```
4) Use Autoencoder to implement anomaly detection. Build the model by using:
a. Import required libraries
b. Upload / access the dataset
c. Encoder converts it into latent representation
d. Decoder networks convert it back to the original input
e. Compile the models with Optimizer, Loss, and Evaluation Metrics
```

```
#a. Import required libraries
#Import TensorFlow and other libraries
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import tensorflow as tf

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

```
#b. Upload / access the dataset
(x_train, _), (x_test, _) = fashion_mnist.load_data()

x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.

print (x_train.shape)
print (x_test.shape)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/tra
29515/29515 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/tra
26421880/26421880 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10
5148/5148 ━━━━━━━━━━━━━━━━━━━━ 0s 1us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10
4422102/4422102 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
(60000, 28, 28)
(10000, 28, 28)
```

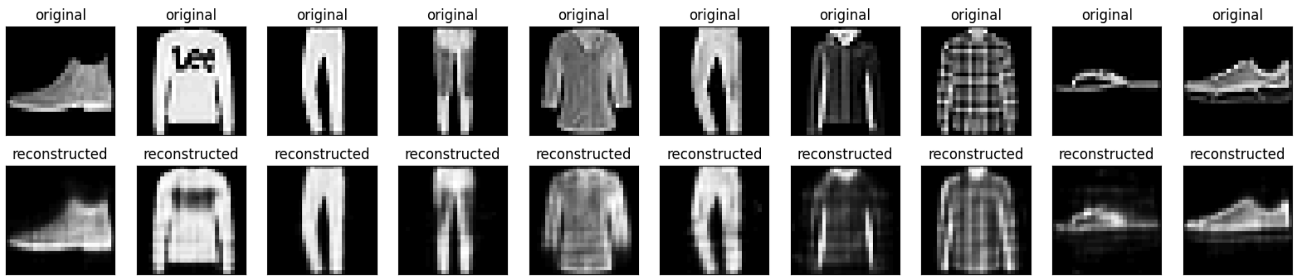
```
#c. Encoder converts it into latent representation
latent_dim = 64

class Autoencoder(Model):
  def __init__(self, latent_dim):
    super(Autoencoder, self).__init__()
    self.latent_dim = latent_dim
    self.encoder = tf.keras.Sequential([
      layers.Flatten(),
      layers.Dense(latent_dim, activation='relu'),
    ])
```

```
    self.decoder = tf.keras.Sequential([
      layers.Dense(784, activation='sigmoid'),
      layers.Reshape((28, 28))
    ])

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

autoencoder = Autoencoder(latent_dim)


autoencoder.compile(optimizer='adam', loss=losses.MeanSquaredError())


autoencoder.fit(x_train, x_train,
                epochs=10,
                shuffle=True,
                validation_data=(x_test, x_test))
```

```
Epoch 1/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 9s 4ms/step - loss: 0.0394 - val_loss: 0.0132
Epoch 2/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 12s 6ms/step - loss: 0.0123 - val_loss: 0.0107
Epoch 3/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - loss: 0.0102 - val_loss: 0.0097
Epoch 4/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 3ms/step - loss: 0.0095 - val_loss: 0.0094
Epoch 5/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - loss: 0.0093 - val_loss: 0.0092
Epoch 6/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 7s 4ms/step - loss: 0.0090 - val_loss: 0.0090
Epoch 7/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 3ms/step - loss: 0.0089 - val_loss: 0.0090
Epoch 8/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - loss: 0.0089 - val_loss: 0.0090
Epoch 9/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step - loss: 0.0088 - val_loss: 0.0090
Epoch 10/10
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 11s 4ms/step - loss: 0.0088 - val_loss: 0.0089
<keras.src.callbacks.history.History at 0x7c764df215a0>
```

```
encoded_imgs = autoencoder.encoder(x_test).numpy()
#d. Decoder networks convert it back to the original input
decoded_imgs = autoencoder.decoder(encoded_imgs).numpy()


n = 10
plt.figure(figsize=(20, 4))
for i in range(n):
  # display original
  ax = plt.subplot(2, n, i + 1)
  plt.imshow(x_test[i])
  plt.title("original")
  plt.gray()
  ax.get_xaxis().set_visible(False)
```

```
    ax.get_yaxis().set_visible(False)

    # display reconstruction
    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(decoded_imgs[i])
    plt.title("reconstructed")
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
plt.show()
```



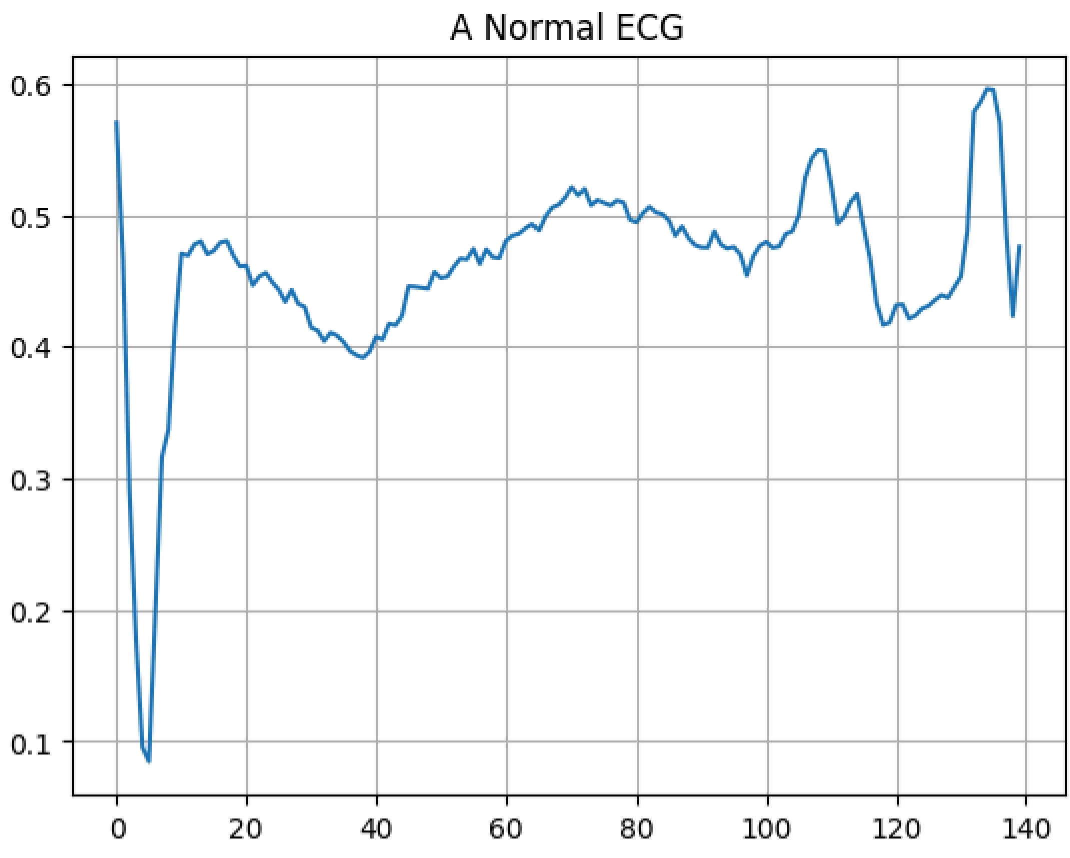

```
#Load ECG data
# Download the dataset
dataframe = pd.read_csv('http://storage.googleapis.com/download.tensorflow.org/data/ecg.c
raw_data = dataframe.values
dataframe.tail()
```

	0	1	2	3	4	5	6	7
4993	0.608558	-0.335651	-0.990948	-1.784153	-2.626145	-2.957065	-2.931897	-2.66481
4994	-2.060402	-2.860116	-3.405074	-3.748719	-3.513561	-3.006545	-2.234850	-1.59327
4995	-1.122969	-2.252925	-2.867628	-3.358605	-3.167849	-2.638360	-1.664162	-0.93565
4996	-0.547705	-1.889545	-2.839779	-3.457912	-3.929149	-3.966026	-3.492560	-2.69527
4997	-1.351779	-2.209006	-2.520225	-3.061475	-3.065141	-3.030739	-2.622720	-2.04409

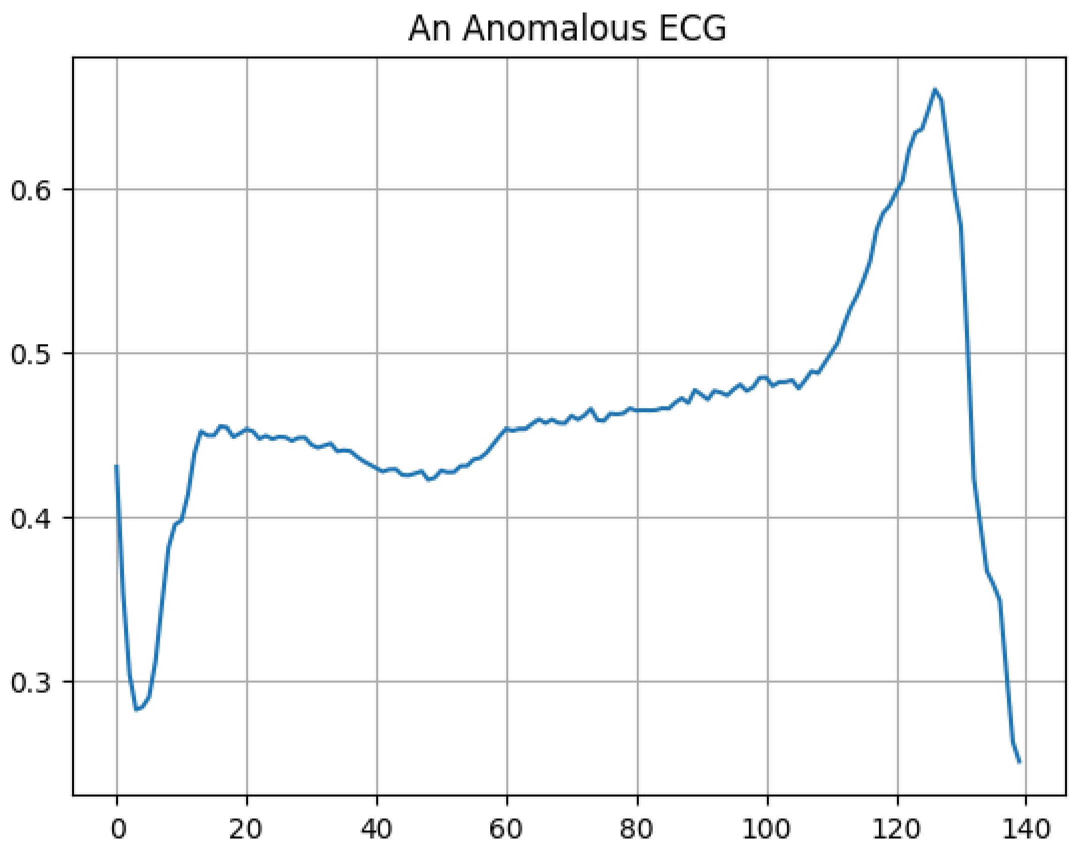
5 rows × 141 columns

```
# 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
)


#Normalize the data to [0,1].

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)


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

normal_train_data = train_data[train_labels]
normal_test_data = test_data[test_labels]

anomalous_train_data = train_data[~train_labels]
anomalous_test_data = test_data[~test_labels]


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




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




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

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

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

autoencoder = AnomalyDetector()
```

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

```
#Notice that the autoencoder is trained using only the normal ECGs, but is evaluated usin
```

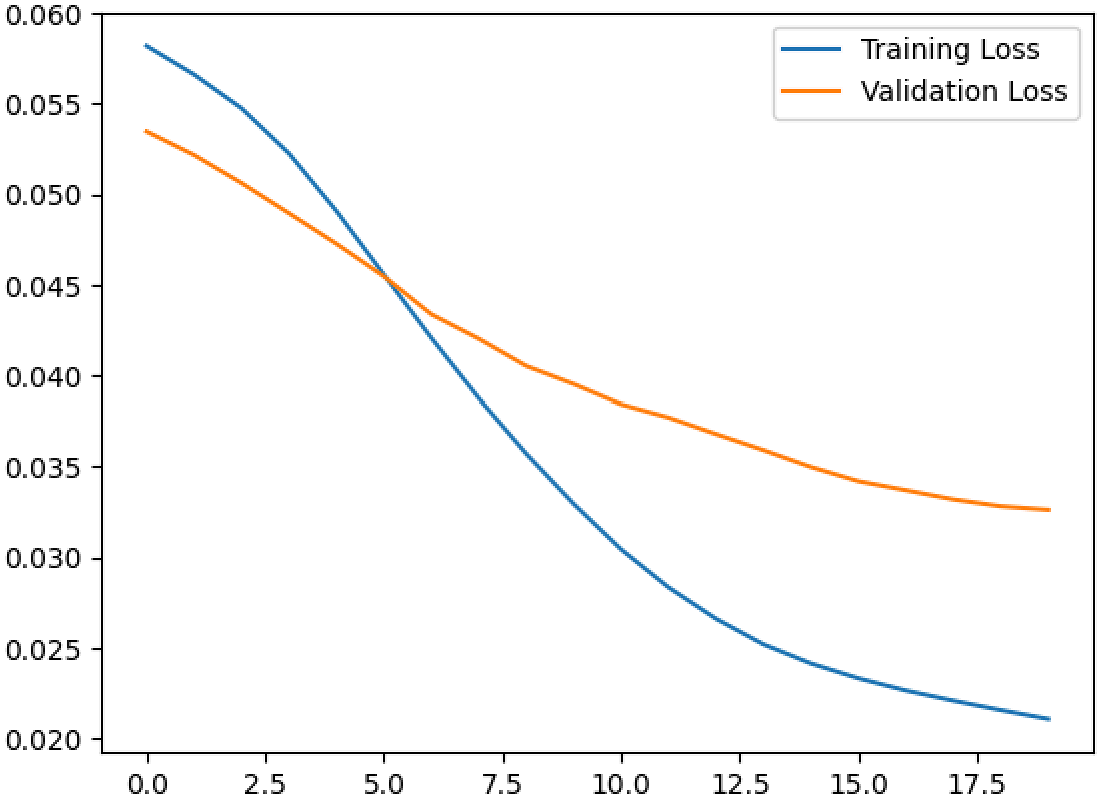
```
history = autoencoder.fit(normal_train_data, normal_train_data,
          epochs=20,
          batch_size=512,
```

```
      validation_data=(test_data, test_data),
      shuffle=True)
```

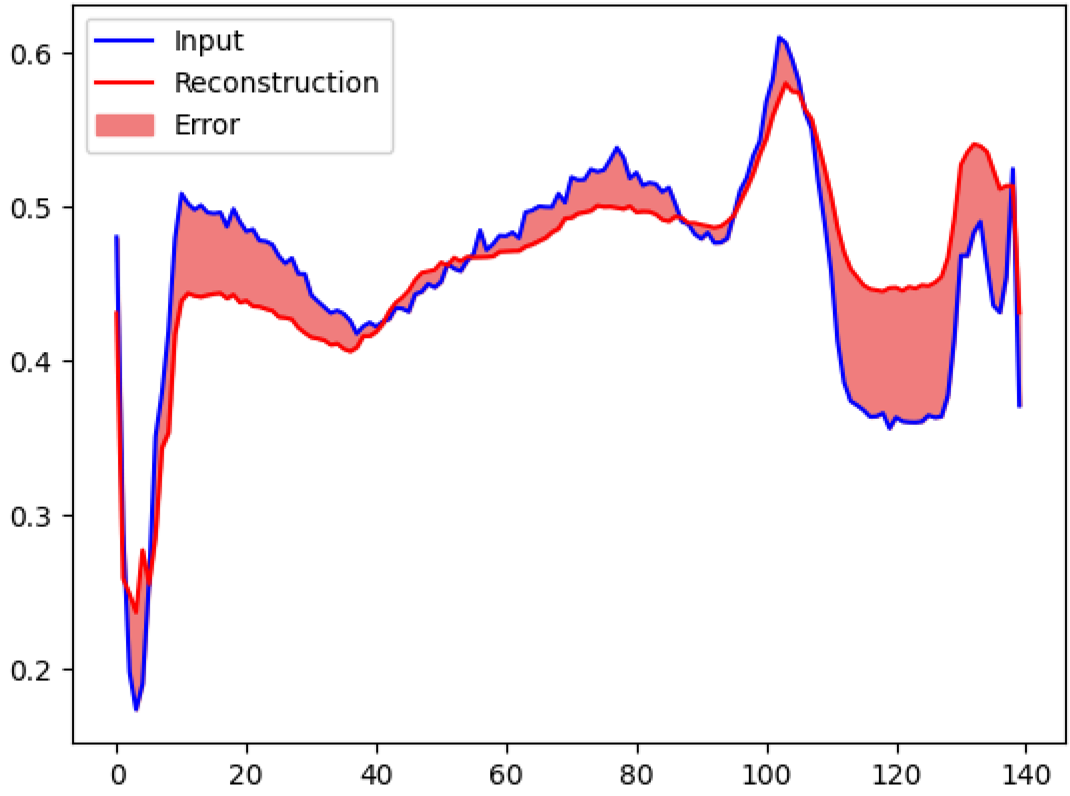
```
Epoch 1/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 2s 53ms/step - loss: 0.0586 - val_loss: 0.0535
Epoch 2/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 0.0569 - val_loss: 0.0522
Epoch 3/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0550 - val_loss: 0.0506
Epoch 4/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0527 - val_loss: 0.0490
Epoch 5/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0496 - val_loss: 0.0473
Epoch 6/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0461 - val_loss: 0.0455
Epoch 7/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0427 - val_loss: 0.0434
Epoch 8/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0392 - val_loss: 0.0420
Epoch 9/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - loss: 0.0362 - val_loss: 0.0405
Epoch 10/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - loss: 0.0333 - val_loss: 0.0395
Epoch 11/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0308 - val_loss: 0.0384
Epoch 12/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0286 - val_loss: 0.0377
Epoch 13/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0268 - val_loss: 0.0368
Epoch 14/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0253 - val_loss: 0.0359
Epoch 15/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0242 - val_loss: 0.0350
Epoch 16/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0233 - val_loss: 0.0342
Epoch 17/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0226 - val_loss: 0.0337
Epoch 18/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0222 - val_loss: 0.0332
Epoch 19/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0215 - val_loss: 0.0328
Epoch 20/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 0.0211 - val_loss: 0.0326
```

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

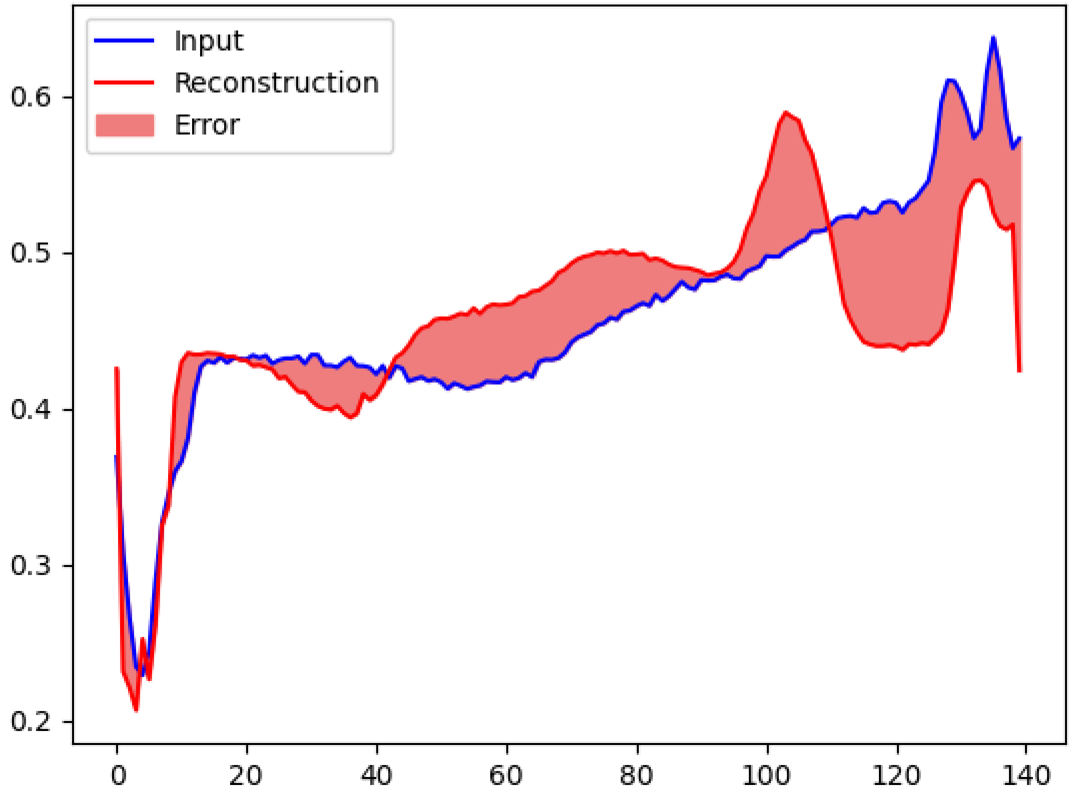
```
<matplotlib.legend.Legend at 0x7c7648ec4250>
```




```
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='lightcoral'
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```

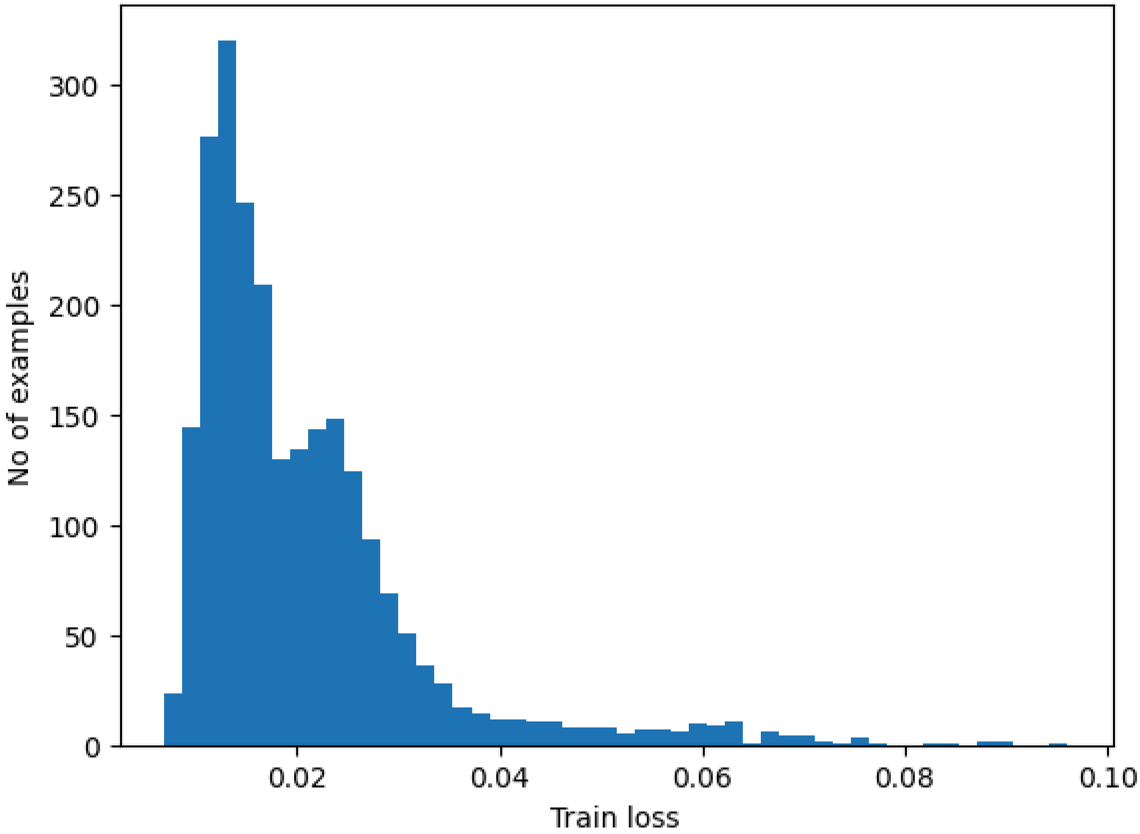



```
encoded_data = autoencoder.encoder(anomalous_test_data).numpy()
decoded_data = autoencoder.decoder(encoded_data).numpy()

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='lightcor
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```



```
#Plot the reconstruction error on normal ECGs from the training set
reconstructions = autoencoder.predict(normal_train_data)
train_loss = tf.keras.losses.mae(reconstructions, normal_train_data)
plt.hist(train_loss[None,:], bins=50)
plt.xlabel("Train loss")
plt.ylabel("No of examples")
plt.show()
```

```
74/74 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

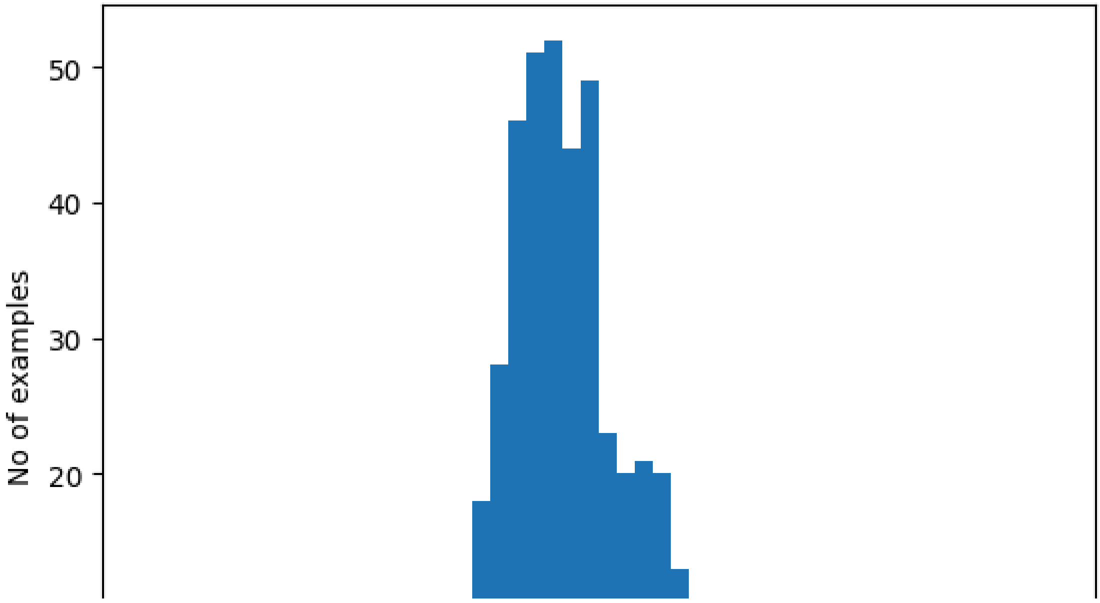



```
threshold = np.mean(train_loss) + np.std(train_loss)
print("Threshold: ", threshold)
```

```
Threshold:  0.032432158
```

```
reconstructions = autoencoder.predict(anomalous_test_data)
test_loss = tf.keras.losses.mae(reconstructions, anomalous_test_data)

plt.hist(test_loss[None, :], bins=50)
plt.xlabel("Test loss")
plt.ylabel("No of examples")
plt.show()
```

14/14 ━━━━━━━━━━━━━━━━━━━━ **0s** 1ms/step




```
#e. Compile the models with Optimizer, Loss, and Evaluation Metrics
def predict(model, data, threshold):
  reconstructions = model(data)
  loss = tf.keras.losses.mae(reconstructions, data)
  return tf.math.less(loss, threshold)

def print_stats(predictions, labels):
  print("Accuracy = {}".format(accuracy_score(labels, predictions)))
  print("Precision = {}".format(precision_score(labels, predictions)))
  print("Recall = {}".format(recall_score(labels, predictions)))


preds = predict(autoencoder, train_data, threshold)
```