In [1]:
```
#Name: Ankita Durgude
#Roll No: 18
#Batch: B1
#RMDSSOE BE IT
```

In [2]:
```
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"]
```

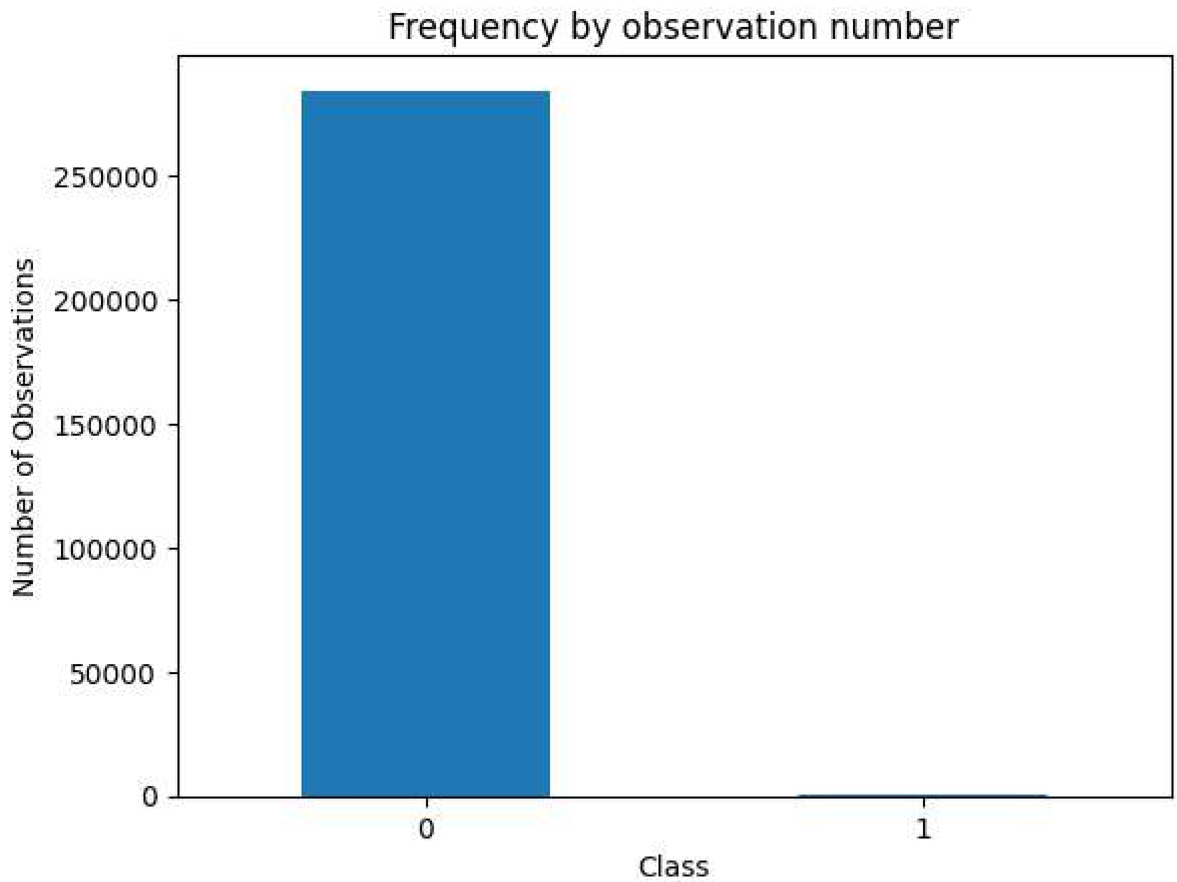
In [3]:
```
dataset = pd.read_csv("creditcard.csv")
```

In [4]:
```
#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))
```

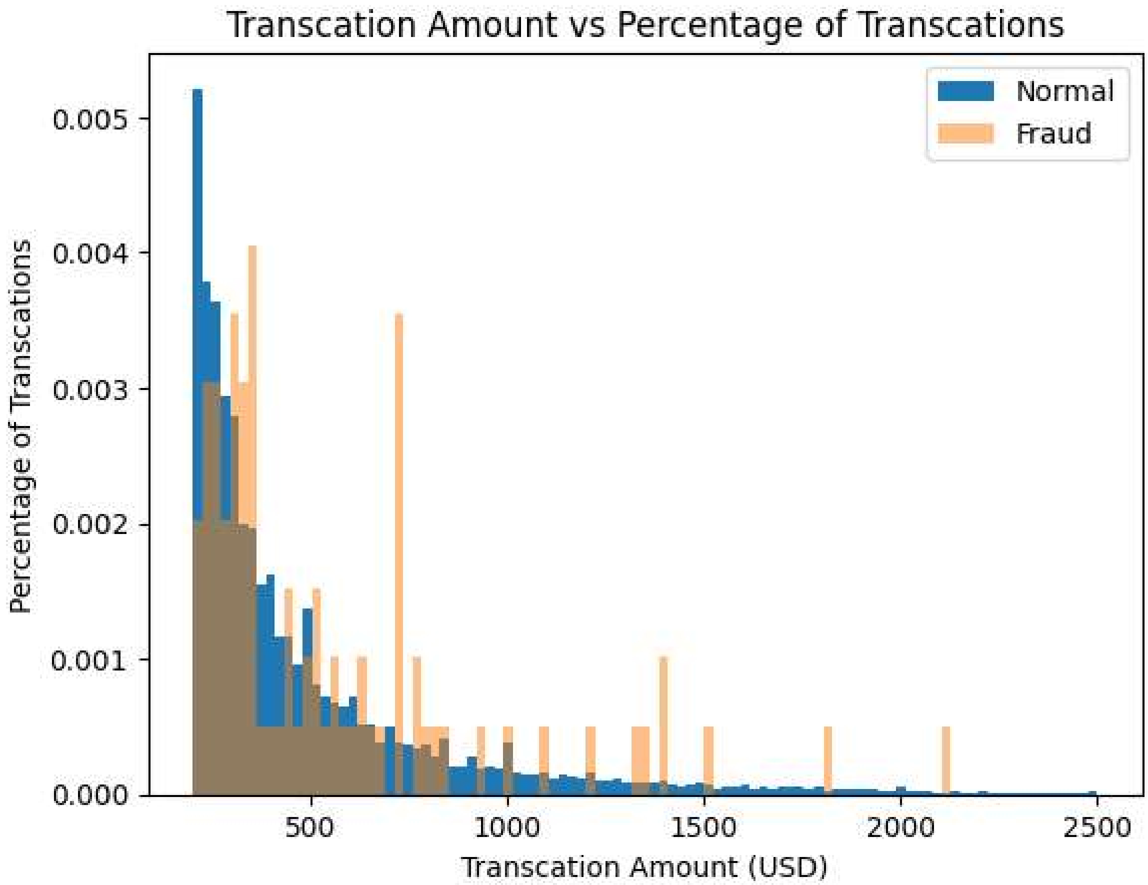
```
Any nulls in the dataset False
-------
No. of unique labels 2
Label values [0 1]
-------
Break down of Normal and Fraud Transcations
0    284315
1       492
Name: Class, dtype: int64
```

In [5]:
```
#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[5]:
```
Text(0, 0.5, 'Number of Observations')
```



In [6]:
```
#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')
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 [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 transcation is normal which is represented by 0 and
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
```

In [9]:
```
dataset
```

Out[9]:

	Time	V1	V2	V3	V4	V5	V6	V7	
0	-1.996583	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098
1	-1.996583	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085
2	-1.996562	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.24
3	-1.996562	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.37
4	-1.996541	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.27
...	...	...	...	...	...	...	...	...	...
284802	1.641931	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	7.30
284803	1.641952	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	0.29
284804	1.641974	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	0.70
284805	1.641974	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	0.67
284806	1.642058	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006	-0.41

284807 rows × 31 columns

In [10]:
```
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 [11]:
```
raw_data = dataset.values
#The last element contains if the transcation is normal which is represented by 0 and
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
```

In [12]:
```
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 [13]:
```
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 [14]:

```
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 [15]:

```
#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: "model"
_________________________________________________________________
 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
_________________________________________________________________
```

In [16]:
```
cp = tf.keras.callbacks.ModelCheckpoint(filepath="autoencoder_fraud.h5",mode='min',mor
#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
)
```

In [17]:
```
autoencoder.compile(metrics=['accuracy'],loss= 'mean_squared_error',optimizer='adam')
```

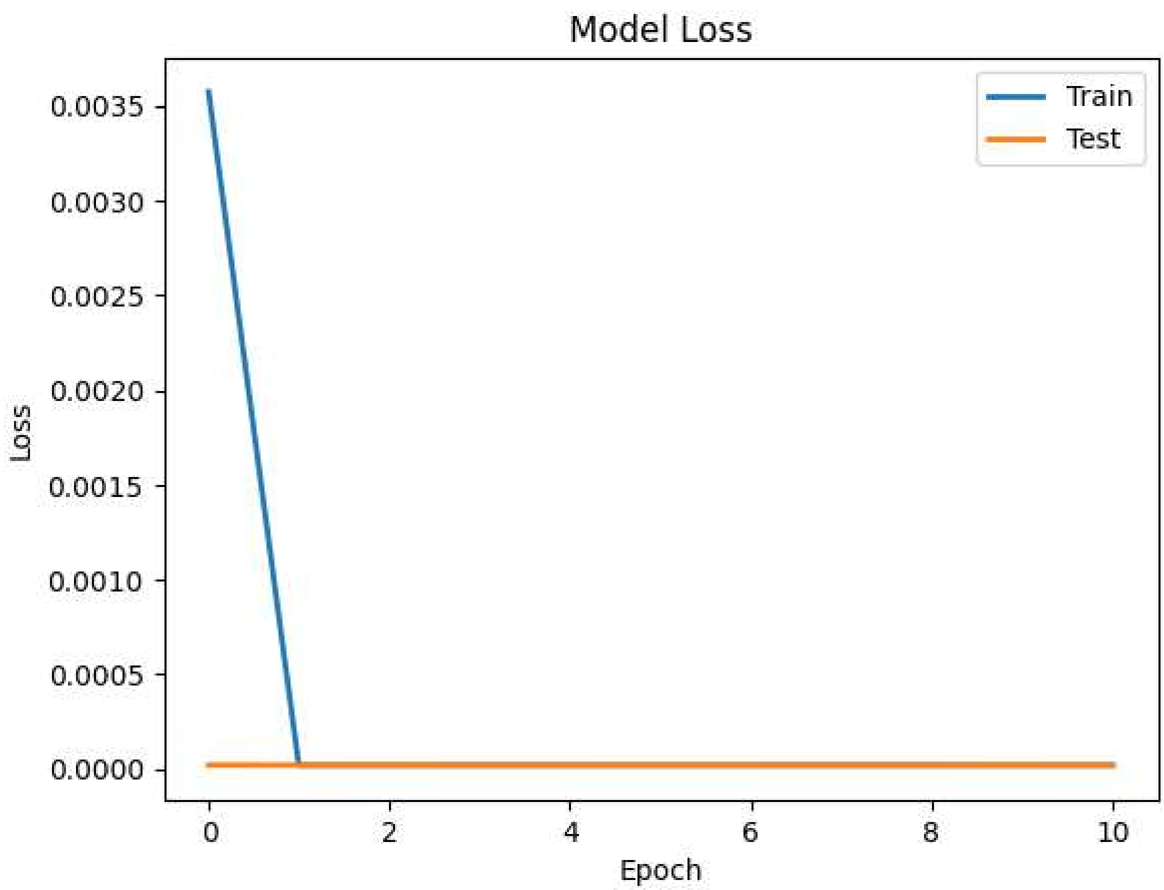
In [18]:
```
history = autoencoder.fit(normal_train_data,normal_train_data,epochs = nb_epoch,
                         batch_size = batch_size,shuffle = True,
                         validation_data = (test_data,test_data),
                         verbose=1,
                         callbacks = [cp,early_stop]).history
```

```
Epoch 1/50
3541/3554 [============================>.] - ETA: 0s - loss: 0.0036 - accuracy: 0.085
4
Epoch 1: val_loss improved from inf to 0.00002, saving model to autoencoder_fraud.h5
3554/3554 [==============================] - 7s 2ms/step - loss: 0.0036 - accuracy:
0.0854 - val_loss: 2.0842e-05 - val_accuracy: 0.1279
Epoch 2/50
3545/3554 [============================>.] - ETA: 0s - loss: 1.9302e-05 - accuracy:
0.0674
Epoch 2: val_loss improved from 0.00002 to 0.00002, saving model to autoencoder_frau
d.h5
3554/3554 [==============================] - 6s 2ms/step - loss: 1.9347e-05 - accurac
y: 0.0675 - val_loss: 2.0363e-05 - val_accuracy: 0.0661
Epoch 3/50
3540/3554 [============================>.] - ETA: 0s - loss: 1.9512e-05 - accuracy:
0.0625
Epoch 3: val_loss did not improve from 0.00002
3554/3554 [==============================] - 6s 2ms/step - loss: 1.9513e-05 - accurac
y: 0.0625 - val_loss: 2.0419e-05 - val_accuracy: 0.0251
Epoch 4/50
3523/3554 [============================>.] - ETA: 0s - loss: 1.9556e-05 - accuracy:
0.0601
Epoch 4: val_loss improved from 0.00002 to 0.00002, saving model to autoencoder_frau
d.h5
3554/3554 [==============================] - 6s 2ms/step - loss: 1.9551e-05 - accurac
y: 0.0601 - val_loss: 1.9851e-05 - val_accuracy: 0.0043
Epoch 5/50
3534/3554 [============================>.] - ETA: 0s - loss: 1.9508e-05 - accuracy:
0.0763
Epoch 5: val_loss did not improve from 0.00002
3554/3554 [==============================] - 7s 2ms/step - loss: 1.9501e-05 - accurac
y: 0.0765 - val_loss: 2.0061e-05 - val_accuracy: 0.0596
Epoch 6/50
3553/3554 [============================>.] - ETA: 0s - loss: 1.9573e-05 - accuracy:
0.0600
Epoch 6: val_loss did not improve from 0.00002
3554/3554 [==============================] - 7s 2ms/step - loss: 1.9573e-05 - accurac
y: 0.0600 - val_loss: 2.0250e-05 - val_accuracy: 0.0133
Epoch 7/50
3531/3554 [============================>.] - ETA: 0s - loss: 1.9576e-05 - accuracy:
0.0608
Epoch 7: val_loss did not improve from 0.00002
3554/3554 [==============================] - 6s 2ms/step - loss: 1.9562e-05 - accurac
y: 0.0608 - val_loss: 2.0168e-05 - val_accuracy: 0.0343
Epoch 8/50
3522/3554 [============================>.] - ETA: 0s - loss: 1.9568e-05 - accuracy:
0.0611
Epoch 8: val_loss did not improve from 0.00002
3554/3554 [==============================] - 6s 2ms/step - loss: 1.9552e-05 - accurac
y: 0.0613 - val_loss: 2.0155e-05 - val_accuracy: 0.0371
Epoch 9/50
3528/3554 [============================>.] - ETA: 0s - loss: 1.9568e-05 - accuracy:
0.0596
Epoch 9: val_loss did not improve from 0.00002
3554/3554 [==============================] - 6s 2ms/step - loss: 1.9561e-05 - accurac
y: 0.0594 - val_loss: 2.0122e-05 - val_accuracy: 0.0596
Epoch 10/50
```

```
3522/3554 [============================>.] - ETA: 0s - loss: 1.9557e-05 - accuracy:
0.0625
Epoch 10: val_loss did not improve from 0.00002
3554/3554 [==============================] - 6s 2ms/step - loss: 1.9549e-05 - accurac
y: 0.0623 - val_loss: 2.0260e-05 - val_accuracy: 0.0236
Epoch 11/50
3535/3554 [============================>.] - ETA: 0s - loss: 1.9545e-05 - accuracy:
0.0617
Epoch 11: val_loss did not improve from 0.00002
Restoring model weights from the end of the best epoch: 1.
3554/3554 [==============================] - 6s 2ms/step - loss: 1.9546e-05 - accurac
y: 0.0617 - val_loss: 2.0145e-05 - val_accuracy: 0.0109
Epoch 11: early stopping
```

In [19]:

```
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()
```

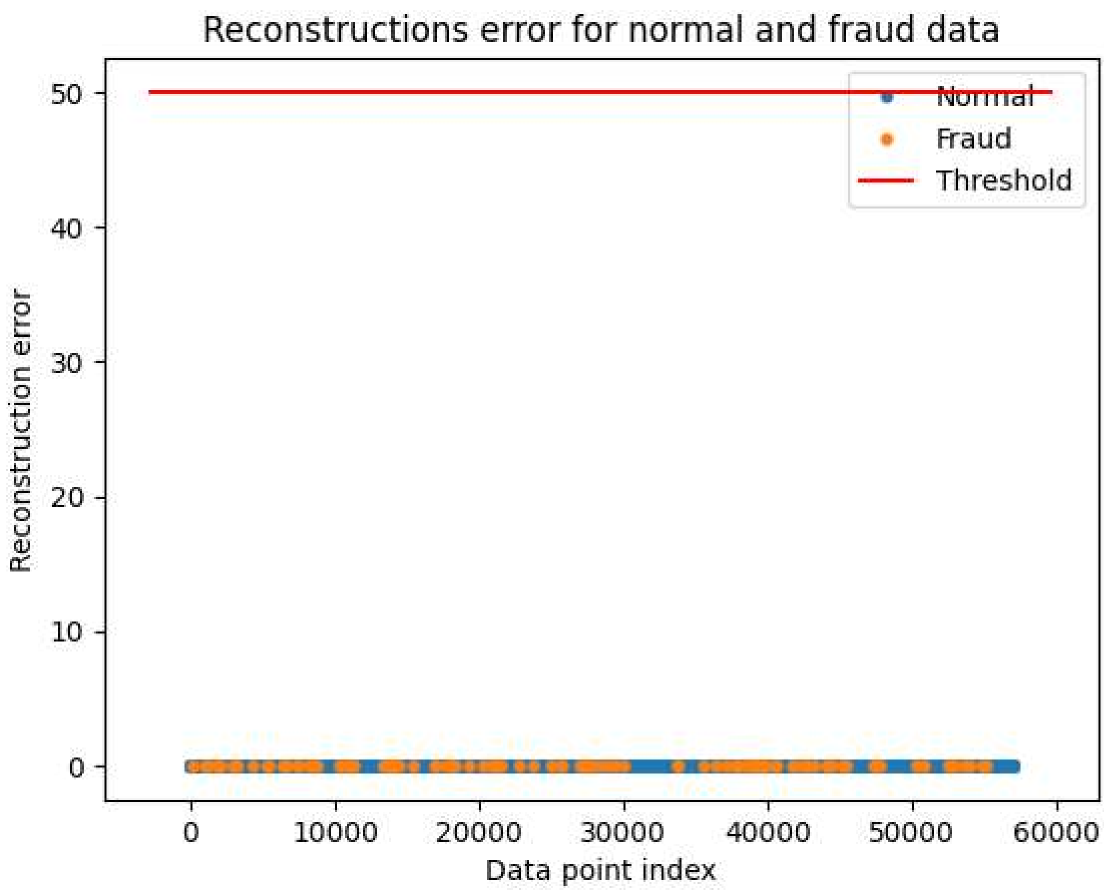


In [20]:

```
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})
```

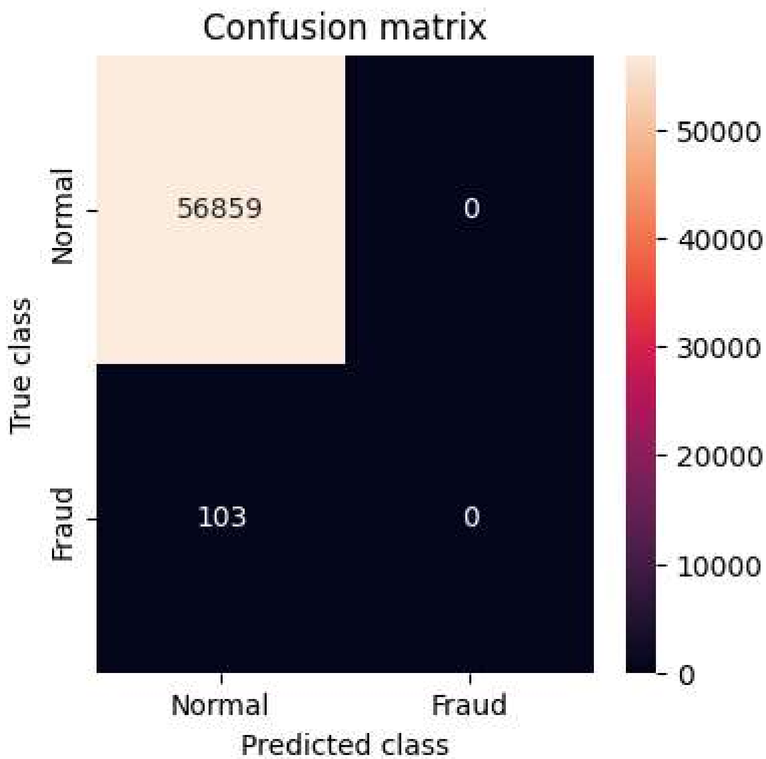
```
1781/1781 [==============================] - 2s 880us/step
```

In [21]:
```
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,labe
ax.legend()
plt.title("Reconstructions error for normal and fraud data")
plt.ylabel("Reconstruction error")
plt.xlabel("Data point index")
plt.show()
```



In [22]:
```
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\admin\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\metr
ics\_classification.py:1334: UndefinedMetricWarning: Precision is ill-defined and bei
ng set to 0.0 due to no predicted samples. Use `zero_division` parameter to control t
his behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [ ]: