
print("Recall :",recall_score(error_df['True_class'],error_df['pred']
))
print("Precision :",precision_score(error_df['True_class'],error_df['p
red']))
```



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))
```