

Final Project

Using Neural Networks to Predict Toughness

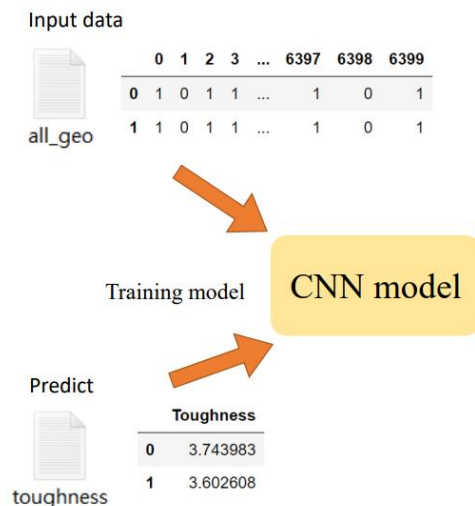
Group_3

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0.摘要

Using Neural Networks to Predict Toughness



1. Please use all_geo.txt and toughness.txt to train the model.
2. Combine all_geo.txt and toughness.txt predict results into the same file (group_0.csv).

	0	1	2	3	...	6398	6399	Toughness	ML
0	1	0	1	1	...	0	1	3.743983	2.585
1	1	0	1	1	...	0	1	3.602608	2.156

3. And please write a report explaining what your code is doing, such as how to process data and how to reduce model errors.
4. Submit Report & csv file to the course website.
5. Upload deadline: 2021/01/13 (Wednesday) 23:59 pm

1.資料前處理

1.把 256*256 的彩色圖片轉成 80*80 的灰階圖片

```
1 #圖片512*512轉成80*80
2 import cv2
3 import matplotlib.pyplot as plt
4
5 folder = 'group_3/'
6 for i in range(0,10000,1):
7     filename = str(i)+'.png'
8
9     img = cv2.imread(folder+filename, cv2.IMREAD_GRAYSCALE)
10    print(type(img))
11    print('shape =', img.shape)
12    img_re = cv2.resize(img, (80,80), interpolation=cv2.INTER_CUBIC)
13    print('re shape =', img_re.shape)
14    cv2.imwrite('./group_3re/'+str(i)+'.png', img_re)
15    print('done')
```

