Reference: Keras tutorial : https://www.tensorflow.org/tutorials/generative/autoencoder

This file trains an autoencoder with the instances of normal ECGs in the training data. Then, it measures the reconstruction loss for both the normal and abnormal ECGs in the test data. The reconstruction loss for the instances of the abnormal ECGs in the test data is higher. A threshold is determined based on the distribution of the reconstruction losses of the normal training data (threshold = mean + 2.5*std of this distribution). Then, if the reconstruction loss of a normal ECG in the training data is higher than this threshold, it is classified as abnormal. By comparing with the known labels of test data (with T for normal ECG(s) and F for abnormal ECG(s)), the confusion matrix and the accuracy is calculated.

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow import keras

from sklearn.metrics import accuracy_score, precision_score, recall_score, confusion_r
from sklearn.model_selection import train_test_split
from keras import layers, losses
from keras.models import Model
```

Loading the ECG5000 data

```
# Download the dataset
dataframe = pd.read_csv('http://storage.googleapis.com/download.tensorflow.org/data/ec
raw_data = dataframe.values
dataframe.head()
```

	0	1	2	3	4	5	6	7	
0	-0.112522	-2.827204	-3.773897	-4.349751	-4.376041	-3.474986	-2.181408	-1.818286	-1.2
1	-1.100878	-3.996840	-4.285843	-4.506579	-4.022377	-3.234368	-1.566126	-0.992258	-0.7
2	-0.567088	-2.593450	-3.874230	-4.584095	-4.187449	-3.151462	-1.742940	-1.490659	-1.1
3	0.490473	-1.914407	-3.616364	-4.318823	-4.268016	-3.881110	-2.993280	-1.671131	-1.3
4	0.800232	-0.874252	-2.384761	-3.973292	-4.338224	-3.802422	-2.534510	-1.783423	-1.5

5 rows × 141 columns

Parse the data so it can be split creating a variable containing the labels and another containing the data. Splitting the data into train, validation, and test set.

```
# The last element contains the labels
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=21
)

train_data, valid_data, train_labels, valid_labels = train_test_split(
    train_data, train_labels, test_size=.1, random_state=21
)
```

Normalize the data so the features are treated equally, normalizing using the overall min and max value of all training data (train/validation set).

```
min_val = tf.reduce_min(tf.concat([train_data, valid_data], 0))
max_val = tf.reduce_max(tf.concat([train_data, valid_data], 0))

train_data = (train_data - min_val) / (max_val - min_val)
valid_data = (valid_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)
valid_data = tf.cast(valid_data, tf.float32)
test_data = tf.cast(test_data, tf.float32)
```

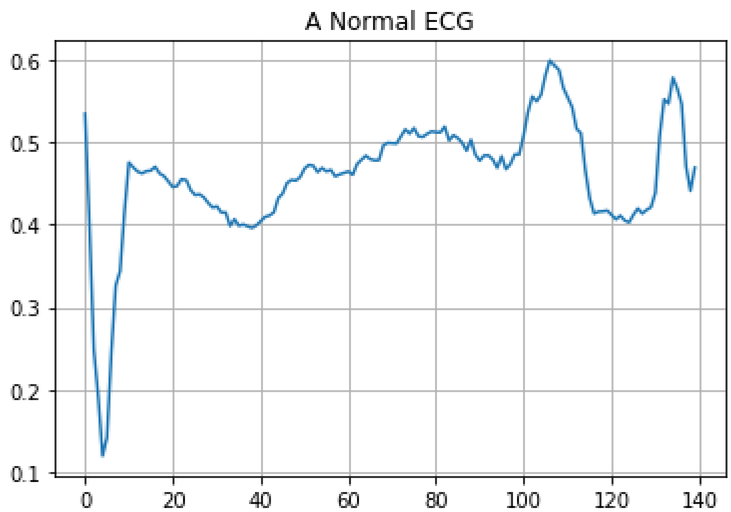
The autoencoder is trained using only the normal rhythms, which are labeled in this dataset as 1. Here the normal rhythms is separated from the abnormal rhythms, and the labels are casted as type bool.

```
train_labels = train_labels.astype(bool)
valid_labels = valid_labels.astype(bool)
test_labels = test_labels.astype(bool)

normal_train_data = train_data[train_labels]
normal_valid_data = valid_data[valid_labels]
normal_test_data = test_data[test_labels]

anomalous_train_data = train_data[~train_labels]
```

```
anomalous_valid_data = valid_data[~valid_labels]
anomalous_test_data = test_data[~test_labels]
```

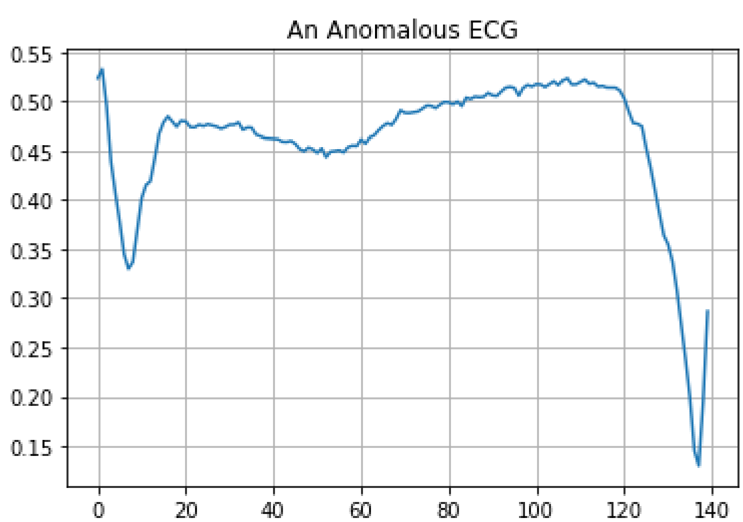
Plotting a normal ECG from the training set

```
plt.grid()
plt.plot(np.arange(140), normal_train_data[0])
plt.title("A Normal ECG")
plt.show()
```



Plotting an anomalous ECG.

```
plt.grid()
plt.plot(np.arange(140), anomalous_train_data[0])
plt.title("An Anomalous ECG")
plt.show()
```



Building the Anomaly Detection Model, the encoder architecture is $140 \rightarrow 32 \rightarrow 16 \rightarrow 8$. Thus,

```
class AnomalyDetector(Model):
  def __init__(self):
    super(AnomalyDetector, self).__init__()
    self.encoder = tf.keras.Sequential([
      layers.Dense(32, activation="selu"),
      layers.Dense(16, activation="selu"),
      layers.Dense(8, activation="selu")])

    self.decoder = tf.keras.Sequential([
      layers.Dense(16, activation="selu"),
      layers.Dense(32, activation="selu"),
      layers.Dense(140, activation="sigmoid")])

  def call(self, x):
    encoded = self.encoder(x)
    decoded = self.decoder(encoded)
    return decoded

autoencoder = AnomalyDetector()
```

Compiling the model using Adam optimizer and Mean Squared Error as the loss function:

```
autoencoder.compile(optimizer='adam', loss='mae')
```

Creating a callback to monitor validation loss to prevent overfitting of the model if the validation loss doesn't go down in 10 epochs, training is stopped.

```
callback = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience = 10)
```

Note we train the Autoencoder only on the normal ECG training set but both the normal and abnormal data is contained in the test set.

```
history = autoencoder.fit(normal_train_data, normal_train_data,
            epochs=100,
            batch_size=128,
            callbacks = [callback],
            validation_data=(normal_valid_data, normal_valid_data),
            shuffle=True)
```

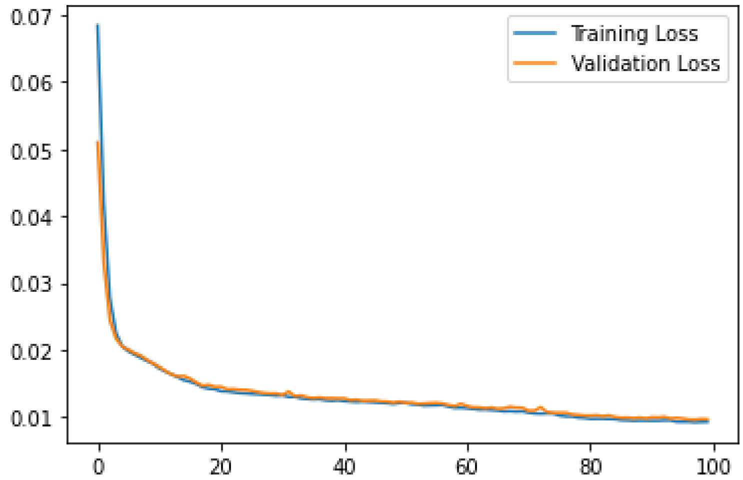
```
Epoch 72/100
17/17 [==============================] - 0s 13ms/step - loss: 0.0105 - val_loss:
Epoch 73/100
17/17 [==============================] - 0s 12ms/step - loss: 0.0105 - val_loss:
Epoch 74/100
17/17 [==============================] - 0s 14ms/step - loss: 0.0105 - val_loss:
Epoch 75/100
```

```
Epoch 75/100
17/17 [==============================] - 0s 14ms/step - loss: 0.0105 - val_loss:
Epoch 76/100
17/17 [==============================] - 0s 9ms/step - loss: 0.0102 - val_loss: 
Epoch 77/100
17/17 [==============================] - 0s 9ms/step - loss: 0.0101 - val_loss: 
Epoch 78/100
17/17 [==============================] - 0s 10ms/step - loss: 0.0101 - val_loss:
Epoch 79/100
17/17 [==============================] - 0s 10ms/step - loss: 0.0099 - val_loss:
Epoch 80/100
17/17 [==============================] - 0s 9ms/step - loss: 0.0099 - val_loss: 
Epoch 81/100
17/17 [==============================] - 0s 10ms/step - loss: 0.0098 - val_loss:
Epoch 82/100
17/17 [==============================] - 0s 8ms/step - loss: 0.0098 - val_loss: 
Epoch 83/100
17/17 [==============================] - 0s 8ms/step - loss: 0.0098 - val_loss: 
Epoch 84/100
17/17 [==============================] - 0s 12ms/step - loss: 0.0097 - val_loss:
Epoch 85/100
17/17 [==============================] - 0s 11ms/step - loss: 0.0097 - val_loss:
Epoch 86/100
17/17 [==============================] - 0s 11ms/step - loss: 0.0096 - val_loss:
Epoch 87/100
17/17 [==============================] - 0s 11ms/step - loss: 0.0095 - val_loss:
Epoch 88/100
17/17 [==============================] - 0s 12ms/step - loss: 0.0095 - val_loss:
Epoch 89/100
17/17 [==============================] - 0s 11ms/step - loss: 0.0095 - val_loss:
Epoch 90/100
17/17 [==============================] - 0s 14ms/step - loss: 0.0095 - val_loss:
Epoch 91/100
17/17 [==============================] - 0s 10ms/step - loss: 0.0095 - val_loss:
Epoch 92/100
17/17 [==============================] - 0s 12ms/step - loss: 0.0095 - val_loss:
Epoch 93/100
17/17 [==============================] - 0s 9ms/step - loss: 0.0095 - val_loss: 
Epoch 94/100
17/17 [==============================] - 0s 13ms/step - loss: 0.0095 - val_loss:
Epoch 95/100
17/17 [==============================] - 0s 13ms/step - loss: 0.0093 - val_loss:
Epoch 96/100
17/17 [==============================] - 0s 13ms/step - loss: 0.0093 - val_loss:
Epoch 97/100
17/17 [==============================] - 0s 12ms/step - loss: 0.0093 - val_loss:
Epoch 98/100
17/17 [==============================] - 0s 15ms/step - loss: 0.0092 - val_loss:
Epoch 99/100
17/17 [==============================] - 0s 9ms/step - loss: 0.0093 - val_loss: 
Epoch 100/100
17/17 [==============================] - 0s 8ms/step - loss: 0.0093 - val_loss: 
```

Plotting the training and validation loss for each epoch of training:

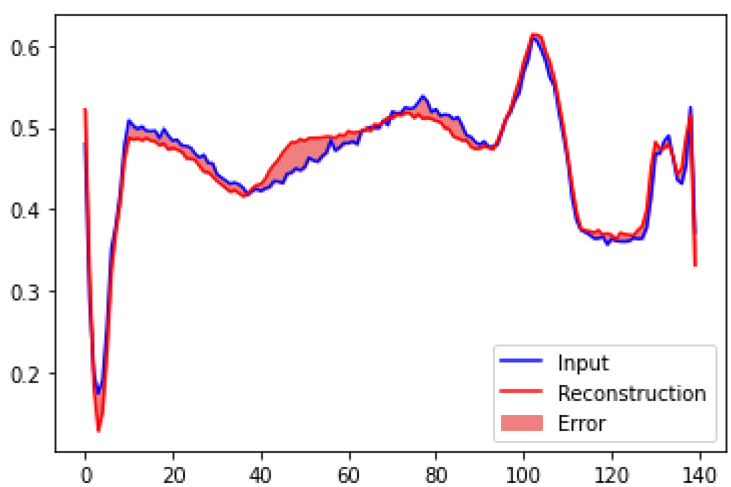
```
plt.plot(history.history["loss"], label="Training Loss")
plt.plot(history.history["val_loss"], label="Validation Loss")
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f7fadee6e50>
```



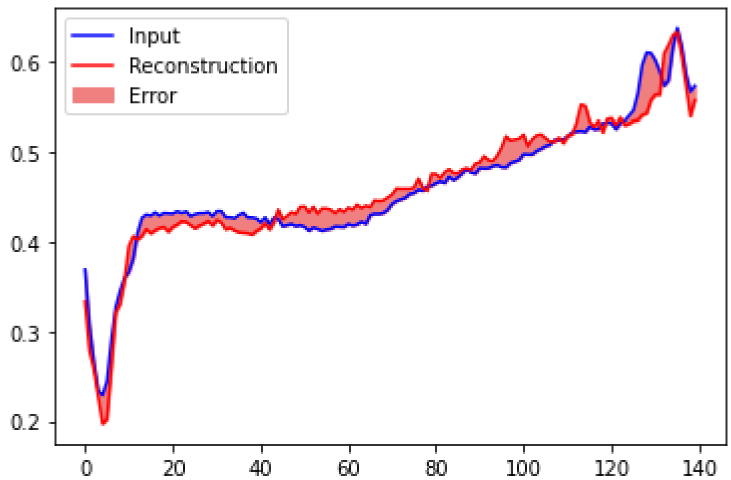
Plotting a normal ECG from the training set, the reconstruction after it's encoded and decoded by the autoencoder, and the reconstruction error.

```
encoded_data = autoencoder.encoder(normal_test_data).numpy()
decoded_data = autoencoder.decoder(encoded_data).numpy()

plt.plot(normal_test_data[0], 'b')
plt.plot(decoded_data[0], 'r')
plt.fill_between(np.arange(140), decoded_data[0], normal_test_data[0], color='lightco
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```



Now, we will do the same for the anomalous data:

```
encoded_data = autoencoder.encoder(anomalous_test_data).numpy()
decoded_data = autoencoder.decoder(encoded_data).numpy()

plt.plot(anomalous_test_data[0], 'b')
plt.plot(decoded_data[0], 'r')
plt.fill_between(np.arange(140), decoded_data[0], anomalous_test_data[0], color='light
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```



Here will compute the normal/abnormal train/validation loss from the model using mean absolute error.

```
# Normal reconstructions
reconstructions_train = autoencoder.predict(normal_train_data)
train_loss = tf.keras.losses.mae(reconstructions_train, normal_train_data)
reconstructions_valid = autoencoder.predict(normal_valid_data)
valid_loss = tf.keras.losses.mae(reconstructions_valid, normal_valid_data)
# Abnormal reconstructions
ab_reconstructions_train = autoencoder.predict(anomalous_train_data)
ab_train_loss = tf.keras.losses.mae(ab_reconstructions_train, anomalous_train_data)
ab_reconstructions_valid = autoencoder.predict(anomalous_valid_data)
ab_valid_loss = tf.keras.losses.mae(ab_reconstructions_valid, anomalous_valid_data)
```

Defining a function predict which takes the model, data, and threshold. Computes the reconstruction loss and returns the truthy value for all elements if they are less than the threshold (True).

```
def predict(model, data, threshold):
  reconstructions = model.predict(data)
  loss = tf.keras.losses.mae(reconstructions, data)
  return tf.math.less(loss, threshold)
```

Computing the abnormal/normal mean of the validation loss

```
abnormal_valid_mean_loss = np.mean(ab_valid_loss)
normal_valid_mean_loss = np.mean(valid_loss)
```

Computing 100 different thresholds that start at the normal threshold and end at the abnormal threshold incrementing by their difference divided by 100.

```
increment = (abnormal_valid_mean_loss - normal_valid_mean_loss)/100
thresholds = np.arange(normal_valid_mean_loss, abnormal_valid_mean_loss,
increment)
```

Creating a numpy array to store the accuracy for each of the different threshold values.

```
thresh_size = thresholds.shape[0]
accuracies = np.zeros(thresh_size)
```

Calculation of the threshold that gives the best accuracy on the validation data. This is done by going through all thresholds and testing the accuracy of the model with each threshold.

```
for i in range(thresh_size):
  preds = predict(autoencoder, valid_data, thresholds[i])
  accuracies[i] = accuracy_score(preds, valid_labels)
```

Setting the threshold to the one in thresholds which gave the best accuracy.

```
argmax = np.argmax(accuracies)
best_threshold = thresholds[argmax]
print("The best threshold based on validation data: ", best_threshold)
```

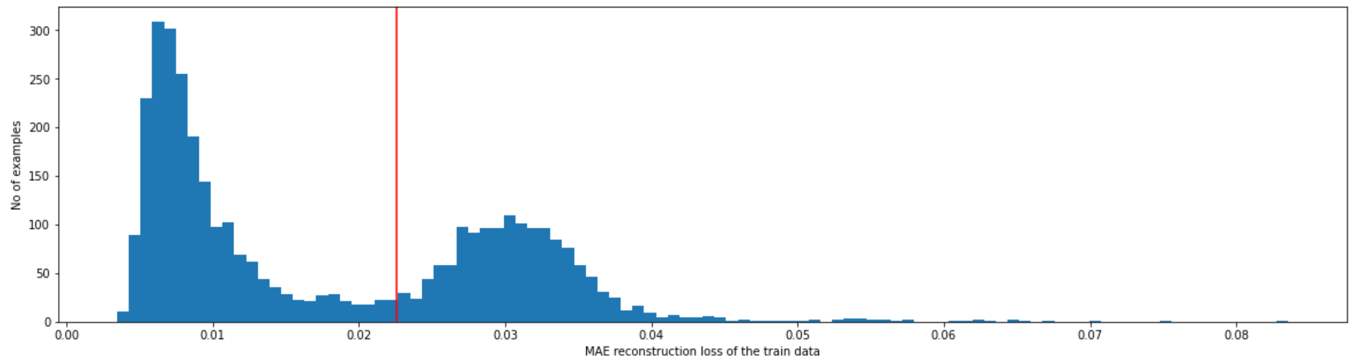
```
The best threshold based on validation data:  0.022547176852822346
```

We now detect anomalies by calculating whether the reconstruction loss is greater than a fixed threshold we just computed. We then will classify future examples as anomalous if the reconstruction error is higher than this threshold.

Plotting the reconstruction error on all ECGs from the training set

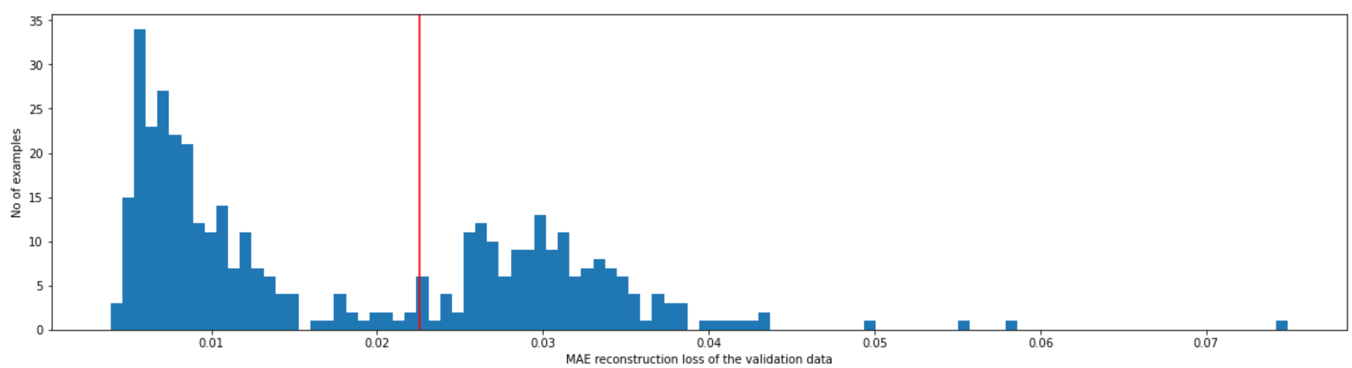
```
reconstructions = autoencoder.predict(train_data)
train_loss = tf.keras.losses.mae(reconstructions, train_data)
```

```
plt.figure(figsize=(20,5))
plt.hist(train_loss[None,:], bins=100)
plt.axvline(best_threshold, c='r')
plt.xlabel("MAE reconstruction loss of the train data")
plt.ylabel("No of examples")
plt.show()
```



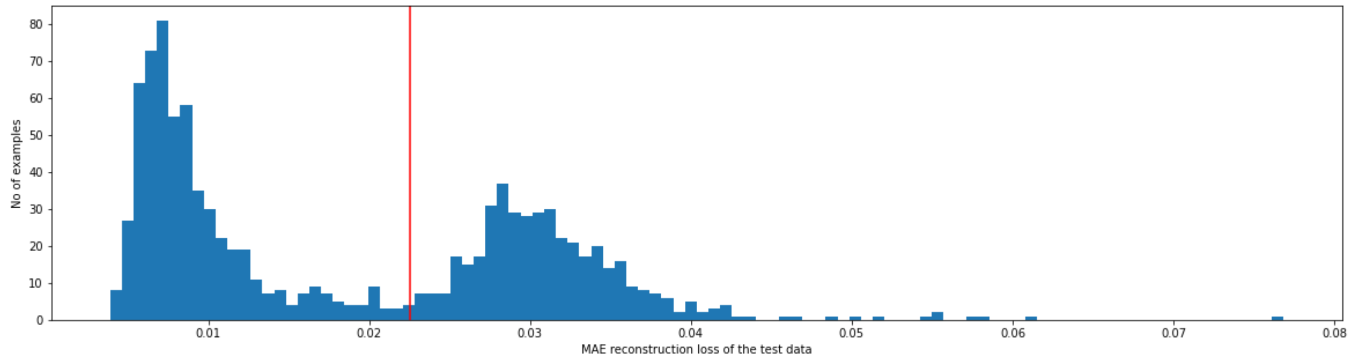
Plotting the reconstruction error on all ECGs from the validation set

```
reconstructions = autoencoder.predict(valid_data)
valid_loss = tf.keras.losses.mae(reconstructions, valid_data)
plt.figure(figsize=(20,5))
plt.hist(valid_loss[None,:], bins=100)
plt.axvline(best_threshold, c='r')
plt.xlabel("MAE reconstruction loss of the validation data")
plt.ylabel("No of examples")
plt.show()
```



Plotting the reconstruction error on all ECGs from the test set

```
reconstructions = autoencoder.predict(test_data)
test_loss = tf.keras.losses.mae(reconstructions, test_data)
plt.figure(figsize=(20,5))
plt.hist(test_loss[None,:], bins=100)
plt.axvline(best_threshold, c='r')
plt.xlabel("MAE reconstruction loss of the test data")
plt.ylabel("No of examples")
plt.show()
```



Classify an ECG as an anomaly if the reconstruction error is greater than the threshold.

```
def print_stats(predictions, labels, model, data):
  cf = confusion_matrix(labels, predictions)
  print("Confusion Matrix: \n prediction: F      T ")
  print("              {}   {}".format(preds[preds == False].shape[0], preds[preds == T
  print(" label: F   [[{}   {}]    {}".format(cf[0,0], cf[0,1], labels[labels == False
  print("        T    [{}   {}]]   {}".format(cf[1,0], cf[1,1], labels[labels == True]
  print("Accuracy = {}".format(accuracy_score(labels, predictions)))
  reconstructions = model.predict(data[labels])
  nl_test_loss =  tf.keras.losses.mae(reconstructions, data[labels])
  print("Normal Test Data Mean = {}".format(np.mean(nl_test_loss)))
  print("Normal Test Data Standard Deviation = {}".format(np.std(nl_test_loss)))
  reconstructions = model.predict(data[~labels])
  ab_test_loss =  tf.keras.losses.mae(reconstructions, data[~labels])
  print("Abnormal Test Data Mean = {}".format(np.mean(ab_test_loss)))
  print("Abnormal Test Data Standard Deviation = {}".format(np.std(ab_test_loss)))
  print("Precision = {}".format(precision_score(labels, predictions)))
  print("Recall = {}".format(recall_score(labels, predictions)))
```

```
thr_acc = np.zeros((thresh_size, 2))
thr_acc[:, 0] = thresholds
thr_acc[:, 1] = accuracies
thr_acc[argmax - 2 : argmax + 3]
```

```
array([[0.02212551, 0.95      ],
       [0.02233634, 0.95      ],
       [0.02254718, 0.9525    ],
       [0.02275801, 0.95      ],
       [0.02296884, 0.9475    ]])
```

Calculation of the accuracy and the confusion matrix on the test data with threshold set based on the best threshold from the validation data

```
preds = predict(autoencoder, test_data, best_threshold)
print_stats(preds, test_labels, autoencoder, test_data)
```

```
Confusion Matrix:
```

```
 prediction: F      T
             424   576
 label: F   [[413   27]    440
        T    [11   549]]   560
Accuracy = 0.962
Normal Test Data Mean = 0.009152278304100037
Normal Test Data Standard Deviation = 0.004508689045906067
Abnormal Test Data Mean = 0.03081071935594082
Abnormal Test Data Standard Deviation = 0.006650075782090425 5
Precision = 0.953125
Recall = 0.9803571428571428
```

```
accuracy = (0.96 + .964 + 0.961 + 0.959 + 0.962 + )/10.
round(accuracy, 4)
```

```
0.9682
```

```
norm_mean = (0.9890310786106032 + 0.9908925318761385 + 0.9890909090909091
round(norm_mean, 4)
```

```
0.9852
```

```
recall = (0.9660714285714286 + 0.9714285714285714 + 0.9714285714285714 + 0


round(recall, 4)
```

```
0.9689
```