

Import Necessary Python Libraries

```
In [1]: #importing the libraries
import tensorflow as tf
from tensorflow import keras
import numpy as np
import pandas as pd
```

WARNING:tensorflow:From C:\Users\Teo Boon Kean\AppData\Local\Programs\Python\Python311\Lib\site-packages\keras\s\nrc\losses.py:2976: The name tf.losses.sparse_softmax_cross_entropy is deprecated. Please use tf.compat.v1.losses.sparse_softmax_cross_entropy instead.

Load the extracted features and process them

```
In [2]: #load the datasets
baseline_df = pd.read_excel('extracted_features_baseline.xlsx')
toolwear_df = pd.read_excel('extracted_features_toolwear.xlsx')
```

```
In [3]: #convert data frame into arrays
good_features = baseline_df.values
bad_features = toolwear_df.values
```

```
In [4]: #train test split to divide the data into training data (70%) and test data (30%)
#This is done on both healthy (good) and toolwear (bad) data

from sklearn.model_selection import train_test_split

good_train, good_test = train_test_split(good_features, test_size=0.2, random_state=40)
bad_train, bad_test = train_test_split(bad_features, test_size=0.2, random_state=40)
```

```
In [5]: #Training data is further split into 70% for model training and 30% for threshold setting

good_train, good_threshold = train_test_split(good_train, test_size=0.3, random_state=40)
bad_train, bad_threshold = train_test_split(bad_train, test_size=0.3, random_state=40)
```

```
In [6]: #data scaling

from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
good_train = sc.fit_transform(good_train)
good_test = sc.transform(good_test)
good_threshold = sc.transform(good_threshold)
bad_train = sc.fit_transform(bad_train)
bad_test = sc.transform(bad_test)
bad_threshold = sc.transform(bad_threshold)
```

```
In [7]: combine_test = np.vstack([good_test , bad_test])
```

Autoencoder Construction

Autoencoder for healthy features (good autoencoder)

```
In [8]: #specify the number of condensed features. This will be the number of neurons in the hidden layer
condensed_f = 20
```

```
In [9]: #constructing the good autoencoder model

#input layer which number of neurons equals the number of original features
l_in_good = keras.Input(good_features.shape[1])

#hidden layer which condenses the feature into the specified number of condensed features
l_condensed_good = keras.layers.Dense(condensed_f)(l_in_good)

#output layer which is the same as the input
l_out_good = keras.layers.Dense(good_features.shape[1])(l_condensed_good)
```

WARNING:tensorflow:From C:\Users\Teo Boon Kean\AppData\Local\Programs\Python\Python311\Lib\site-packages\keras\s\nrc\backend.py:1398: The name tf.executing_eagerly_outside_functions is deprecated. Please use tf.compat.v1.executing_eagerly_outside_functions instead.

```
In [10]: #defining the good autoencoder
autoencoder_good = keras.Model(l_in_good, l_out_good)
```

```
In [11]: autoencoder_good.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 66)]	0
dense (Dense)	(None, 20)	1340
dense_1 (Dense)	(None, 66)	1386

```
=====
Total params: 2726 (10.65 KB)
Trainable params: 2726 (10.65 KB)
Non-trainable params: 0 (0.00 Byte)
```

Autoencoder for toolwear features (bad autoencoder)

```
In [12]: #constructing the bad autoencoder model
```

```
#input layer which number of neurons equals the number of original features
l_in_bad = keras.Input(bad_features.shape[1])

#hidden layer which condenses the feature into the specified number of condensed features
l_condensed_bad = keras.layers.Dense(condensed_f)(l_in_bad)

#output layer which is the same as the input
l_out_bad = keras.layers.Dense(good_features.shape[1])(l_condensed_bad)
```

```
In [13]: #defining the bad autoencoder
```

```
autoencoder_bad = keras.Model(l_in_bad, l_out_bad)
```

```
In [14]: autoencoder_bad.summary()
```

Model: "model_1"

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 66)]	0
dense_2 (Dense)	(None, 20)	1340
dense_3 (Dense)	(None, 66)	1386

```
=====
Total params: 2726 (10.65 KB)
Trainable params: 2726 (10.65 KB)
Non-trainable params: 0 (0.00 Byte)
```

Autoencoder Training

Good Autoencoder (GAE) is fitted with healthy features in the training dataset

```
In [15]: #compile the model
```

```
autoencoder_good.compile(optimizer='adam', loss='mse')
```

```
#train the model
```

```
autoencoder_good.fit(good_train, good_train, epochs = 50, batch_size = 8, validation_split = 0.1)
```

WARNING:tensorflow:From C:\Users\Teo Boon Kean\AppData\Local\Programs\Python\Python311\Lib\site-packages\keras\s\nrc\optimizers__init__.py:309: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

Epoch 1/50

WARNING:tensorflow:From C:\Users\Teo Boon Kean\AppData\Local\Programs\Python\Python311\Lib\site-packages\keras\s\nrc\utils\tf_utils.py:492: The name tf.ragged.RaggedTensorValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.

27/27 [=====] - 1s 13ms/step - loss: 1.3797 - val_loss: 1.2468

Epoch 2/50

27/27 [=====] - 0s 3ms/step - loss: 1.0262 - val_loss: 0.9893

Epoch 3/50

27/27 [=====] - 0s 4ms/step - loss: 0.8301 - val_loss: 0.8198

Epoch 4/50

27/27 [=====] - 0s 4ms/step - loss: 0.6924 - val_loss: 0.6925

Epoch 5/50

27/27 [=====] - 0s 3ms/step - loss: 0.5926 - val_loss: 0.6058

Epoch 6/50

```
27/27 [=====] - 0s 3ms/step - loss: 0.5188 - val_loss: 0.5415
Epoch 7/50
27/27 [=====] - 0s 3ms/step - loss: 0.4670 - val_loss: 0.4929
Epoch 8/50
27/27 [=====] - 0s 3ms/step - loss: 0.4213 - val_loss: 0.4525
Epoch 9/50
27/27 [=====] - 0s 3ms/step - loss: 0.3849 - val_loss: 0.4153
Epoch 10/50
27/27 [=====] - 0s 3ms/step - loss: 0.3506 - val_loss: 0.3845
Epoch 11/50
27/27 [=====] - 0s 3ms/step - loss: 0.3214 - val_loss: 0.3556
Epoch 12/50
27/27 [=====] - 0s 4ms/step - loss: 0.2933 - val_loss: 0.3274
Epoch 13/50
27/27 [=====] - 0s 4ms/step - loss: 0.2690 - val_loss: 0.3041
Epoch 14/50
27/27 [=====] - 0s 4ms/step - loss: 0.2485 - val_loss: 0.2855
Epoch 15/50
27/27 [=====] - 0s 3ms/step - loss: 0.2290 - val_loss: 0.2672
Epoch 16/50
27/27 [=====] - 0s 3ms/step - loss: 0.2135 - val_loss: 0.2536
Epoch 17/50
27/27 [=====] - 0s 3ms/step - loss: 0.1998 - val_loss: 0.2413
Epoch 18/50
27/27 [=====] - 0s 3ms/step - loss: 0.1878 - val_loss: 0.2308
Epoch 19/50
27/27 [=====] - 0s 5ms/step - loss: 0.1769 - val_loss: 0.2214
Epoch 20/50
27/27 [=====] - 0s 3ms/step - loss: 0.1670 - val_loss: 0.2129
Epoch 21/50
27/27 [=====] - 0s 3ms/step - loss: 0.1581 - val_loss: 0.2057
Epoch 22/50
27/27 [=====] - 0s 4ms/step - loss: 0.1508 - val_loss: 0.1965
Epoch 23/50
27/27 [=====] - 0s 5ms/step - loss: 0.1430 - val_loss: 0.1933
Epoch 24/50
27/27 [=====] - 0s 4ms/step - loss: 0.1352 - val_loss: 0.1861
Epoch 25/50
27/27 [=====] - 0s 4ms/step - loss: 0.1289 - val_loss: 0.1795
Epoch 26/50
27/27 [=====] - 0s 4ms/step - loss: 0.1238 - val_loss: 0.1745
Epoch 27/50
27/27 [=====] - 0s 5ms/step - loss: 0.1187 - val_loss: 0.1675
Epoch 28/50
27/27 [=====] - 0s 5ms/step - loss: 0.1141 - val_loss: 0.1635
Epoch 29/50
27/27 [=====] - 0s 5ms/step - loss: 0.1085 - val_loss: 0.1603
Epoch 30/50
27/27 [=====] - 0s 4ms/step - loss: 0.1057 - val_loss: 0.1564
Epoch 31/50
27/27 [=====] - 0s 3ms/step - loss: 0.1019 - val_loss: 0.1514
Epoch 32/50
27/27 [=====] - 0s 3ms/step - loss: 0.0982 - val_loss: 0.1478
Epoch 33/50
27/27 [=====] - 0s 3ms/step - loss: 0.0952 - val_loss: 0.1436
Epoch 34/50
27/27 [=====] - 0s 3ms/step - loss: 0.0928 - val_loss: 0.1390
Epoch 35/50
27/27 [=====] - 0s 2ms/step - loss: 0.0900 - val_loss: 0.1382
Epoch 36/50
27/27 [=====] - 0s 2ms/step - loss: 0.0871 - val_loss: 0.1339
Epoch 37/50
27/27 [=====] - 0s 4ms/step - loss: 0.0854 - val_loss: 0.1293
Epoch 38/50
27/27 [=====] - 0s 4ms/step - loss: 0.0826 - val_loss: 0.1268
Epoch 39/50
27/27 [=====] - 0s 4ms/step - loss: 0.0806 - val_loss: 0.1240
Epoch 40/50
27/27 [=====] - 0s 4ms/step - loss: 0.0786 - val_loss: 0.1216
Epoch 41/50
27/27 [=====] - 0s 3ms/step - loss: 0.0768 - val_loss: 0.1187
Epoch 42/50
27/27 [=====] - 0s 4ms/step - loss: 0.0751 - val_loss: 0.1170
Epoch 43/50
27/27 [=====] - 0s 3ms/step - loss: 0.0734 - val_loss: 0.1138
Epoch 44/50
27/27 [=====] - 0s 3ms/step - loss: 0.0717 - val_loss: 0.1117
Epoch 45/50
27/27 [=====] - 0s 4ms/step - loss: 0.0702 - val_loss: 0.1089
Epoch 46/50
27/27 [=====] - 0s 4ms/step - loss: 0.0686 - val_loss: 0.1074
Epoch 47/50
27/27 [=====] - 0s 4ms/step - loss: 0.0677 - val_loss: 0.1039
```

```
Epoch 48/50
27/27 [=====] - 0s 4ms/step - loss: 0.0665 - val_loss: 0.1027
Epoch 49/50
27/27 [=====] - 0s 3ms/step - loss: 0.0647 - val_loss: 0.1009
Epoch 50/50
27/27 [=====] - 0s 3ms/step - loss: 0.0637 - val_loss: 0.0990
```

Out[15]: <keras.src.callbacks.History at 0x1e986cd9a50>

Bad Autoencoder (BAE) is fitted with toolwear features in the training dataset

```
In [16]: #compile the model
autoencoder_bad.compile(optimizer='adam', loss='mse')
#train the model
autoencoder_bad.fit(bad_train, bad_train, epochs = 50, batch_size = 8, validation_split = 0.1)
```

```
Epoch 1/50
27/27 [=====] - 1s 12ms/step - loss: 1.3189 - val_loss: 1.1886
Epoch 2/50
27/27 [=====] - 0s 4ms/step - loss: 0.9361 - val_loss: 0.9232
Epoch 3/50
27/27 [=====] - 0s 5ms/step - loss: 0.7245 - val_loss: 0.7330
Epoch 4/50
27/27 [=====] - 0s 5ms/step - loss: 0.5765 - val_loss: 0.5901
Epoch 5/50
27/27 [=====] - 0s 4ms/step - loss: 0.4737 - val_loss: 0.4960
Epoch 6/50
27/27 [=====] - 0s 3ms/step - loss: 0.4045 - val_loss: 0.4347
Epoch 7/50
27/27 [=====] - 0s 4ms/step - loss: 0.3565 - val_loss: 0.3923
Epoch 8/50
27/27 [=====] - 0s 4ms/step - loss: 0.3217 - val_loss: 0.3580
Epoch 9/50
27/27 [=====] - 0s 3ms/step - loss: 0.2940 - val_loss: 0.3307
Epoch 10/50
27/27 [=====] - 0s 3ms/step - loss: 0.2726 - val_loss: 0.3107
Epoch 11/50
27/27 [=====] - 0s 3ms/step - loss: 0.2533 - val_loss: 0.2909
Epoch 12/50
27/27 [=====] - 0s 4ms/step - loss: 0.2362 - val_loss: 0.2737
Epoch 13/50
27/27 [=====] - 0s 3ms/step - loss: 0.2211 - val_loss: 0.2581
Epoch 14/50
27/27 [=====] - 0s 2ms/step - loss: 0.2068 - val_loss: 0.2427
Epoch 15/50
27/27 [=====] - 0s 3ms/step - loss: 0.1943 - val_loss: 0.2289
Epoch 16/50
27/27 [=====] - 0s 3ms/step - loss: 0.1824 - val_loss: 0.2155
Epoch 17/50
27/27 [=====] - 0s 4ms/step - loss: 0.1719 - val_loss: 0.2046
Epoch 18/50
27/27 [=====] - 0s 3ms/step - loss: 0.1629 - val_loss: 0.1955
Epoch 19/50
27/27 [=====] - 0s 3ms/step - loss: 0.1535 - val_loss: 0.1832
Epoch 20/50
27/27 [=====] - 0s 3ms/step - loss: 0.1451 - val_loss: 0.1724
Epoch 21/50
27/27 [=====] - 0s 3ms/step - loss: 0.1370 - val_loss: 0.1639
Epoch 22/50
27/27 [=====] - 0s 3ms/step - loss: 0.1300 - val_loss: 0.1539
Epoch 23/50
27/27 [=====] - 0s 3ms/step - loss: 0.1235 - val_loss: 0.1474
Epoch 24/50
27/27 [=====] - 0s 2ms/step - loss: 0.1175 - val_loss: 0.1393
Epoch 25/50
27/27 [=====] - 0s 2ms/step - loss: 0.1122 - val_loss: 0.1328
Epoch 26/50
27/27 [=====] - 0s 2ms/step - loss: 0.1070 - val_loss: 0.1260
Epoch 27/50
27/27 [=====] - 0s 2ms/step - loss: 0.1025 - val_loss: 0.1220
Epoch 28/50
27/27 [=====] - 0s 3ms/step - loss: 0.0988 - val_loss: 0.1167
Epoch 29/50
27/27 [=====] - 0s 2ms/step - loss: 0.0946 - val_loss: 0.1130
Epoch 30/50
27/27 [=====] - 0s 3ms/step - loss: 0.0908 - val_loss: 0.1087
Epoch 31/50
27/27 [=====] - 0s 3ms/step - loss: 0.0876 - val_loss: 0.1042
Epoch 32/50
27/27 [=====] - 0s 2ms/step - loss: 0.0847 - val_loss: 0.1017
Epoch 33/50
27/27 [=====] - 0s 2ms/step - loss: 0.0822 - val_loss: 0.0987
Epoch 34/50
```

```

27/27 [=====] - 0s 2ms/step - loss: 0.0796 - val_loss: 0.0960
Epoch 35/50
27/27 [=====] - 0s 2ms/step - loss: 0.0778 - val_loss: 0.0931
Epoch 36/50
27/27 [=====] - 0s 4ms/step - loss: 0.0750 - val_loss: 0.0908
Epoch 37/50
27/27 [=====] - 0s 4ms/step - loss: 0.0729 - val_loss: 0.0891
Epoch 38/50
27/27 [=====] - 0s 3ms/step - loss: 0.0714 - val_loss: 0.0869
Epoch 39/50
27/27 [=====] - 0s 3ms/step - loss: 0.0694 - val_loss: 0.0852
Epoch 40/50
27/27 [=====] - 0s 3ms/step - loss: 0.0678 - val_loss: 0.0819
Epoch 41/50
27/27 [=====] - 0s 3ms/step - loss: 0.0660 - val_loss: 0.0797
Epoch 42/50
27/27 [=====] - 0s 3ms/step - loss: 0.0645 - val_loss: 0.0783
Epoch 43/50
27/27 [=====] - 0s 2ms/step - loss: 0.0632 - val_loss: 0.0766
Epoch 44/50
27/27 [=====] - 0s 3ms/step - loss: 0.0620 - val_loss: 0.0753
Epoch 45/50
27/27 [=====] - 0s 4ms/step - loss: 0.0604 - val_loss: 0.0740
Epoch 46/50
27/27 [=====] - 0s 4ms/step - loss: 0.0592 - val_loss: 0.0720
Epoch 47/50
27/27 [=====] - 0s 4ms/step - loss: 0.0584 - val_loss: 0.0716
Epoch 48/50
27/27 [=====] - 0s 3ms/step - loss: 0.0572 - val_loss: 0.0695
Epoch 49/50
27/27 [=====] - 0s 3ms/step - loss: 0.0561 - val_loss: 0.0682
Epoch 50/50
27/27 [=====] - 0s 4ms/step - loss: 0.0552 - val_loss: 0.0675

```

Out[16]: <keras.src.callbacks.History at 0x1e989251310>

Testing the Autoencoders with Threshold Datasets for both healthy and toolwear features to determine the threshold for classification

```

In [17]: from sklearn.metrics import mean_absolute_error

#Testing the good autoencoder with healthy datasets
GAE_pred_good = autoencoder_good.predict(good_threshold)
print(mean_absolute_error(good_threshold,GAE_pred_good))

```

```

4/4 [=====] - 0s 2ms/step
0.22003999693790322

```

```

In [18]: #Testing the good autoencoder with toolwear datasets
GAE_pred_bad = autoencoder_good.predict(bad_threshold)
print(mean_absolute_error(bad_threshold,GAE_pred_bad))

```

```

4/4 [=====] - 0s 2ms/step
0.48120671119111247

```

```

In [19]: #Testing the bad autoencoder with healthy datasets
BAE_pred_good = autoencoder_bad.predict(good_threshold)
print(mean_absolute_error(good_threshold,BAE_pred_good))

```

```

4/4 [=====] - 0s 3ms/step
0.44380762844704685

```

```

In [20]: #Testing the bad autoencoder with healthy datasets
BAE_pred_bad = autoencoder_bad.predict(bad_threshold)
print(mean_absolute_error(bad_threshold,BAE_pred_bad))

```

```

4/4 [=====] - 0s 3ms/step
0.19736847225720194

```

Visualisation of Mean Square Error (MSE) of Threshold Dataset

Good Autoencoder

```

In [21]: #Record the MSE of each entry in the threshold dataset in an array to be used for plotting after

GAE_MSE_toolwear = []
GAE_MSE_healthy = []

for i in range(len(bad_threshold)):
    GAE_MSE_healthy.append(mean_absolute_error(good_threshold[i],GAE_pred_good[i]))

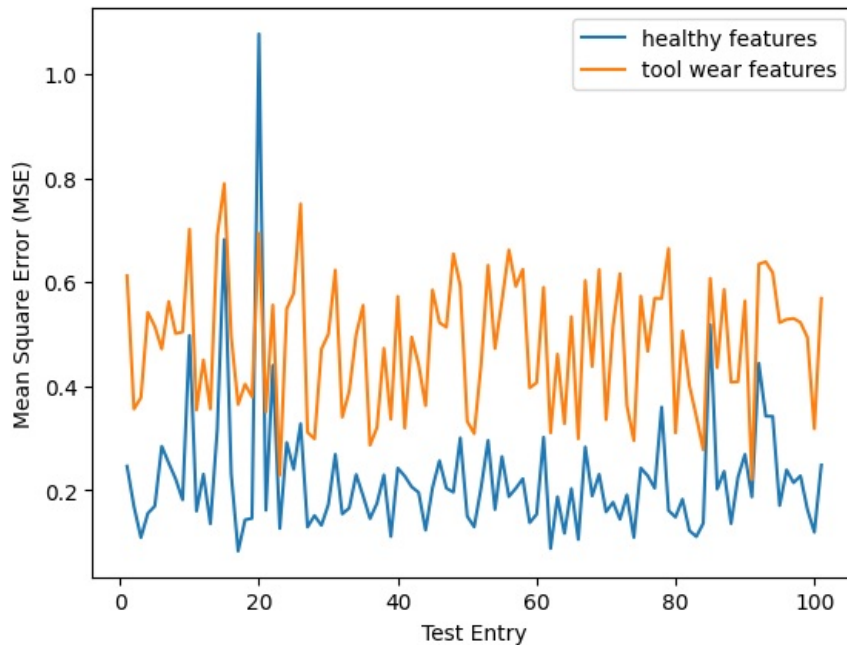
```

```
GAE_MSE_toolwear.append(mean_absolute_error(bad_threshold[i],GAE_pred_bad[i]))
```

```
In [22]: import matplotlib.pyplot as plt
```

```
#create index for x axis
index = list(range(1,(len(bad_threshold)+1)))

# plot lines
plt.plot(index, GAE_MSE_healthy, label = "healthy features")
plt.plot(index, GAE_MSE_toolwear, label = "tool wear features")
plt.xlabel("Test Entry")
plt.ylabel("Mean Square Error (MSE)")
plt.legend(loc='upper right')
plt.show()
```



Bad Autoencoder

```
In [23]: #Record the MSE of each entry in the threshold dataset in an array to be used for plotting after
```

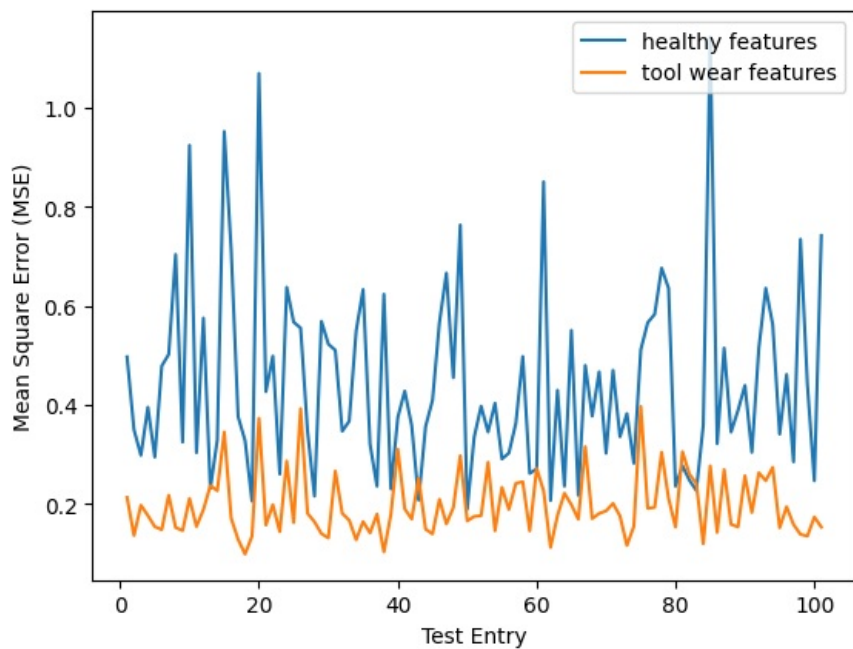
```
BAE_MSE_toolwear = []
BAE_MSE_healthy = []

for i in range(len(bad_threshold)):
    BAE_MSE_healthy.append(mean_absolute_error(good_threshold[i],BAE_pred_good[i]))
    BAE_MSE_toolwear.append(mean_absolute_error(bad_threshold[i],BAE_pred_bad[i]))
```

```
In [24]: import matplotlib.pyplot as plt
```

```
#create index for x axis
index = list(range(1,(len(bad_threshold)+1)))

# plot lines
plt.plot(index, BAE_MSE_healthy, label = "healthy features")
plt.plot(index, BAE_MSE_toolwear, label = "tool wear features")
plt.xlabel("Test Entry")
plt.ylabel("Mean Square Error (MSE)")
plt.legend(loc='upper right')
plt.show()
```



Applying Moving Average Filter

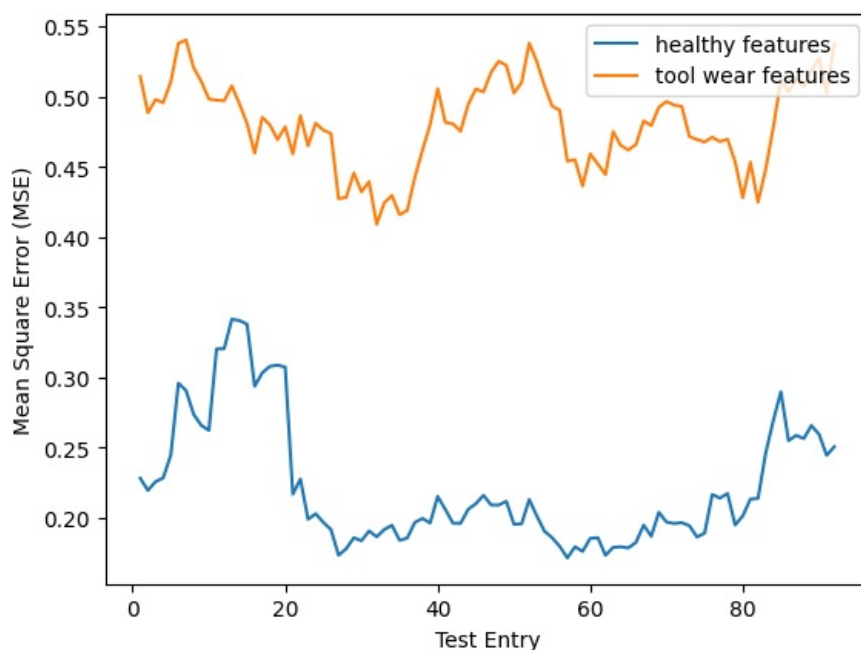
Good Autoencoder

```
In [25]: #defining the window size of the filter
window_size = 10
GAE_average_healthy = []
GAE_average_toolwear = []

#Instead of the MSE of individual entries, the average MSE in a window is calculated and added into the array f
for ind in range(len(GAE_MSE_healthy) - window_size + 1):
    GAE_average_healthy.append(np.mean(GAE_MSE_healthy[ind:ind+window_size]))
    GAE_average_toolwear.append(np.mean(GAE_MSE_toolwear[ind:ind+window_size]))
```

```
In [26]: test_entries = list(range(1, len(GAE_average_healthy)+1))

# plot lines
plt.plot(test_entries, GAE_average_healthy, label = "healthy features")
plt.plot(test_entries, GAE_average_toolwear, label = "tool wear features")
plt.xlabel("Test Entry")
plt.ylabel("Mean Square Error (MSE)")
plt.legend(loc='upper right')
plt.show()
```



Bad Autoencoder

```
In [27]: #defining the window size of the filter
```

```

window_size = 10
BAE_average_healthy = []
BAE_average_toolwear = []

#Instead of the MSE of individual entries, the average MSE in a window is calculated and added into the array for
for ind in range(len(BAE_MSE_healthy) - window_size + 1):
    BAE_average_healthy.append(np.mean(BAE_MSE_healthy[ind:ind+window_size]))
    BAE_average_toolwear.append(np.mean(BAE_MSE_toolwear[ind:ind+window_size]))

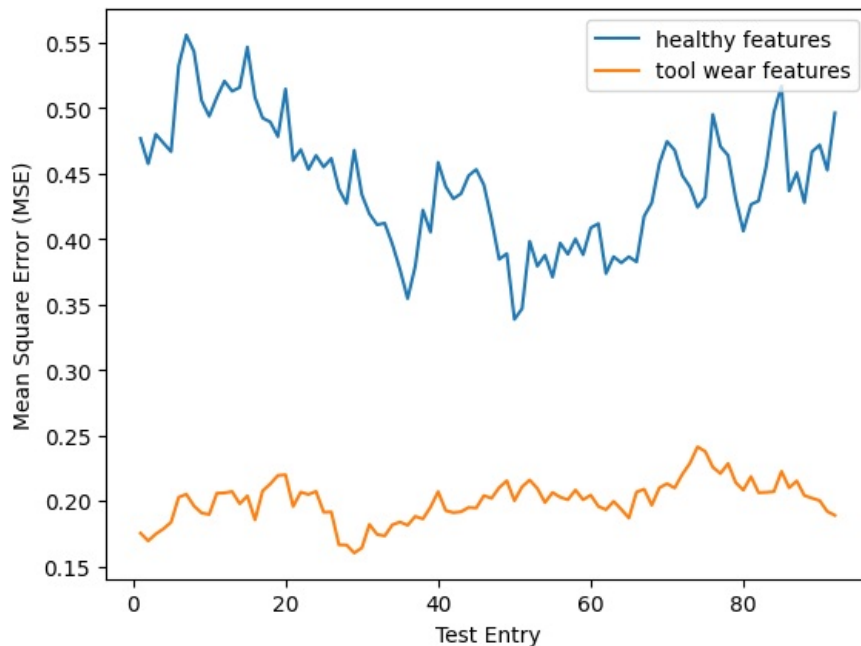
```

```

In [28]: index = list(range(1, len(BAE_average_healthy)+1))

# plot lines
plt.plot(index, BAE_average_healthy, label = "healthy features")
plt.plot(index, BAE_average_toolwear, label = "tool wear features")
plt.xlabel("Test Entry")
plt.ylabel("Mean Square Error (MSE)")
plt.legend(loc='upper right')
plt.show()

```



Determining the MSE threshold for classification from test result

```

In [29]: #Threshold is determined as the mid point

#Threshold for good autoencoder
GAE_threshold = max(GAE_average_healthy) + (min(GAE_average_toolwear) - max(GAE_average_healthy))/2
print(GAE_threshold)

#Threshold for bad autoencoder
BAE_threshold = max(BAE_average_toolwear) + (min(BAE_average_healthy) - max(BAE_average_toolwear))/2
print(BAE_threshold)

```

```

0.37520191640790823
0.2899028862592756

```

Predicting in Production Environment (Assuming data input is real time)

Test data is used for demonstration as the models have not seen these data before

```

In [30]: #Moving average filter is also applied to the data.
#To implement this 10 data entries are inputted into the model in each iteration.
#The MSE from each iteration is compared with the threshold to determine the state of toolwear

import time
import timeit
window_size = 10
result = []
MSE_GAE = []
MSE_BAE = []
time_passed = 0

for j in range(0, combine_test.shape[0] - window_size):
    #prediction process starts so record start time

```



```

start = time.time()

#the autoencoders are inputted with all the entries in the filter window and asked to reconstruct the feature
gae_pred = autoencoder_good.predict(combine_test[j: j + window_size])
bae_pred = autoencoder_bad.predict(combine_test[j: j + window_size])

#The average MSE of all the entries in the filter window is determined
gae_error = mean_absolute_error(combine_test[j: j + window_size],gae_pred)
bae_error = mean_absolute_error(combine_test[j: j + window_size],bae_pred)

#The average MSE of the window is compared with the threshold for classification
if ((gae_error < GAE_threshold) and (bae_error > BAE_threshold)):
    result.append("healthy")
elif ((gae_error > GAE_threshold) and (bae_error < BAE_threshold)):
    result.append("toolwear")
else:
    result.append("anomaly")

#prediction process ends so record end time
end = time.time()
time_passed = time_passed + (end-start)

#Appending the MSE into an array so it can be used for plotting later
MSE_GAE.append(gae_error)
MSE_BAE.append(bae_error)

```

```

1/1 [=====] - 0s 24ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 23ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 25ms/step
1/1 [=====] - 0s 25ms/step
1/1 [=====] - 0s 24ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 23ms/step
1/1 [=====] - 0s 25ms/step
1/1 [=====] - 0s 29ms/step
1/1 [=====] - 0s 26ms/step
1/1 [=====] - 0s 24ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 23ms/step
1/1 [=====] - 0s 25ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 24ms/step
1/1 [=====] - 0s 39ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 23ms/step
1/1 [=====] - 0s 24ms/step
1/1 [=====] - 0s 24ms/step
1/1 [=====] - 0s 24ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 23ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 23ms/step
1/1 [=====] - 0s 24ms/step
1/1 [=====] - 0s 23ms/step
1/1 [=====] - 0s 26ms/step
1/1 [=====] - 0s 26ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 23ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 23ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 23ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 23ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 24ms/step
1/1 [=====] - 0s 24ms/step
1/1 [=====] - 0s 26ms/step
1/1 [=====] - 0s 24ms/step
1/1 [=====] - 0s 24ms/step
1/1 [=====] - 0s 25ms/step

```

[illegible]

[illegible]

[illegible]

```

1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 33ms/step
1/1 [=====] - 0s 25ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 25ms/step
1/1 [=====] - 0s 23ms/step
1/1 [=====] - 0s 23ms/step
1/1 [=====] - 0s 22ms/step
1/1 [=====] - 0s 21ms/step

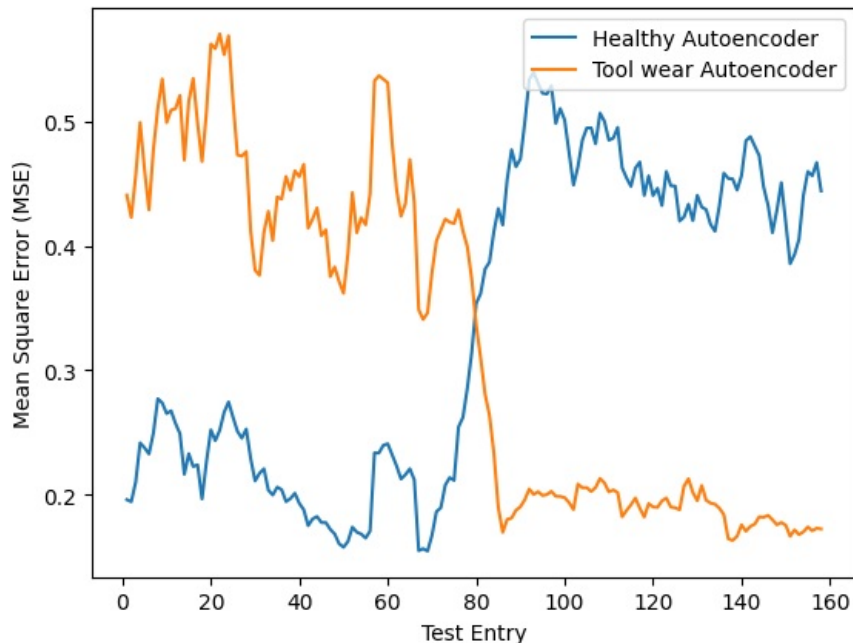
```

```
In [31]: test_entries = list(range(1,len(MSE_BAE)+1))
```

```

# plot lines
plt.plot(test_entries, MSE_GAE, label = "Healthy Autoencoder")
plt.plot(test_entries, MSE_BAE, label = "Tool wear Autoencoder")
plt.xlabel("Test Entry")
plt.ylabel("Mean Square Error (MSE)")
plt.legend(loc='upper right')
plt.show()

```



```
In [32]: #The predicted class of tool wear is printed
print(result)
```

```

['healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', '
healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'h
ealthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'heal
thy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'health
y', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy'
, 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy',
'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'h
ealthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'h
ealthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'healthy', 'too
lwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwea
r', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear',
'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'too
lwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwea
r', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear',
'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'too
lwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwea
r', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear', 'toolwear',
'toolwear', 'toolwear']

```

Timing Analysis

```
In [33]: print(time_passed)
```

```
24.597632884979248
```

```
In [34]: # The average time is calculated by dividing the total time with the number of predictions
avg_time = time_passed / len(result)
print(avg_time)
```

```
0.1556812207910079
```