Autoencoder anomaly detection

October 2, 2023

[37]:
```
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"]
```

[38]:
```
dataset = pd.read_csv("F:\College Data\Deep L\PV 4\DL\creditcard.csv")
```

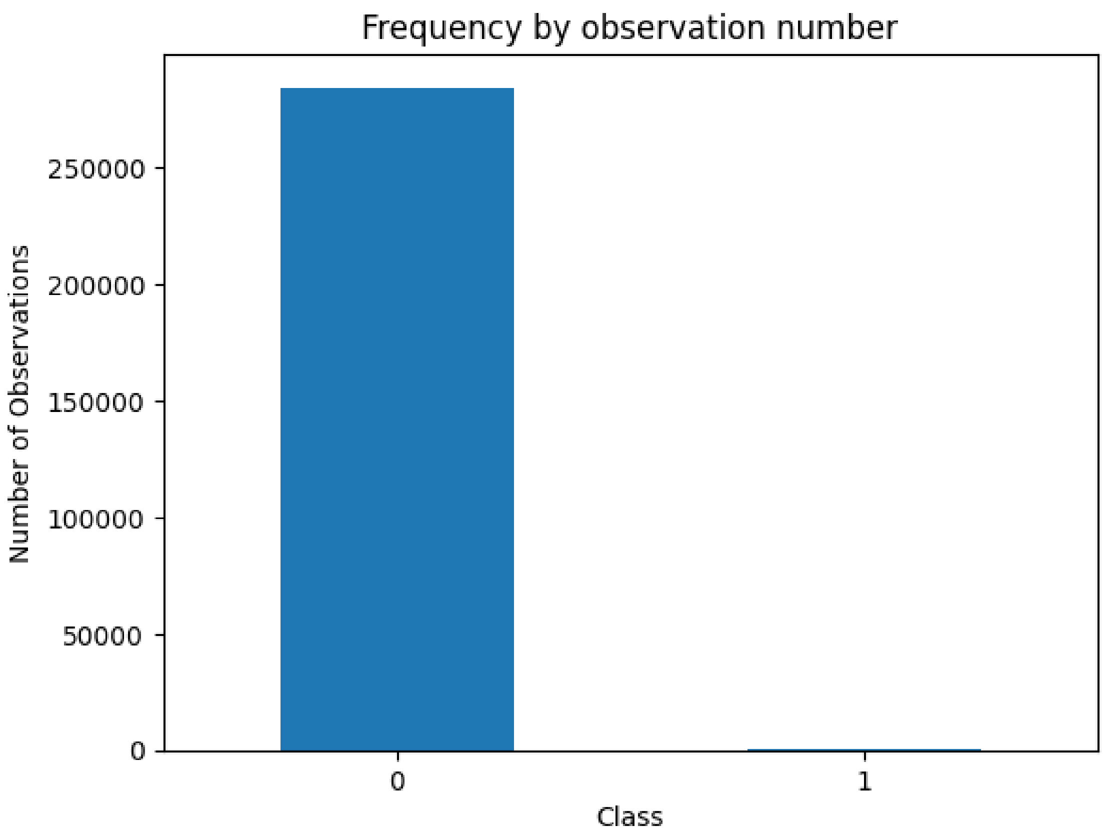
[39]:
```
#check for any null values
print("Any nulls in the dataset",dataset.isnull().values.any())
print('-------')
print("No. of unique labels",len(dataset['Class'].unique()))
print("Label values",dataset.Class.unique())

#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
Class
0    284315
1       492
```

```
Name: count, dtype: int64
```

