In [ ]:
```
                              DL Expt-4
```

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, precisi

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

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

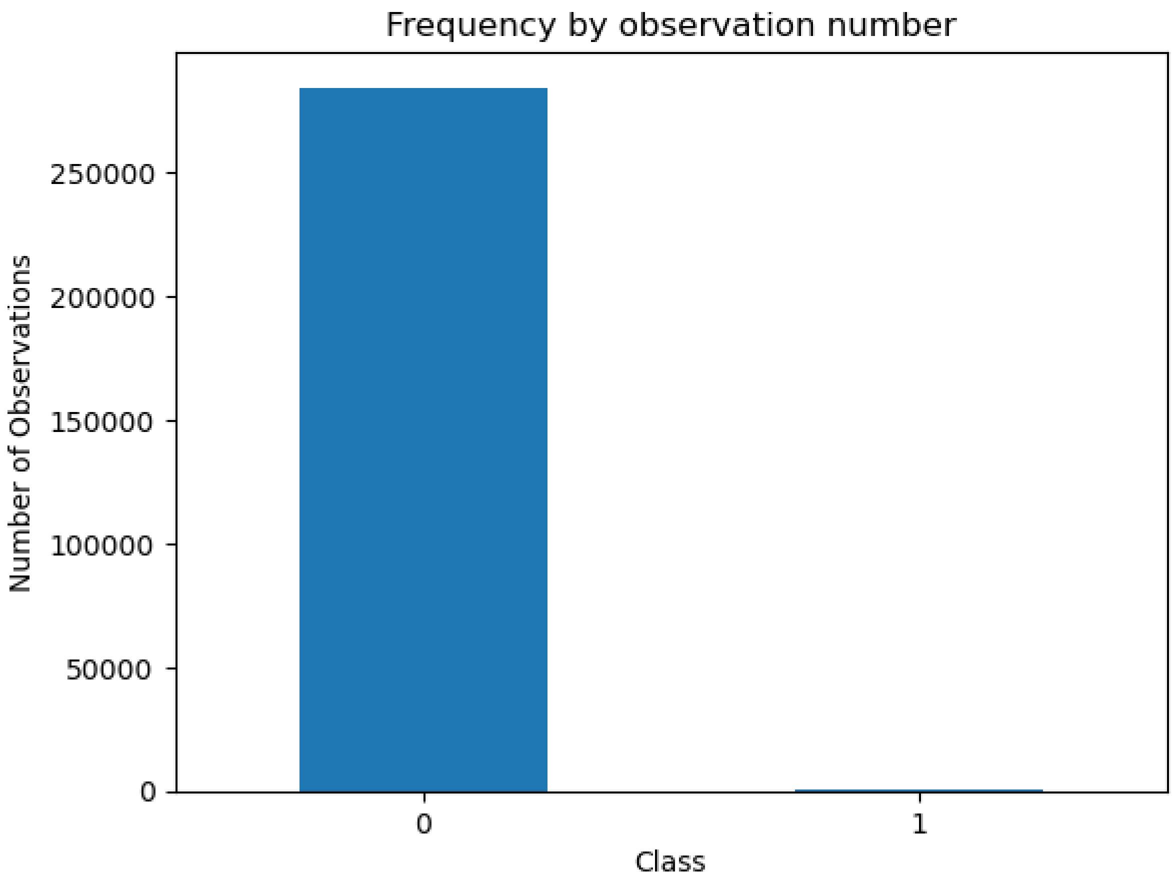
In [3]:
```
#check for any null values
print("Any nulls in the dataset",dataset.isnull().values.any())
print('-------')
print("No. of unique labels",len(dataset['Class'].unique()))
print("Label values",dataset.Class.unique())

#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")
```