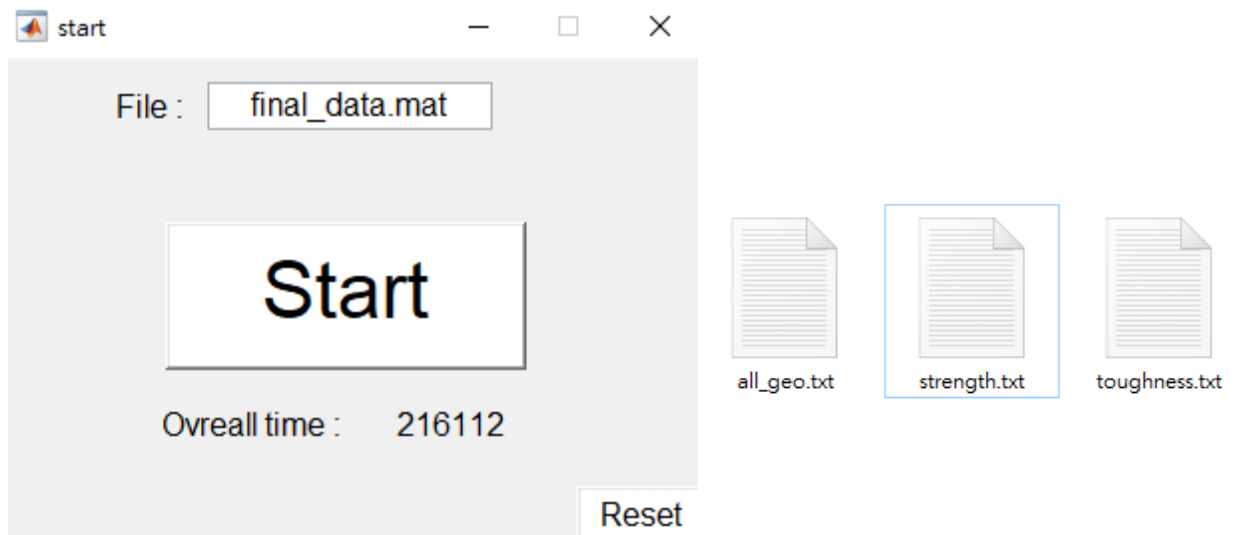
2. 讀取灰階圖片 將 pixel 換成 0/1 ,接所有結果加入

final_data[],輸出成 final_data.mat

```
1 # 讀取灰階圖片 將pixel換成0/1 ,接所有結果加入final_data[],輸出成 final_data.mat
2 import cv2
3 import matplotlib.pyplot as plt
4 from scipy.io import savemat
5 from sklearn.preprocessing import Binarizer
6 from sklearn import preprocessing
7 import numpy as np
8 folder = 'group_3re/'
9 encoder = Binarizer()
10 final_data = np.array([])
11 size=2
12
13
14 for i in range(0, size, 1):
15     filename = str(i)+'.png'
16     img = cv2.imread(folder+filename, cv2.IMREAD_GRAYSCALE)
17     np.savetxt('img_0.txt', img)
18     # 先資料做標準化StandardScaler
19     scaler = preprocessing.StandardScaler().fit(img)
20     X_scaled = scaler.transform(img)
21     np.savetxt('x_sc.txt', X_scaled)
22     # 再做二元化Binarizer
23     encoder.fit(X_scaled)
24     img = encoder.transform(X_scaled)
25
26     np.savetxt('img_re.txt', img, fmt='%i')
27     final_data = np.append(final_data, img)
28
29     print(i, 'done')
30
31
32 print('fin=', final_data)
33 print(final_data.shape)
34 final_data = final_data.reshape(size, 6400)
35 print('re_fin= ', final_data)
36 print(final_data.shape)
37 savemat('final_data.mat', {'random': final_data})
38 np.savetxt('final_data.txt', final_data, fmt='%i')
```

3. final_data.mat 資料 丟進 Matlab 進行計算,完成後會得

到 all_geo.txt , strength.txt , toughness.txt



4. 進入 model 前先將 all_geo.txt 和 toughness.txt

合起來變成一個 Fin_train.csv 檔方便使用。

```
1 from google.colab import drive
2 drive.mount('/content/gdrive')
3 import pandas as pd
4 import numpy as np
5 data = pd.read_table('/content/gdrive/My Drive/ML_Final/all_geo.txt', header=None, encoding='gb2312', sep=' ')
6 print(data.shape)
7 data_0=data.iloc[:, :-1]
8 print(data_0.shape)
9
10 toug = pd.read_table('/content/gdrive/My Drive/ML_Final/toughness.txt', header=None, encoding='gb2312')
11 traindata=np.column_stack((data_0, toug))
12 traindata_pd = pd.DataFrame(data=traindata)
13 traindata_pd.to_csv('Fin_train.csv', index=0)
14 traindata_pd=traindata_pd.rename(columns={traindata_pd.columns[6400]:'Toughness'}, inplace=True)
```

```
1 raw_file = pd.read_csv('/content/gdrive/My Drive/ML_Final/Fin_train.csv')
2 print(raw_file.head(5))
```

```
0 0 1 2 3 4 5 6 7 ... 6393 6394 6395 6396 6397 6398 6399 Toughness
0 1 1 1 1 1 0 0 0 0 ... 0 0 0 1 1 1 1 2.413495
1 1 1 1 0 0 0 0 1 ... 0 0 0 0 1 1 1 2.900767
2 1 1 1 0 0 0 0 0 ... 0 0 0 0 1 1 1 3.326615
3 1 1 1 1 1 0 1 1 ... 1 0 1 1 1 1 1 1.638111
4 0 0 0 1 1 1 1 0 ... 1 1 1 1 0 0 0 6.759200
```

[5 rows x 6401 columns]

2.建構模型

1.讀入資料切分成訓練集和驗證集

```
1 from sklearn.model_selection import train_test_split
2 train_file, val_file = train_test_split(raw_file, random_state=777, train_size=0.8)
3
4 train_data=train_file.iloc[:, :-1]
5 train_label=train_file.iloc[:, -1:]
6 val_data=val_file.iloc[:, :-1]
7 val_label=val_file.iloc[:, -1:]
```

2.將訓練集和測試集合轉換成要丟進模型的形狀

```
1 #訓練集 前處理
2 print('x_train_image: ', train_data.shape)
3 print('y_train_image: ', train_label.shape)
4 train_data_re = train_data.values.reshape(8000, 80, 80)
5 print('train data re', train_data_re.shape)
6 train_label_re = train_label.values.reshape(8000,)
7 print('train label re', train_label_re.shape)
8 print('train label re data type is', train_label_re[0].dtype)
9 print('train_data_re[0]', train_data_re[0].shape)
```

```
x_train_image: (8000, 6400)
y_train_image: (8000, 1)
train data re (8000, 80, 80)
train label re (8000,)
train label re data type is float64
train_data_re[0] (80, 80)
```

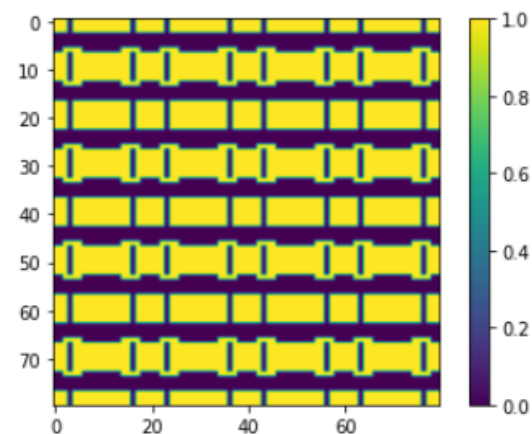
```
1 #驗證集 前處理
2 print('val data: ', val_data.shape)
3 print('val label: ', val_label.shape)
4
5 val_data_re = val_data.values.reshape(2000, 80, 80)
6 print('val_data_re: ', val_data_re.shape)
7
8 val_label_re = val_label.values.reshape(2000,)
9 print('val_label_re', val_label_re.shape)
```

```
val data: (2000, 6400)
val label: (2000, 1)
val_data_re: (2000, 80, 80)
val_label_re (2000,)
```

```
1 train_data4D = train_data_re.reshape(train_data_re.shape[0], 80, 80, 1).astype('float32')
2 val_data4D = val_data_re.reshape(val_data_re.shape[0], 80, 80, 1).astype('float32')
3 print('train_data4D', train_data4D.shape)
4 print('val_data4D', val_data4D.shape)
```

```
train_data4D (8000, 80, 80, 1)
val_data4D (2000, 80, 80, 1)
```

```
1 from matplotlib.pyplot import *
2 plt.figure()
3 plt.imshow(train_data_re[0])
4 plt.colorbar()
5 plt.grid(False)
6 plt.show()
```



3.建立模型

```

1 from keras.models import Sequential
2 from keras.layers import Dense,Dropout, Flatten, Conv2D, MaxPooling2D

1 model = Sequential()

1 model.add(Conv2D(
2     filters=16,
3     kernel_size=(5,5),
4     padding='same',
5     input_shape=(80,80,1),
6     activation='relu'
))

1 model.add(MaxPooling2D(pool_size=(2,2)))

1 model.add(Conv2D(filters=36,
2     kernel_size=(5,5),
3     padding = 'same',
4     activation='relu'))

1 model.add(MaxPooling2D(pool_size=(2,2)))
2 model.add(Dropout(0.25))
3 model.add(Flatten())
4 model.add(Dense(128, activation='relu'))
5 model.add(Dropout(0.5))
6 model.add(Dense(1,activation='relu'))
7 model.compile(loss='mean_squared_error', optimizer='adam', metrics=['accuracy'])

1 model.save('initial.h5')

```

```

1 print(model.summary())

```

Model: "sequential"

Layer (type)	Output Shape	Param
conv2d (Conv2D)	(None, 80, 80, 16)	416
max_pooling2d (MaxPooling2D)	(None, 40, 40, 16)	0
conv2d_1 (Conv2D)	(None, 40, 40, 36)	14436
max_pooling2d_1 (MaxPooling2D)	(None, 20, 20, 36)	0
dropout (Dropout)	(None, 20, 20, 36)	0
flatten (Flatten)	(None, 14400)	0
dense (Dense)	(None, 128)	1843328
dropout_1 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129

Total params: 1,858,309
Trainable params: 1,858,309
Non-trainable params: 0

None

4.進行訓練 250epochs

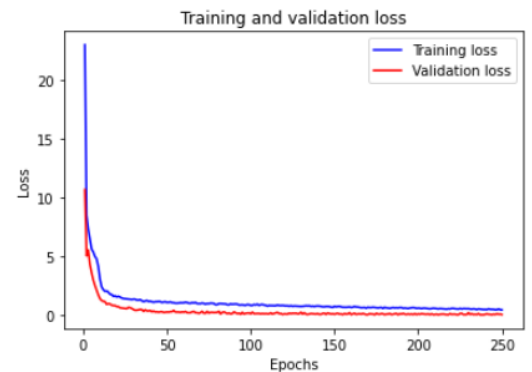
<pre> 1 train_history=model.fit(x=train_data4D, 2 y=train_label_re, validation_split=0.2, 3 epochs=250, batch_size=500, verbose=2, 4 validation_data=(val_data4D, val_label_re)) </pre>	<pre> Epoch 1/250 13/13 - 9s - loss: 22.9415 - accuracy: 0.0000e+00 - val_loss: 10.6694 - val_accuracy: 0.0000e+00 Epoch 2/250 13/13 - 1s - loss: 8.5026 - accuracy: 0.0000e+00 - val_loss: 5.0632 - val_accuracy: 0.0000e+00 Epoch 3/250 13/13 - 1s - loss: 7.3551 - accuracy: 0.0000e+00 - val_loss: 5.5618 - val_accuracy: 0.0000e+00 Epoch 4/250 13/13 - 1s - loss: 6.5116 - accuracy: 0.0000e+00 - val_loss: 4.3365 - val_accuracy: 0.0000e+00 Epoch 5/250 13/13 - 1s - loss: 5.6409 - accuracy: 0.0000e+00 - val_loss: 3.6371 - val_accuracy: 0.0000e+00 Epoch 245/250 13/13 - 1s - loss: 0.5273 - accuracy: 0.0000e+00 - val_loss: 0.1206 - val_accuracy: 0.0000e+00 Epoch 246/250 13/13 - 1s - loss: 0.4996 - accuracy: 0.0000e+00 - val_loss: 0.0880 - val_accuracy: 0.0000e+00 Epoch 247/250 13/13 - 1s - loss: 0.5006 - accuracy: 0.0000e+00 - val_loss: 0.1549 - val_accuracy: 0.0000e+00 Epoch 248/250 13/13 - 1s - loss: 0.5691 - accuracy: 0.0000e+00 - val_loss: 0.1079 - val_accuracy: 0.0000e+00 Epoch 249/250 13/13 - 1s - loss: 0.4968 - accuracy: 0.0000e+00 - val_loss: 0.1264 - val_accuracy: 0.0000e+00 Epoch 250/250 13/13 - 1s - loss: 0.4858 - accuracy: 0.0000e+00 - val_loss: 0.0872 - val_accuracy: 0.0000e+00 </pre>
---	--

5. loss /epochs 圖表

```

1 %matplotlib inline
2 acc = train_history.history['accuracy']
3 val_acc = train_history.history['val_accuracy']
4 loss = train_history.history['loss']
5 val_loss = train_history.history['val_loss']
6
7 epochs = range(1, len(acc) + 1)
8
9 # "b" is for "blue line"
10 plt.plot(epochs, loss, 'b', label='Training loss')
11 # r is for "solid red line"
12 plt.plot(epochs, val_loss, 'r', label='Validation loss')
13 plt.title('Training and validation loss')
14 # plt.xlim((0, 250))
15 # plt.ylim((0, 10000))
16 plt.xlabel('Epochs')
17 plt.ylabel('Loss')
18 plt.legend()
19
20 plt.show()

```



3.預測 Toughness

1.讀入目標輸出資料集，並轉成模型接受的形狀

```

1 # 目標輸出
2 raw_data=raw_file.iloc[:, :-1]
3 raw_label=raw_file.iloc[:, -1:]
4 print('label:', raw_label.shape)
5 raw_label_re = raw_label.values.reshape(10000,)
6 print('label re:', raw_label_re.shape)
7 print(raw_data.head(5))
8 print(raw_data.shape)
9 raw_data_re = raw_data.values.reshape(10000, 80, 80)
10 print(raw_data_re.shape)
11 raw_data4D = raw_data_re.reshape(raw_data_re.shape[0], 80, 80, 1).astype('float32')
12 print(raw_data4D.shape)