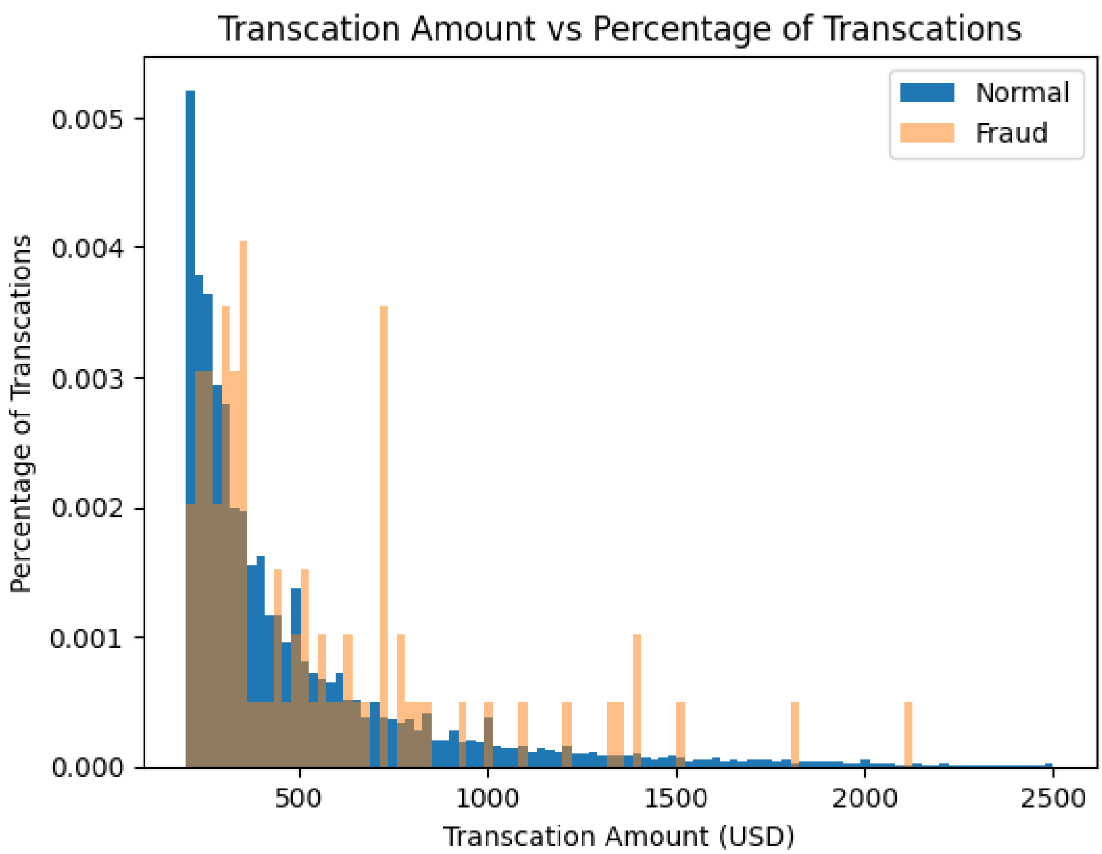
[40]:
```python
#visualizing the imbalanced dataset
count_classes = pd.value_counts(dataset['Class'],sort=True)
count_classes.plot(kind='bar',rot=0)
plt.xticks(range(len(dataset['Class'].unique())),dataset.Class.unique())
plt.title("Frequency by observation number")
plt.xlabel("Class")
plt.ylabel("Number of Observations")
```

[40]:
```
Text(0, 0.5, 'Number of Observations')
```



[41]:
```python
#Save the normal and fradulent transcations in seperate dataframe
normal_dataset = dataset[dataset.Class == 0]
fraud_dataset = dataset[dataset.Class == 1]

#Visualize transcation amounts for normal and fraudulent transcations
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')
```

```python
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()
```



[42]:
```python
dataset
```

[42]:
```
            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]
```

[43]:
```python
sc = StandardScaler()
dataset['Time'] = sc.fit_transform(dataset['Time'].values.reshape(-1,1))
dataset['Amount'] = sc.fit_transform(dataset['Amount'].values.reshape(-1,1))
```

[44]:
```
raw_data = dataset.values
#The last element contains if the transcation is normal which is represented by␣
↪0 and if fraud then 1
labels = raw_data[:,-1]

#The other data points are the electrocadriogram 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)
```

[45]:
```
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)
```

[46]:
```
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
```

[47]:
```
nb_epoch = 20
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
```

[48]:

```python
#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: "model_2"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_3 (InputLayer)        [(None, 30)]              0

 dense_12 (Dense)            (None, 14)                434

 dropout_4 (Dropout)         (None, 14)                0

 dense_13 (Dense)            (None, 7)                 105

 dense_14 (Dense)            (None, 4)                 32

 dense_15 (Dense)            (None, 7)                 35

 dropout_5 (Dropout)         (None, 7)                 0

 dense_16 (Dense)            (None, 14)                112

 dense_17 (Dense)            (None, 30)                450

=================================================================
Total params: 1168 (4.56 KB)
Trainable params: 1168 (4.56 KB)
Non-trainable params: 0 (0.00 Byte)
```

```
-----------------------------------------------------------------
```

[49]:
```
cp = tf.keras.callbacks.ModelCheckpoint(filepath="autoencoder_fraud.
 ↪h5",mode='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
)
```

