

```
'''4ECG
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
'''
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'4ECG\nUse Autoencoder to implement anomaly detection. Build the model
by using:\na. Import required libraries\nb. Upload / access the
dataset\nc. Encoder converts it into latent representation\nd. Decoder
networks convert it back to the original input\ne. Compile the models
with Optimizer, Loss, and Evaluation Metrics\n'
```

```
#Aa. Import required libraries
```

```
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
```

```
# Load the ECG dataset
```

```
ecg_dataset = pd.read_csv("ecg.csv")
```

```
# 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=42)
```

```
# Build and train the Autoencoder model
```

```
input_dim = X_train.shape[1]
```

```
#Cc. Encoder converts it into latent representation
```

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

```

#DDecoder networks convert it back to the original input
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 for reconstruction
])

#Ee. Compile the models with Optimizer, Loss, and Evaluation Metrics
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 _____ 4s 4ms/step - loss: 0.7232
Epoch 2/100
125/125 _____ 1s 4ms/step - loss: 0.4107
Epoch 3/100
125/125 _____ 1s 4ms/step - loss: 0.3435
Epoch 4/100
125/125 _____ 1s 4ms/step - loss: 0.3052
Epoch 5/100
125/125 _____ 1s 4ms/step - loss: 0.2742
Epoch 6/100
125/125 _____ 1s 4ms/step - loss: 0.2607
Epoch 7/100
125/125 _____ 1s 4ms/step - loss: 0.2491
Epoch 8/100
125/125 _____ 1s 4ms/step - loss: 0.2386
Epoch 9/100
125/125 _____ 1s 4ms/step - loss: 0.2254
Epoch 10/100
125/125 _____ 1s 4ms/step - loss: 0.2120
Epoch 11/100
125/125 _____ 1s 4ms/step - loss: 0.2020
Epoch 12/100
125/125 _____ 1s 4ms/step - loss: 0.1935
Epoch 13/100
125/125 _____ 1s 4ms/step - loss: 0.1879
Epoch 14/100
125/125 _____ 1s 4ms/step - loss: 0.1819
Epoch 15/100
125/125 _____ 1s 4ms/step - loss: 0.1764
Epoch 16/100
125/125 _____ 1s 4ms/step - loss: 0.1712

```

```
Epoch 17/100
125/125 _____ 1s 4ms/step - loss: 0.1652
Epoch 18/100
125/125 _____ 1s 4ms/step - loss: 0.1602
Epoch 19/100
125/125 _____ 1s 4ms/step - loss: 0.1539
Epoch 20/100
125/125 _____ 1s 4ms/step - loss: 0.1507
Epoch 21/100
125/125 _____ 1s 4ms/step - loss: 0.1473
Epoch 22/100
125/125 _____ 1s 4ms/step - loss: 0.1457
Epoch 23/100
125/125 _____ 1s 4ms/step - loss: 0.1435
Epoch 24/100
125/125 _____ 1s 4ms/step - loss: 0.1421
Epoch 25/100
125/125 _____ 1s 4ms/step - loss: 0.1403
Epoch 26/100
125/125 _____ 1s 4ms/step - loss: 0.1389
Epoch 27/100
125/125 _____ 1s 4ms/step - loss: 0.1369
Epoch 28/100
125/125 _____ 1s 4ms/step - loss: 0.1357
Epoch 29/100
125/125 _____ 1s 5ms/step - loss: 0.1344
Epoch 30/100
125/125 _____ 1s 4ms/step - loss: 0.1334
Epoch 31/100
125/125 _____ 1s 4ms/step - loss: 0.1318
Epoch 32/100
125/125 _____ 1s 4ms/step - loss: 0.1306
Epoch 33/100
125/125 _____ 1s 4ms/step - loss: 0.1298
Epoch 34/100
125/125 _____ 1s 4ms/step - loss: 0.1289
Epoch 35/100
125/125 _____ 1s 4ms/step - loss: 0.1275
Epoch 36/100
125/125 _____ 1s 4ms/step - loss: 0.1261
Epoch 37/100
125/125 _____ 1s 4ms/step - loss: 0.1260
Epoch 38/100
125/125 _____ 1s 4ms/step - loss: 0.1247
Epoch 39/100
125/125 _____ 1s 4ms/step - loss: 0.1238
Epoch 40/100
125/125 _____ 1s 4ms/step - loss: 0.1227
Epoch 41/100
```

```
125/125 _____ 1s 4ms/step - loss: 0.1228
Epoch 42/100
125/125 _____ 1s 5ms/step - loss: 0.1212
Epoch 43/100
125/125 _____ 1s 4ms/step - loss: 0.1208
Epoch 44/100
125/125 _____ 1s 5ms/step - loss: 0.1202
Epoch 45/100
125/125 _____ 1s 4ms/step - loss: 0.1193
Epoch 46/100
125/125 _____ 1s 4ms/step - loss: 0.1186
Epoch 47/100
125/125 _____ 1s 4ms/step - loss: 0.1186
Epoch 48/100
125/125 _____ 1s 4ms/step - loss: 0.1176
Epoch 49/100
125/125 _____ 1s 5ms/step - loss: 0.1162
Epoch 50/100
125/125 _____ 1s 4ms/step - loss: 0.1162
Epoch 51/100
125/125 _____ 1s 4ms/step - loss: 0.1154
Epoch 52/100
125/125 _____ 1s 4ms/step - loss: 0.1147
Epoch 53/100
125/125 _____ 1s 4ms/step - loss: 0.1149
Epoch 54/100
125/125 _____ 1s 4ms/step - loss: 0.1141
Epoch 55/100
125/125 _____ 1s 4ms/step - loss: 0.1138
Epoch 56/100
125/125 _____ 1s 4ms/step - loss: 0.1137
Epoch 57/100
125/125 _____ 1s 4ms/step - loss: 0.1130
Epoch 58/100
125/125 _____ 1s 4ms/step - loss: 0.1130
Epoch 59/100
125/125 _____ 1s 4ms/step - loss: 0.1121
Epoch 60/100
125/125 _____ 1s 4ms/step - loss: 0.1114
Epoch 61/100
125/125 _____ 1s 4ms/step - loss: 0.1110
Epoch 62/100
125/125 _____ 1s 4ms/step - loss: 0.1107
Epoch 63/100
125/125 _____ 1s 4ms/step - loss: 0.1103
Epoch 64/100
125/125 _____ 1s 4ms/step - loss: 0.1104
Epoch 65/100
125/125 _____ 1s 4ms/step - loss: 0.1100
```

```
Epoch 66/100
125/125 _____ 1s 4ms/step - loss: 0.1094
Epoch 67/100
125/125 _____ 1s 4ms/step - loss: 0.1092
Epoch 68/100
125/125 _____ 1s 4ms/step - loss: 0.1086
Epoch 69/100
125/125 _____ 1s 4ms/step - loss: 0.1087
Epoch 70/100
125/125 _____ 1s 4ms/step - loss: 0.1085
Epoch 71/100
125/125 _____ 1s 4ms/step - loss: 0.1081
Epoch 72/100
125/125 _____ 1s 4ms/step - loss: 0.1076
Epoch 73/100
125/125 _____ 1s 4ms/step - loss: 0.1072
Epoch 74/100
125/125 _____ 1s 4ms/step - loss: 0.1077
Epoch 75/100
125/125 _____ 1s 4ms/step - loss: 0.1067
Epoch 76/100
125/125 _____ 1s 4ms/step - loss: 0.1064
Epoch 77/100
125/125 _____ 1s 4ms/step - loss: 0.1060
Epoch 78/100
125/125 _____ 1s 4ms/step - loss: 0.1056
Epoch 79/100
125/125 _____ 0s 3ms/step - loss: 0.1045
Epoch 80/100
125/125 _____ 1s 4ms/step - loss: 0.1036
Epoch 81/100
125/125 _____ 1s 4ms/step - loss: 0.1034
Epoch 82/100
125/125 _____ 1s 4ms/step - loss: 0.1030
Epoch 83/100
125/125 _____ 1s 4ms/step - loss: 0.1022
Epoch 84/100
125/125 _____ 1s 4ms/step - loss: 0.1019
Epoch 85/100
125/125 _____ 1s 4ms/step - loss: 0.1012
Epoch 86/100
125/125 _____ 1s 4ms/step - loss: 0.1006
Epoch 87/100
125/125 _____ 1s 4ms/step - loss: 0.1004
Epoch 88/100
125/125 _____ 1s 4ms/step - loss: 0.1001
Epoch 89/100
125/125 _____ 1s 4ms/step - loss: 0.0995
Epoch 90/100
```

```

125/125 _____ 1s 4ms/step - loss: 0.0990
Epoch 91/100
125/125 _____ 1s 4ms/step - loss: 0.0989
Epoch 92/100
125/125 _____ 1s 4ms/step - loss: 0.0981
Epoch 93/100
125/125 _____ 1s 4ms/step - loss: 0.0976
Epoch 94/100
125/125 _____ 1s 4ms/step - loss: 0.0983
Epoch 95/100
125/125 _____ 1s 4ms/step - loss: 0.0976
Epoch 96/100
125/125 _____ 1s 4ms/step - loss: 0.0971
Epoch 97/100
125/125 _____ 1s 4ms/step - loss: 0.0965
Epoch 98/100
125/125 _____ 1s 4ms/step - loss: 0.0968
Epoch 99/100
125/125 _____ 1s 4ms/step - loss: 0.0964
Epoch 100/100
125/125 _____ 1s 4ms/step - loss: 0.0961

```

```
<keras.src.callbacks.history.History at 0x1578fb1a900>
```

```
# Detect anomalies
```

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

```
32/32 _____ 0s 9ms/step
```

```
# Define a threshold for anomaly detection
```

```
threshold = np.percentile(mse, 95) # Adjust the percentile as needed
```

```
# Predict anomalies
```

```
anomalies = mse > threshold
```

```
# Calculate the number of anomalies
```

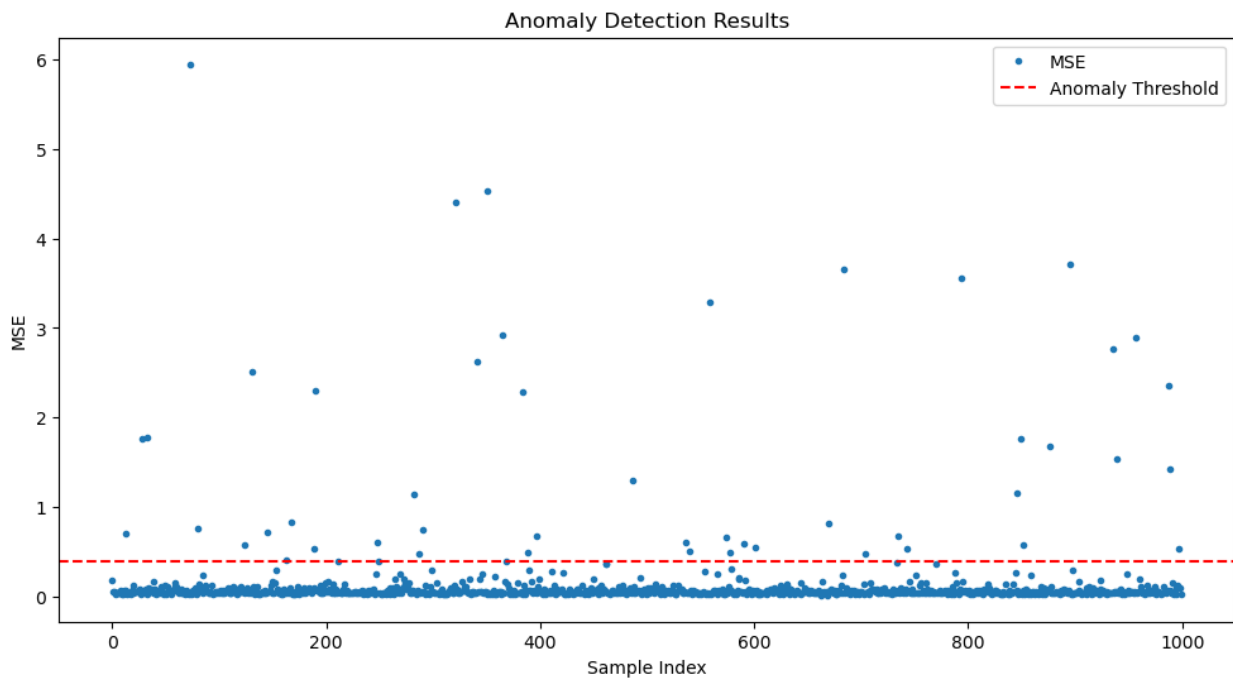
```
num_anomalies = np.sum(anomalies)
print(f"Number of Anomalies: {num_anomalies}")
```

```
Number of Anomalies: 50
```

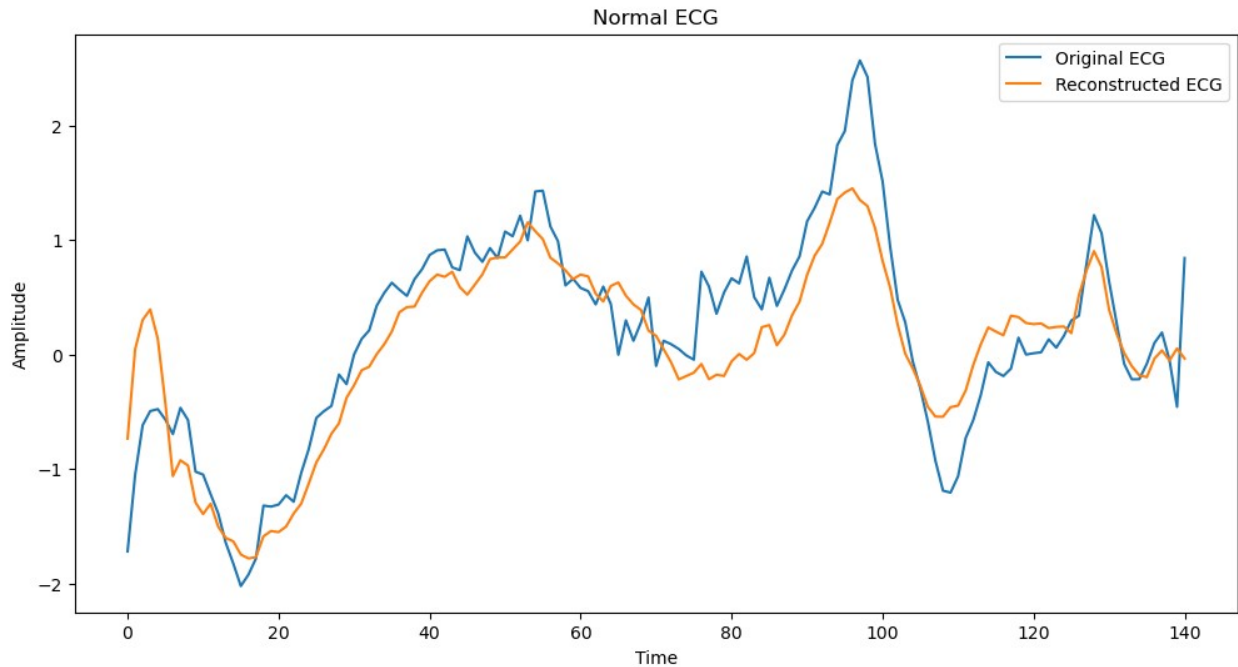
```
# Plot the anomalies
```

```
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()
```



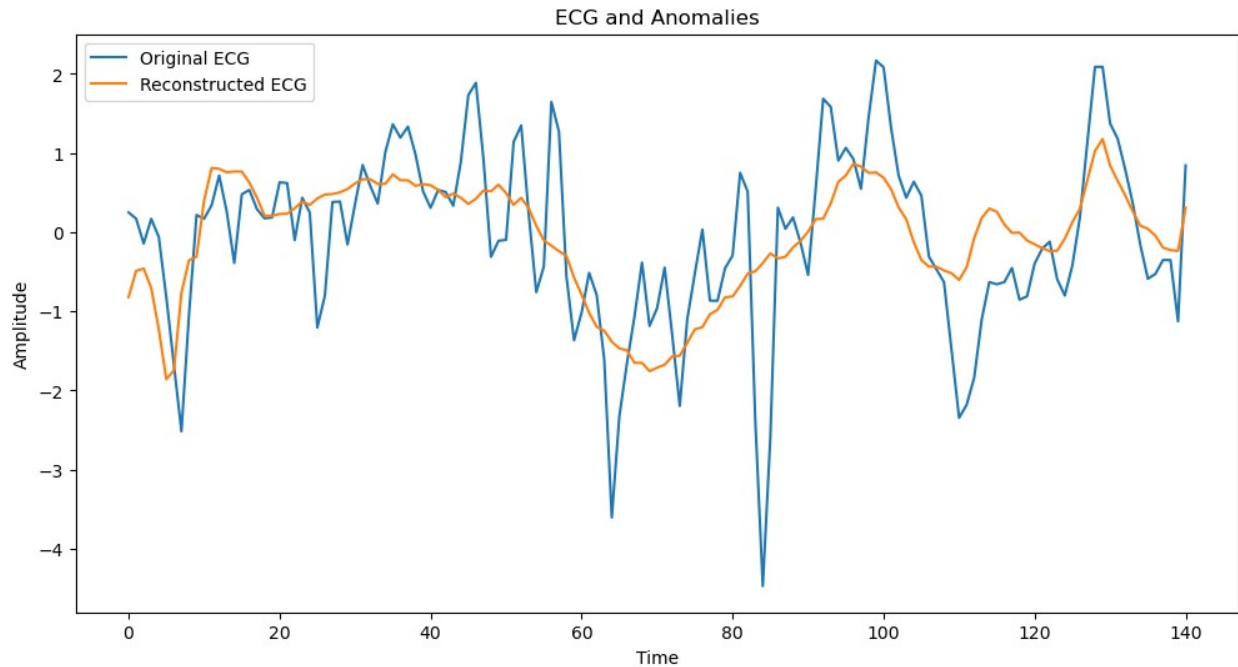
```
plt.figure(figsize=(12, 6))
plt.plot(X_test[0], label='Original ECG')
plt.plot(y_pred[0], label='Reconstructed ECG')
plt.xlabel('Time')
plt.ylabel('Amplitude')
plt.legend()
plt.title('Normal ECG')
plt.show()
```



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

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()
```





```
# 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