```

```

label: (10000, 1)
label re: (10000,)
0 1 2 3 4 5 6 7 ... 6392 6393 6394 6395 6396 6397 6398 6399
0 1 1 1 1 0 0 0 0 ... 0 0 0 0 1 1 1 1
1 1 1 1 0 0 0 0 1 ... 1 0 0 0 0 1 1 1
2 1 1 1 0 0 0 0 0 ... 0 0 0 0 0 1 1 1
3 1 1 1 1 1 0 1 1 ... 1 1 0 1 1 1 1 1
4 0 0 0 1 1 1 1 0 ... 0 1 1 1 1 0 0 0

[5 rows x 6400 columns]
(10000, 6400)
(10000, 80, 80)
(10000, 80, 80, 1)

```

2.評估預測誤差

```

1 # 評估預測誤差
2 def Mape(data_true, data_pred):
3     return np.mean(np.abs((data_true - data_pred) / data_true)) * 100
4
5 Mape(raw_label_re, data_pred)

```

5. 722297580361968

3. 輸出目標資料檔 group_3.csv

```
1 fin = pd.read_csv('/content/gdrive/My Drive/ML_Final/group_3.csv')
2 print(fin.head(5))
```

```
   0  1  2  3  4  5  6  ...  6395  6396  6397  6398  6399  Toughness      ML
0  1  1  1  1  1  0  0  ...    0    1    1    1    1    2.413495  2.498423
1  1  1  1  1  0  0  0  ...    0    0    1    1    1    2.900767  2.856366
2  1  1  1  1  0  0  0  ...    0    0    1    1    1    3.326615  3.262297
3  1  1  1  1  1  0  1  ...    1    1    1    1    1    1.638111  1.662913
4  0  0  0  1  1  1  1  ...    1    1    0    0    0    6.759200  6.111736
```

```
[5 rows x 6402 columns]
```

4. 與其他模型比較

1. 模型架構

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 80, 80, 16)	416
max_pooling2d (MaxPooling2D)	(None, 40, 40, 16)	0
conv2d_1 (Conv2D)	(None, 40, 40, 36)	14436
max_pooling2d_1 (MaxPooling2D)	(None, 20, 20, 36)	0
dropout (Dropout)	(None, 20, 20, 36)	0
flatten (Flatten)	(None, 14400)	0
dense (Dense)	(None, 128)	184328
dropout_1 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129

Total params: 1,858,309
Trainable params: 1,858,309
Non-trainable params: 0

None

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 32)	204832
dense_2 (Dense)	(None, 32)	1056
dense_3 (Dense)	(None, 32)	1056
dense_4 (Dense)	(None, 1)	33

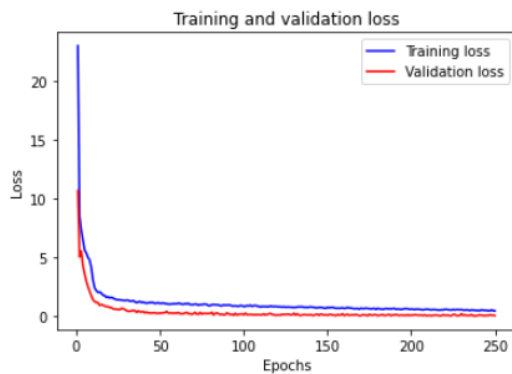
Total params: 206,977
Trainable params: 206,977
Non-trainable params: 0

None

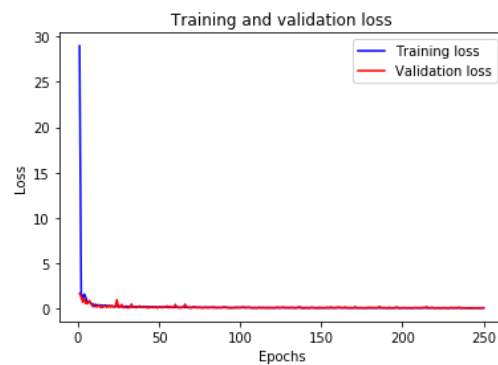
模型一(2*Convolution Layer 模型)

模型二(hw4 模型)

2. loss /epochs 圖表



圖表一



圖表二

3. 評估預測誤差

```
1 # 評估預測誤差
2 def Mape(data_true, data_pred):
3     return np.mean(np.abs((data_true - data_pred) / data_true)) * 100
4
5 Mape(raw_label_re, data_pred)
```

5.722297580361968

結果一

```
# 評估誤差誤差
import numpy as np
def Mape(data_true, data_pred):
    return np.mean(np.abs((data_true - data_pred) / data_true)) * 100
ans=Mape(output['Toughness'],output['ML'])
ans
```

6.139292834639335

結果二

5. 提升模型準確度

1. 增加 Convolution Layer:

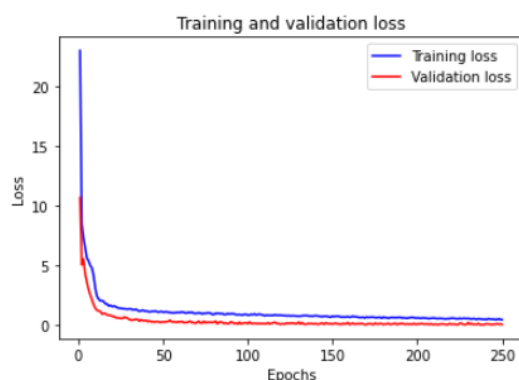
Model: "sequential"		
Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 80, 80, 16)	416
max_pooling2d (MaxPooling2D)	(None, 40, 40, 16)	0
conv2d_1 (Conv2D)	(None, 40, 40, 36)	14436
max_pooling2d_1 (MaxPooling2D)	(None, 20, 20, 36)	0
dropout (Dropout)	(None, 20, 20, 36)	0
flatten (Flatten)	(None, 14400)	0
dense (Dense)	(None, 128)	1843328
dropout_1 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129
=====		
Total params: 1,858,309		
Trainable params: 1,858,309		
Non-trainable params: 0		
None		

一開始設計的模型架構

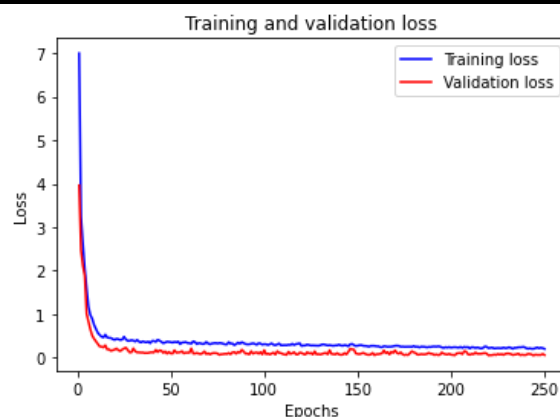
Model: "sequential"		
Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 80, 80, 16)	416
max_pooling2d (MaxPooling2D)	(None, 40, 40, 16)	0
conv2d_1 (Conv2D)	(None, 40, 40, 32)	12832
max_pooling2d_1 (MaxPooling2D)	(None, 20, 20, 32)	0
conv2d_2 (Conv2D)	(None, 20, 20, 64)	51264
conv2d_3 (Conv2D)	(None, 20, 20, 128)	204928
max_pooling2d_2 (MaxPooling2D)	(None, 10, 10, 128)	0
flatten (Flatten)	(None, 12800)	0
dense (Dense)	(None, 128)	1638528
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129
=====		
Total params: 1,908,097		
Trainable params: 1,908,097		
Non-trainable params: 0		
None		

新增兩層卷積層,並且拿掉 flatten 前的 dropout 層

2. loss/epoch 曲線 · Mape 只有 3.548%



原始模型的 loss/epoch 曲線



新模型的 loss/epoch 曲線

```

1 # 評估預測誤差
2 def Mape(data_true, data_pred):
3     return np.mean(np.abs((data_true - data_pred) / data_true)) * 100
4
5 Mape(raw_label_re, data_pred)

```

3.548472889463808

6. Conclusion

一開始使用 hw4 的模型(4*Dense Layer)和設計的 2* Convolution Layer + 2*Pooling Layer + 2*Dense Layer 模型來對資料進行評估。MAPE(平均絕對百分比誤差)分別是 6.139%和 5.722%。在這點上可以看到,CNN 的強大之處,只要把資料前處理完畢,丟進 model 內,儘管 model 架構很簡單,model 可以給出不錯的回饋。

為了提升模型預測數據的準確度,我嘗試在 model 中新增幾層 Convolution Layer , 建立一個包含 4*Convolution Layer + 2*Pooling Layer + 2*Dense Layer 的模型。除此之外將 Dense Layer 前,在 Convolution Layer 階段的 dropout 拿掉,避免丟失特徵值造成模型預測時,準確度飄忽不定的狀況。對資料進行評估, MAPE 的結果是 3.548%。