[50]:
```
autoencoder.compile(metrics=['accuracy'],loss=␣
 ↪'mean_squared_error',optimizer='adam')
```

[51]:
```
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
```

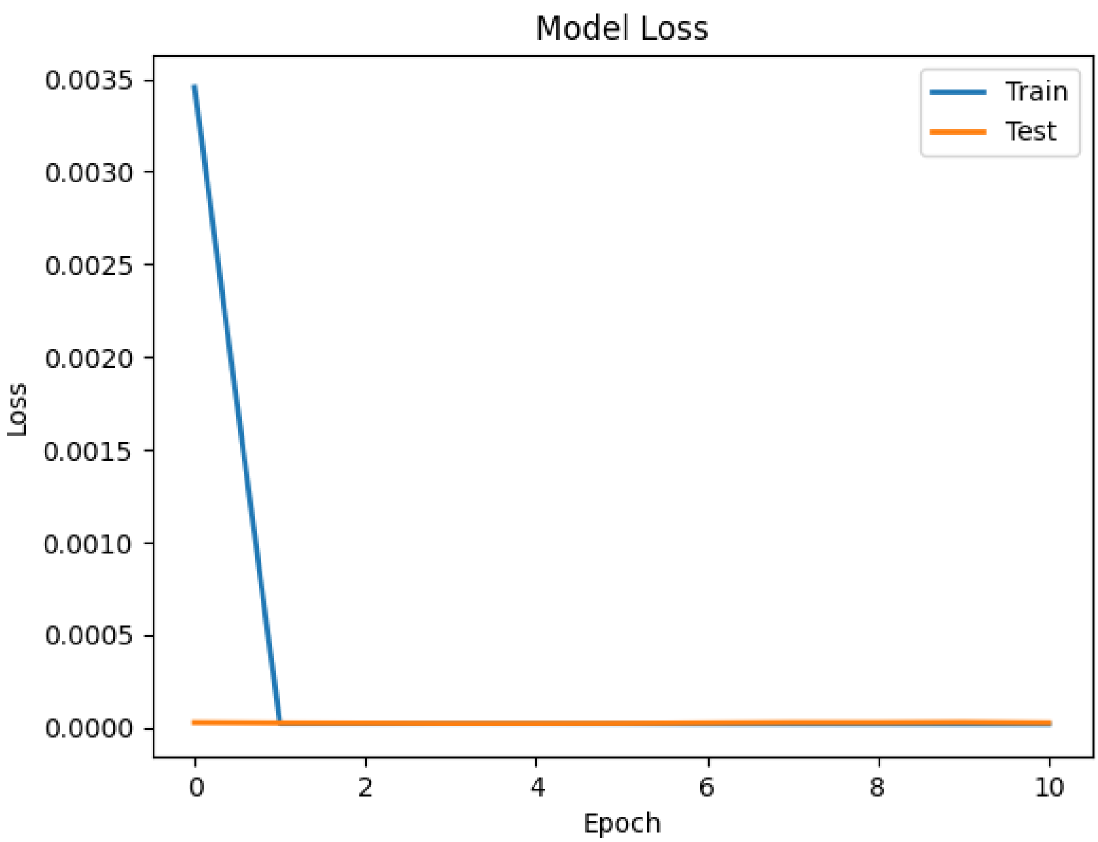
```
Epoch 1/20
3545/3554 [============================>.] - ETA: 0s - loss: 0.0035 - accuracy:
0.0305
Epoch 1: val_loss improved from inf to 0.00003, saving model to
autoencoder_fraud.h5

C:\Users\Acer\AppData\Local\Programs\Python\Python311\Lib\site-
packages\keras\src\engine\training.py:3000: UserWarning: You are saving your
model as an HDF5 file via `model.save()`. This file format is considered legacy.
We recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')`.
  saving_api.save_model(

3554/3554 [==============================] - 14s 3ms/step - loss: 0.0035 -
accuracy: 0.0304 - val_loss: 2.5545e-05 - val_accuracy: 0.0024
Epoch 2/20
3541/3554 [============================>.] - ETA: 0s - loss: 1.9480e-05 -
accuracy: 0.0564
Epoch 2: val_loss improved from 0.00003 to 0.00002, saving model to
autoencoder_fraud.h5
3554/3554 [==============================] - 11s 3ms/step - loss: 1.9475e-05 -
accuracy: 0.0563 - val_loss: 2.3230e-05 - val_accuracy: 0.0024
Epoch 3/20
3548/3554 [============================>.] - ETA: 0s - loss: 1.9425e-05 -
accuracy: 0.0657
Epoch 3: val_loss improved from 0.00002 to 0.00002, saving model to
```

```
autoencoder_fraud.h5
3554/3554 [==============================] - 12s 3ms/step - loss: 1.9421e-05 -
accuracy: 0.0658 - val_loss: 2.2306e-05 - val_accuracy: 0.0010
Epoch 4/20
3547/3554 [============================>.] - ETA: 0s - loss: 1.9538e-05 -
accuracy: 0.0587
Epoch 4: val_loss improved from 0.00002 to 0.00002, saving model to
autoencoder_fraud.h5
3554/3554 [==============================] - 12s 3ms/step - loss: 1.9538e-05 -
accuracy: 0.0586 - val_loss: 2.0339e-05 - val_accuracy: 0.0024
Epoch 5/20
3553/3554 [============================>.] - ETA: 0s - loss: 1.9482e-05 -
accuracy: 0.0615
Epoch 5: val_loss did not improve from 0.00002
