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

In [1]:
```
# Importing libraries
import numpy as np
import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras import Model, Sequential
from tensorflow.keras.layers import Dense, Dropout
from sklearn.model_selection import train_test_split

# Define the path to the dataset. You can change this to your local file pat
path = 'http://storage.googleapis.com/download.tensorflow.org/data/ecg.csv'

# Read the ECG dataset into a Pandas DataFrame
data = pd.read_csv(path, header=None)
```

In [2]:
```
data.head()
```

Out[2]:

	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	-1.25
1	-1.100878	-3.996840	-4.285843	-4.506579	-4.022377	-3.234368	-1.566126	-0.992258	-0.75
2	-0.567088	-2.593450	-3.874230	-4.584095	-4.187449	-3.151462	-1.742940	-1.490659	-1.18
3	0.490473	-1.914407	-3.616364	-4.318823	-4.268016	-3.881110	-2.993280	-1.671131	-1.33
4	0.800232	-0.874252	-2.384761	-3.973292	-4.338224	-3.802422	-2.534510	-1.783423	-1.59

5 rows × 141 columns

In [3]:
```
# Get information about the dataset, such as column data types and non-null
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4998 entries, 0 to 4997
Columns: 141 entries, 0 to 140
dtypes: float64(141)
memory usage: 5.4 MB
```

In [4]:
```
# Splitting the dataset into features and target
features = data.drop(140, axis=1)  # Features are all columns except the las
target = data[140]  # Target is the last column (column 140)

# Split the data into training and testing sets (80% training, 20% testing)
x_train, x_test, y_train, y_test = train_test_split(
    features, target, test_size=0.2
)

# Get the indices of the training data points labeled as "1" (anomalies)
train_index = y_train[y_train == 1].index

# Select the training data points that are anomalies
train_data = x_train.loc[train_index]
```

In [5]:
```
# Initialize the Min-Max Scaler to scale the data between 0 and 1
min_max_scaler = MinMaxScaler(feature_range=(0, 1))

# Scale the training data
x_train_scaled = min_max_scaler.fit_transform(train_data.copy())

# Scale the testing data using the same scaler
x_test_scaled = min_max_scaler.transform(x_test.copy())
```

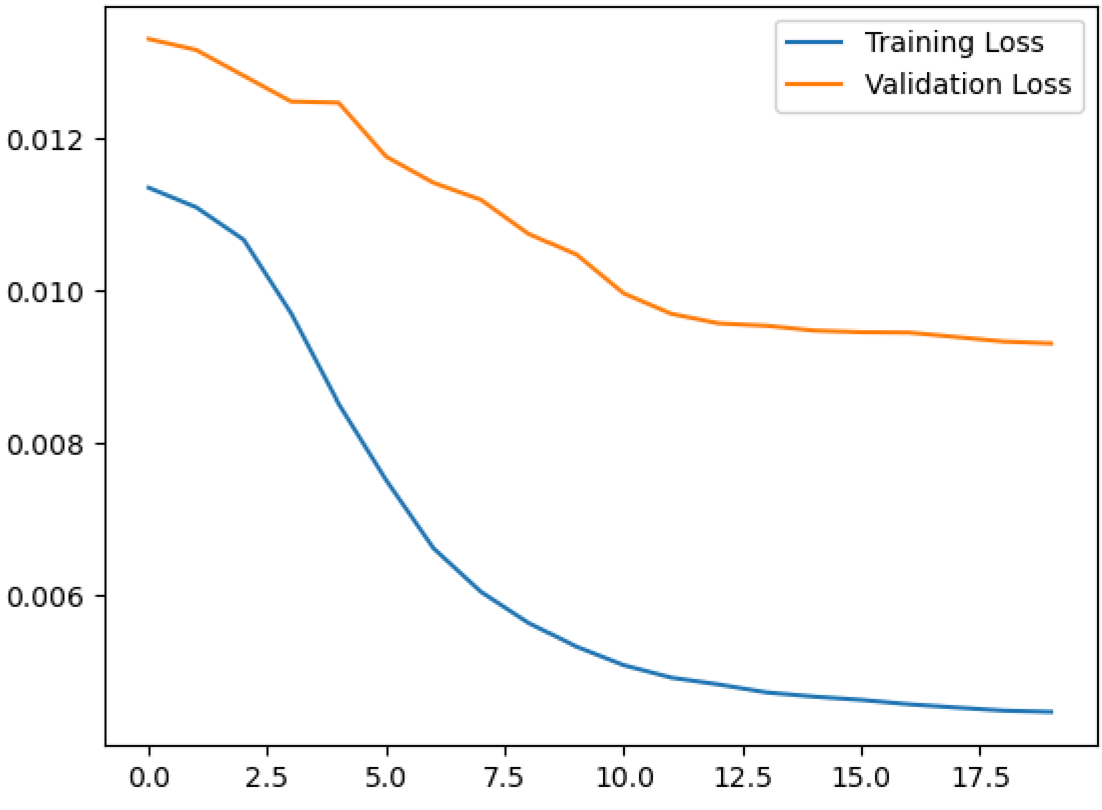
In [6]:
```
# Creating an Autoencoder model by extending the Model class from Keras
class AutoEncoder(Model):
    def __init__(self, output_units, ldim=8):
        super().__init__()
        # Define the encoder part of the Autoencoder
        self.encoder = Sequential([
            Dense(64, activation='relu'),
            Dropout(0.1),
            Dense(32, activation='relu'),
            Dropout(0.1),
            Dense(16, activation='relu'),
            Dropout(0.1),
            Dense(ldim, activation='relu')
        ])
        # Define the decoder part of the Autoencoder
        self.decoder = Sequential([
            Dense(16, activation='relu'),
            Dropout(0.1),
            Dense(32, activation='relu'),
            Dropout(0.1),
            Dense(64, activation='relu'),
            Dropout(0.1),
            Dense(output_units, activation='sigmoid')
        ])

    def call(self, inputs):
        # Forward pass through the Autoencoder
        encoded = self.encoder(inputs)
        decoded = self.decoder(encoded)
        return decoded
```

In [7]:
```
# Create an instance of the AutoEncoder model with the appropriate output ur
model = AutoEncoder(output_units=x_train_scaled.shape[1])

# Compile the model with Mean Squared Logarithmic Error (MSLE) loss and Mear
model.compile(loss='msle', metrics=['mse'], optimizer='adam')

# Train the model using the scaled training data
history = model.fit(
    x_train_scaled,  # Input data for training
    x_train_scaled,  # Target data for training (autoencoder reconstructs tl
    epochs=20,        # Number of training epochs
    batch_size=512,   # Batch size
    validation_data=(x_test_scaled, x_test_scaled),  # Validation data
    shuffle=True     # Shuffle the data during training
)
```

```
Epoch 1/20
5/5 [==============================] - 11s 96ms/step - loss: 0.0114 - mse:
0.0254 - val_loss: 0.0133 - val_mse: 0.0309
Epoch 2/20
5/5 [==============================] - 0s 13ms/step - loss: 0.0111 - mse:
0.0248 - val_loss: 0.0132 - val_mse: 0.0306
Epoch 3/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0107 - mse:
0.0238 - val_loss: 0.0128 - val_mse: 0.0298
Epoch 4/20
5/5 [==============================] - 0s 13ms/step - loss: 0.0097 - mse:
0.0216 - val_loss: 0.0125 - val_mse: 0.0289
Epoch 5/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0085 - mse:
0.0189 - val_loss: 0.0125 - val_mse: 0.0288
Epoch 6/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0075 - mse:
0.0167 - val_loss: 0.0118 - val_mse: 0.0272
Epoch 7/20
5/5 [==============================] - 0s 13ms/step - loss: 0.0066 - mse:
0.0147 - val_loss: 0.0114 - val_mse: 0.0265
Epoch 8/20
5/5 [==============================] - 0s 14ms/step - loss: 0.0060 - mse:
0.0134 - val_loss: 0.0112 - val_mse: 0.0260
Epoch 9/20
5/5 [==============================] - 0s 14ms/step - loss: 0.0056 - mse:
0.0125 - val_loss: 0.0107 - val_mse: 0.0250
Epoch 10/20
5/5 [==============================] - 0s 14ms/step - loss: 0.0053 - mse:
0.0118 - val_loss: 0.0105 - val_mse: 0.0244
Epoch 11/20
5/5 [==============================] - 0s 11ms/step - loss: 0.0051 - mse:
0.0113 - val_loss: 0.0100 - val_mse: 0.0233
Epoch 12/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0049 - mse:
0.0110 - val_loss: 0.0097 - val_mse: 0.0227
Epoch 13/20
5/5 [==============================] - 0s 11ms/step - loss: 0.0048 - mse:
0.0108 - val_loss: 0.0096 - val_mse: 0.0224
Epoch 14/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0047 - mse:
0.0106 - val_loss: 0.0095 - val_mse: 0.0224
Epoch 15/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0047 - mse:
0.0105 - val_loss: 0.0095 - val_mse: 0.0222
Epoch 16/20
5/5 [==============================] - 0s 11ms/step - loss: 0.0046 - mse:
0.0104 - val_loss: 0.0094 - val_mse: 0.0222
Epoch 17/20
5/5 [==============================] - 0s 13ms/step - loss: 0.0046 - mse:
0.0103 - val_loss: 0.0094 - val_mse: 0.0222
Epoch 18/20
5/5 [==============================] - 0s 11ms/step - loss: 0.0045 - mse:
0.0102 - val_loss: 0.0094 - val_mse: 0.0220
Epoch 19/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0045 - mse:
0.0101 - val_loss: 0.0093 - val_mse: 0.0219
Epoch 20/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0045 - mse:
0.0100 - val_loss: 0.0093 - val_mse: 0.0219
```

In [8]:
```
plt.plot(history.history["loss"], label="Training Loss")
plt.plot(history.history["val_loss"], label="Validation Loss")
plt.legend()
```

Out[8]: <matplotlib.legend.Legend at 0x1705de6d950>



In [9]:
```
# Function to find the threshold for anomalies based on the training data
def find_threshold(model, x_train_scaled):
    # Reconstruct the data using the model
    recons = model.predict(x_train_scaled)

    # Calculate the mean squared log error between reconstructed data and th
    recons_error = tf.keras.metrics.msle(recons, x_train_scaled)

    # Set the threshold as the mean error plus one standard deviation
    threshold = np.mean(recons_error.numpy()) + np.std(recons_error.numpy()

    return threshold

# Function to make predictions for anomalies based on the threshold
def get_predictions(model, x_test_scaled, threshold):
    # Reconstruct the data using the model
    predictions = model.predict(x_test_scaled)

    # Calculate the mean squared log error between reconstructed data and th
    errors = tf.keras.losses.msle(predictions, x_test_scaled)

    # Create a mask for anomalies based on the threshold
    anomaly_mask = pd.Series(errors) > threshold

    # Map True (anomalies) to 0 and False (normal data) to 1
    preds = anomaly_mask.map(lambda x: 0.0 if x == True else 1.0)

    return preds

# Find the threshold for anomalies
threshold = find_threshold(model, x_train_scaled)
print(f"Threshold: {threshold}")
```

```
73/73 [==============================] - 0s 1ms/step
Threshold: 0.009651090617132171
```

In [10]:
```
# Get predictions for anomalies based on the model and threshold
predictions = get_predictions(model, x_test_scaled, threshold)

# Calculate the accuracy score by comparing the predicted anomalies to the t
accuracy = accuracy_score(predictions, y_test)

# Print the accuracy score
print(f"Accuracy Score: {accuracy}")
```

```
32/32 [==============================] - 0s 1ms/step
Accuracy Score: 0.94
```

In [ ]:

In [ ]: