```
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
```

```
!pip install tensorflow --user
!pip install keras
!pip install daytime
!pip install torch
```

```
Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow)
Requirement already satisfied: h5py>=2.9.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.9.0)
Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (16
Requirement already satisfied: ml-dtypes==0.2.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.
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Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from tensorflow) (23.2)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<5.0.0dev,>=3.20.3
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from tensorflow) (67.7.2)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.16.0)
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Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/python3.10/dist-packages (from tensorf
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Requirement already satisfied: tensorboard<2.15,>=2.14 in /usr/local/lib/python3.10/dist-packages (from tensorfl
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Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.10/dist-packages (from astunparse>=1
Requirement already satisfied: google-auth<3,>=1.6.3 in /usr/local/lib/python3.10/dist-packages (from tensorboar
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Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.10/dist-packages (from tensorboar
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/lib/python3.10/dist-package
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.
Requirement already satisfied: cachetools<6.0,>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from google-
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.10/dist-packages (from google-a
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.10/dist-packages (from google-auth<3,>=
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/python3.10/dist-packages (from googl
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Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=
Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.10/dist-packages (from werkzeug>=1.0.
Requirement already satisfied: pyasn1<0.6.0,>=0.4.6 in /usr/local/lib/python3.10/dist-packages (from pyasn1-modu
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.10/dist-packages (from requests-oauthli
Requirement already satisfied: keras in /usr/local/lib/python3.10/dist-packages (2.14.0)
Collecting daytime
  Downloading daytime-0.4.tar.gz (2.4 kB)
  Preparing metadata (setup.py) ... done
Building wheels for collected packages: daytime
  Building wheel for daytime (setup.py) ... done
  Created wheel for daytime: filename=daytime-0.4-py3-none-any.whl size=2401 sha256=4d3bcd094918929853f2f1e7b78b
  Stored in directory: /root/.cache/pip/wheels/cd/40/c7/fc109bc6716d31e4d5fdc0cd72891253fa46032e71d9aa1b93
Successfully built daytime
Installing collected packages: daytime
Successfully installed daytime-0.4
Requirement already satisfied: torch in /usr/local/lib/python3.10/dist-packages (2.1.0+cu118)
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from torch) (3.12.4)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.10/dist-packages (from torch) (4.5.0)
Requirement already satisfied: sympy in /usr/local/lib/python3.10/dist-packages (from torch) (1.12)
Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-packages (from torch) (3.2)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (from torch) (3.1.2)
Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages (from torch) (2023.6.0)
Requirement already satisfied: triton==2.1.0 in /usr/local/lib/python3.10/dist-packages (from torch) (2.1.0)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from jinja2->torch) (
Requirement already satisfied: mpmath>=0.19 in /usr/local/lib/python3.10/dist-packages (from sympy->torch) (1.3.
```

```
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"]
```

```
#from google.colab import files
#from IPython.display import Image
```

```
#uploaded = files.upload()
```

Choose files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
#dataset = pd.read_csv("E:\Teachning material\Deep learning BE IT 2019 course\creditcard.csv")
dataset = pd.read_csv("creditcard.csv")
#dataset.head
print(list(dataset.columns))
dataset.describe()
```

```
['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10', 'V11', 'V12',
```

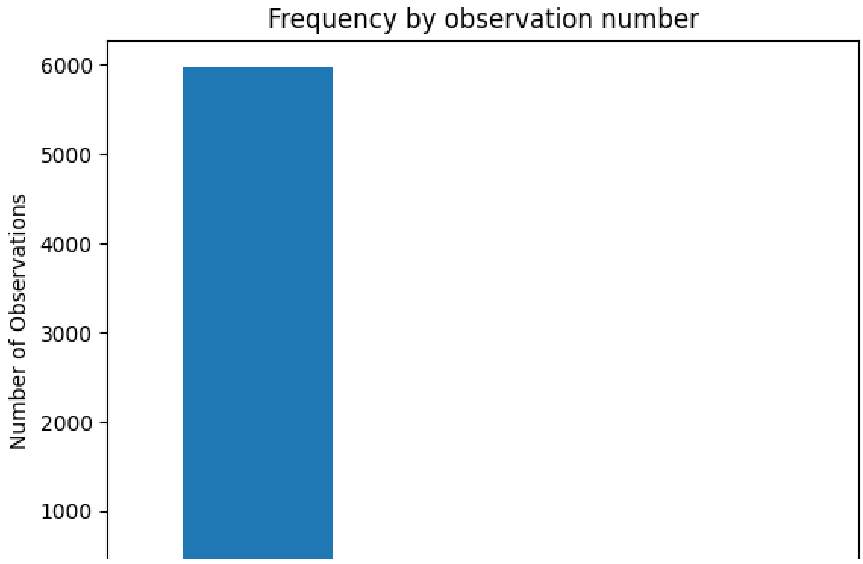
	Time	V1	V2	V3	V4	V5	
count	5974.000000	5974.000000	5974.000000	5974.000000	5974.000000	5974.000000	59
mean	2677.615501	-0.266159	0.285505	0.844231	0.104200	0.000709	
std	1765.025532	1.395405	1.208867	1.031448	1.442339	1.185900	
min	0.000000	-12.168192	-15.732974	-12.389545	-4.657545	-32.092129	
25%	1162.250000	-1.015749	-0.280054	0.295701	-0.839417	-0.609206	
50%	2537.000000	-0.420703	0.346083	0.882882	0.161767	-0.083983	
75%	3781.750000	1.115402	0.941548	1.504158	1.071412	0.441406	
max	6645.000000	1.685314	7.467017	4.101716	6.013346	10.658654	

8 rows × 31 columns

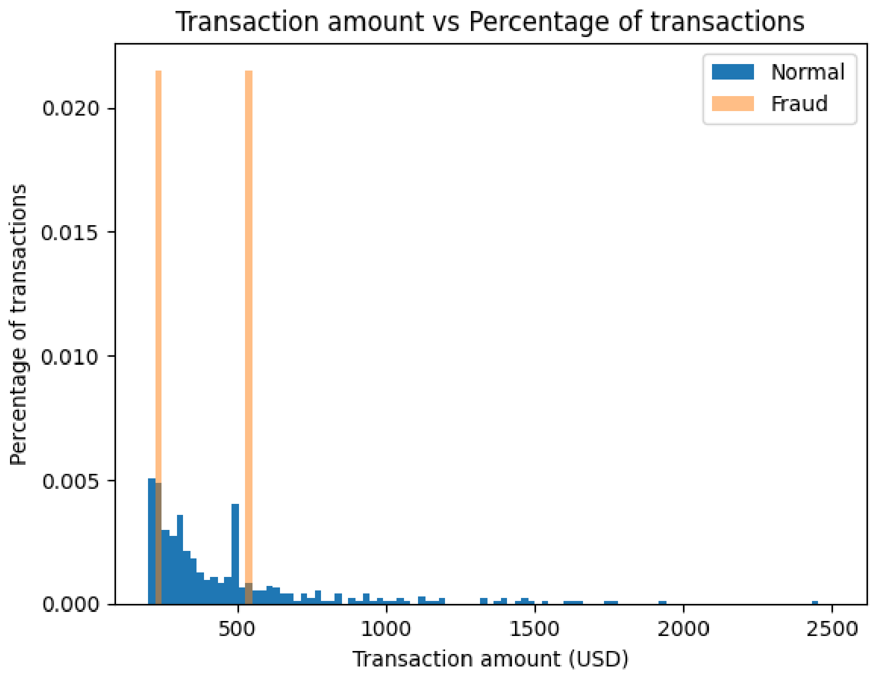
```
#check for any  nullvalues
print("Any nulls in the dataset ",dataset.isnull().values.any() )
print('-------')
print("No. of unique labels ", len(dataset['Class'].unique()))
print("Label values ",dataset.Class.unique())
#0 is for normal credit card transaction
#1 is for fraudulent credit card transaction
print('-------')
print("Break down of the Normal and Fraud Transactions")
print(pd.value_counts(dataset['Class'], sort = True) )
```

```
Any nulls in the dataset  True
-------
No. of unique labels  3
Label values  [ 0.  1. nan]
-------
Break down of the Normal and Fraud Transactions
0.0    5970
1.0       3
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");
```




```
# Save the normal and fradulent transactions in separate dataframe
normal_dataset = dataset[dataset.Class == 0]
fraud_dataset = dataset[dataset.Class == 1]
#Visualize transactionamounts 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()
```




```
'''Time and Amount are the columns that are not scaled, so applying StandardScaler to only Amount and Time columns.
Normalizing the values between 0 and 1 did not work great for the dataset.'''
```

```
'Time and Amount are the columns that are not scaled, so applying StandardScaler to
only Amount and Time columns.\nNormalizing the values between 0 and 1 did not work g
reat for the dataset.'
```

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

```
'''The last column in the dataset is our target variable.'''
```

```
raw_data = dataset.values
# The last element contains if the transaction is normal which is represented by a 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
)


'''Normalize the data to have a value between 0 and 1'''

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)


'''Use only normal transactions to train the Autoencoder.

Normal data has a value of 0 in the target variable. Using the target variable to create a normal and fraud dataset.'''

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= 3
 No. of records in Normal Train data= 4776
 No. of records in Fraud Test Data= 1
 No. of records in Normal Test data= 1194
```

```
nb_epoch = 50
batch_size = 64
input_dim = normal_train_data.shape[1] #num of columns, 30
encoding_dim = 14
hidden_dim_1 = int(encoding_dim / 2) #
hidden_dim_2=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_dim_1, activation='relu')(encoder)
encoder = tf.keras.layers.Dense(hidden_dim_2, activation=tf.nn.leaky_relu)(encoder)

# Decoder
decoder = tf.keras.layers.Dense(hidden_dim_1, 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()
```

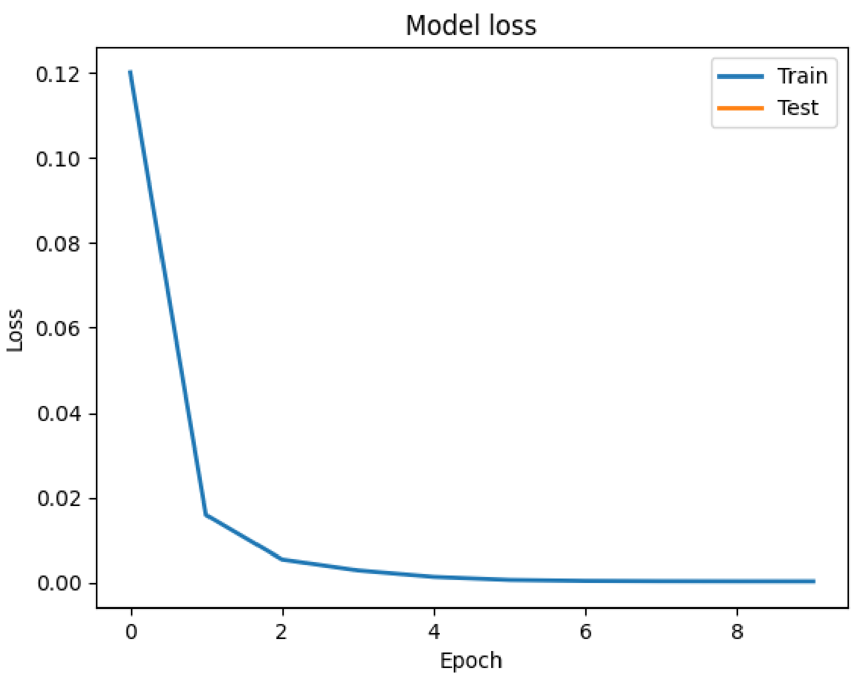
```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_1 (InputLayer)        [(None, 30)]              0         
                                                                 
 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: 1168 (4.56 KB)
Trainable params: 1168 (4.56 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
"""Define the callbacks for checkpoints and early stopping"""

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=1,
    mode='min',
    restore_best_weights=True)


#Compile the Autoencoder

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


#Train the Autoencoder

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
62/75 [=======================>......] - ETA: 0s - loss: 0.1343 - accuracy: 0.0769
Epoch 1: val_loss did not improve from inf
75/75 [==============================] - 2s 7ms/step - loss: 0.1202 - accuracy: 0.0720 - val_loss: nan - val_accur
Epoch 2/50
58/75 [======================>.......] - ETA: 0s - loss: 0.0180 - accuracy: 0.0253
Epoch 2: val_loss did not improve from inf
75/75 [==============================] - 0s 3ms/step - loss: 0.0159 - accuracy: 0.0258 - val_loss: nan - val_accur
Epoch 3/50
58/75 [======================>.......] - ETA: 0s - loss: 0.0056 - accuracy: 0.0587
Epoch 3: val_loss did not improve from inf
75/75 [==============================] - 0s 4ms/step - loss: 0.0054 - accuracy: 0.0549 - val_loss: nan - val_accur
Epoch 4/50
75/75 [==============================] - ETA: 0s - loss: 0.0028 - accuracy: 0.0509
Epoch 4: val_loss did not improve from inf
```

```
75/75 [==============================] - 0s 4ms/step - loss: 0.0028 - accuracy: 0.0509 - val_loss: nan - val_accur
Epoch 5/50
74/75 [============================>.] - ETA: 0s - loss: 0.0013 - accuracy: 0.0699
Epoch 5: val_loss did not improve from inf
75/75 [==============================] - 0s 4ms/step - loss: 0.0013 - accuracy: 0.0697 - val_loss: nan - val_accur
Epoch 6/50
68/75 [==========================>...] - ETA: 0s - loss: 5.7019e-04 - accuracy: 0.0855
Epoch 6: val_loss did not improve from inf
75/75 [==============================] - 0s 4ms/step - loss: 5.5415e-04 - accuracy: 0.0844 - val_loss: nan - _a
Epoch 7/50
60/75 [=======================>......] - ETA: 0s - loss: 3.4165e-04 - accuracy: 0.0901
Epoch 7: val_loss did not improve from inf
75/75 [==============================] - 0s 4ms/step - loss: 3.2805e-04 - accuracy: 0.0894 - val_loss: nan - val_a
Epoch 8/50
63/75 [========================>.....] - ETA: 0s - loss: 2.4691e-04 - accuracy: 0.1119
Epoch 8: val_loss did not improve from inf
75/75 [==============================] - 0s 4ms/step - loss: 2.5314e-04 - accuracy: 0.1137 - val_loss: nan - val_a
Epoch 9/50
63/75 [========================>.....] - ETA: 0s - loss: 2.2175e-04 - accuracy: 0.1411
Epoch 9: val_loss did not improve from inf
75/75 [==============================] - 0s 4ms/step - loss: 2.2262e-04 - accuracy: 0.1376 - val_loss: nan - val_a
Epoch 10/50
62/75 [=======================>......] - ETA: 0s - loss: 2.1684e-04 - accuracy: 0.1356
Epoch 10: val_loss did not improve from inf
Restoring model weights from the end of the best epoch: 1.
75/75 [==============================] - 0s 3ms/step - loss: 2.1241e-04 - accuracy: 0.1418 - val_loss: nan - val_a
Epoch 10: early stopping
```

```
#Plot training and test loss

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()
```

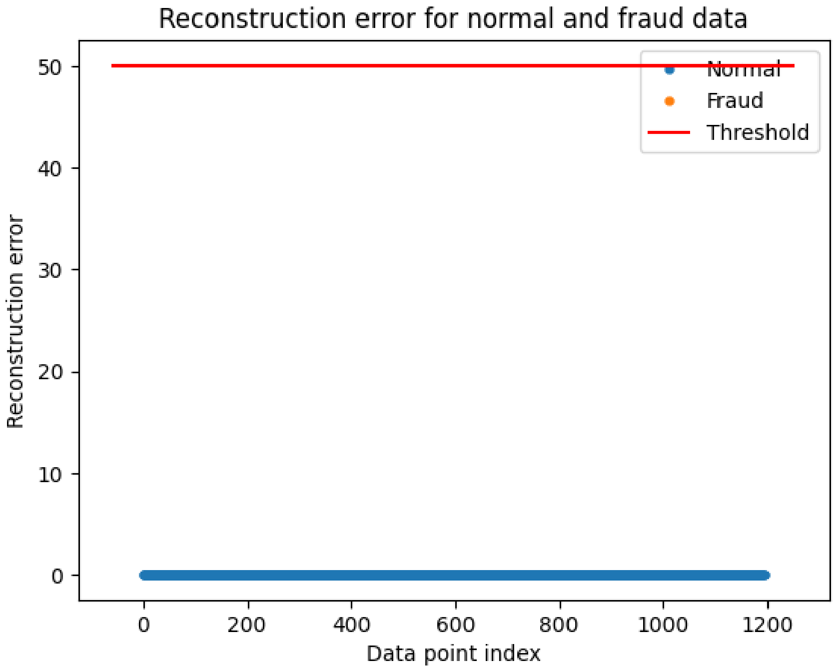



