Practical No.4

```
import numpy as np
import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score
from tensorflow.keras.optimizers import Adam
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
from tensorflow.keras.losses import MeanSquaredLogarithmicError


# Download the dataset
PATH_TO_DATA = 'http://storage.googleapis.com/download.tensorflow.org/data/ecg.csv'
data = pd.read_csv(PATH_TO_DATA, header=None)
data.head()
```

Output:

0123456789101112131415161718192021222324252627282930313233343536373839...101
102103104105106107108109110111112113114115116117118119120121122123124125126
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1.6143921.4214561.0

```
# 0 = anomaly, 1 = normal
TARGET = 140

features = data.drop(TARGET, axis=1)
target = data[TARGET]

x_train, x_test, y_train, y_test = train_test_split(
    features, target, test_size=0.2, stratify=target
)

# use case is novelty detection so use only the normal data
# for training
train_index = y_train[y_train == 1].index
train_data = x_train.loc[train_index]

# min max scale the input data
min_max_scaler = MinMaxScaler(feature_range=(0, 1))
x_train_scaled = min_max_scaler.fit_transform(train_data.copy())
x_test_scaled = min_max_scaler.transform(x_test.copy())


# create a model by subclassing Model class in tensorflow
```

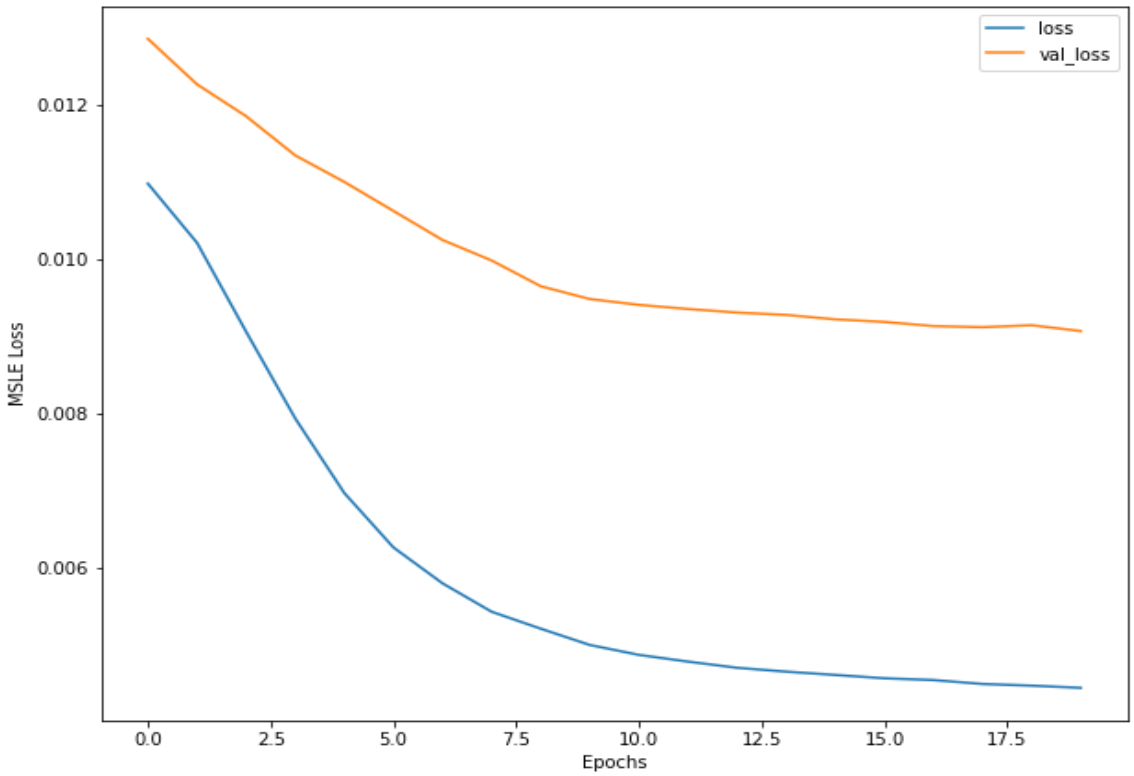
```
class AutoEncoder(Model):
  """
  Parameters
  ----------
  output_units: int
    Number of output units

  code_size: int
    Number of units in bottle neck
  """

  def __init__(self, output_units, code_size=8):
    super().__init__()
    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(code_size, activation='relu')
    ])
    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):
    encoded = self.encoder(inputs)
    decoded = self.decoder(encoded)
    return decoded

model = AutoEncoder(output_units=x_train_scaled.shape[1])
# configurations of model
model.compile(loss='msle', metrics=['mse'], optimizer='adam')

history = model.fit(
    x_train_scaled,
    x_train_scaled,
    epochs=20,
    batch_size=512,
    validation_data=(x_test_scaled, x_test_scaled)
)
```
Output:

```
Epoch 1/20
5/5 [==============================] - 1s 49ms/step - loss: 0.0110 - mse: 0.0247 - val_loss: 0.0128 - val_mse: 0.0295
Epoch 2/20
5/5 [==============================] - 0s 11ms/step - loss: 0.0102 - mse: 0.0229 - val_loss: 0.0123 - val_mse: 0.0280
Epoch 3/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0091 - mse: 0.0203 - val_loss: 0.0118 - val_mse: 0.0270
Epoch 4/20
5/5 [==============================] - 0s 11ms/step - loss: 0.0079 - mse: 0.0177 - val_loss: 0.0113 - val_mse: 0.0259
Epoch 5/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0070 - mse: 0.0156 - val_loss: 0.0110 - val_mse: 0.0251
Epoch 6/20
5/5 [==============================] - 0s 11ms/step - loss: 0.0063 - mse: 0.0140 - val_loss: 0.0106 - val_mse: 0.0243
Epoch 7/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0058 - mse: 0.0129 - val_loss: 0.0102 - val_mse: 0.0235
Epoch 8/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0054 - mse: 0.0121 - val_loss: 0.0100 - val_mse: 0.0229
Epoch 9/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0052 - mse: 0.0116 - val_loss: 0.0096 - val_mse: 0.0222
Epoch 10/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0050 - mse: 0.0112 - val_loss: 0.0095 - val_mse: 0.0218
Epoch 11/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0049 - mse: 0.0109 - val_loss: 0.0094 - val_mse: 0.0216
Epoch 12/20
5/5 [==============================] - 0s 15ms/step - loss: 0.0048 - mse: 0.0107 - val_loss: 0.0094 - val_mse: 0.0215
Epoch 13/20
5/5 [==============================] - 0s 12ms/step - loss: 0.0047 - mse: 0.0105 - val_loss: 0.0093 - val_mse: 0.0214
Epoch 14/20
5/5 [==============================] - 0s 13ms/step - loss: 0.0047 - mse: 0.0104 - val_loss: 0.0093 - val_mse: 0.0214
Epoch 15/20
5/5 [==============================] - 0s 15ms/step - loss: 0.0046 - mse: 0.0103 - val_loss: 0.0092 - val_mse: 0.0212
Epoch 16/20
5/5 [==============================] - 0s 13ms/step - loss: 0.0046 - mse: 0.0102 - val_loss: 0.0092 - val_mse: 0.0212
Epoch 17/20
```

```
5/5 [==============================] - 0s 14ms/step - loss: 0.0045 - mse: 0.0102 -
val_loss: 0.0091 - val_mse: 0.0210
Epoch 18/20
5/5 [==============================] - 0s 17ms/step - loss: 0.0045 - mse: 0.0100 -
val_loss: 0.0091 - val_mse: 0.0210
Epoch 19/20
5/5 [==============================] - 0s 13ms/step - loss: 0.0045 - mse: 0.0100 -
val_loss: 0.0091 - val_mse: 0.0211
Epoch 20/20
5/5 [==============================] - 0s 13ms/step - loss: 0.0044 - mse: 0.0099 -
val_loss: 0.0091 - val_mse: 0.0209
```

```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.xlabel('Epochs')
plt.ylabel('MSLE Loss')
plt.legend(['loss', 'val_loss'])
plt.show()
```

Output:




```
def find_threshold(model, x_train_scaled):
  reconstructions = model.predict(x_train_scaled)
  # provides losses of individual instances
  reconstruction_errors = tf.keras.losses.msle(reconstructions, x_train_scaled)
  # threshold for anomaly scores
```

```
  threshold = np.mean(reconstruction_errors.numpy()) \
      + np.std(reconstruction_errors.numpy())
  return threshold

def get_predictions(model, x_test_scaled, threshold):
  predictions = model.predict(x_test_scaled)
  # provides losses of individual instances
  errors = tf.keras.losses.msle(predictions, x_test_scaled)
  # 0 = anomaly, 1 = normal
  anomaly_mask = pd.Series(errors) > threshold
  preds = anomaly_mask.map(lambda x: 0.0 if x == True else 1.0)
  return preds

threshold = find_threshold(model, x_train_scaled)
print(f"Threshold: {threshold}")
# Threshold: 0.01001314025746261
predictions = get_predictions(model, x_test_scaled, threshold)
accuracy_score(predictions, y_test)
# 0.944
```

Output:

```
73/73 [==============================] - 0s 990us/step
Threshold: 0.009627700998111052
32/32 [==============================] - 0s 981us/step
0.947
```