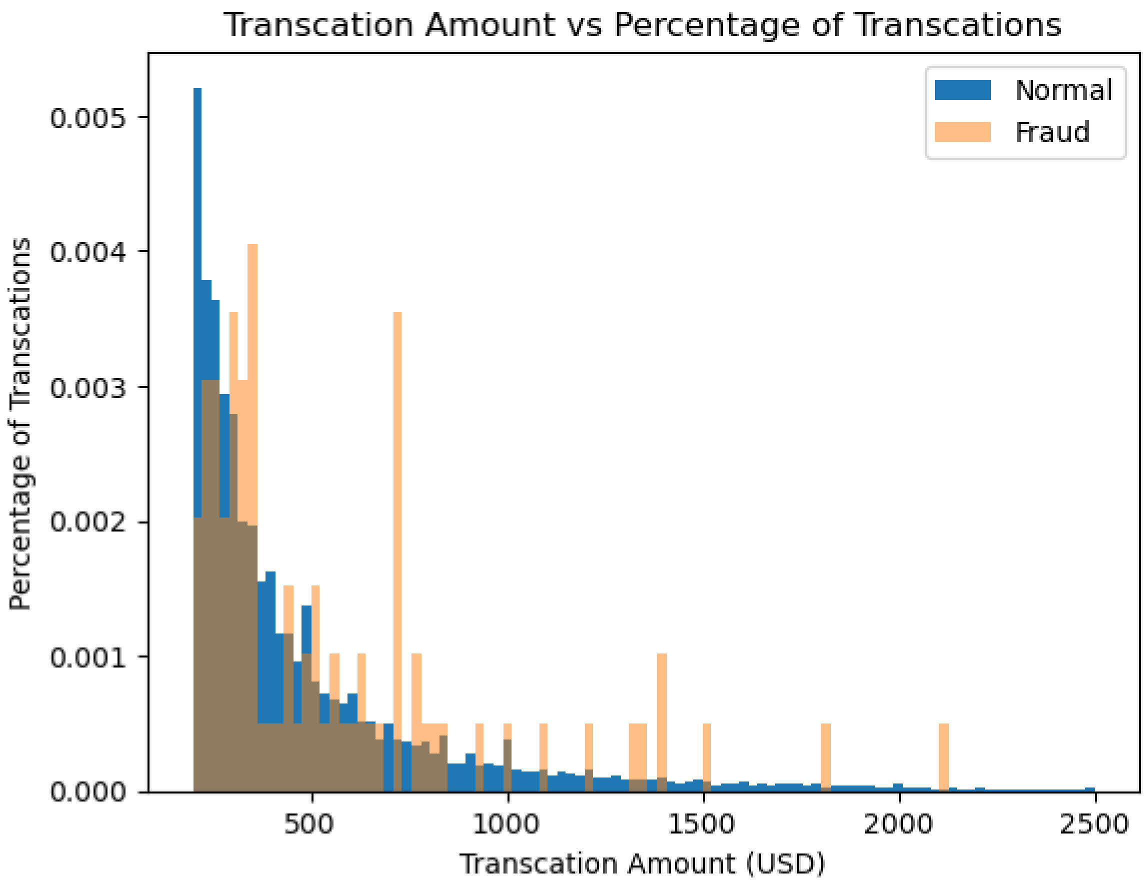
Out[4]:
```
Text(0, 0.5, 'Number of Observations')
```



In [5]:

```
#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 [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	0.0
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.0
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.2
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.3
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.2
...	...	...	...	...	...	...	...	...	
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	7.3
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	0.2
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	0.7
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	0.6
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006	-0.4

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 transcation is normal which is represented by 0 a
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_s
```

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 #   
=================================================================
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 [13]:

```
cp = tf.keras.callbacks.ModelCheckpoint(filepath="autoencoder_fraud.h5",mode='min',
#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 [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.
0312WARNING:tensorflow:Callbacks method `on_train_batch_end` is slow compared to t
he batch time (batch time: 0.0000s vs `on_train_batch_end` time: 0.0010s). Check y
our 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_fr
aud.h5
3554/3554 [==============================] - 2s 642us/step - loss: 0.0050 - accura
cy: 0.0562 - val_loss: 5.2896e-04 - val_accuracy: 0.0236
Epoch 2/50
3469/3554 [============================>.] - ETA: 0s - loss: 1.9377e-05 - accurac
y: 0.0736
Epoch 00002: val_loss improved from 0.00053 to 0.00046, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 566us/step - loss: 1.9396e-05 - ac
curacy: 0.0737 - val_loss: 4.5975e-04 - val_accuracy: 0.0236
Epoch 3/50
3495/3554 [============================>.] - ETA: 0s - loss: 1.9433e-05 - accurac
y: 0.0639
Epoch 00003: val_loss improved from 0.00046 to 0.00043, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 592us/step - loss: 1.9440e-05 - ac
curacy: 0.0636 - val_loss: 4.3223e-04 - val_accuracy: 0.0236
Epoch 4/50
3508/3554 [============================>.] - ETA: 0s - loss: 1.9483e-05 - accurac
y: 0.0640
Epoch 00004: val_loss improved from 0.00043 to 0.00038, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 693us/step - loss: 1.9526e-05 - ac
curacy: 0.0641 - val_loss: 3.8281e-04 - val_accuracy: 0.0236
Epoch 5/50
3516/3554 [============================>.] - ETA: 0s - loss: 1.9479e-05 - accurac
y: 0.0620
Epoch 00005: val_loss improved from 0.00038 to 0.00033, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 576us/step - loss: 1.9505e-05 - ac
curacy: 0.0621 - val_loss: 3.3468e-04 - val_accuracy: 0.1279
Epoch 6/50
3501/3554 [============================>.] - ETA: 0s - loss: 1.9459e-05 - accurac
y: 0.0663
Epoch 00006: val_loss improved from 0.00033 to 0.00027, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 579us/step - loss: 1.9461e-05 - ac
curacy: 0.0664 - val_loss: 2.7270e-04 - val_accuracy: 0.1279
Epoch 7/50
3451/3554 [============================>.] - ETA: 0s - loss: 1.9352e-05 - accurac
y: 0.0638
Epoch 00007: val_loss improved from 0.00027 to 0.00024, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 600us/step - loss: 1.9421e-05 - ac
curacy: 0.0643 - val_loss: 2.3810e-04 - val_accuracy: 0.0251
Epoch 8/50
3503/3554 [============================>.] - ETA: 0s - loss: 1.9365e-05 - accurac
y: 0.0710
Epoch 00008: val_loss improved from 0.00024 to 0.00019, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 566us/step - loss: 1.9355e-05 - ac
curacy: 0.0708 - val_loss: 1.9277e-04 - val_accuracy: 0.0251
Epoch 9/50
3536/3554 [============================>.] - ETA: 0s - loss: 1.9274e-05 - accurac
y: 0.0710
Epoch 00009: val_loss improved from 0.00019 to 0.00016, saving model to autoencode
```

```
r_fraud.h5
3554/3554 [==============================] - 2s 575us/step - loss: 1.9277e-05 - ac
curacy: 0.0711 - val_loss: 1.6159e-04 - val_accuracy: 0.0251
Epoch 10/50
3470/3554 [============================>.] - ETA: 0s - loss: 1.9170e-05 - accurac
y: 0.0754
Epoch 00010: val_loss improved from 0.00016 to 0.00011, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 598us/step - loss: 1.9138e-05 - ac
curacy: 0.0758 - val_loss: 1.0516e-04 - val_accuracy: 0.0251
Epoch 11/50
3511/3554 [============================>.] - ETA: 0s - loss: 1.8960e-05 - accurac
y: 0.0844
Epoch 00011: val_loss improved from 0.00011 to 0.00009, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 689us/step - loss: 1.8965e-05 - ac
curacy: 0.0843 - val_loss: 9.0067e-05 - val_accuracy: 0.0252
Epoch 12/50
3502/3554 [============================>.] - ETA: 0s - loss: 1.8767e-05 - accurac
y: 0.0838
Epoch 00012: val_loss improved from 0.00009 to 0.00007, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 606us/step - loss: 1.8748e-05 - ac
curacy: 0.0845 - val_loss: 6.6048e-05 - val_accuracy: 0.0252
Epoch 13/50
3449/3554 [============================>.] - ETA: 0s - loss: 1.8550e-05 - accurac
y: 0.0849
Epoch 00013: val_loss improved from 0.00007 to 0.00005, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 599us/step - loss: 1.8576e-05 - ac
curacy: 0.0855 - val_loss: 5.4927e-05 - val_accuracy: 0.0253
Epoch 14/50
3500/3554 [============================>.] - ETA: 0s - loss: 1.8386e-05 - accurac
y: 0.0892
Epoch 00014: val_loss improved from 0.00005 to 0.00003, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 578us/step - loss: 1.8389e-05 - ac
curacy: 0.0892 - val_loss: 3.3855e-05 - val_accuracy: 0.0253
Epoch 15/50
3517/3554 [============================>.] - ETA: 0s - loss: 1.8035e-05 - accurac
y: 0.0925
Epoch 00015: val_loss did not improve from 0.00003
3554/3554 [==============================] - 2s 560us/step - loss: 1.8029e-05 - ac
curacy: 0.0924 - val_loss: 4.0921e-05 - val_accuracy: 0.0253
Epoch 16/50
3535/3554 [============================>.] - ETA: 0s - loss: 1.7700e-05 - accurac
y: 0.1055
Epoch 00016: val_loss did not improve from 0.00003
3554/3554 [==============================] - 2s 572us/step - loss: 1.7701e-05 - ac
curacy: 0.1056 - val_loss: 3.6986e-05 - val_accuracy: 0.0252
Epoch 17/50
3488/3554 [============================>.] - ETA: 0s - loss: 1.7497e-05 - accurac
y: 0.1210
Epoch 00017: val_loss did not improve from 0.00003
3554/3554 [==============================] - 2s 562us/step - loss: 1.7491e-05 - ac
curacy: 0.1214 - val_loss: 3.6741e-05 - val_accuracy: 0.0252
Epoch 18/50
3494/3554 [============================>.] - ETA: 0s - loss: 1.7332e-05 - accurac
y: 0.1364
Epoch 00018: val_loss improved from 0.00003 to 0.00003, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 585us/step - loss: 1.7327e-05 - ac
curacy: 0.1367 - val_loss: 3.0728e-05 - val_accuracy: 0.0253
Epoch 19/50
```

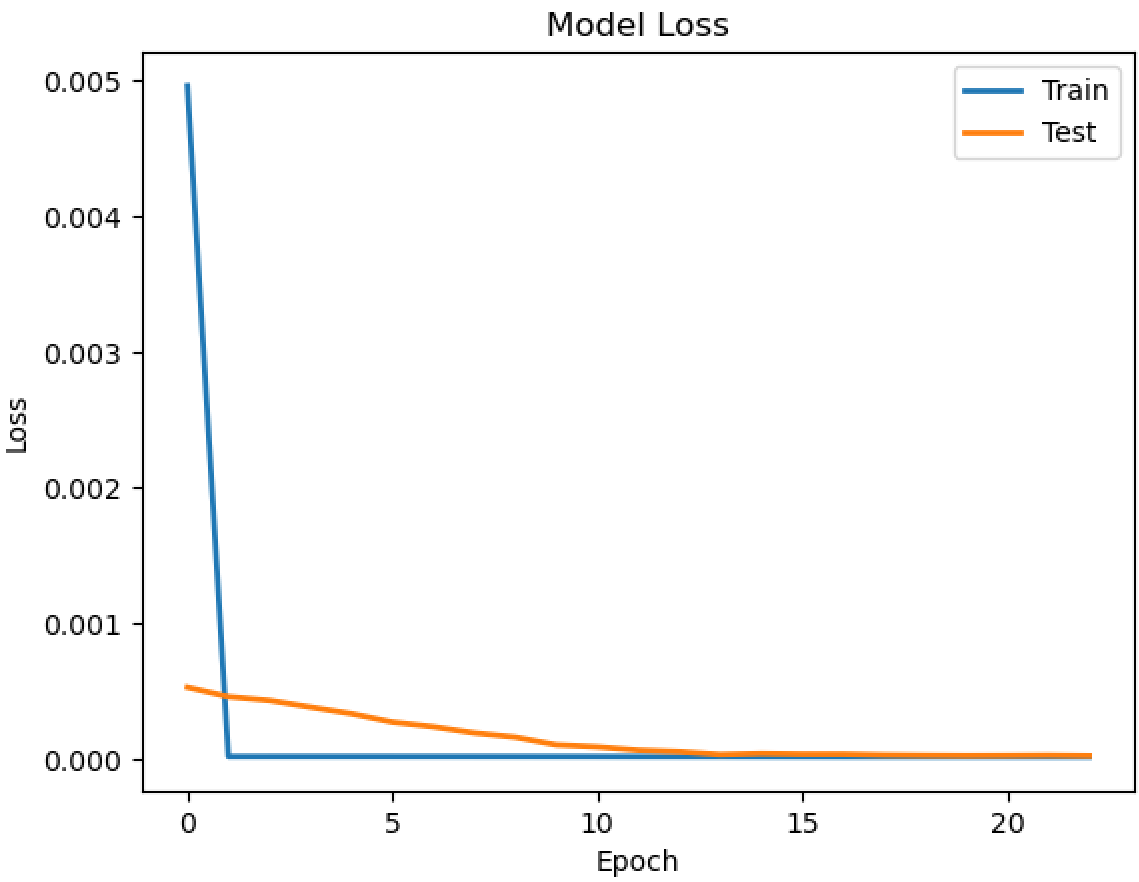
```
3523/3554 [============================>.] - ETA: 0s - loss: 1.7232e-05 - accurac
y: 0.1513
Epoch 00019: val_loss improved from 0.00003 to 0.00003, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 691us/step - loss: 1.7230e-05 - ac
curacy: 0.1514 - val_loss: 2.7787e-05 - val_accuracy: 0.0253
Epoch 20/50
3499/3554 [============================>.] - ETA: 0s - loss: 1.7147e-05 - accurac
y: 0.1674
Epoch 00020: val_loss improved from 0.00003 to 0.00003, saving model to autoencode
r_fraud.h5
3554/3554 [==============================] - 2s 594us/step - loss: 1.7145e-05 - ac
curacy: 0.1674 - val_loss: 2.5756e-05 - val_accuracy: 0.0253
Epoch 21/50
3524/3554 [============================>.] - ETA: 0s - loss: 1.7070e-05 - accurac
y: 0.1872
Epoch 00021: val_loss did not improve from 0.00003
3554/3554 [==============================] - 2s 559us/step - loss: 1.7076e-05 - ac
curacy: 0.1871 - val_loss: 2.6697e-05 - val_accuracy: 0.0252
Epoch 22/50
3489/3554 [============================>.] - ETA: 0s - loss: 1.7009e-05 - accurac
y: 0.2023
Epoch 00022: val_loss did not improve from 0.00003
3554/3554 [==============================] - 2s 622us/step - loss: 1.7025e-05 - ac
curacy: 0.2026 - val_loss: 2.8282e-05 - val_accuracy: 0.0251
Epoch 23/50
3539/3554 [============================>.] - ETA: 0s - loss: 1.6937e-05 - accurac
y: 0.2238
Epoch 00023: val_loss improved from 0.00003 to 0.00002, saving model to autoencode
r_fraud.h5
Restoring model weights from the end of the best epoch.
3554/3554 [==============================] - 2s 625us/step - loss: 1.6938e-05 - ac
curacy: 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})
```

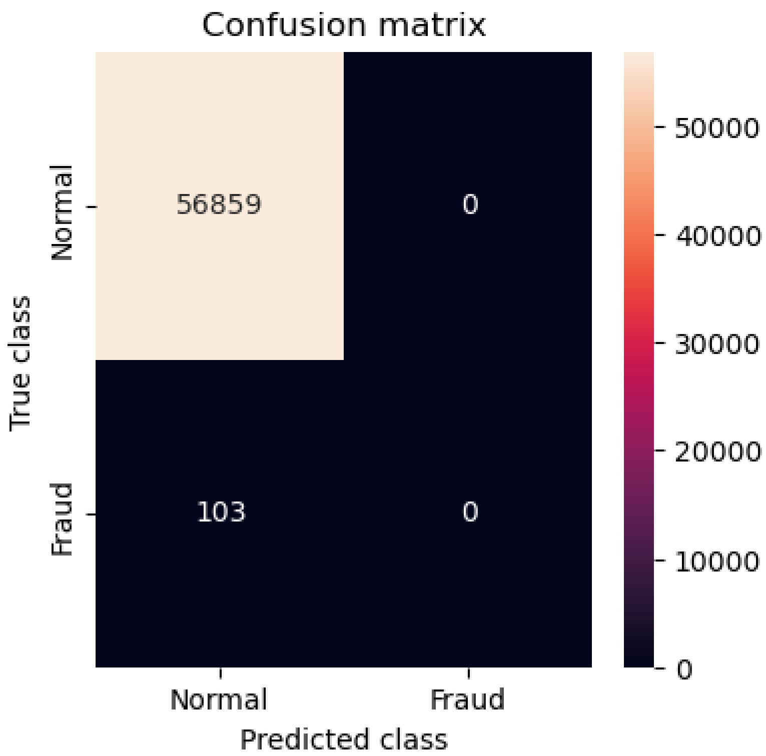
In [18]:
```
threshold_fixed = 50
groups = error_df.groupby('True_class')
fig,ax = plt.subplots()

for name,group in groups:
        ax.plot(group.index,group.Reconstruction_error,marker='o',ms = 3.5,linestyl
                label = "Fraud" if  name==1 else "Normal")
ax.hlines(threshold_fixed,ax.get_xlim()[0],ax.get_xlim()[1],colors="r",zorder=100,l
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=
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\_classifi
cation.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 beh
avior.
  _warn_prf(average, modifier, msg_start, len(result))
```