

1. 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

```
In [68]: import numpy as np
import pandas as pd
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, classification_report
from tensorflow.keras import layers, models
import matplotlib.pyplot as plt
```

b. Upload / access the dataset

```
In [69]: # Load the ECG dataset
ecg_dataset = pd.read_csv("Datasets/ecg-csv/ecg.csv")
```

```
In [70]: # Preprocess the data
scaler = StandardScaler()
X = scaler.fit_transform(ecg_dataset.values)
y = X # Autoencoder input and output are the same

X_train, X_test, _, _ = train_test_split(X, X, test_size=0.2, random_state
```

```
In [71]: # Build and train the Autoencoder model
input_dim = X_train.shape[1]
```

c. Encoder converts it into latent representation

```
In [72]: encoder = models.Sequential([
    layers.Input(shape=(input_dim,)),
    layers.Dense(32, activation='relu'),
    layers.Dense(16, activation='relu'),
    layers.Dense(8, activation='relu')
])
```

d. Decoder networks convert it back to the original input

```
In [73]: decoder = models.Sequential([
    layers.Input(shape=(8,)),
    layers.Dense(16, activation='relu'),
    layers.Dense(32, activation='relu'),
```

```
layers.Dense(input_dim, activation='linear') # Use linear activation  
)
```

e. Compile the models with Optimizer, Loss, and Evaluation Metrics

```
In [74]: autoencoder = models.Sequential([  
          encoder,  
          decoder  
        ])  
autoencoder.compile(optimizer='adam', loss='mean_squared_error')  
autoencoder.fit(X_train, X_train, epochs=100, batch_size=32, shuffle=True)
```

Epoch 1/100
125/125 [=====] - 1s 2ms/step - loss: 0.6891
Epoch 2/100
125/125 [=====] - 0s 1ms/step - loss: 0.3301
Epoch 3/100
125/125 [=====] - 0s 1ms/step - loss: 0.2722
Epoch 4/100
125/125 [=====] - 0s 2ms/step - loss: 0.2358
Epoch 5/100
125/125 [=====] - 0s 1ms/step - loss: 0.2116
Epoch 6/100
125/125 [=====] - 0s 1ms/step - loss: 0.1937
Epoch 7/100
125/125 [=====] - 0s 1ms/step - loss: 0.1807
Epoch 8/100
125/125 [=====] - 0s 1ms/step - loss: 0.1683
Epoch 9/100
125/125 [=====] - 0s 1ms/step - loss: 0.1581
Epoch 10/100
125/125 [=====] - 0s 1ms/step - loss: 0.1510
Epoch 11/100
125/125 [=====] - 0s 1ms/step - loss: 0.1454
Epoch 12/100
125/125 [=====] - 0s 1ms/step - loss: 0.1408
Epoch 13/100
125/125 [=====] - 0s 1ms/step - loss: 0.1358
Epoch 14/100
125/125 [=====] - 0s 2ms/step - loss: 0.1332
Epoch 15/100
125/125 [=====] - 0s 2ms/step - loss: 0.1302
Epoch 16/100
125/125 [=====] - 0s 2ms/step - loss: 0.1284
Epoch 17/100
125/125 [=====] - 0s 2ms/step - loss: 0.1252
Epoch 18/100
125/125 [=====] - 0s 1ms/step - loss: 0.1238
Epoch 19/100
125/125 [=====] - 0s 1ms/step - loss: 0.1221
Epoch 20/100
125/125 [=====] - 0s 1ms/step - loss: 0.1206
Epoch 21/100
125/125 [=====] - 0s 1ms/step - loss: 0.1193
Epoch 22/100
125/125 [=====] - 0s 1ms/step - loss: 0.1176
Epoch 23/100
125/125 [=====] - 0s 1ms/step - loss: 0.1164
Epoch 24/100
125/125 [=====] - 0s 1ms/step - loss: 0.1152
Epoch 25/100
125/125 [=====] - 0s 1ms/step - loss: 0.1141
Epoch 26/100
125/125 [=====] - 0s 1ms/step - loss: 0.1124
Epoch 27/100
125/125 [=====] - 0s 1ms/step - loss: 0.1119
Epoch 28/100
125/125 [=====] - 0s 1ms/step - loss: 0.1097
Epoch 29/100
125/125 [=====] - 0s 1ms/step - loss: 0.1084
Epoch 30/100

125/125 [=====] - 0s 1ms/step - loss: 0.1070
Epoch 31/100
125/125 [=====] - 0s 1ms/step - loss: 0.1066
Epoch 32/100
125/125 [=====] - 0s 1ms/step - loss: 0.1058
Epoch 33/100
125/125 [=====] - 0s 1ms/step - loss: 0.1048
Epoch 34/100
125/125 [=====] - 0s 1ms/step - loss: 0.1042
Epoch 35/100
125/125 [=====] - 0s 1ms/step - loss: 0.1031
Epoch 36/100
125/125 [=====] - 0s 1ms/step - loss: 0.1023
Epoch 37/100
125/125 [=====] - 0s 1ms/step - loss: 0.1023
Epoch 38/100
125/125 [=====] - 0s 1ms/step - loss: 0.1012
Epoch 39/100
125/125 [=====] - 0s 1ms/step - loss: 0.1005
Epoch 40/100
125/125 [=====] - 0s 1ms/step - loss: 0.1001
Epoch 41/100
125/125 [=====] - 0s 1ms/step - loss: 0.0996
Epoch 42/100
125/125 [=====] - 0s 1ms/step - loss: 0.0995
Epoch 43/100
125/125 [=====] - 0s 1ms/step - loss: 0.0988
Epoch 44/100
125/125 [=====] - 0s 1ms/step - loss: 0.0982
Epoch 45/100
125/125 [=====] - 0s 1ms/step - loss: 0.0976
Epoch 46/100
125/125 [=====] - 0s 1ms/step - loss: 0.0975
Epoch 47/100
125/125 [=====] - 0s 1ms/step - loss: 0.0969
Epoch 48/100
125/125 [=====] - 0s 1ms/step - loss: 0.0960
Epoch 49/100
125/125 [=====] - 0s 1ms/step - loss: 0.0963
Epoch 50/100
125/125 [=====] - 0s 1ms/step - loss: 0.0961
Epoch 51/100
125/125 [=====] - 0s 1ms/step - loss: 0.0958
Epoch 52/100
125/125 [=====] - 0s 1ms/step - loss: 0.0959
Epoch 53/100
125/125 [=====] - 0s 1ms/step - loss: 0.0944
Epoch 54/100
125/125 [=====] - 0s 1ms/step - loss: 0.0949
Epoch 55/100
125/125 [=====] - 0s 1ms/step - loss: 0.0938
Epoch 56/100
125/125 [=====] - 0s 1ms/step - loss: 0.0934
Epoch 57/100
125/125 [=====] - 0s 1ms/step - loss: 0.0932
Epoch 58/100
125/125 [=====] - 0s 1ms/step - loss: 0.0931
Epoch 59/100
125/125 [=====] - 0s 1ms/step - loss: 0.0928

Epoch 60/100
125/125 [=====] - 0s 1ms/step - loss: 0.0927
Epoch 61/100
125/125 [=====] - 0s 1ms/step - loss: 0.0924
Epoch 62/100
125/125 [=====] - 0s 1ms/step - loss: 0.0922
Epoch 63/100
125/125 [=====] - 0s 1ms/step - loss: 0.0913
Epoch 64/100
125/125 [=====] - 0s 1ms/step - loss: 0.0911
Epoch 65/100
125/125 [=====] - 0s 1ms/step - loss: 0.0911
Epoch 66/100
125/125 [=====] - 0s 1ms/step - loss: 0.0910
Epoch 67/100
125/125 [=====] - 0s 1ms/step - loss: 0.0905
Epoch 68/100
125/125 [=====] - 0s 1ms/step - loss: 0.0903
Epoch 69/100
125/125 [=====] - 0s 1ms/step - loss: 0.0904
Epoch 70/100
125/125 [=====] - 0s 1ms/step - loss: 0.0912
Epoch 71/100
125/125 [=====] - 0s 1ms/step - loss: 0.0903
Epoch 72/100
125/125 [=====] - 0s 1ms/step - loss: 0.0904
Epoch 73/100
125/125 [=====] - 0s 1ms/step - loss: 0.0895
Epoch 74/100
125/125 [=====] - 0s 1ms/step - loss: 0.0893
Epoch 75/100
125/125 [=====] - 0s 1ms/step - loss: 0.0893
Epoch 76/100
125/125 [=====] - 0s 1ms/step - loss: 0.0887
Epoch 77/100
125/125 [=====] - 0s 1ms/step - loss: 0.0888
Epoch 78/100
125/125 [=====] - 0s 1ms/step - loss: 0.0885
Epoch 79/100
125/125 [=====] - 0s 1ms/step - loss: 0.0883
Epoch 80/100
125/125 [=====] - 0s 1ms/step - loss: 0.0885
Epoch 81/100
125/125 [=====] - 0s 1ms/step - loss: 0.0884
Epoch 82/100
125/125 [=====] - 0s 1ms/step - loss: 0.0878
Epoch 83/100
125/125 [=====] - 0s 1ms/step - loss: 0.0877
Epoch 84/100
125/125 [=====] - 0s 1ms/step - loss: 0.0878
Epoch 85/100
125/125 [=====] - 0s 1ms/step - loss: 0.0870
Epoch 86/100
125/125 [=====] - 0s 1ms/step - loss: 0.0874
Epoch 87/100
125/125 [=====] - 0s 1ms/step - loss: 0.0872
Epoch 88/100
125/125 [=====] - 0s 1ms/step - loss: 0.0874
Epoch 89/100

```

125/125 [=====] - 0s 1ms/step - loss: 0.0870
Epoch 90/100
125/125 [=====] - 0s 1ms/step - loss: 0.0866
Epoch 91/100
125/125 [=====] - 0s 1ms/step - loss: 0.0867
Epoch 92/100
125/125 [=====] - 0s 1ms/step - loss: 0.0867
Epoch 93/100
125/125 [=====] - 0s 1ms/step - loss: 0.0861
Epoch 94/100
125/125 [=====] - 0s 1ms/step - loss: 0.0865
Epoch 95/100
125/125 [=====] - 0s 1ms/step - loss: 0.0859
Epoch 96/100
125/125 [=====] - 0s 1ms/step - loss: 0.0859
Epoch 97/100
125/125 [=====] - 0s 1ms/step - loss: 0.0862
Epoch 98/100
125/125 [=====] - 0s 1ms/step - loss: 0.0858
Epoch 99/100
125/125 [=====] - 0s 1ms/step - loss: 0.0855
Epoch 100/100
125/125 [=====] - 0s 1ms/step - loss: 0.0854
<keras.src.callbacks.History at 0x7f9b14231ed0>

```

Out[74]:

```

In [75]: # Detect anomalies
y_pred = autoencoder.predict(X_test)
mse = np.mean(np.power(X_test - y_pred, 2), axis=1)

```

```

32/32 [=====] - 0s 907us/step

```

```

In [76]: # Define a threshold for anomaly detection
threshold = np.percentile(mse, 95) # Adjust the percentile as needed

```

```

In [77]: # Predict anomalies
anomalies = mse > threshold

```

```

In [78]: # Calculate the number of anomalies
num_anomalies = np.sum(anomalies)
print(f"Number of Anomalies: {num_anomalies}")

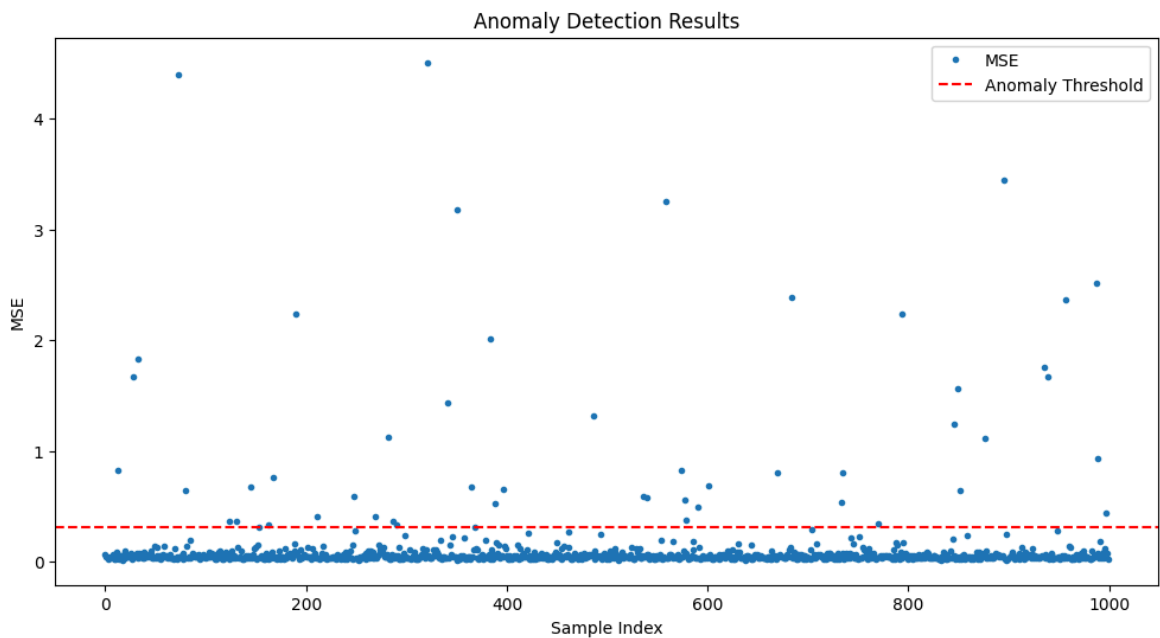
```

Number of Anomalies: 50

```

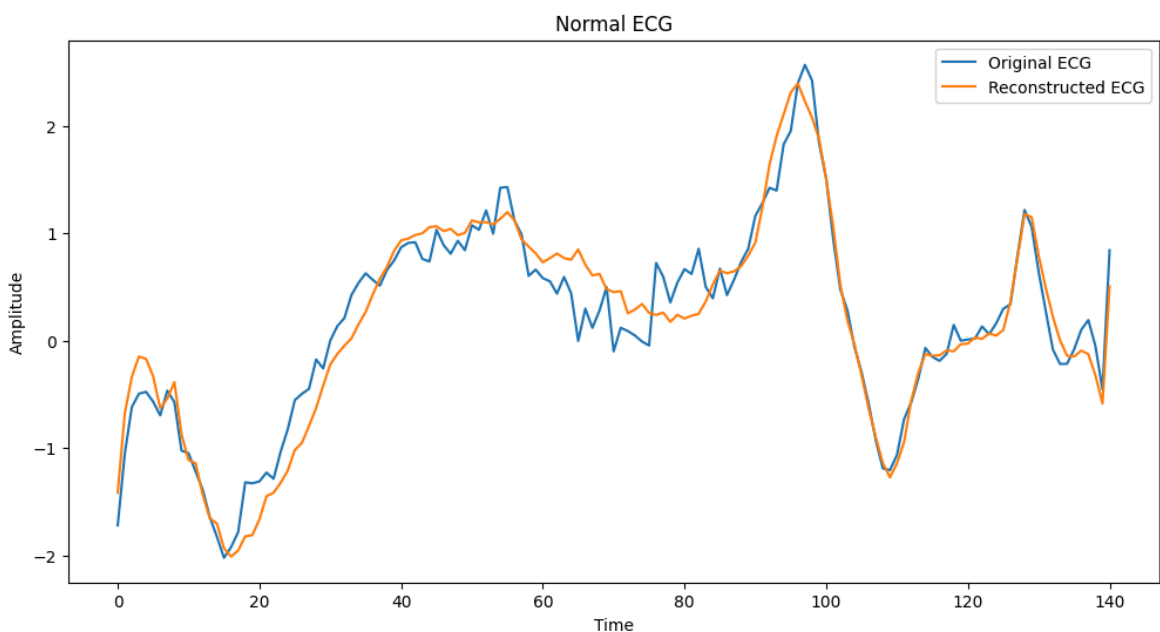
In [79]: # Plot the anomalies
plt.figure(figsize=(12, 6))
plt.plot(mse, marker='o', linestyle='', markersize=3, label='MSE')
plt.axhline(threshold, color='r', linestyle='--', label='Anomaly Threshold')
plt.xlabel('Sample Index')
plt.ylabel('MSE')
plt.title('Anomaly Detection Results')
plt.legend()
plt.show()

```



Visualize Normal

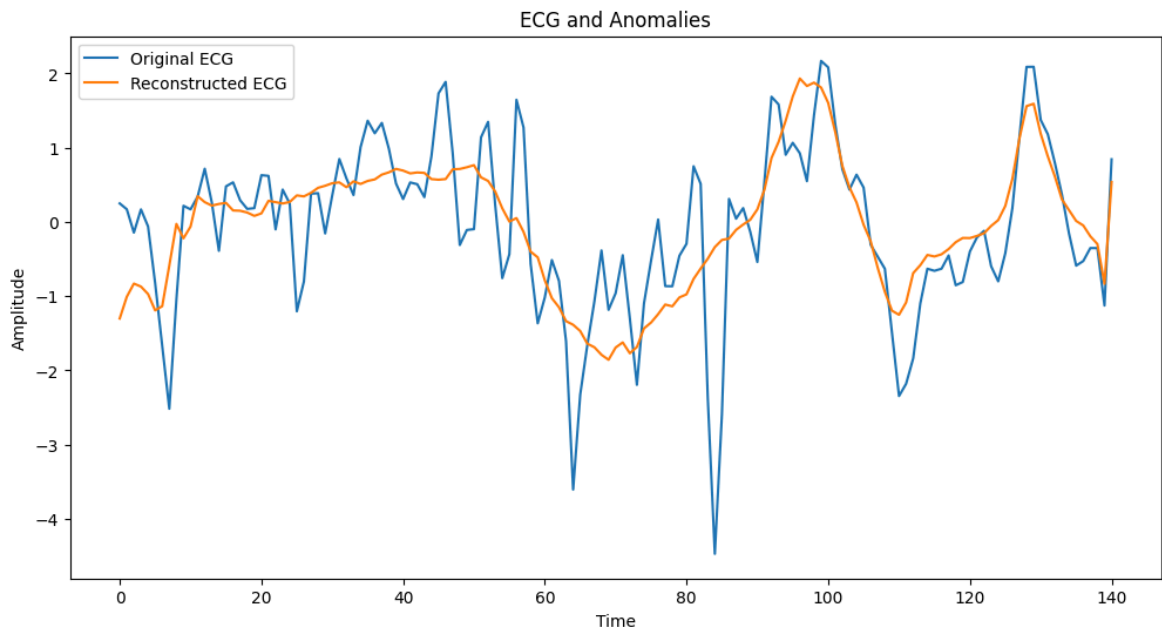
```
In [80]: plt.figure(figsize=(12, 6))
plt.plot(X_test[0], label='Original ECG')
plt.plot(y_pred[0], label='Reconstructed ECG')
plt.xlabel('Time')
plt.ylabel('Amplitude')
plt.legend()
plt.title('Normal ECG')
plt.show()
```



Visualize Anomaly

```
In [81]: # listing the index of anomalies in X_test
anomalies_index = []
for index, anomaly in enumerate(anomalies):
    if anomaly == True :
        anomalies_index.append(index)
```

```
In [82]: n = 4
anomaly_index = anomalies_index[n]
plt.figure(figsize=(12, 6))
plt.plot(X_test[anomaly_index], label='Original ECG')
plt.plot(y_pred[anomaly_index], label='Reconstructed ECG')
plt.xlabel('Time')
plt.ylabel('Amplitude')
plt.legend()
plt.title('ECG and Anomalies')
plt.show()
```



```
In [83]: # Evaluate the model
y_true = np.zeros(len(X_test))
print("Confusion Matrix:")
print(confusion_matrix(anomalies, anomalies))

print("\nClassification Report:")
print(classification_report(anomalies, anomalies))
```

Confusion Matrix:

```
[[950  0]
 [ 0  50]]
```

Classification Report:

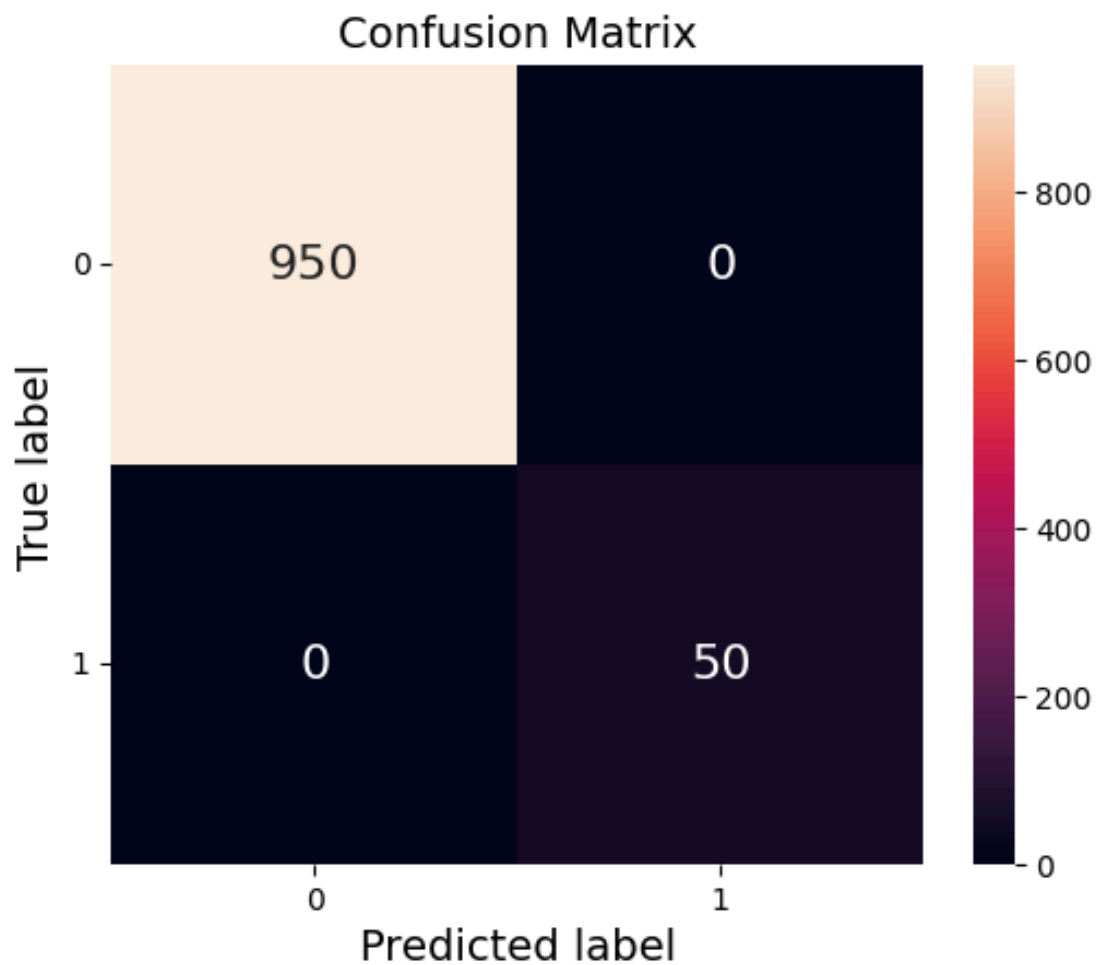
	precision	recall	f1-score	support
False	1.00	1.00	1.00	950
True	1.00	1.00	1.00	50
accuracy			1.00	1000
macro avg	1.00	1.00	1.00	1000
weighted avg	1.00	1.00	1.00	1000

```
In [84]: import seaborn as sns
```

```
In [85]: plt.figure(figsize = (6, 4.75))
sns.heatmap(confusion_matrix(anomalies, anomalies), annot = True, annot_kw
plt.xticks([0.5, 1.5], rotation = 'horizontal')
```



```
plt.yticks([0.5, 1.5], rotation = 'horizontal')
plt.xlabel("Predicted label", fontsize = 14)
plt.ylabel("True label", fontsize = 14)
plt.title("Confusion Matrix", fontsize = 14)
plt.grid(False)
plt.show()
```



In []: