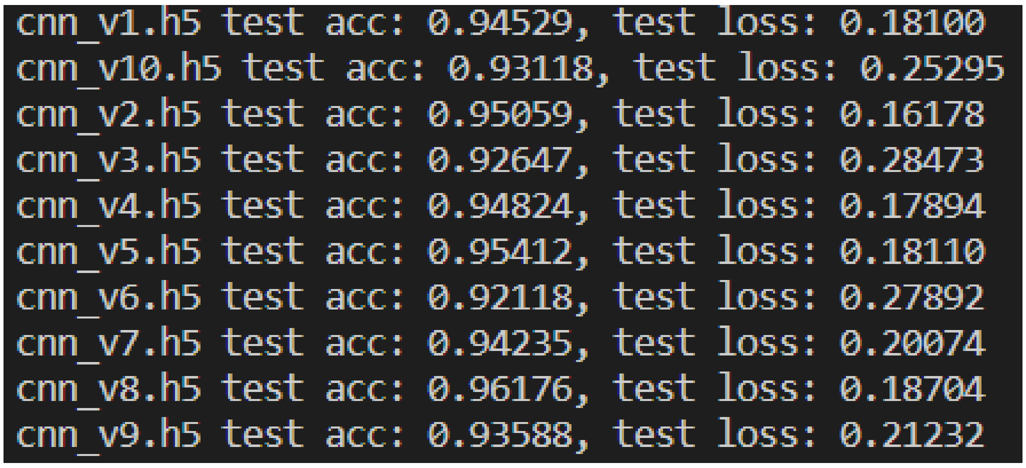
演算法 Term_Project 報告 大氣 4A　106601015　黃展皇

1. 中文手寫辨識準確率(accuracy)，以截圖方式呈現：

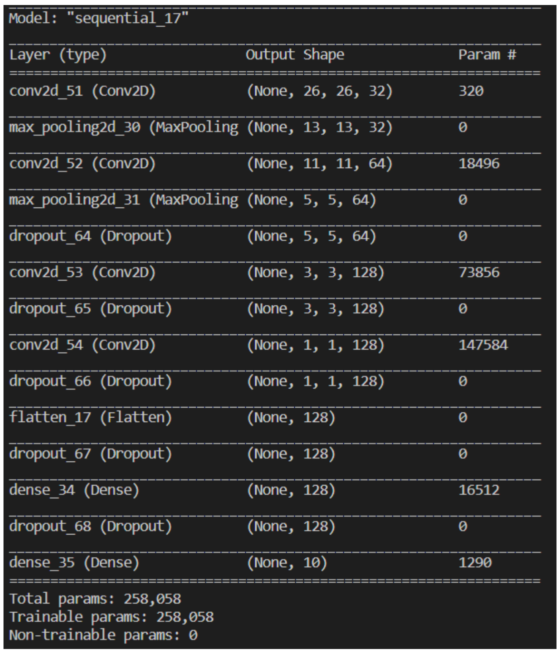


```
cnn_v1.h5 test acc: 0.94529, test loss: 0.18100
cnn_v10.h5 test acc: 0.93118, test loss: 0.25295
cnn_v2.h5 test acc: 0.95059, test loss: 0.16178
cnn_v3.h5 test acc: 0.92647, test loss: 0.28473
cnn_v4.h5 test acc: 0.94824, test loss: 0.17894
cnn_v5.h5 test acc: 0.95412, test loss: 0.18110
cnn_v6.h5 test acc: 0.92118, test loss: 0.27892
cnn_v7.h5 test acc: 0.94235, test loss: 0.20074
cnn_v8.h5 test acc: 0.96176, test loss: 0.18704
cnn_v9.h5 test acc: 0.93588, test loss: 0.21232
```

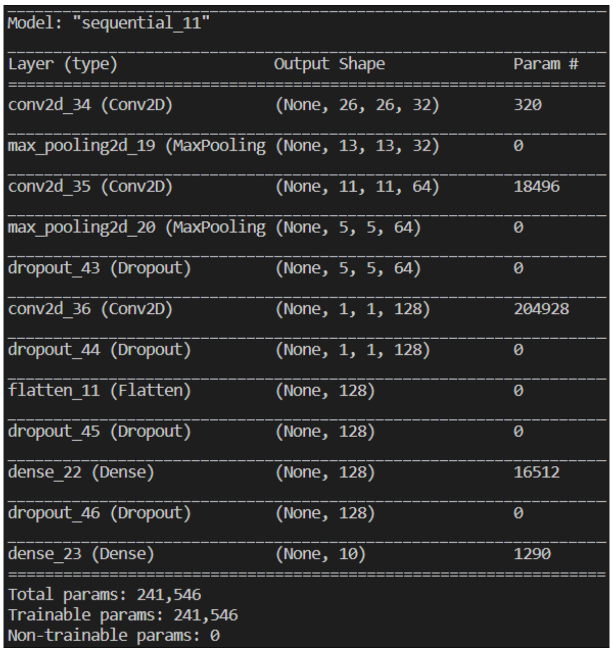
如圖，共做了 10 種版本的 CNN 模型，分別測試深度、kernel 大小及其排列組合、Dropout 大小、有無 Pooling 等等。

其中 acc 表現最好的是 v8(下左圖)，得到 0.96176 的準確度

loss 表現最好的是 v2(下右圖) ，loss 下降到 0.16178



```
Model: "sequential_17"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_51 (Conv2D)           (None, 26, 26, 32)        320
_________________________________________________________________
max_pooling2d_30 (MaxPooling (None, 13, 13, 32)        0
_________________________________________________________________
conv2d_52 (Conv2D)           (None, 11, 11, 64)        18496
_________________________________________________________________
max_pooling2d_31 (MaxPooling (None, 5, 5, 64)          0
_________________________________________________________________
dropout_64 (Dropout)         (None, 5, 5, 64)          0
_________________________________________________________________
conv2d_53 (Conv2D)           (None, 3, 3, 128)         73856
_________________________________________________________________
dropout_65 (Dropout)         (None, 3, 3, 128)         0
_________________________________________________________________
conv2d_54 (Conv2D)           (None, 1, 1, 128)         147584
_________________________________________________________________
dropout_66 (Dropout)         (None, 1, 1, 128)         0
_________________________________________________________________
flatten_17 (Flatten)         (None, 128)               0
_________________________________________________________________
dropout_67 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_34 (Dense)             (None, 128)               16512
_________________________________________________________________
dropout_68 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_35 (Dense)             (None, 10)                1290
=================================================================
Total params: 258,058
Trainable params: 258,058
Non-trainable params: 0
```



```
Model: "sequential_11"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_34 (Conv2D)           (None, 26, 26, 32)        320
_________________________________________________________________
max_pooling2d_19 (MaxPooling (None, 13, 13, 32)        0
_________________________________________________________________
conv2d_35 (Conv2D)           (None, 11, 11, 64)        18496
_________________________________________________________________
max_pooling2d_20 (MaxPooling (None, 5, 5, 64)          0
_________________________________________________________________
dropout_43 (Dropout)         (None, 5, 5, 64)          0
_________________________________________________________________
conv2d_36 (Conv2D)           (None, 1, 1, 128)         204928
_________________________________________________________________
dropout_44 (Dropout)         (None, 1, 1, 128)         0
_________________________________________________________________
flatten_11 (Flatten)         (None, 128)               0
_________________________________________________________________
dropout_45 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_22 (Dense)             (None, 128)               16512
_________________________________________________________________
dropout_46 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_23 (Dense)             (None, 10)                1290
=================================================================
Total params: 241,546
Trainable params: 241,546
Non-trainable params: 0
```

2. Source code 之逐行解釋：下方用中文做詳細解釋

```
# import the following packages
import os
import random
import numpy as np
from PIL import Image
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Flatten
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from tensorflow.keras.models import save_model, load_model
from tensorflow.keras.applications import ResNet152V2, ResNet50
from tensorflow.keras.utils import to_categorical
from matplotlib import pyplot as plt
import datetime
→以上 import 需要用到的套件，版本放在最後附錄

#x, y(label) preprocess
→輸入 datapath 路徑(只會是 train_image/test_image)，並且 os.walk 對 datapath
內的所有圖片做讀取、nomalize、reshape，並對 labels 做 to_categorical，最後
return data_x, data_y 分別對應資料以及 labels
def data_x_y_preprocess(datapath):                →定義方法，輸入資料路徑
    print('data_x_y_preprocess init')             →調用到這方法的測試
    img_row, img_col = 28, 28                     →定義圖片大小
    data_x = np.zeros((img_row, img_col)).reshape(1, img_row, img_col)
    →定義空圖片 array，形狀是(1, 28, 28)(數量, 高, 寬)
    pic_counter = 0                               →初始化圖片數量=0
    data_y = []                                   →圖形分類結果
    num_class = 10                                →分類結果總數(0~9)

    for root, dirs, files in os.walk(datapath):   →走訪 datapath
        for f in files:                           →對所有圖片檔案迴圈
            data_y.append(int(root.split('\\')[-1]))
            →f 的 root 尾段即為該數字分類類別
            fullpath = os.path.join(root, f)      →更新檔案完整位置
            img = Image.open(fullpath)            →用 Image 套件開圖片
            img = (np.array(img)/255).reshape(1, 28, 28) #nomalize
            →做 nomalize，0~255 大小同除 255 即可，再 reshape 成 data_x 大小
            data_x = np.vstack((data_x, img))
            →在 shape[0]拼接 data_x 與 img
            pic_counter += 1                         →圖片數量+1
    data_x = np.delete(data_x, 0, axis=0)            →刪除原本的空 array
    data_x = data_x.reshape(pic_counter, img_row, img_col, 1)
    →擴充 shape 多一維
    #data_y = np_utils.to_categorical(data_y, num_class)
    data_y = to_categorical(data_y, num_class)
    →將 data_y  list 做 to_categorical(做 one-hot  encoding)
    return data_x, data_y                            →回傳 x, y
```

接下來的 create_cnn_model_{1~10}系列皆為回傳一個 Sequential 模型的方法：
建立 model 為 Sequential 模型，並不斷.add 堆疊 Conv2D、MaxPooling2D、
Dropout、Flatten 等層做組合排列，最後 Dense 層用'softmax'方法做分類，完成模型
建構，.Summary()觀察模型架構，最後回傳 model

```
# basic version
def create_cnn_model_v1():                       →定義方法 version1
    model = Sequential()
    model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(28, 28, 1)))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.1))

    model.add(Flatten())
    model.add(Dropout(0.1))

    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.25))

    model.add(Dense(10, activation='softmax'))
    model.summary()
    return model

# deeper version
```

```
def create_cnn_model_v2():                                  →定義方法 version2
    model = Sequential()
    model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_s
hape=(28, 28, 1)))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.1))

    model.add(Conv2D(128, kernel_size=(5, 5), activation='relu'))
    model.add(Dropout(0.1))

    model.add(Flatten())
    model.add(Dropout(0.1))

    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.25))

    model.add(Dense(10, activation='softmax'))
    model.summary()
    return model

# kernel_size 7->5->3 version
def create_cnn_model_v3():                                  →定義方法 version3
    model = Sequential()
    model.add(Conv2D(32, kernel_size=(7, 7), activation='relu', input_s
hape=(28, 28, 1)))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.1))

    model.add(Conv2D(64, kernel_size=(5, 5), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.1))

    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
    model.add(Dropout(0.1))
    model.add(Flatten())
    model.add(Dropout(0.1))

    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.25))

    model.add(Dense(10, activation='softmax'))
    model.summary()
    return model

# just test
def create_cnn_model_v4():                           →定義方法 version4
    model = Sequential()
    model.add(Conv2D(16, kernel_size=(5, 5), activation='relu', padding='same', input_shape=(28, 28, 1)))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.1))

    model.add(Conv2D(36, kernel_size=(5, 5), activation='relu', padding='same'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.1))

    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(10, activation='softmax'))
    model.summary()
    return model

# just test2
def create_cnn_model_v5():                           →定義方法 version5
    model = Sequential()

    model.add(Conv2D(32, (5,5), activation="relu", padding="same", input_shape=(28,28,1)))
    model.add(Conv2D(32, (5,5), activation="relu", padding="same", input_shape=(28,28,1)))
    model.add(MaxPooling2D(pool_size=(2,2)))
    model.add(Dropout(0.25))

    model.add(Conv2D(64, (3,3), activation="relu", padding="same"))
    model.add(Conv2D(64, (3,3), activation="relu", padding="same"))
    model.add(MaxPooling2D(pool_size=(2,2)))
    model.add(Dropout(0.25))

    model.add(Flatten())
    model.add(Dense(256, activation="relu"))
    model.add(Dropout(0.5))
    model.add(Dense(10, activation="softmax"))
    model.summary()
    return model

# just test3
def create_cnn_model_v6():                          →定義方法 version6
    model = Sequential()

    model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_s
hape=(28, 28, 1)))
    model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.25))
    model.add(Flatten())
    model.add(Dense(128, activation="relu"))
    model.add(Dropout(0.5))
    model.add(Dense(10, activation="softmax"))
    model.summary()

    return model

# deeper 3 3 3 version
def create_cnn_model_v7():                          →定義方法 version7
    model = Sequential()
    model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_s
hape=(28, 28, 1)))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.1))

    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
    model.add(Dropout(0.1))

    model.add(Flatten())
    model.add(Dropout(0.1))

    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.25))

    model.add(Dense(10, activation='softmax'))
    model.summary()
    return model

# more deeper 3 3 3 3 version
def create_cnn_model_v8():                        →定義方法 version8
    model = Sequential()
    model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_s
hape=(28, 28, 1)))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.1))

    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
    model.add(Dropout(0.1))

    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
    model.add(Dropout(0.1))

    model.add(Flatten())
    model.add(Dropout(0.1))
    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.25))

    model.add(Dense(10, activation='softmax'))
    model.summary()
    return model

# no MaxPooling2D, more deeper 3 3 3 3 3 version
def create_cnn_model_v9():                    →定義方法 version9
    model = Sequential()
    model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_s
hape=(28, 28, 1)))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
    model.add(Dropout(0.1))

    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
    model.add(Dropout(0.1))

    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
    model.add(Dropout(0.1))

    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
    model.add(Dropout(0.1))

    model.add(Flatten())
    model.add(Dropout(0.1))

    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.25))

    model.add(Dense(10, activation='softmax'))
    model.summary()
    return model

# more deeper 3->3->5->7 version
def create_cnn_model_v10():                   →定義方法 version10
```

```
    model = Sequential()
    model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(28, 28, 1)))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
    model.add(Dropout(0.1))

    model.add(Conv2D(128, kernel_size=(5, 5), activation='relu'))
    model.add(Dropout(0.1))

    model.add(Conv2D(128, kernel_size=(7, 7), activation='relu'))
    model.add(Dropout(0.1))

    model.add(Flatten())
    model.add(Dropout(0.1))

    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.25))

    model.add(Dense(10, activation='softmax'))
    model.summary()
    return model

'''
def create_ResNet50():
    model = ResNet50(include_top=False, weights='imagenet', input_tensor=None, input_shape=(28, 28, 1)) #[(None, 224, 224, 3)
    #model = ResNet50()
    model.summary()
    return model
'''

def show_training_curve(train_history):
→定義接收訓練歷史物件的方法，畫出並儲存 loss 下降曲線
    plt.plot(train_history.history['loss'])        →畫出 loss 曲線
    plt.plot(train_history.history['val_loss'])    →畫出 val_loss 曲線
    plt.title('train history')                     →定義 title
    plt.ylabel('loss')                                →ylabel 為 loss
    plt.xlabel('epochs')                              →xlabel 為 epochs
    plt.legend(['loss', 'val_loss'], loc='upper left') →上圖標在左上區
    plt.savefig(os.path.join('.', 'term_project', datetime.datetime.now
().strftime("%Y_%m_%d__%H_%M_%S")))                   →用給定名字存在給定路徑
    #plt.show()

def main(operator='train'):            →主程式，有 train 與 test 兩種動作型態
    print('-----main {} init-----'.format(operator))   →驗證用
    term_project_path = os.path.join('C:\\', 'Users', 'user', 'Desktop'
, 'algorithm', 'term_project')                        →定義路徑
    model_dict = {                                    →用 dict.儲存模型
        'cnn_v1':create_cnn_model_v1(),
        'cnn_v2':create_cnn_model_v2(),
        'cnn_v3':create_cnn_model_v3(),
        'cnn_v4':create_cnn_model_v4(),
        'cnn_v5':create_cnn_model_v5(),
        'cnn_v6':create_cnn_model_v6(),
        'cnn_v7':create_cnn_model_v7(),
        'cnn_v8':create_cnn_model_v8(), #best
        'cnn_v9':create_cnn_model_v9(),
        'cnn_v10':create_cnn_model_v10(),
        #'ResNet50':create_ResNet50(),
    }

    if operator == 'train':                           →若為 train 動作：
        train_datapath = os.path.join(term_project_path, 'train_image')
        →定義 train_datapath(一個系統路徑，裡面有多個訓練圖片子資料夾樹)
        # get train data
        if os.path.isfile(os.path.join(term_project_path, 'train_data_x
.npy')):
        →若.npy 檔案存在，則直接 np.load 進來分 train_data_x, train_data_y
            train_data_x, train_data_y = np.load(os.path.join(term_proj
ect_path, 'train_data_x.npy')), np.load(os.path.join(term_project_path,
 'train_data_y.npy'))
        else:
        →若.npy 檔案不存在，則調用 data_x_y_preprocess 取得資料
```

```
            train_data_x, train_data_y = data_x_y_preprocess(train_data
path)
            np.save(os.path.join(term_project_path, 'train_data_x.npy')
, train_data_x)              →將資料儲存為.npy 檔案(下次就不用重新處理資料)
            np.save(os.path.join(term_project_path, 'train_data_y.npy')
, train_data_y)              →將資料儲存為.npy 檔案(下次就不用重新處理資料)
        print('---
> train_data_x.shape, train_data_y.shape:', train_data_x.shape, train_d
ata_y.shape)                 →驗證用
        # loop in model_dict
        for model_name, model in model_dict.items():   →for 所有模型迴圈
            if os.path.isfile(os.path.join(term_project_path, '{}.h5'.f
ormat(model_name))):
                 →如果.h5(模型網路結果)存在則呈現已訓練過
                print('{} has been train!!!'.format(model_name))
            else:
                 →如果找不到.h5 檔案(還沒訓練)：
                model.compile(
                    loss='categorical_crossentropy',
                    optimizer='adam',
                    metrics=['accuracy']
                )
→ compile 模型(loss 用類別的 crossentropy，優化器用 adam，測量方式只放準確度)
                train_history = model.fit(
                    train_data_x, train_data_y,
                    batch_size=32,
                    epochs=30,
                    verbose=1,
                    validation_split=0.1
                )
→ fit 模型(當然用 train_x/y, 設定基本的 batch_size=32, epochs=30, 其中設定
validation_split=0.1，會從 train 資料裡面選 0.1 比例的資料做驗證)
                show_training_curve(train_history)
→繪製訓練時的 loss 曲線
                save_model(model, os.path.join(term_project_path, '{}.h
5'.format(model_name)))
→儲存訓練好的模型
    elif operator == 'test':              →若為 test 動作
```

```
        test_datapath = os.path.join(term_project_path, 'test_image')
        →定義 test_datapath(一個系統路徑，裡面有多個測試圖片子資料夾樹)
        if os.path.isfile(os.path.join(term_project_path, 'test_data_x.
npy')):
        →若.npy 檔案存在，則直接 np.load 進來分 test_data_x, test_data_y
            test_data_x, test_data_y = np.load(os.path.join(term_projec
t_path, 'test_data_x.npy')), np.load(os.path.join(term_project_path, 't
est_data_y.npy'))
        else:
        →若.npy 檔案不存在，則調用 data_x_y_preprocess 取得資料
            test_data_x, test_data_y = data_x_y_preprocess(test_datapat
h)
            np.save(os.path.join(term_project_path, 'test_data_x.npy'),
 test_data_x)
            →將資料儲存為.npy 檔案(下次就不用重新處理資料)
            np.save(os.path.join(term_project_path, 'test_data_y.npy'),
 test_data_y)
            →將資料儲存為.npy 檔案(下次就不用重新處理資料)
        print('test_data_x.shape, test_data_y.shape:', test_data_x.shap
e, test_data_y.shape)

        #for all h5
        for file_name in os.listdir(term_project_path):→for 所有.h5 模型
            if file_name.split('.')[-1] == 'h5':
                model = load_model(os.path.join(term_project_path, file
_name))          →讀進 model
                score = model.evaluate(test_data_x, test_data_y, verbos
e=0)             → 用 test_data_x, test_data_y 對 model evaluate 分數
                print('{} test acc: {:.5f}, test loss: {:.5f}'.format(f
ile_name, score[1], score[0]))
                →秀出測試的準確度與 loss
    else:
        print('operator error!!!')


if __name__ == '__main__':
    main(operator='train')         →對所有 model_dict 中的模型做訓練
    main(operator='test')          →對所有 model_dict 中的模型做測試
```

補充以上程式所需要的套件及版本：

tensorflow (-gpu)=2.4.0、pillow =7.2.0、numpy =1.19.0、matplotlib=3.2.2

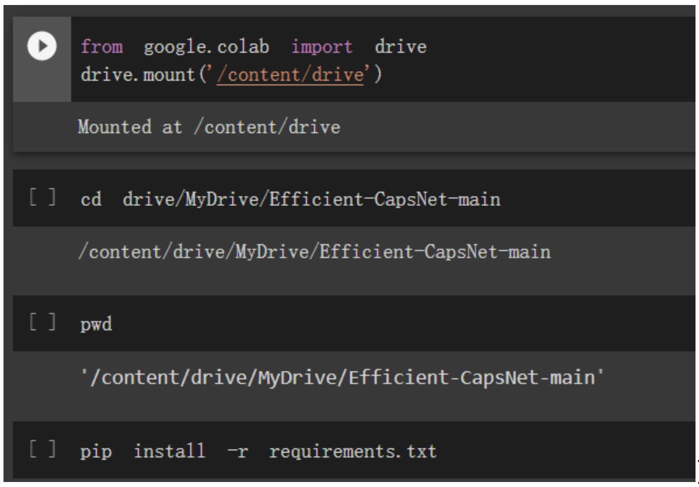
電腦配置：~~垃圾~~windows10、conda env、tensorflow-gpu、GeForce GTX 1050 Ti 4GB、DDR4-2666 8G*2

另外補充：

另外自行參考 2021 年的論文”EFFICIENT-CAPSNET: CAPSULE NETWORK WITH SELF-ATTENTION ROUTING”(https://arxiv.org/abs/2101.12491) 實作 Efficient-CapsNet 用於本次的中文手寫辨識。

附件中有 efficient_capsnet_train.ipynb/efficient_capsnet_test.ipynb 分別用於呼叫寫好的 preprocess 或 model 等等方式並加以訓練/測試，詳細程式碼與註解附於 ipynb 檔案內。

環境採用 colab(tf 2.5 以上，GPU 加速，依賴套件如 requirements.txt 所示)



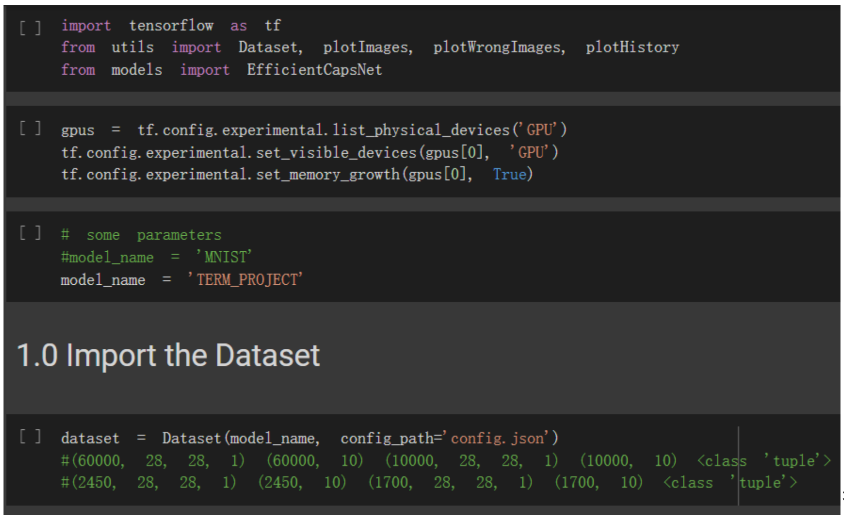
```
from google.colab import drive
drive.mount('/content/drive')

Mounted at /content/drive
```

```
[ ] cd drive/MyDrive/Efficient-CapsNet-main

/content/drive/MyDrive/Efficient-CapsNet-main
```

```
[ ] pwd

'/content/drive/MyDrive/Efficient-CapsNet-main'
```

```
[ ] pip install -r requirements.txt
```

前處理與環境設置



```
[ ] import tensorflow as tf
    from utils import Dataset, plotImages, plotWrongImages, plotHistory
    from models import EfficientCapsNet
```

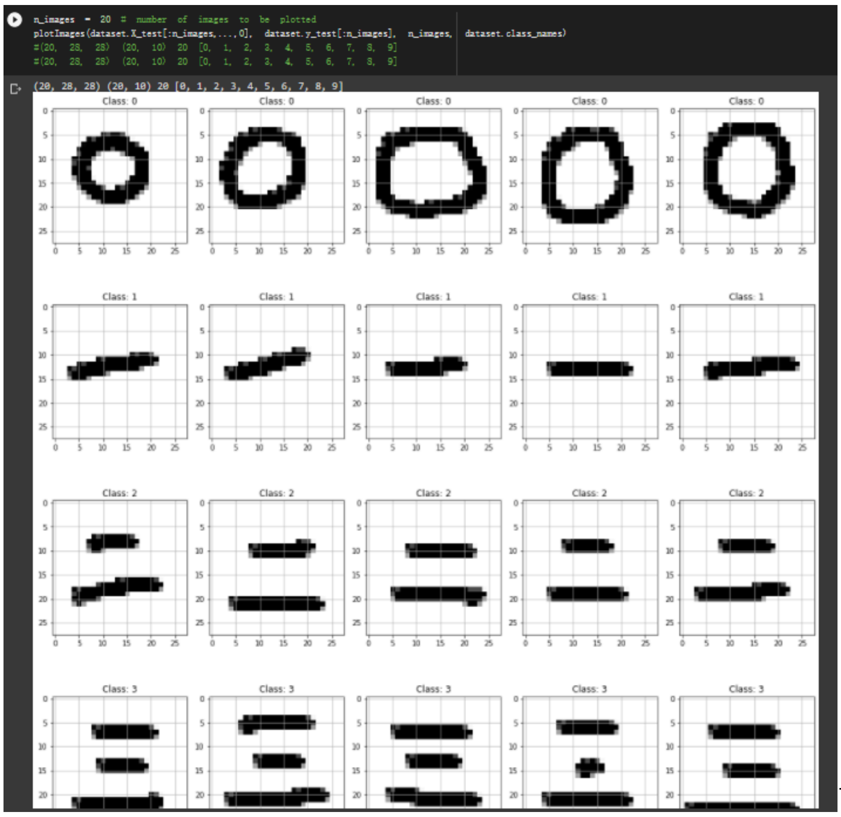
```
[ ] gpus = tf.config.experimental.list_physical_devices('GPU')
    tf.config.experimental.set_visible_devices(gpus[0], 'GPU')
    tf.config.experimental.set_memory_growth(gpus[0], True)
```

```
[ ] # some parameters
    #model_name = 'MNIST'
    model_name = 'TERM_PROJECT'
```

1.0 Import the Dataset

```
[ ] dataset = Dataset(model_name, config_path='config.json')
    #(60000, 28, 28, 1) (60000, 10) (10000, 28, 28, 1) (10000, 10) <class 'tuple'>
    #(2450, 28, 28, 1) (2450, 10) (1700, 28, 28, 1) (1700, 10) <class 'tuple'>
```

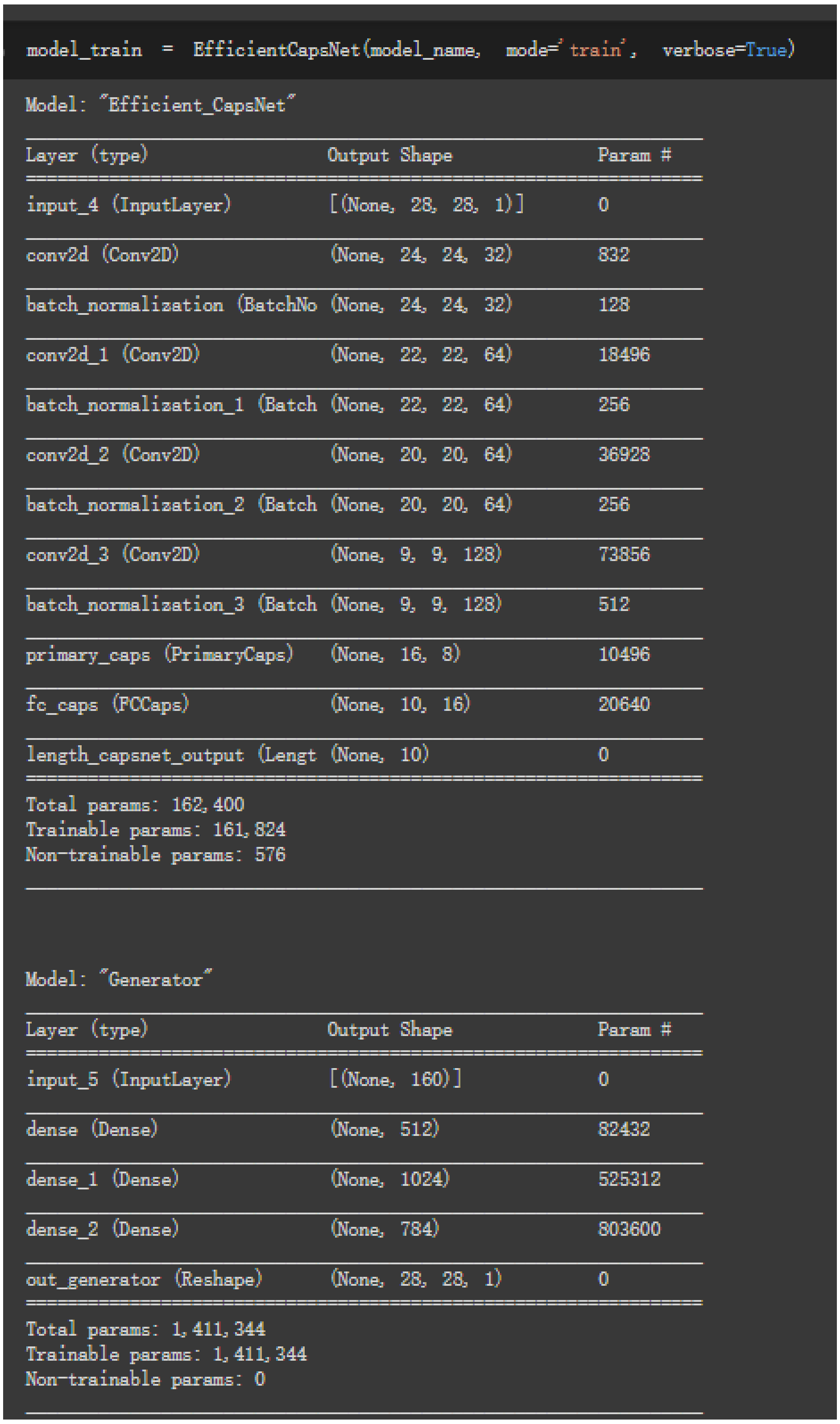
套件與資料集設置



```
n_images = 20 # number of images to be plotted
plotImages(dataset.X_test[:n_images,...,0], dataset.y_test[:n_images], n_images, dataset.class_names)
#(20, 28, 28) (20, 10) 20 [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
#(20, 28, 28) (20, 10) 20 [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

```
(20, 28, 28) (20, 10) 20 [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

可視化



```
model_train = EfficientCapsNet(model_name, mode='train', verbose=True)
```

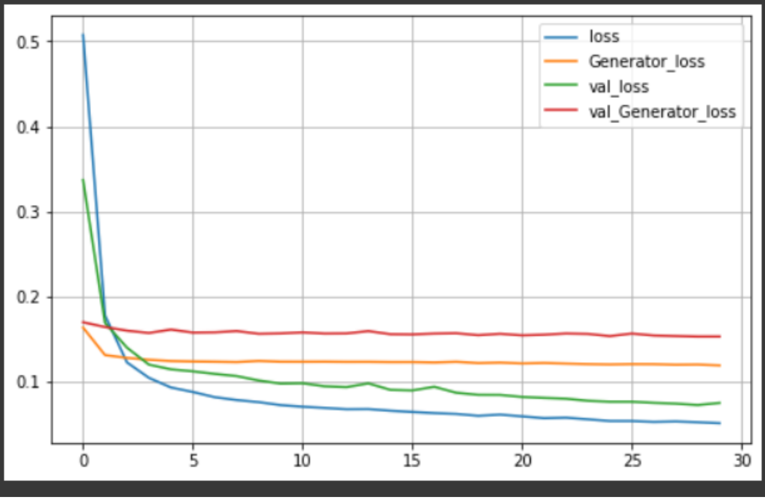
```
Model: "Efficient_CapsNet"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_4 (InputLayer)         [(None, 28, 28, 1)]       0
_________________________________________________________________
conv2d (Conv2D)              (None, 24, 24, 32)        832
_________________________________________________________________
batch_normalization (BatchNo (None, 24, 24, 32)        128
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 22, 22, 64)        18496
_________________________________________________________________
batch_normalization_1 (Batch (None, 22, 22, 64)        256
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 20, 20, 64)        36928
_________________________________________________________________
batch_normalization_2 (Batch (None, 20, 20, 64)        256
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 9, 9, 128)         73856
_________________________________________________________________
batch_normalization_3 (Batch (None, 9, 9, 128)         512
_________________________________________________________________
primary_caps (PrimaryCaps)   (None, 16, 8)             10496
_________________________________________________________________
fc_caps (FCCaps)             (None, 10, 16)            20640
_________________________________________________________________
length_capsnet_output (Lengt (None, 10)                0
=================================================================
Total params: 162,400
Trainable params: 161,824
Non-trainable params: 576
_________________________________________________________________


Model: "Generator"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_5 (InputLayer)         [(None, 160)]             0
_________________________________________________________________
dense (Dense)                (None, 512)               82432
_________________________________________________________________
dense_1 (Dense)              (None, 1024)              525312
_________________________________________________________________
dense_2 (Dense)              (None, 784)               803600
_________________________________________________________________
out_generator (Reshape)      (None, 28, 28, 1)         0
=================================================================
Total params: 1,411,344
Trainable params: 1,411,344
Non-trainable params: 0
_________________________________________________________________
```

模型参數

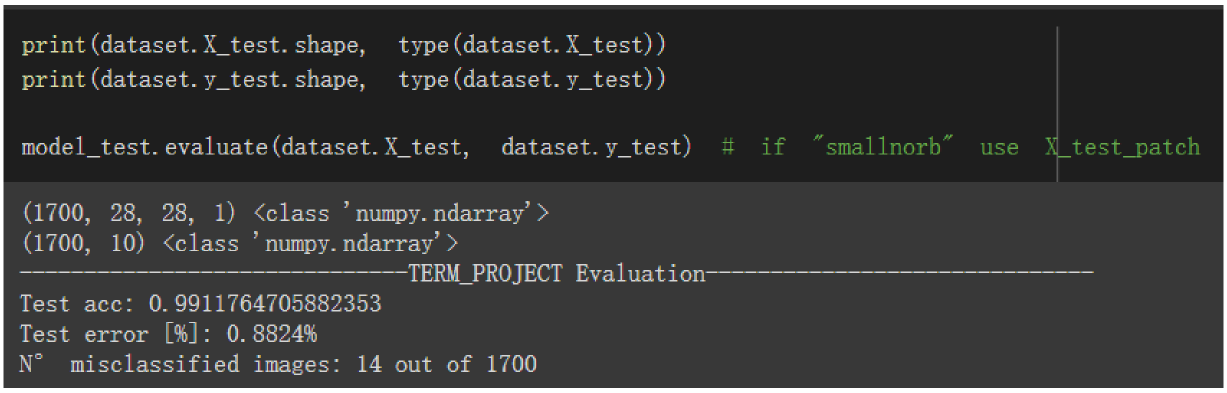
單一個案測試，預測 96%為” 五” ，生成器產生圖片雖略帶模糊但能看出五

```
history = model_train.train(dataset, initial_epoch=0)
```

```
plotHistory(history)
```



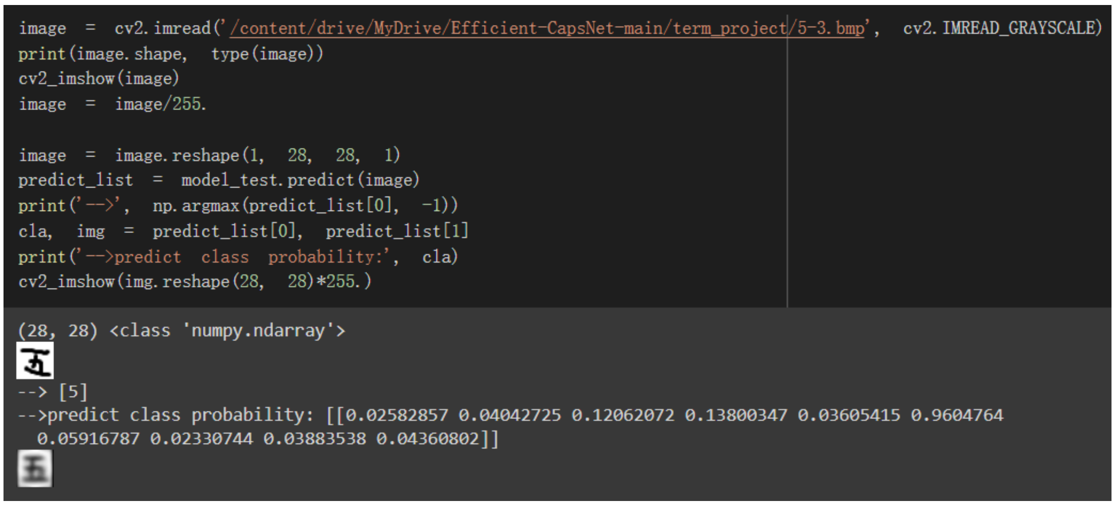
訓練結果與 loss 曲線



```
print(dataset.X_test.shape, type(dataset.X_test))
print(dataset.y_test.shape, type(dataset.y_test))

model_test.evaluate(dataset.X_test, dataset.y_test) # if "smallnorb" use X_test_patch
```

```
(1700, 28, 28, 1) <class 'numpy.ndarray'>
(1700, 10) <class 'numpy.ndarray'>
------------------------------TERM_PROJECT Evaluation------------------------------
Test acc: 0.9911764705882353
Test error [%]: 0.8824%
N° misclassified images: 14 out of 1700
```

測試結果：準確度 99.118%，1700 個測試案例中只錯誤 14 個案例



```
image = cv2.imread('/content/drive/MyDrive/Efficient-CapsNet-main/term_project/5-3.bmp', cv2.IMREAD_GRAYSCALE)
print(image.shape, type(image))
cv2_imshow(image)
image = image/255.

image = image.reshape(1, 28, 28, 1)
predict_list = model_test.predict(image)
print('-->', np.argmax(predict_list[0], -1))
cla, img = predict_list[0], predict_list[1]
print('-->predict class probability:', cla)
cv2_imshow(img.reshape(28, 28)*255.)
```

```
(28, 28) <class 'numpy.ndarray'>
五
--> [5]
-->predict class probability: [[0.02582857 0.04042725 0.12062072 0.13800347 0.03605415 0.9604764
  0.05916787 0.02330744 0.03883538 0.04360802]]
五
```

單一個案測試，預測 96%為” 五” ，生成器產生圖片雖略帶模糊但能看出五