3554/3554 [==============================] - 11s 3ms/step - loss: 1.9483e-05 -
accuracy: 0.0615 - val_loss: 2.0421e-05 - val_accuracy: 0.0661
Epoch 6/20
3552/3554 [============================>.] - ETA: 0s - loss: 1.9032e-05 -
accuracy: 0.0696
Epoch 6: val_loss did not improve from 0.00002
3554/3554 [==============================] - 11s 3ms/step - loss: 1.9030e-05 -
accuracy: 0.0695 - val_loss: 2.1059e-05 - val_accuracy: 0.0514
Epoch 7/20
3551/3554 [============================>.] - ETA: 0s - loss: 1.8035e-05 -
accuracy: 0.1084
Epoch 7: val_loss did not improve from 0.00002
3554/3554 [==============================] - 11s 3ms/step - loss: 1.8035e-05 -
accuracy: 0.1084 - val_loss: 2.3646e-05 - val_accuracy: 0.0257
Epoch 8/20
3538/3554 [============================>.] - ETA: 0s - loss: 1.7710e-05 -
accuracy: 0.1286
Epoch 8: val_loss did not improve from 0.00002
3554/3554 [==============================] - 12s 3ms/step - loss: 1.7702e-05 -
accuracy: 0.1286 - val_loss: 2.5736e-05 - val_accuracy: 0.0257
Epoch 9/20
3541/3554 [============================>.] - ETA: 0s - loss: 1.7467e-05 -
accuracy: 0.1511
Epoch 9: val_loss did not improve from 0.00002
3554/3554 [==============================] - 12s 3ms/step - loss: 1.7465e-05 -
accuracy: 0.1511 - val_loss: 2.5645e-05 - val_accuracy: 0.0270
Epoch 10/20
3552/3554 [============================>.] - ETA: 0s - loss: 1.7224e-05 -
accuracy: 0.1891
Epoch 10: val_loss did not improve from 0.00002
3554/3554 [==============================] - 12s 3ms/step - loss: 1.7226e-05 -
accuracy: 0.1891 - val_loss: 2.7170e-05 - val_accuracy: 0.0284
Epoch 11/20
3548/3554 [============================>.] - ETA: 0s - loss: 1.6969e-05 -
```

```
accuracy: 0.2355
Epoch 11: val_loss did not improve from 0.00002
Restoring model weights from the end of the best epoch: 1.
3554/3554 [==============================] - 12s 3ms/step - loss: 1.6970e-05 -
accuracy: 0.2356 - val_loss: 2.4134e-05 - val_accuracy: 0.0262
Epoch 11: early stopping
```

[52]:

```
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()
```



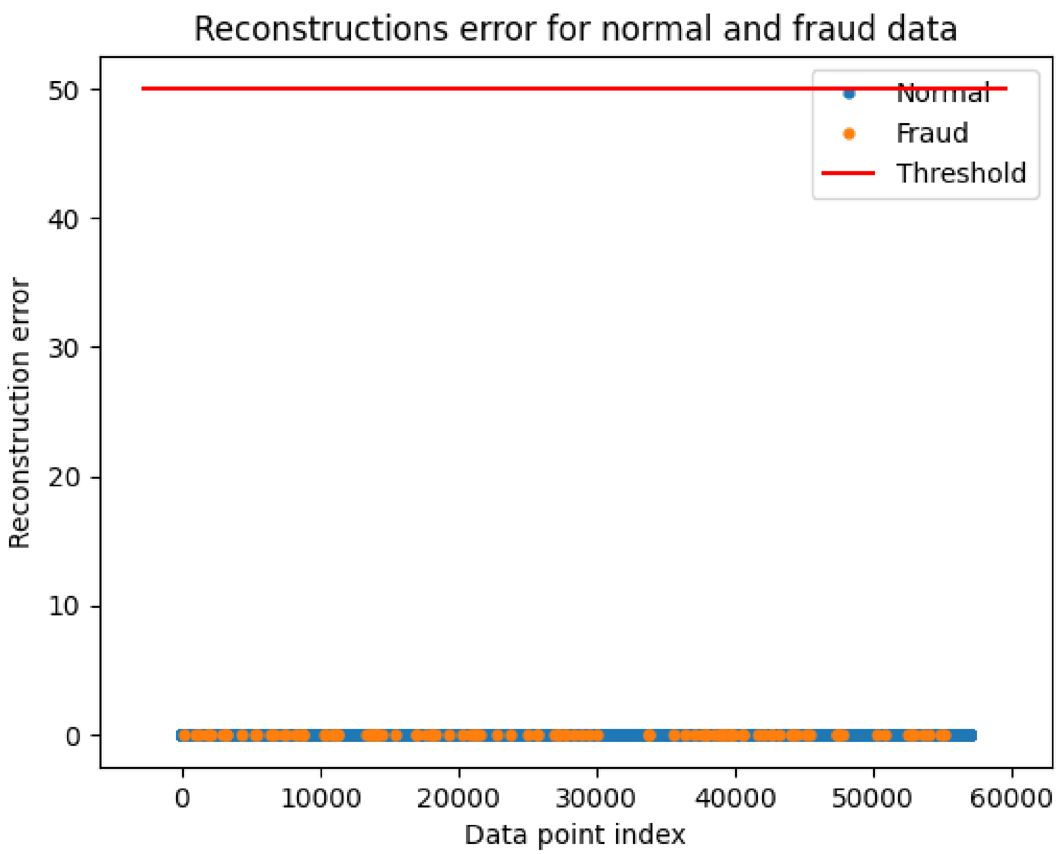
[53]:

```
test_x_predictions = autoencoder.predict(test_data)
mse = np.mean(np.power(test_data - test_x_predictions, 2),axis = 1)
```

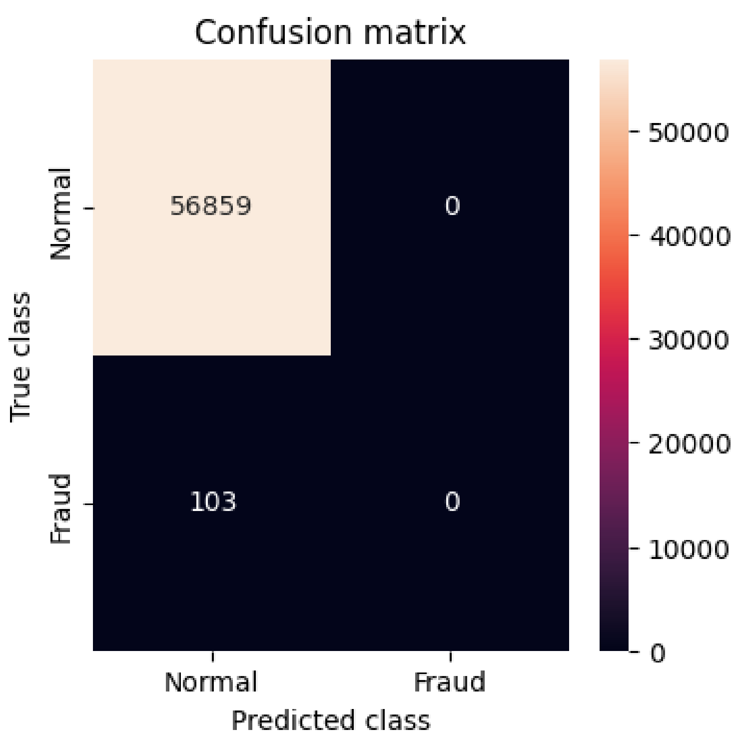
```
error_df = pd.DataFrame({'Reconstruction_error':mse,
                         'True_class':test_labels})
```

```
1781/1781 [==============================] - 3s 2ms/step
```

[54]:
```
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()
```



[55]:
```
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\Acer\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_classification.py:1469: 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))
```

[ ]:

[ ]: