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

```
# 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 path if needed.
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)
```

```
data.head()
```

	0	1	2	3	4	5	6	7	8	9	...	131	132
0	-0.112522	-2.827204	-3.773897	-4.349751	-4.376041	-3.474986	-2.181408	-1.818286	-1.250522	-0.477492	...	0.792168	0.933541
1	-1.100878	-3.996840	-4.285843	-4.506579	-4.022377	-3.234368	-1.566126	-0.992258	-0.754680	0.042321	...	0.538356	0.656881
2	-0.567088	-2.593450	-3.874230	-4.584095	-4.187449	-3.151462	-1.742940	-1.490659	-1.183580	-0.394229	...	0.886073	0.531452
3	0.490473	-1.914407	-3.616364	-4.318823	-4.268016	-3.881110	-2.993280	-1.671131	-1.333884	-0.965629	...	0.350816	0.499111
4	0.800232	-0.874252	-2.384761	-3.973292	-4.338224	-3.802422	-2.534510	-1.783423	-1.594450	-0.753199	...	1.148884	0.958434

5 rows × 141 columns

```
# Get information about the dataset, such as column data types and non-null counts
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
```

```
# Splitting the dataset into features and target
features = data.drop(140, axis=1)  # Features are all columns except the last (column 140)
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]
```

```
# 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())
```

```
# 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
```

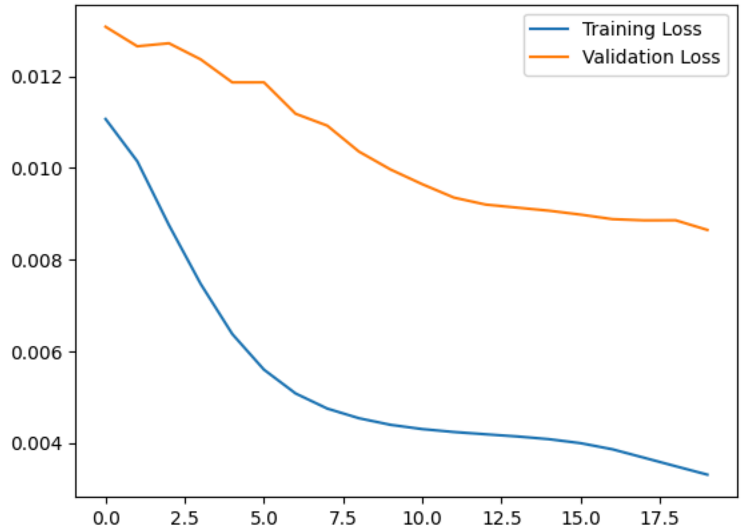
```
# Create an instance of the AutoEncoder model with the appropriate output units
model = AutoEncoder(output_units=x_train_scaled.shape[1])

# Compile the model with Mean Squared Logarithmic Error (MSLE) loss and Mean Squared Error (MSE) metric
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 the input)
    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 ━━━━━━━━━━━━━━━━━━━━ 19s 652ms/step - loss: 0.0111 - mse: 0.0252 - val_loss: 0.0131 - val_mse: 0.0304
Epoch 2/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 132ms/step - loss: 0.0101 - mse: 0.0231 - val_loss: 0.0127 - val_mse: 0.0294
Epoch 3/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 116ms/step - loss: 0.0087 - mse: 0.0199 - val_loss: 0.0127 - val_mse: 0.0293
Epoch 4/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 87ms/step - loss: 0.0075 - mse: 0.0169 - val_loss: 0.0124 - val_mse: 0.0284
Epoch 5/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 97ms/step - loss: 0.0064 - mse: 0.0144 - val_loss: 0.0119 - val_mse: 0.0273
Epoch 6/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 115ms/step - loss: 0.0056 - mse: 0.0126 - val_loss: 0.0119 - val_mse: 0.0272
Epoch 7/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 108ms/step - loss: 0.0051 - mse: 0.0114 - val_loss: 0.0112 - val_mse: 0.0257
Epoch 8/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 127ms/step - loss: 0.0047 - mse: 0.0106 - val_loss: 0.0109 - val_mse: 0.0251
Epoch 9/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 97ms/step - loss: 0.0045 - mse: 0.0102 - val_loss: 0.0104 - val_mse: 0.0238
Epoch 10/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 119ms/step - loss: 0.0044 - mse: 0.0098 - val_loss: 0.0100 - val_mse: 0.0230
Epoch 11/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 134ms/step - loss: 0.0043 - mse: 0.0096 - val_loss: 0.0096 - val_mse: 0.0223
Epoch 12/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 104ms/step - loss: 0.0042 - mse: 0.0095 - val_loss: 0.0093 - val_mse: 0.0216
Epoch 13/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 101ms/step - loss: 0.0042 - mse: 0.0094 - val_loss: 0.0092 - val_mse: 0.0213
Epoch 14/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 127ms/step - loss: 0.0041 - mse: 0.0093 - val_loss: 0.0091 - val_mse: 0.0212
Epoch 15/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 100ms/step - loss: 0.0041 - mse: 0.0092 - val_loss: 0.0091 - val_mse: 0.0210
Epoch 16/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 94ms/step - loss: 0.0040 - mse: 0.0090 - val_loss: 0.0090 - val_mse: 0.0208
```

```
Epoch 17/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 82ms/step - loss: 0.0039 - mse: 0.0087 - val_loss: 0.0089 - val_mse: 0.0206
Epoch 18/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 86ms/step - loss: 0.0037 - mse: 0.0083 - val_loss: 0.0089 - val_mse: 0.0204
Epoch 19/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 116ms/step - loss: 0.0035 - mse: 0.0079 - val_loss: 0.0089 - val_mse: 0.0204
Epoch 20/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 87ms/step - loss: 0.0033 - mse: 0.0074 - val_loss: 0.0086 - val_mse: 0.0198
```

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

```
<matplotlib.legend.Legend at 0x18e264da210>
```




```
# 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 the original data
    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 the original data
    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 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step
Threshold: 0.0074161197146449575
```

```
# 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 true labels
accuracy = accuracy_score(predictions, y_test)

# Print the accuracy score
```

```
print(f"Accuracy Score: {accuracy}")
```

```
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
Accuracy Score: 0.951
```