```
"""Detect Anomalies on test data

Anomalies are data points where the reconstruction loss is higher

To calculate the reconstruction loss on test data,
predict the test data and calculate the mean square error between the test data and the reconstructed test data."""

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

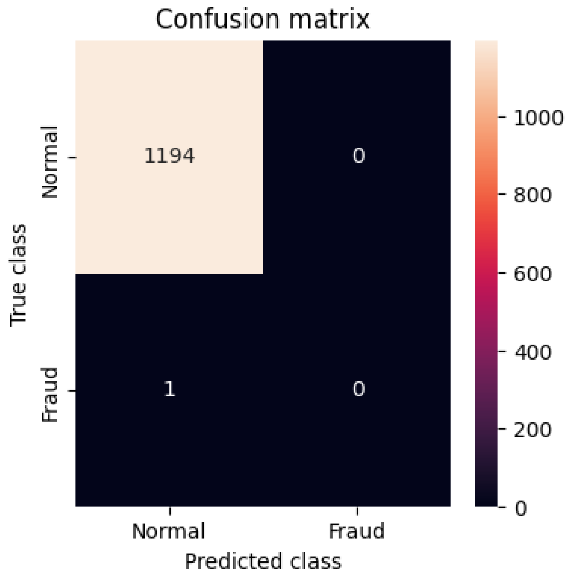
```
error_df = pd.DataFrame({'Reconstruction_error': mse,
                        'True_class': test_labels})
```

```
38/38 [==============================] - 0s 2ms/step
```

```
#Plotting the test data points and their respective reconstruction error sets a threshold value to visualize
#if the threshold value needs to be adjusted.

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("Reconstruction error for normal and fraud data")
plt.ylabel("Reconstruction error")
plt.xlabel("Data point index")
plt.show();
```




```
'''Detect anomalies as points where the reconstruction loss is greater than a fixed threshold.
Here we see that a value of 52 for the threshold will be good.

Evaluating the performance of the anomaly detection'''

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:  0.999163179916318
```

```
'''As our dataset is highly imbalanced, we see a high accuracy but a low recall and precision.

Things to further improve precision and recall would add more relevant features,
different architecture for autoencoder, different hyperparameters, or a different algorithm.'''
```

```
'As our dataset is highly imbalanced, we see a high accuracy but a low recall and pr
ecision.\n\nThings to further improve precision and recall would add more relevant f
eatures,\ndifferent architecture for autoencoder, different hyperparameters, or a di
fferent algorithm.'
```

```
history
```

```
{'loss': [0.12019588053226471,
  0.0158808883279562,
  0.005402295384556055,
  0.002820003079250455,
  0.0012772884219884872,
  0.0005541512509807944,
  0.0003280547389294952,
  0.00025314290542155504,
  0.00022261805133894086,
  0.00021240743808448315],
 'accuracy': [0.0720268040895462,
  0.025753768160939217,
  0.05485762283205986,
  0.05087939649820328,
  0.06972362101078033,
  0.08438023179769516,
  0.089405357837677,
  0.113693468272686,
  0.1375628113746643,
  0.14175042510032654],
 'val_loss': [nan, nan, nan, nan, nan, nan, nan, nan, nan, nan],
 'val_accuracy': [0.02092050202190876,
  0.17489539086818695,
  0.17573221027851105,
  0.17489539086818695,
  0.17489539086818695,
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  0.17489539086818695,
  0.17489539086818695,
  0.17489539086818695]}
```