智慧化企業整合

Intelligent Integration of Enterprise

Project 3

透過胸腔X-光片影像進行肺炎偵測

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目錄

一、 研究背景

1. 情境描述：

肺炎（Pneumonia）是指左右肺單葉其一或整個肺部的感染或非感染所引起的發炎症狀，由於負責氣體交換的肺泡此時會被發炎物質佔據，患者會出現咳嗽、多痰等現象。肺炎的初期症狀和一般流感十分相似，例如：咳嗽、發燒、沒精神、呼吸喘等皆為肺炎初期之症狀，因此肺炎經常被誤診為只是一般感冒或流感，但是肺炎症狀通常持續的時間較長且症狀也較為嚴重，可能因錯失治療先機使病人增加死亡風險。也因為時常誤診導致延誤治療，肺炎名列國人十大死因第六位，更佔老年人十大死因之第五位，肺炎病情可能快速惡化，短至一天、甚至幾小時內，病菌就可能快速大量繁殖，跑到血液裡變成菌血症、接著引發敗血症、敗血性休克、多重器官衰竭等十分危險，因此快速地確診並進行正確地治療才能使病人遠離這些危險。

醫師通常透過患者之症狀、胸部 X 光檢查、血液檢查和痰培養去確認患者是否為肺炎，而台灣 X 光專科醫師人數實在有限，需要判讀的 X 光影像又非常多，以傳統人力判讀的方式，不僅沒有效率也很容易發生錯誤。因此許多人提倡醫療導入人工智慧，透過人工智慧挑選出可能罹患肺炎的 X 光影像，再交由 X 光科醫師去判讀，以增加效率與伴讀準確度，因此本小組欲透過胸腔 X-光片影像進行肺炎偵測，以協助醫師增加判定的準確性以及加快確診之速度，進而爭取更多時間搶救病患。

2.　問題描述（5W1H）：

針對此研究主題，5W1H 分析說明如下表：

項目	內容
What	欲解決單獨由醫生判斷肺炎不僅耗時且可能有誤判之問題。
Where	各醫院之胸腔內科。
Who	欲透過 X 光片判定病患是否罹患肺炎之人。
When	當醫生欲確認並辨別病人是否罹患肺炎時。
Why	避免錯誤診斷導致病人看診時間延誤，以及減少檢驗人員之工作量使檢驗人員能更快速地做出診斷。
How	利用 CNN 建構神經網路模型，以協助醫生透過 X 光片進行肺炎病徵的判斷。

3.　CNN 簡介：

CNN 是深度學習在影像處理領域的成功應用，作為一種具有深度結構的前向型神經網路，一般由卷積層、池化層、全連接層與輸出層組成。相較於傳統的人工神經網路，兩者主要的區別就在於前者通過卷積核及權值共用大幅降低了參數數量與訓練難度。再結合大量資料的訓練，使 CNN 突破了傳統網路的限制，在影像處理領域取得了很大的進展。

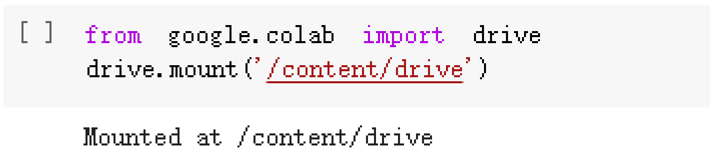
二、 資料前處理過程

1. 資料集簡介：

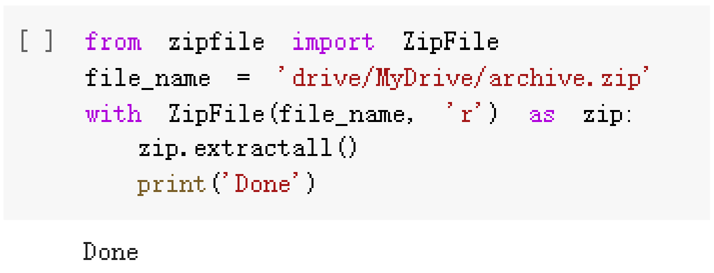
由 Kaggle 公開數據集中取得胸腔 X 光片的圖像資料集。

2. CNN Model by tf.keras：

（1） 於 colab 導入資料集

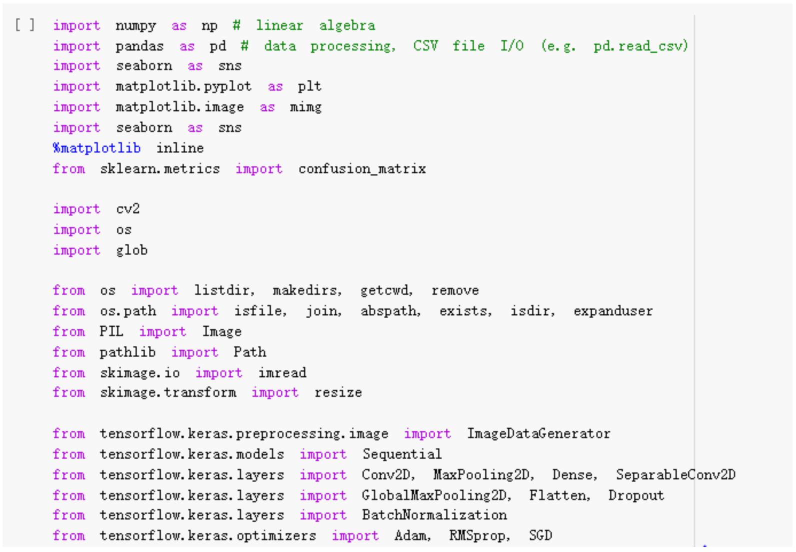


```
[ ] from google.colab import drive
    drive.mount('/content/drive')

    Mounted at /content/drive
```



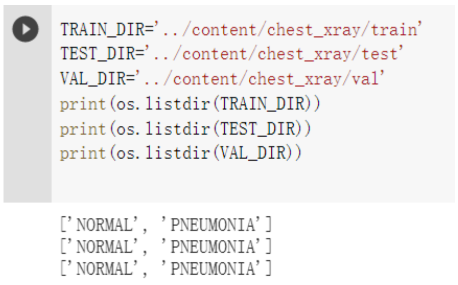
```
[ ] from zipfile import ZipFile
    file_name = 'drive/MyDrive/archive.zip'
    with ZipFile(file_name, 'r') as zip:
      zip.extractall()
      print('Done')

    Done
```

（2） 載入會使用到的套件 Importing Various Modules



```
[ ] import numpy as np # linear algebra
    import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
    import seaborn as sns
    import matplotlib.pyplot as plt
    import matplotlib.image as mimg
    import seaborn as sns
    %matplotlib inline
    from sklearn.metrics import confusion_matrix

    import cv2
    import os
    import glob

    from os import listdir, makedirs, getcwd, remove
    from os.path import isfile, join, abspath, exists, isdir, expanduser
    from PIL import Image
    from pathlib import Path
    from skimage.io import imread
    from skimage.transform import resize

    from tensorflow.keras.preprocessing.image import ImageDataGenerator
    from tensorflow.keras.models import Sequential
    from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dense, SeparableConv2D
    from tensorflow.keras.layers import GlobalMaxPooling2D, Flatten, Dropout
    from tensorflow.keras.layers import BatchNormalization
    from tensorflow.keras.optimizers import Adam, RMSprop, SGD
```

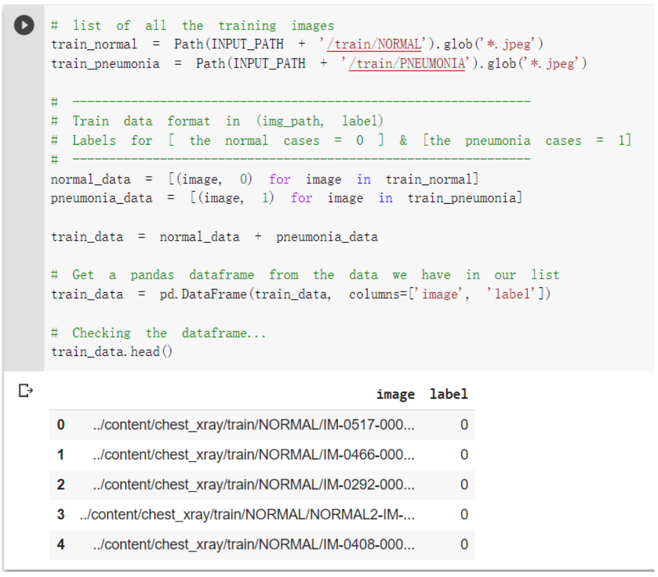
（3） 定義 X、Y 資料集，定義目錄以便導入資料



```
TRAIN_DIR='../content/chest_xray/train'
TEST_DIR='../content/chest_xray/test'
VAL_DIR='../content/chest_xray/val'
print(os.listdir(TRAIN_DIR))
print(os.listdir(TEST_DIR))
print(os.listdir(VAL_DIR))

['NORMAL', 'PNEUMONIA']
['NORMAL', 'PNEUMONIA']
['NORMAL', 'PNEUMONIA']
```

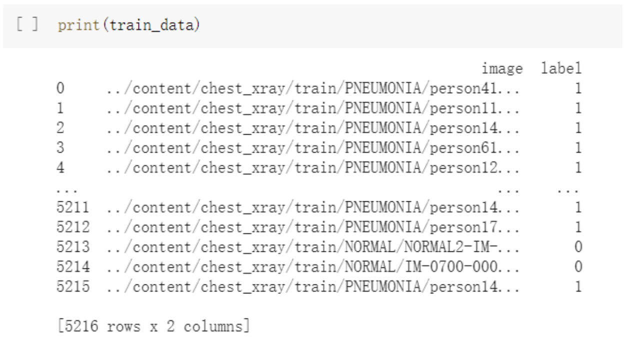
3.　Training Data 處理：

（1）將 Normal 的圖片資料轉換為 Label 0、Pneumonia 的圖片資料轉換為 Label 1，以利後續進行，並將所有的結果列出。



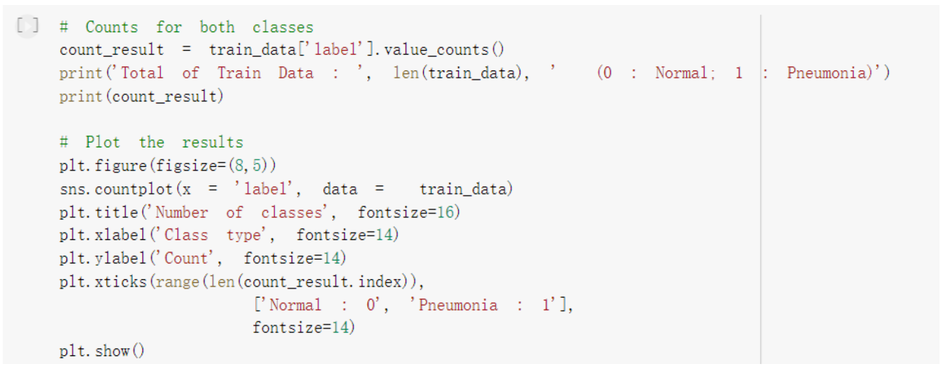
```
# list of all the training images
train_normal = Path(INPUT_PATH + '/train/NORMAL').glob('*.jpeg')
train_pneumonia = Path(INPUT_PATH + '/train/PNEUMONIA').glob('*.jpeg')

# ----------------------------------------------------------------
# Train data format in (img_path, label)
# Labels for [ the normal cases = 0 ] & [the pneumonia cases = 1]
# ----------------------------------------------------------------
normal_data = [(image, 0) for image in train_normal]
pneumonia_data = [(image, 1) for image in train_pneumonia]

train_data = normal_data + pneumonia_data

# Get a pandas dataframe from the data we have in our list
train_data = pd.DataFrame(train_data, columns=['image', 'label'])

# Checking the dataframe...
train_data.head()
```

	image	label
0	../content/chest_xray/train/NORMAL/IM-0517-000...	0
1	../content/chest_xray/train/NORMAL/IM-0466-000...	0
2	../content/chest_xray/train/NORMAL/IM-0292-000...	0
3	../content/chest_xray/train/NORMAL/NORMAL2-IM-...	0
4	../content/chest_xray/train/NORMAL/IM-0408-000...	0



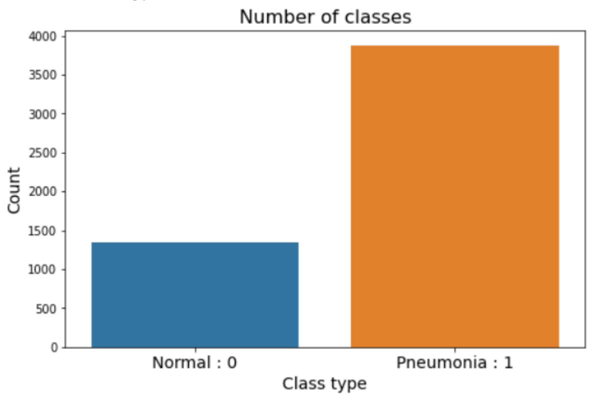
```
[ ] print(train_data)

                                                 image  label
0     ../content/chest_xray/train/PNEUMONIA/person41...      1
1     ../content/chest_xray/train/PNEUMONIA/person11...      1
2     ../content/chest_xray/train/PNEUMONIA/person14...      1
3     ../content/chest_xray/train/PNEUMONIA/person61...      1
4     ../content/chest_xray/train/PNEUMONIA/person12...      1
...                                                ...    ...
5211  ../content/chest_xray/train/PNEUMONIA/person14...      1
5212  ../content/chest_xray/train/PNEUMONIA/person17...      1
5213  ../content/chest_xray/train/NORMAL/NORMAL2-IM-...      0
5214  ../content/chest_xray/train/NORMAL/IM-0700-000...      0
5215  ../content/chest_xray/train/PNEUMONIA/person14...      1

[5216 rows x 2 columns]
```

（2）　查看所有 Training Data 中 Normal 以及 Pneumonia 之數量，並以圖表顯示之。

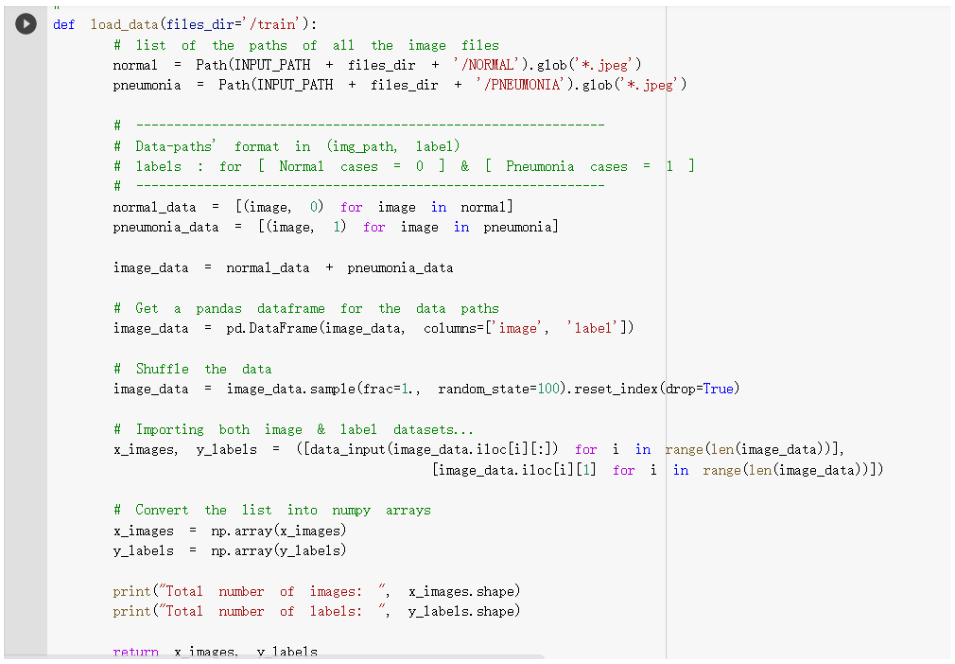


```
[ ] # Counts for both classes
    count_result = train_data['label'].value_counts()
    print('Total of Train Data : ', len(train_data), '   (0 : Normal; 1 : Pneumonia)')
    print(count_result)

    # Plot the results
    plt.figure(figsize=(8,5))
    sns.countplot(x = 'label', data =  train_data)
    plt.title('Number of classes', fontsize=16)
    plt.xlabel('Class type', fontsize=14)
    plt.ylabel('Count', fontsize=14)
    plt.xticks(range(len(count_result.index)),
                          ['Normal : 0', 'Pneumonia : 1'],
                          fontsize=14)
    plt.show()
```

```
Total of Train Data :  5216   (0 : Normal; 1 : Pneumonia)
1    3875
0    1341
Name: label, dtype: int64
```

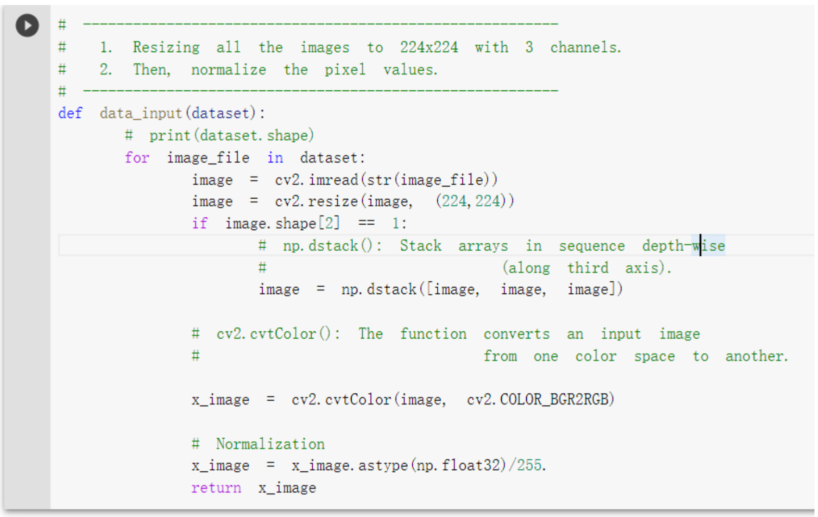


(3) 定義 load_data 函式：以方便將 Train、Test、Validation Datasets，以 Normal=0、Pneumonia=1 之形式匯入。



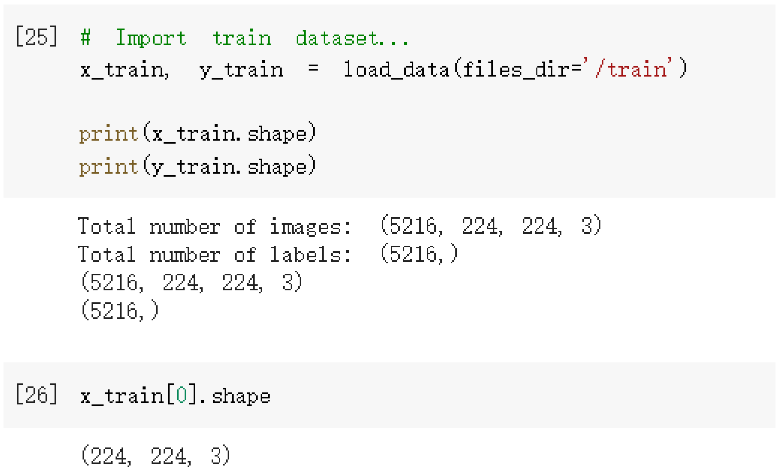
```
def load_data(files_dir='/train'):
    # list of the paths of all the image files
    normal = Path(INPUT_PATH + files_dir + '/NORMAL').glob('*.jpeg')
    pneumonia = Path(INPUT_PATH + files_dir + '/PNEUMONIA').glob('*.jpeg')

    # -------------------------------------------------------------
    # Data-paths' format in (img_path, label)
    # labels : for [ Normal cases = 0 ] & [ Pneumonia cases = 1 ]
    # -------------------------------------------------------------
    normal_data = [(image, 0) for image in normal]
    pneumonia_data = [(image, 1) for image in pneumonia]

    image_data = normal_data + pneumonia_data

    # Get a pandas dataframe for the data paths
    image_data = pd.DataFrame(image_data, columns=['image', 'label'])

    # Shuffle the data
    image_data = image_data.sample(frac=1., random_state=100).reset_index(drop=True)

    # Importing both image & label datasets...
    x_images, y_labels = ([data_input(image_data.iloc[i][:]) for i in range(len(image_data))],
                          [image_data.iloc[i][1] for i in range(len(image_data))])

    # Convert the list into numpy arrays
    x_images = np.array(x_images)
    y_labels = np.array(y_labels)

    print("Total number of images: ", x_images.shape)
    print("Total number of labels: ", y_labels.shape)

    return x_images, y_labels
```

(4) 定義 data_input 函式：讀入彩色之圖像，並調整圖像的大小（尺寸 224x224 with 3 channels），且標準化像素。



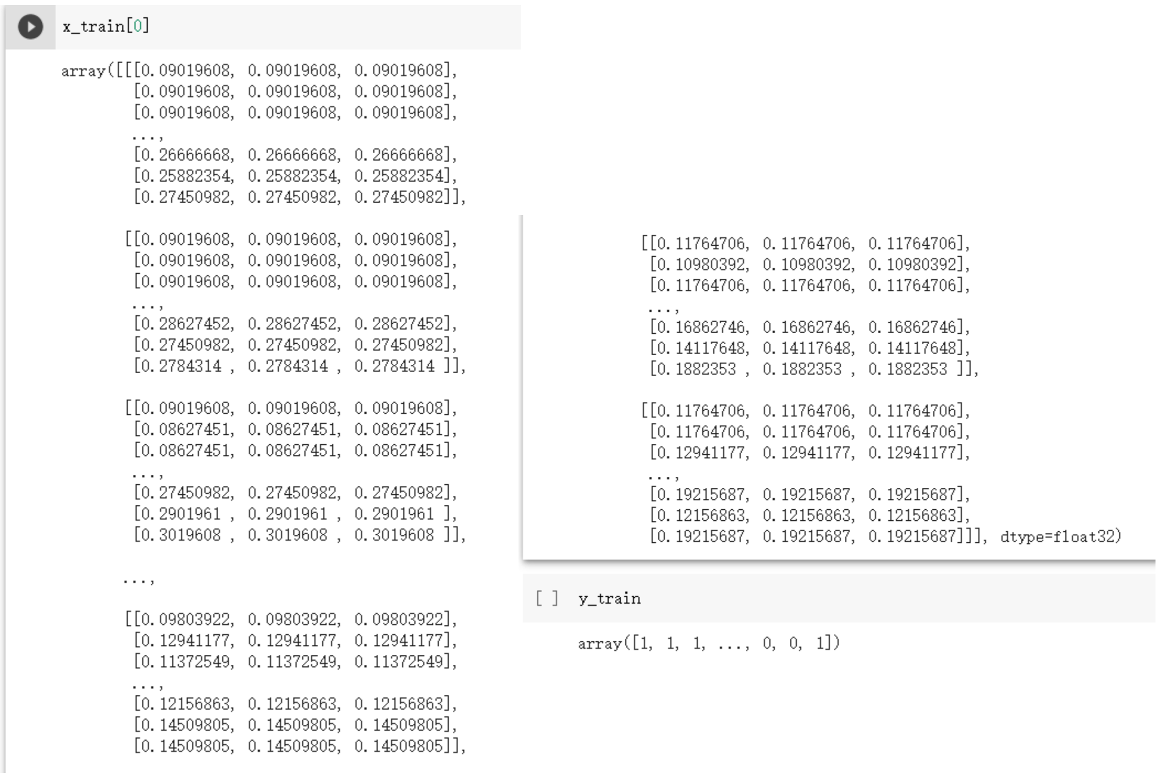
```
# -------------------------------------------------------------
#    1. Resizing all the images to 224x224 with 3 channels.
#    2. Then, normalize the pixel values.
# -------------------------------------------------------------
def data_input(dataset):
    # print(dataset.shape)
    for image_file in dataset:
        image = cv2.imread(str(image_file))
        image = cv2.resize(image, (224,224))
        if image.shape[2] == 1:
            # np.dstack(): Stack arrays in sequence depth-wise
            #                    (along third axis).
            image = np.dstack([image, image, image])

        # cv2.cvtColor(): The function converts an input image
        #                       from one color space to another.

        x_image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

        # Normalization
        x_image = x_image.astype(np.float32)/255.
        return x_image
```

(5) 將所有 Dataset 之圖像以標準型式匯入，以 Train Data 為例：



```
[25] # Import train dataset...
     x_train, y_train = load_data(files_dir='/train')

     print(x_train.shape)
     print(y_train.shape)

     Total number of images: (5216, 224, 224, 3)
     Total number of labels: (5216,)
     (5216, 224, 224, 3)
     (5216,)
```

```
[26] x_train[0].shape

     (224, 224, 3)
```

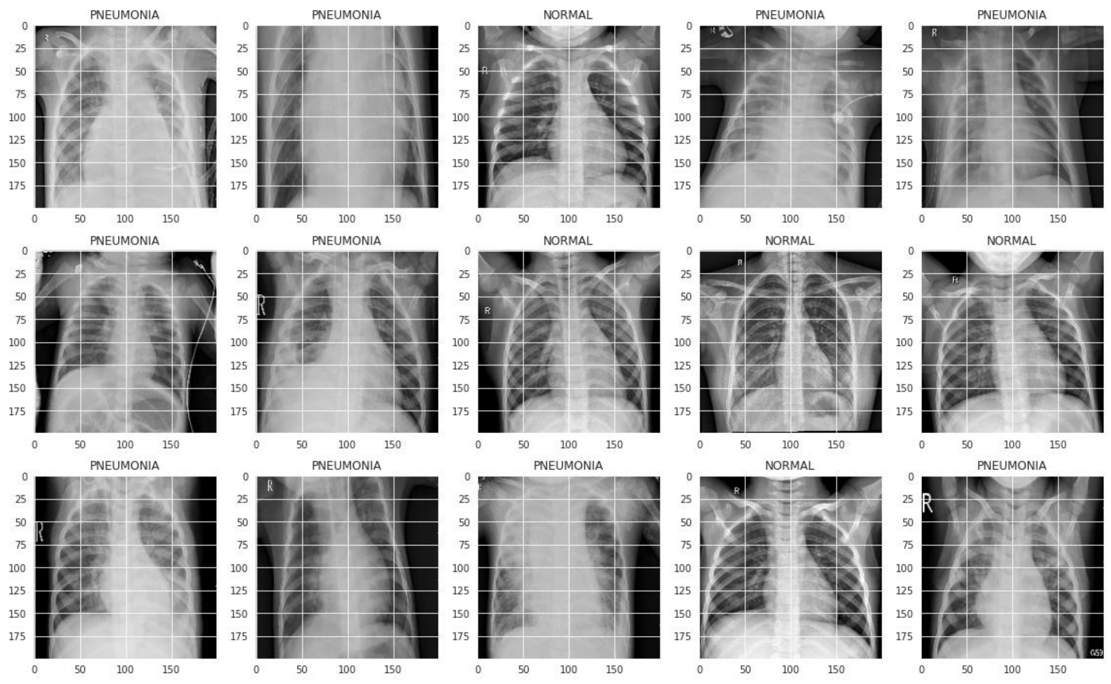


```
x_train[0]

array([[[0.09019608, 0.09019608, 0.09019608],
        [0.09019608, 0.09019608, 0.09019608],
        [0.09019608, 0.09019608, 0.09019608],
        ...,
        [0.26666668, 0.26666668, 0.26666668],
        [0.25882354, 0.25882354, 0.25882354],
        [0.27450982, 0.27450982, 0.27450982]],

       [[0.09019608, 0.09019608, 0.09019608],
        [0.09019608, 0.09019608, 0.09019608],
        [0.09019608, 0.09019608, 0.09019608],
        ...,
        [0.28627452, 0.28627452, 0.28627452],
        [0.27450982, 0.27450982, 0.27450982],
        [0.2784314 , 0.2784314 , 0.2784314 ]],

       [[0.09019608, 0.09019608, 0.09019608],
        [0.08627451, 0.08627451, 0.08627451],
        [0.08627451, 0.08627451, 0.08627451],
        ...,
        [0.27450982, 0.27450982, 0.27450982],
        [0.2901961 , 0.2901961 , 0.2901961 ],
        [0.3019608 , 0.3019608 , 0.3019608 ]],

       ...,

       [[0.09803922, 0.09803922, 0.09803922],
        [0.12941177, 0.12941177, 0.12941177],
        [0.11372549, 0.11372549, 0.11372549],
        ...,
        [0.12156863, 0.12156863, 0.12156863],
        [0.14509805, 0.14509805, 0.14509805],
        [0.14509805, 0.14509805, 0.14509805]],

       [[0.11764706, 0.11764706, 0.11764706],
        [0.10980392, 0.10980392, 0.10980392],
        [0.11764706, 0.11764706, 0.11764706],
        ...,
        [0.16862746, 0.16862746, 0.16862746],
        [0.14117648, 0.14117648, 0.14117648],
        [0.1882353 , 0.1882353 , 0.1882353 ]],

       [[0.11764706, 0.11764706, 0.11764706],
        [0.11764706, 0.11764706, 0.11764706],
        [0.12941177, 0.12941177, 0.12941177],
        ...,
        [0.19215687, 0.19215687, 0.19215687],
        [0.12156863, 0.12156863, 0.12156863],
        [0.19215687, 0.19215687, 0.19215687]]], dtype=float32)
```

```
[ ] y_train

    array([1, 1, 1, ..., 0, 0, 1])
```

(6) 以視覺化的方式呈現

```
[ ] fig, ax = plt.subplots(3, 4, figsize=(20,15))
    for i, axi in enumerate(ax.flat):
          image = imread(train_data.image[i])
          axi.imshow(image, cmap='bone')
          axi.set_title(('Normal' if train_data.label[i] == 0 else 'Pneumonia')
                                   + '  [size=' + str(image.shape) +']',
                                   fontsize=14)
          axi.set(xticks=[], yticks=[])
```

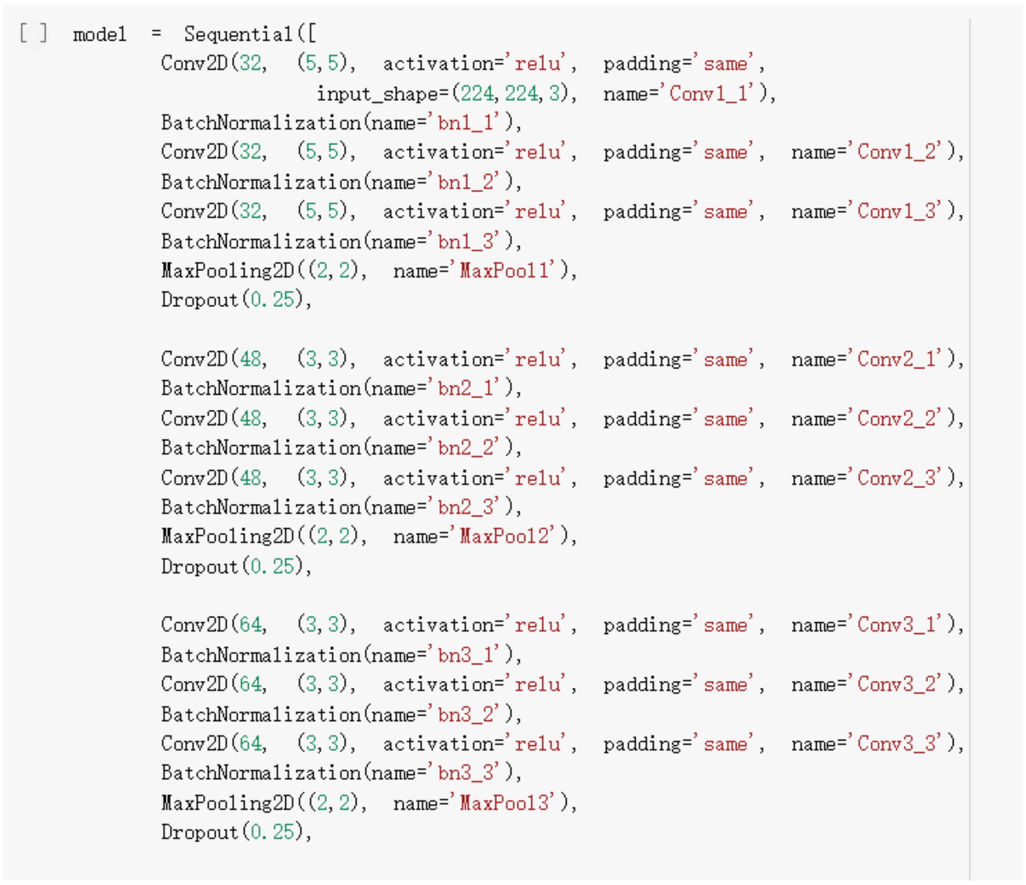


(7) 將數據擴充以防止過擬合的情況發生。由於 validation dataset 只有 16 筆影像資料，因此，直接將 training datasets (5216 images) 分割出 4200 筆的 training 資料 (80.5% 資料量)，其餘的 1016 張 X-ray 影像資料做為 validation 資料集。

```
[ ] def data_augm():
        print('Using real-time data augmentation.')
        # This will do preprocessing and realtime data augmentation:
        datagen = ImageDataGenerator(
              # randomly shift images horizontally (fraction of total width)
              width_shift_range=0.05,
              # randomly shift images vertically (fraction of total height)
              height_shift_range=0.05,
              # rotation_range=20,
              horizontal_flip=True,    # Randomly flip inputs horizontally.
              # vertical_flip=True,    # Randomly flip inputs vertically.
              # zoom_range=[0.95, 1.05]  # Range for random zoom
        )
        return datagen
```

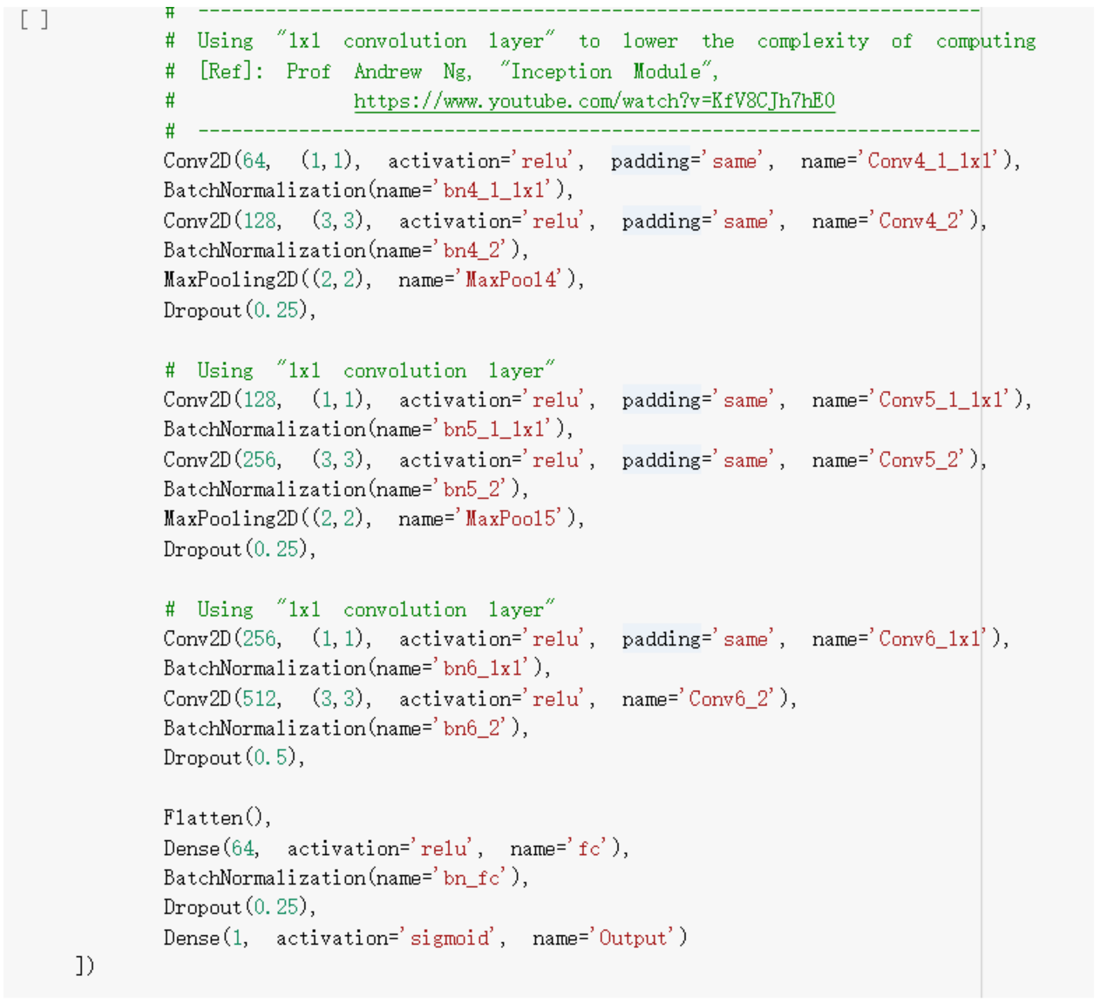
三、 模型建構

1. 發展模型：建立簡單的線性執行的模型為 Sequential；建立第一層卷積層 filters 為 32，Kernal Size 為 5 X 5；第二層卷積層 filters 為 48 ，Kernal Size 為 3 X 3；第三層卷積層 filters 為 64，Kernal Size 為 3 X 3；而建立池化層大小皆為 2x2，且 Dropout 層隨機斷開輸入神經元，用於防止過度擬合，斷開比例:0.25， activation 皆設為 relu。



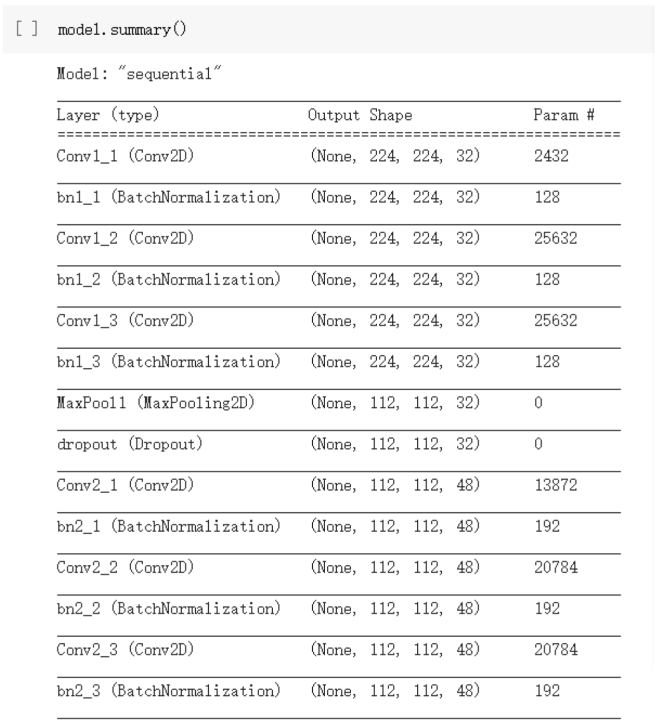
```
[ ] model = Sequential([
        Conv2D(32, (5,5), activation='relu', padding='same',
                    input_shape=(224,224,3), name='Conv1_1'),
        BatchNormalization(name='bn1_1'),
        Conv2D(32, (5,5), activation='relu', padding='same', name='Conv1_2'),
        BatchNormalization(name='bn1_2'),
        Conv2D(32, (5,5), activation='relu', padding='same', name='Conv1_3'),
        BatchNormalization(name='bn1_3'),
        MaxPooling2D((2,2), name='MaxPool1'),
        Dropout(0.25),

        Conv2D(48, (3,3), activation='relu', padding='same', name='Conv2_1'),
        BatchNormalization(name='bn2_1'),
        Conv2D(48, (3,3), activation='relu', padding='same', name='Conv2_2'),
        BatchNormalization(name='bn2_2'),
        Conv2D(48, (3,3), activation='relu', padding='same', name='Conv2_3'),
        BatchNormalization(name='bn2_3'),
        MaxPooling2D((2,2), name='MaxPool2'),
        Dropout(0.25),

        Conv2D(64, (3,3), activation='relu', padding='same', name='Conv3_1'),
        BatchNormalization(name='bn3_1'),
        Conv2D(64, (3,3), activation='relu', padding='same', name='Conv3_2'),
        BatchNormalization(name='bn3_2'),
        Conv2D(64, (3,3), activation='relu', padding='same', name='Conv3_3'),
        BatchNormalization(name='bn3_3'),
        MaxPooling2D((2,2), name='MaxPool3'),
        Dropout(0.25),
```

2. 接著，利用 1x1 convolution layer 建立第四、五、六階層，1x1 convolution filter 的作用在於降低深度，但不降低原輸入維度情況下，降低計算量。Flatten 層把多維的輸入一維化，常用在從卷積層到全連接層的過渡。而建立池化層大小皆為 2x2，且 Dropout 層隨機斷開輸入神經元，用於防止過度擬合，斷開比例:0.25， activation 皆設為 relu。

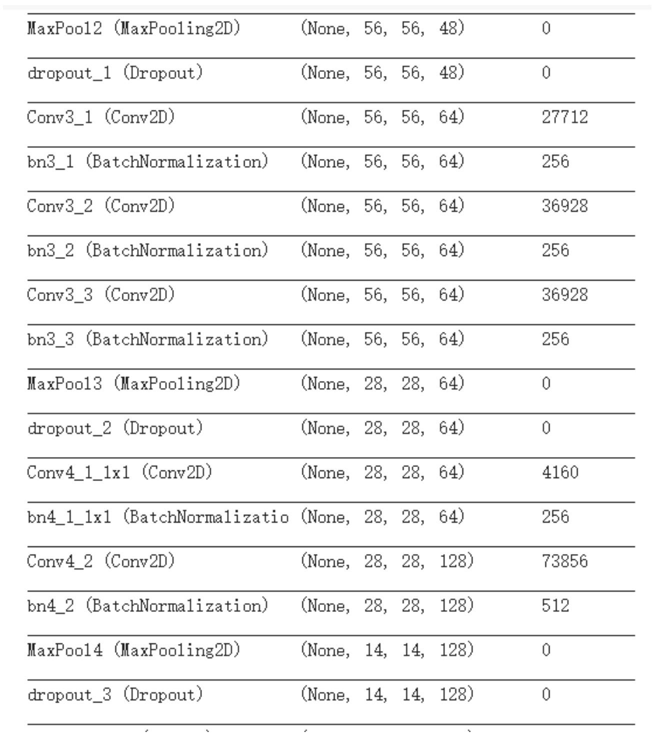


```
[ ]         # -----------------------------------------------------------------------
            # Using "1x1 convolution layer" to lower the complexity of computing
            # [Ref]: Prof Andrew Ng, "Inception Module",
            #             https://www.youtube.com/watch?v=KfV8CJh7hE0
            # -----------------------------------------------------------------------
            Conv2D(64, (1,1), activation='relu', padding='same', name='Conv4_1_1x1'),
            BatchNormalization(name='bn4_1_1x1'),
            Conv2D(128, (3,3), activation='relu', padding='same', name='Conv4_2'),
            BatchNormalization(name='bn4_2'),
            MaxPooling2D((2,2), name='MaxPool4'),
            Dropout(0.25),

            # Using "1x1 convolution layer"
            Conv2D(128, (1,1), activation='relu', padding='same', name='Conv5_1_1x1'),
            BatchNormalization(name='bn5_1_1x1'),
            Conv2D(256, (3,3), activation='relu', padding='same', name='Conv5_2'),
            BatchNormalization(name='bn5_2'),
            MaxPooling2D((2,2), name='MaxPool5'),
            Dropout(0.25),

            # Using "1x1 convolution layer"
            Conv2D(256, (1,1), activation='relu', padding='same', name='Conv6_1x1'),
            BatchNormalization(name='bn6_1x1'),
            Conv2D(512, (3,3), activation='relu', name='Conv6_2'),
            BatchNormalization(name='bn6_2'),
            Dropout(0.5),

            Flatten(),
            Dense(64, activation='relu', name='fc'),
            BatchNormalization(name='bn_fc'),
            Dropout(0.25),
            Dense(1, activation='sigmoid', name='Output')
    ])
```

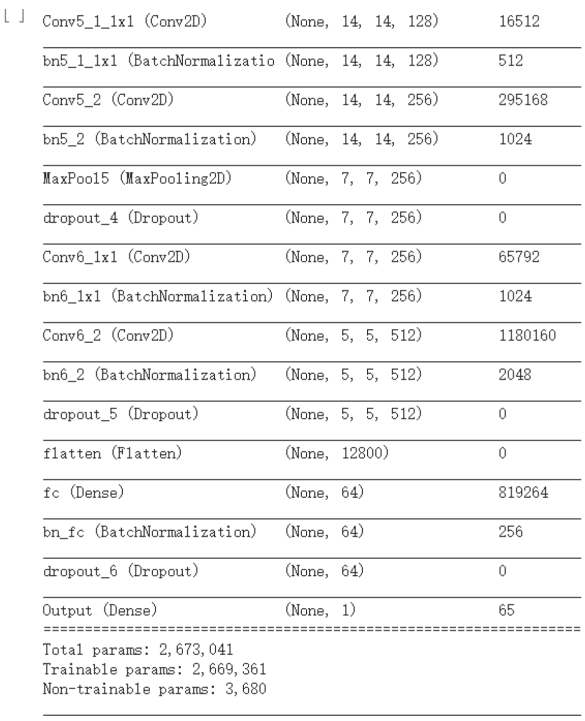
結果如下所示：此處可見 CNN Model 有 2,669,361 個參數需要進行訓練、調校。



```
[ ]  model.summary()

     Model: "sequential"
     _________________________________________________________________
     Layer (type)                 Output Shape              Param #
     =================================================================
     Conv1_1 (Conv2D)             (None, 224, 224, 32)      2432
     _________________________________________________________________
     bn1_1 (BatchNormalization)   (None, 224, 224, 32)      128
     _________________________________________________________________
     Conv1_2 (Conv2D)             (None, 224, 224, 32)      25632
     _________________________________________________________________
     bn1_2 (BatchNormalization)   (None, 224, 224, 32)      128
     _________________________________________________________________
     Conv1_3 (Conv2D)             (None, 224, 224, 32)      25632
     _________________________________________________________________
     bn1_3 (BatchNormalization)   (None, 224, 224, 32)      128
     _________________________________________________________________
     MaxPool1 (MaxPooling2D)      (None, 112, 112, 32)      0
     _________________________________________________________________
     dropout (Dropout)            (None, 112, 112, 32)      0
     _________________________________________________________________
     Conv2_1 (Conv2D)             (None, 112, 112, 48)      13872
     _________________________________________________________________
     bn2_1 (BatchNormalization)   (None, 112, 112, 48)      192
     _________________________________________________________________
     Conv2_2 (Conv2D)             (None, 112, 112, 48)      20784
     _________________________________________________________________
     bn2_2 (BatchNormalization)   (None, 112, 112, 48)      192
     _________________________________________________________________
     Conv2_3 (Conv2D)             (None, 112, 112, 48)      20784
     _________________________________________________________________
     bn2_3 (BatchNormalization)   (None, 112, 112, 48)      192
     _________________________________________________________________
```

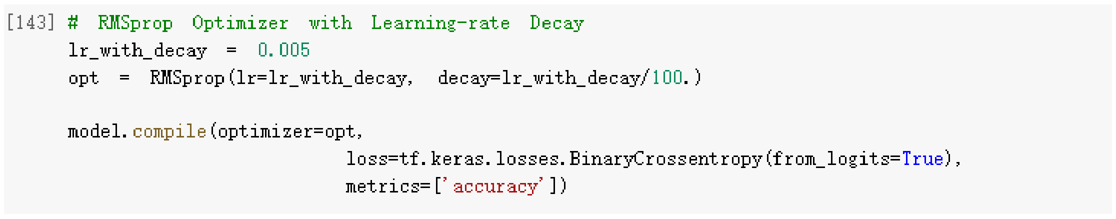


```
MaxPool2 (MaxPooling2D)      (None, 56, 56, 48)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 56, 56, 48)        0
_________________________________________________________________
Conv3_1 (Conv2D)             (None, 56, 56, 64)        27712
_________________________________________________________________
bn3_1 (BatchNormalization)   (None, 56, 56, 64)        256
_________________________________________________________________
Conv3_2 (Conv2D)             (None, 56, 56, 64)        36928
_________________________________________________________________
bn3_2 (BatchNormalization)   (None, 56, 56, 64)        256
_________________________________________________________________
Conv3_3 (Conv2D)             (None, 56, 56, 64)        36928
_________________________________________________________________
bn3_3 (BatchNormalization)   (None, 56, 56, 64)        256
_________________________________________________________________
MaxPool3 (MaxPooling2D)      (None, 28, 28, 64)        0
_________________________________________________________________
dropout_2 (Dropout)          (None, 28, 28, 64)        0
_________________________________________________________________
Conv4_1_1x1 (Conv2D)         (None, 28, 28, 64)        4160
_________________________________________________________________
bn4_1_1x1 (BatchNormalizatio (None, 28, 28, 64)        256
_________________________________________________________________
Conv4_2 (Conv2D)             (None, 28, 28, 128)       73856
_________________________________________________________________
bn4_2 (BatchNormalization)   (None, 28, 28, 128)       512
_________________________________________________________________
MaxPool4 (MaxPooling2D)      (None, 14, 14, 128)       0
_________________________________________________________________
dropout_3 (Dropout)          (None, 14, 14, 128)       0
_________________________________________________________________
```



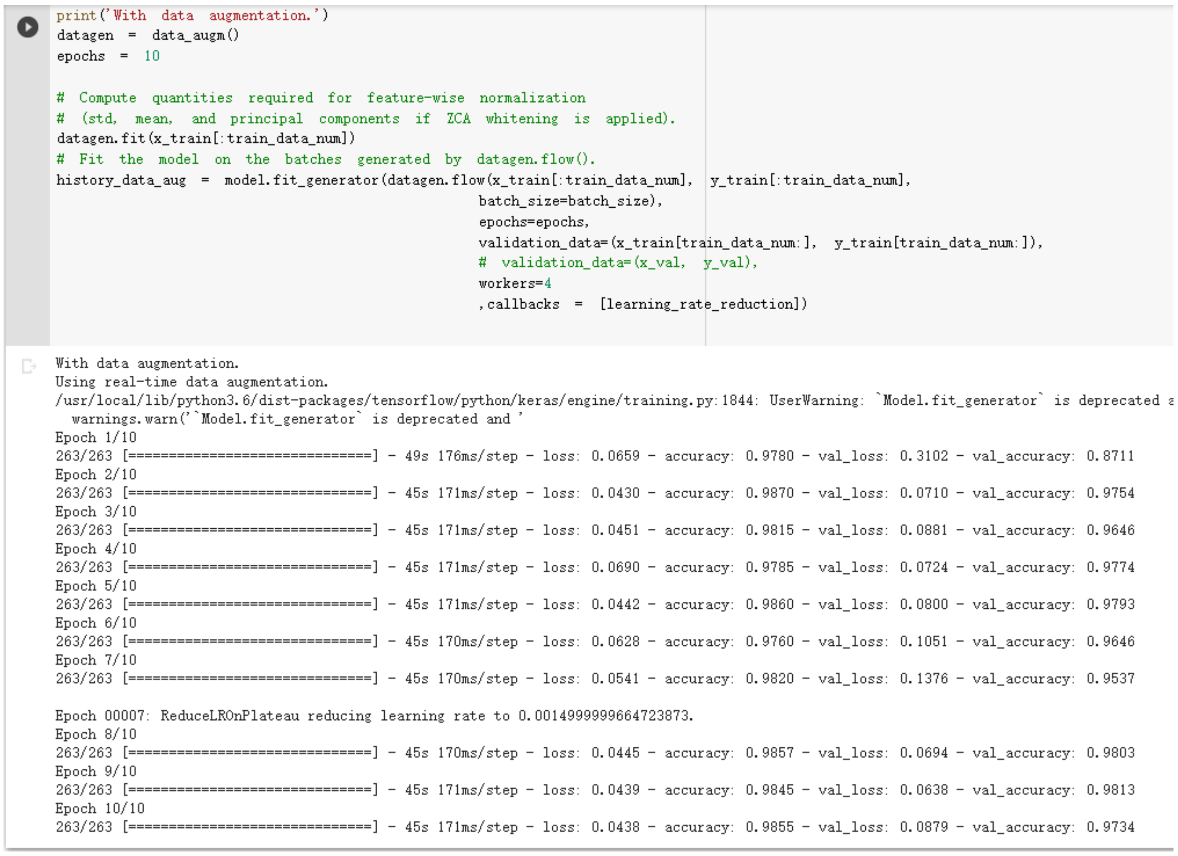
```
[ ]  Conv5_1_1x1 (Conv2D)         (None, 14, 14, 128)       16512
     _________________________________________________________________
     bn5_1_1x1 (BatchNormalizatio (None, 14, 14, 128)       512
     _________________________________________________________________
     Conv5_2 (Conv2D)             (None, 14, 14, 256)       295168
     _________________________________________________________________
     bn5_2 (BatchNormalization)   (None, 14, 14, 256)       1024
     _________________________________________________________________
     MaxPool5 (MaxPooling2D)      (None, 7, 7, 256)         0
     _________________________________________________________________
     dropout_4 (Dropout)          (None, 7, 7, 256)         0
     _________________________________________________________________
     Conv6_1x1 (Conv2D)           (None, 7, 7, 256)         65792
     _________________________________________________________________
     bn6_1x1 (BatchNormalization) (None, 7, 7, 256)         1024
     _________________________________________________________________
     Conv6_2 (Conv2D)             (None, 5, 5, 512)         1180160
     _________________________________________________________________
     bn6_2 (BatchNormalization)   (None, 5, 5, 512)         2048
     _________________________________________________________________
     dropout_5 (Dropout)          (None, 5, 5, 512)         0
     _________________________________________________________________
     flatten (Flatten)            (None, 12800)             0
     _________________________________________________________________
     fc (Dense)                   (None, 64)                819264
     _________________________________________________________________
     bn_fc (BatchNormalization)   (None, 64)                256
     _________________________________________________________________
     dropout_6 (Dropout)          (None, 64)                0
     _________________________________________________________________
     Output (Dense)               (None, 1)                 65
     =================================================================
     Total params: 2,673,041
     Trainable params: 2,669,361
     Non-trainable params: 3,680
     _________________________________________________________________
```

3. 設定模型參數，使用的 optimizer 為 RMSprop，學習率為 0.005。



```
[143] # RMSprop Optimizer with Learning-rate Decay
      lr_with_decay = 0.005
      opt = RMSprop(lr=lr_with_decay, decay=lr_with_decay/100.)

      model.compile(optimizer=opt,
                                    loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
                                    metrics=['accuracy'])
```

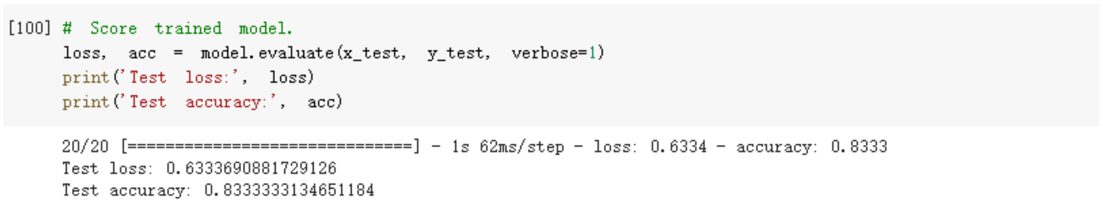
4. 模型擬合訓練數據並驗證測試數據



```
print('With data augmentation.')
datagen = data_augm()
epochs = 10

# Compute quantities required for feature-wise normalization
# (std, mean, and principal components if ZCA whitening is applied).
datagen.fit(x_train[:train_data_num])
# Fit the model on the batches generated by datagen.flow().
history_data_aug = model.fit_generator(datagen.flow(x_train[:train_data_num], y_train[:train_data_num],
                                       batch_size=batch_size),
                                       epochs=epochs,
                                       validation_data=(x_train[train_data_num:], y_train[train_data_num:]),
                                       # validation_data=(x_val, y_val),
                                       workers=4
                                       ,callbacks = [learning_rate_reduction])
```

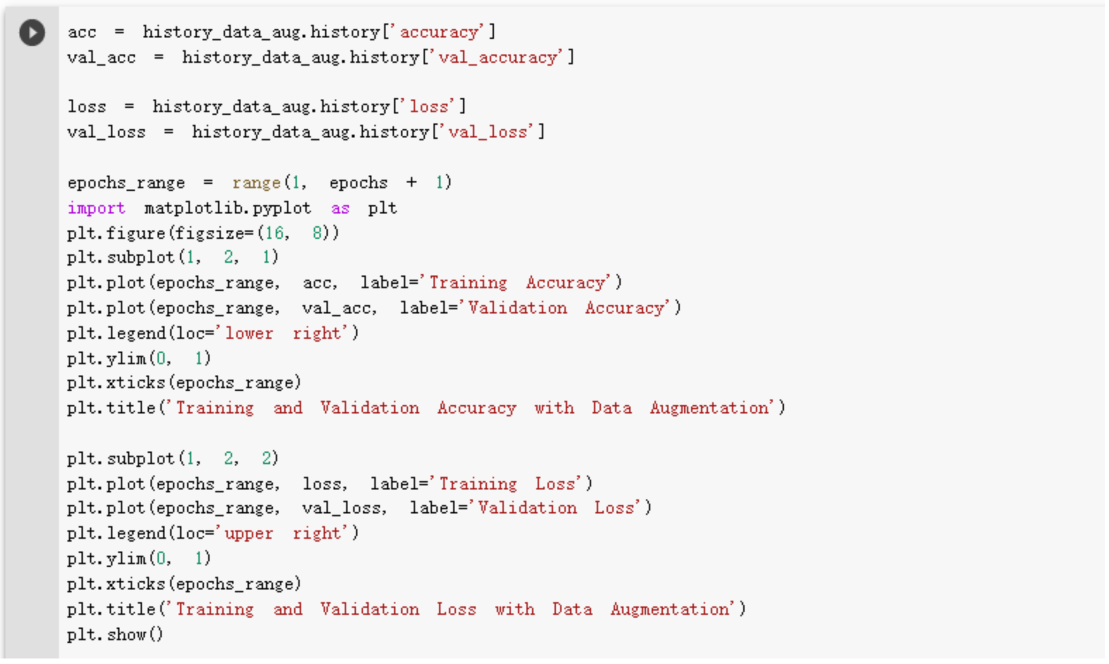
```
With data augmentation.
Using real-time data augmentation.
/usr/local/lib/python3.6/dist-packages/tensorflow/python/keras/engine/training.py:1844: UserWarning: `Model.fit_generator` is deprecated a
  warnings.warn('`Model.fit_generator` is deprecated and '
Epoch 1/10
263/263 [==============================] - 49s 176ms/step - loss: 0.0659 - accuracy: 0.9780 - val_loss: 0.3102 - val_accuracy: 0.8711
Epoch 2/10
263/263 [==============================] - 45s 171ms/step - loss: 0.0430 - accuracy: 0.9870 - val_loss: 0.0710 - val_accuracy: 0.9754
Epoch 3/10
263/263 [==============================] - 45s 171ms/step - loss: 0.0451 - accuracy: 0.9815 - val_loss: 0.0881 - val_accuracy: 0.9646
Epoch 4/10
263/263 [==============================] - 45s 171ms/step - loss: 0.0690 - accuracy: 0.9785 - val_loss: 0.0724 - val_accuracy: 0.9774
Epoch 5/10
263/263 [==============================] - 45s 171ms/step - loss: 0.0442 - accuracy: 0.9860 - val_loss: 0.0800 - val_accuracy: 0.9793
Epoch 6/10
263/263 [==============================] - 45s 170ms/step - loss: 0.0628 - accuracy: 0.9760 - val_loss: 0.1051 - val_accuracy: 0.9646
Epoch 7/10
263/263 [==============================] - 45s 170ms/step - loss: 0.0541 - accuracy: 0.9820 - val_loss: 0.1376 - val_accuracy: 0.9537

Epoch 00007: ReduceLROnPlateau reducing learning rate to 0.0014999999664723873.
Epoch 8/10
263/263 [==============================] - 45s 170ms/step - loss: 0.0445 - accuracy: 0.9857 - val_loss: 0.0694 - val_accuracy: 0.9803
Epoch 9/10
263/263 [==============================] - 45s 171ms/step - loss: 0.0439 - accuracy: 0.9845 - val_loss: 0.0638 - val_accuracy: 0.9813
Epoch 10/10
263/263 [==============================] - 45s 171ms/step - loss: 0.0438 - accuracy: 0.9855 - val_loss: 0.0879 - val_accuracy: 0.9734
```

5.　模型校度分析：取得測試集準確率，test accuracy 為 83.33%，如下圖所示

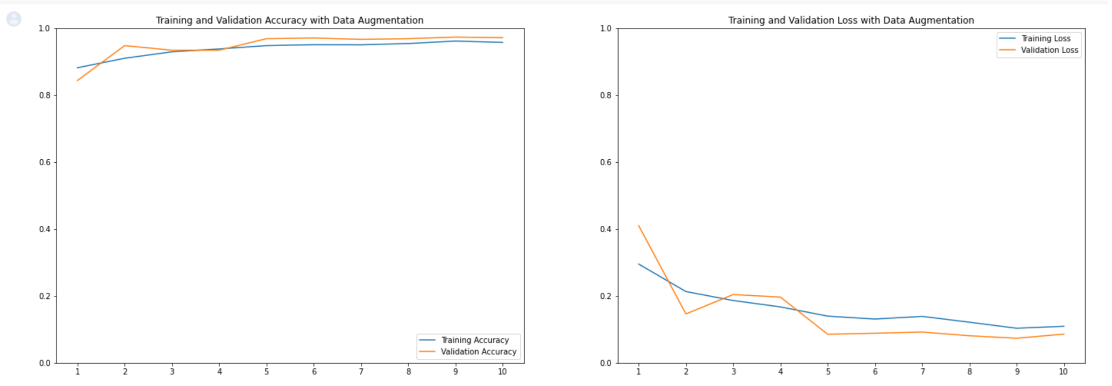


```
[100] # Score trained model.
      loss, acc = model.evaluate(x_test, y_test, verbose=1)
      print('Test loss:', loss)
      print('Test accuracy:', acc)

      20/20 [==============================] - 1s 62ms/step - loss: 0.6334 - accuracy: 0.8333
      Test loss: 0.6333690881729126
      Test accuracy: 0.8333333134651184
```

6.　分別繪製 Loss、Accuracy 與 Epochs 之關係圖

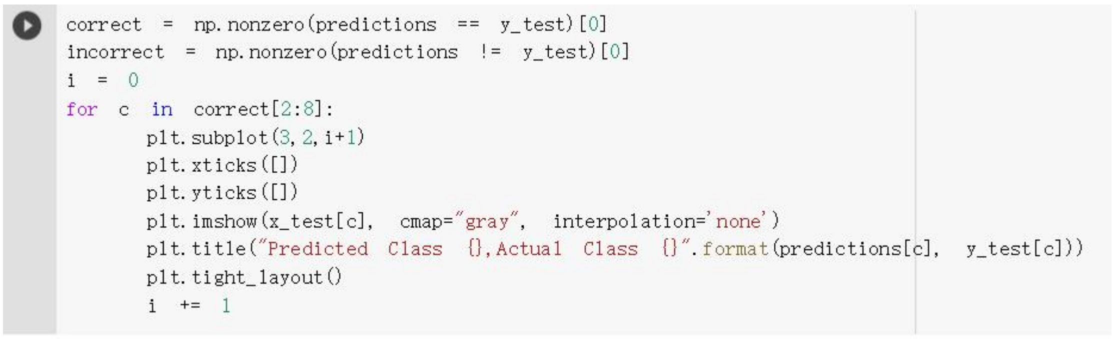


```
acc = history_data_aug.history['accuracy']
val_acc = history_data_aug.history['val_accuracy']

loss = history_data_aug.history['loss']
val_loss = history_data_aug.history['val_loss']

epochs_range = range(1, epochs + 1)
import matplotlib.pyplot as plt
plt.figure(figsize=(16, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.ylim(0, 1)
plt.xticks(epochs_range)
plt.title('Training and Validation Accuracy with Data Augmentation')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.ylim(0, 1)
plt.xticks(epochs_range)
plt.title('Training and Validation Loss with Data Augmentation')
plt.show()
```

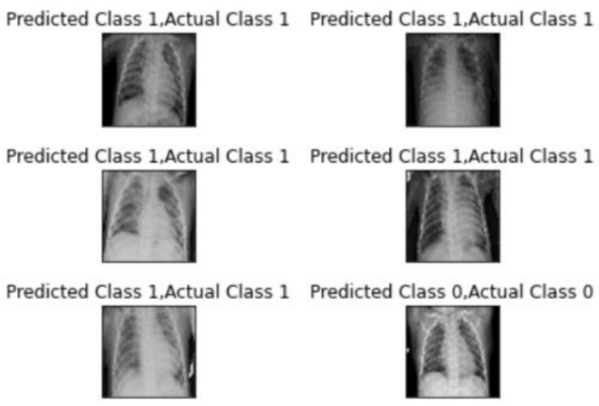


7.　視覺化預測結果與實際結果

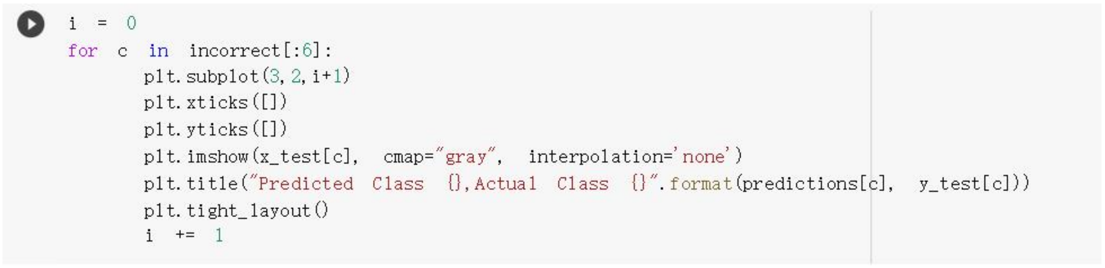
（1）預測結果與實際結果相同



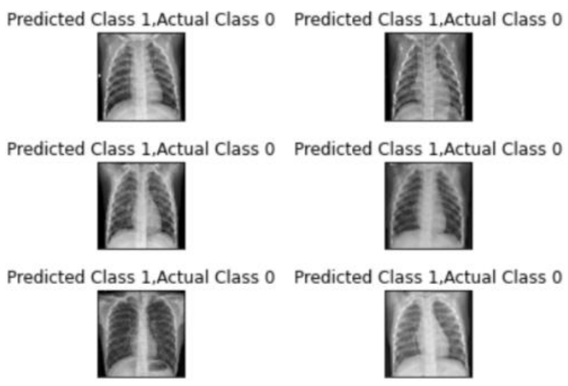
```
correct = np.nonzero(predictions == y_test)[0]
incorrect = np.nonzero(predictions != y_test)[0]
i = 0
for c in correct[2:8]:
        plt.subplot(3,2,i+1)
        plt.xticks([])
        plt.yticks([])
        plt.imshow(x_test[c], cmap="gray", interpolation='none')
        plt.title("Predicted Class {},Actual Class {}".format(predictions[c], y_test[c]))
        plt.tight_layout()
        i += 1
```


Predicted Class 1,Actual Class 1
Predicted Class 1,Actual Class 1
Predicted Class 1,Actual Class 1
Predicted Class 1,Actual Class 1
Predicted Class 1,Actual Class 1
Predicted Class 0,Actual Class 0

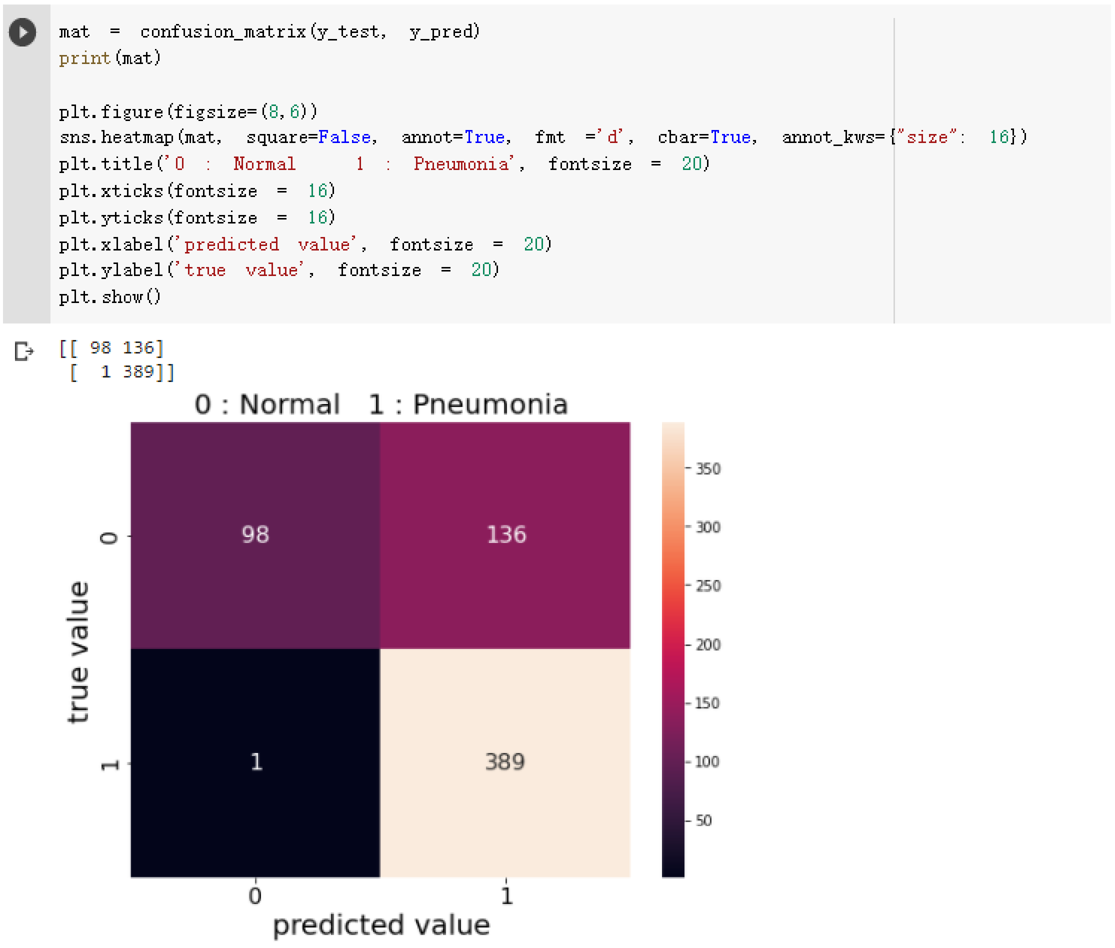
（2）預測結果與實際結果不同



```
i = 0
for c in incorrect[:6]:
        plt.subplot(3,2,i+1)
        plt.xticks([])
        plt.yticks([])
        plt.imshow(x_test[c], cmap="gray", interpolation='none')
        plt.title("Predicted Class {},Actual Class {}".format(predictions[c], y_test[c]))
        plt.tight_layout()
        i += 1
```


Predicted Class 1,Actual Class 0
Predicted Class 1,Actual Class 0
Predicted Class 1,Actual Class 0
Predicted Class 1,Actual Class 0
Predicted Class 1,Actual Class 0
Predicted Class 1,Actual Class 0

8.　混淆矩陣 Confusion Matrix



```
mat = confusion_matrix(y_test, y_pred)
print(mat)

plt.figure(figsize=(8,6))
sns.heatmap(mat, square=False, annot=True, fmt ='d', cbar=True, annot_kws={"size": 16})
plt.title('0 : Normal   1 : Pneumonia', fontsize = 20)
plt.xticks(fontsize = 16)
plt.yticks(fontsize = 16)
plt.xlabel('predicted value', fontsize = 20)
plt.ylabel('true value', fontsize = 20)
plt.show()
```

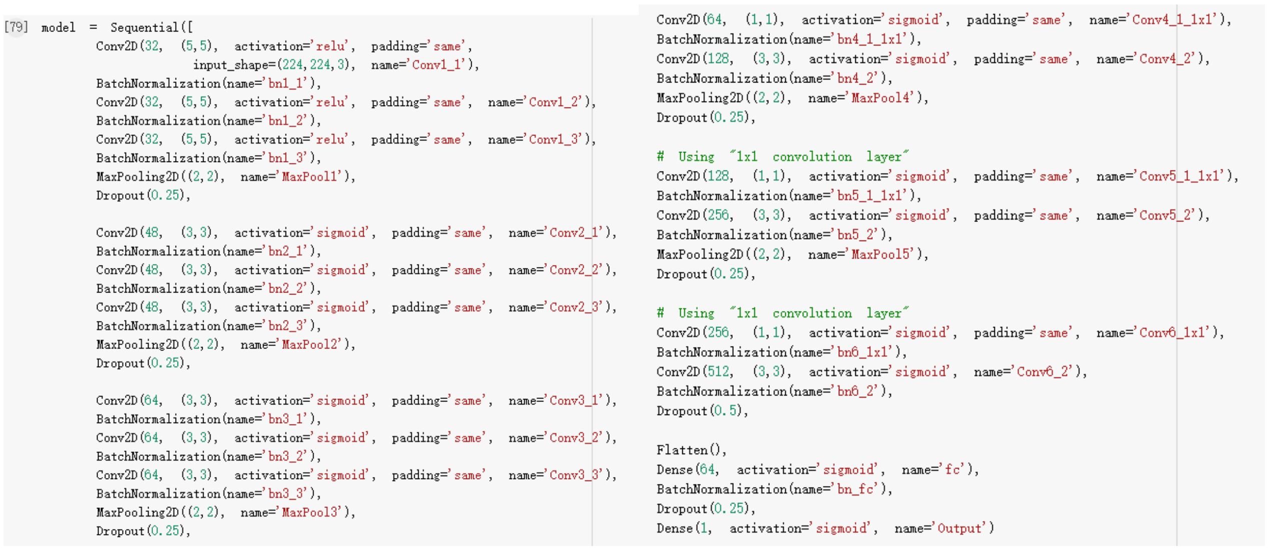
```
[[ 98 136]
 [  1 389]]
```

四、 參數優化

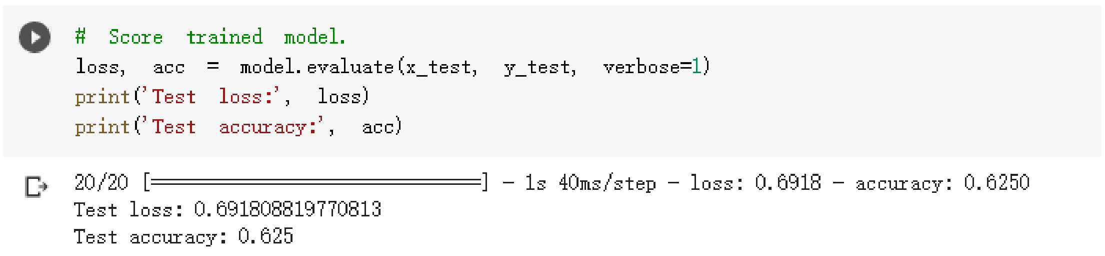
為了增加準確率，本組嘗試調整 Activation、Filters、Learning Rate、Optimizer，並分別採用 test accuracy 較高之參數。

1. 調整 Activation 參數，並分別取得 Sigmoid、Relu、Tanh 之 test accuracy。

   (1) 將 Activation 設為 Sigmoid，並取得 Sigmoid 之 test accuracy 約為 62.5%。



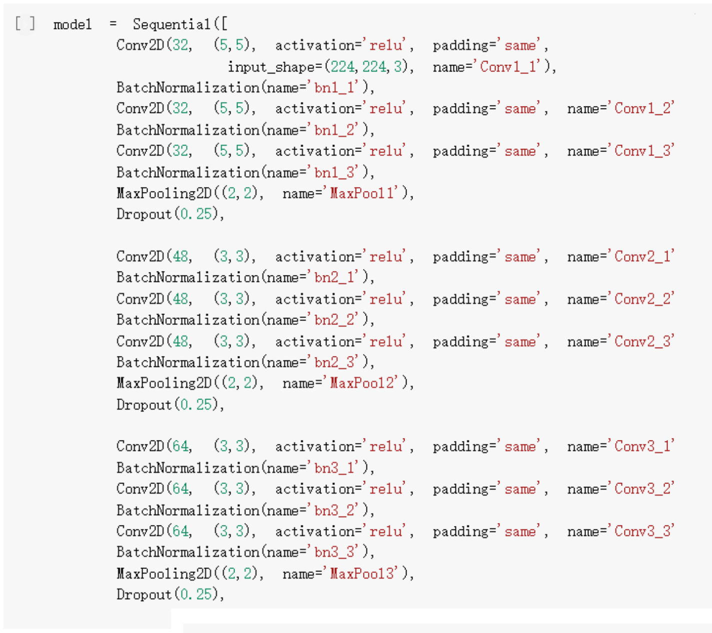
```
[79] model = Sequential([
        Conv2D(32, (5,5), activation='relu', padding='same',
                input_shape=(224,224,3), name='Conv1_1'),
        BatchNormalization(name='bn1_1'),
        Conv2D(32, (5,5), activation='relu', padding='same', name='Conv1_2'),
        BatchNormalization(name='bn1_2'),
        Conv2D(32, (5,5), activation='relu', padding='same', name='Conv1_3'),
        BatchNormalization(name='bn1_3'),
        MaxPooling2D((2,2), name='MaxPool1'),
        Dropout(0.25),

        Conv2D(48, (3,3), activation='sigmoid', padding='same', name='Conv2_1'),
        BatchNormalization(name='bn2_1'),
        Conv2D(48, (3,3), activation='sigmoid', padding='same', name='Conv2_2'),
        BatchNormalization(name='bn2_2'),
        Conv2D(48, (3,3), activation='sigmoid', padding='same', name='Conv2_3'),
        BatchNormalization(name='bn2_3'),
        MaxPooling2D((2,2), name='MaxPool2'),
        Dropout(0.25),

        Conv2D(64, (3,3), activation='sigmoid', padding='same', name='Conv3_1'),
        BatchNormalization(name='bn3_1'),
        Conv2D(64, (3,3), activation='sigmoid', padding='same', name='Conv3_2'),
        BatchNormalization(name='bn3_2'),
        Conv2D(64, (3,3), activation='sigmoid', padding='same', name='Conv3_3'),
        BatchNormalization(name='bn3_3'),
        MaxPooling2D((2,2), name='MaxPool3'),
        Dropout(0.25),
        Conv2D(64, (1,1), activation='sigmoid', padding='same', name='Conv4_1_1x1'),
        BatchNormalization(name='bn4_1_1x1'),
        Conv2D(128, (3,3), activation='sigmoid', padding='same', name='Conv4_2'),
        BatchNormalization(name='bn4_2'),
        MaxPooling2D((2,2), name='MaxPool4'),
        Dropout(0.25),

        # Using "1x1 convolution layer"
        Conv2D(128, (1,1), activation='sigmoid', padding='same', name='Conv5_1_1x1'),
        BatchNormalization(name='bn5_1_1x1'),
        Conv2D(256, (3,3), activation='sigmoid', padding='same', name='Conv5_2'),
        BatchNormalization(name='bn5_2'),
        MaxPooling2D((2,2), name='MaxPool5'),
        Dropout(0.25),

        # Using "1x1 convolution layer"
        Conv2D(256, (1,1), activation='sigmoid', padding='same', name='Conv6_1x1'),
        BatchNormalization(name='bn6_1x1'),
        Conv2D(512, (3,3), activation='sigmoid', name='Conv6_2'),
        BatchNormalization(name='bn6_2'),
        Dropout(0.5),

        Flatten(),
        Dense(64, activation='sigmoid', name='fc'),
        BatchNormalization(name='bn_fc'),
        Dropout(0.25),
        Dense(1, activation='sigmoid', name='Output')
```



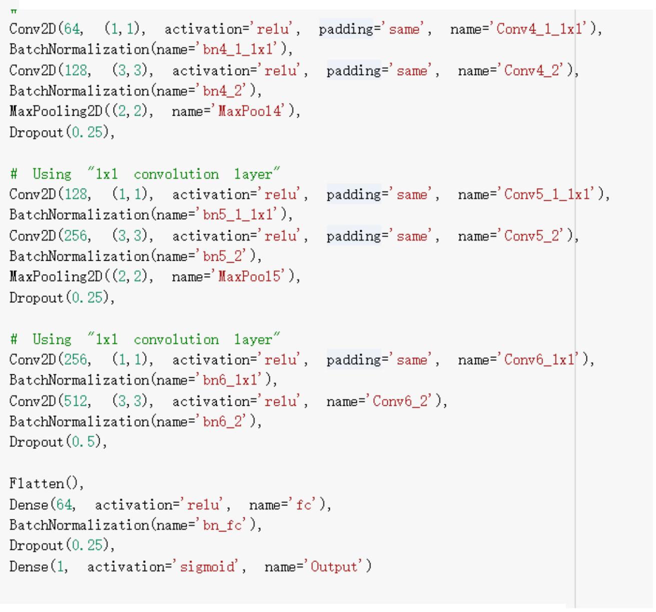
```
# Score trained model.
loss, acc = model.evaluate(x_test, y_test, verbose=1)
print('Test loss:', loss)
print('Test accuracy:', acc)
```

```
20/20 [==============================] - 1s 40ms/step - loss: 0.6918 - accuracy: 0.6250
Test loss: 0.691808819770813
Test accuracy: 0.625
```

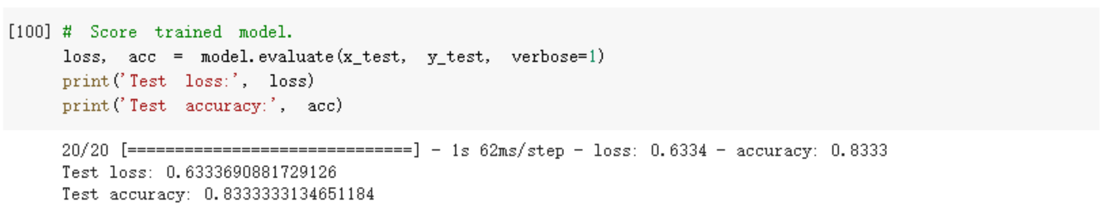
（2）將 Activation 設為 Relu，並取得 Relu 之 test accuracy 約為 83%。



```
[ ]  model = Sequential([
         Conv2D(32, (5,5), activation='relu', padding='same',
                input_shape=(224,224,3), name='Conv1_1'),
         BatchNormalization(name='bn1_1'),
         Conv2D(32, (5,5), activation='relu', padding='same', name='Conv1_2'
         BatchNormalization(name='bn1_2'),
         Conv2D(32, (5,5), activation='relu', padding='same', name='Conv1_3'
         BatchNormalization(name='bn1_3'),
         MaxPooling2D((2,2), name='MaxPool1'),
         Dropout(0.25),

         Conv2D(48, (3,3), activation='relu', padding='same', name='Conv2_1'
         BatchNormalization(name='bn2_1'),
         Conv2D(48, (3,3), activation='relu', padding='same', name='Conv2_2'
         BatchNormalization(name='bn2_2'),
         Conv2D(48, (3,3), activation='relu', padding='same', name='Conv2_3'
         BatchNormalization(name='bn2_3'),
         MaxPooling2D((2,2), name='MaxPool2'),
         Dropout(0.25),

         Conv2D(64, (3,3), activation='relu', padding='same', name='Conv3_1'
         BatchNormalization(name='bn3_1'),
         Conv2D(64, (3,3), activation='relu', padding='same', name='Conv3_2'
         BatchNormalization(name='bn3_2'),
         Conv2D(64, (3,3), activation='relu', padding='same', name='Conv3_3'
         BatchNormalization(name='bn3_3'),
         MaxPooling2D((2,2), name='MaxPool3'),
         Dropout(0.25),
```



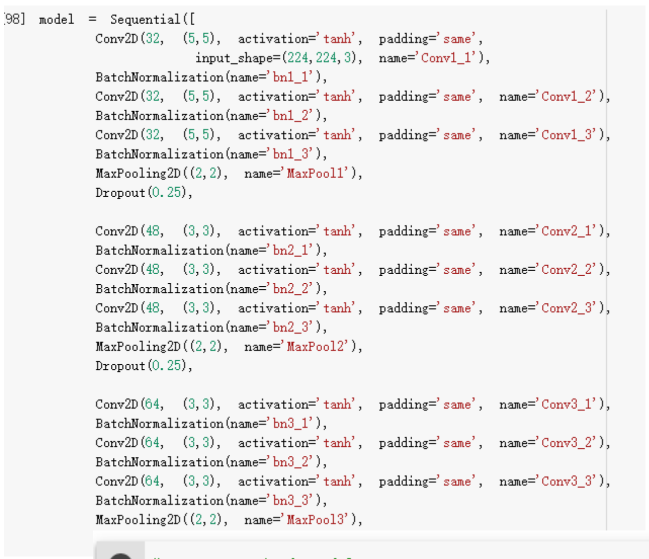
```
"
Conv2D(64, (1,1), activation='relu', padding='same', name='Conv4_1_1x1'),
BatchNormalization(name='bn4_1_1x1'),
Conv2D(128, (3,3), activation='relu', padding='same', name='Conv4_2'),
BatchNormalization(name='bn4_2'),
MaxPooling2D((2,2), name='MaxPool4'),
Dropout(0.25),

# Using "1x1 convolution layer"
Conv2D(128, (1,1), activation='relu', padding='same', name='Conv5_1_1x1'),
BatchNormalization(name='bn5_1_1x1'),
Conv2D(256, (3,3), activation='relu', padding='same', name='Conv5_2'),
BatchNormalization(name='bn5_2'),
MaxPooling2D((2,2), name='MaxPool5'),
Dropout(0.25),

# Using "1x1 convolution layer"
Conv2D(256, (1,1), activation='relu', padding='same', name='Conv6_1x1'),
BatchNormalization(name='bn6_1x1'),
Conv2D(512, (3,3), activation='relu', name='Conv6_2'),
BatchNormalization(name='bn6_2'),
Dropout(0.5),

Flatten(),
Dense(64, activation='relu', name='fc'),
BatchNormalization(name='bn_fc'),
Dropout(0.25),
Dense(1, activation='sigmoid', name='Output')
```



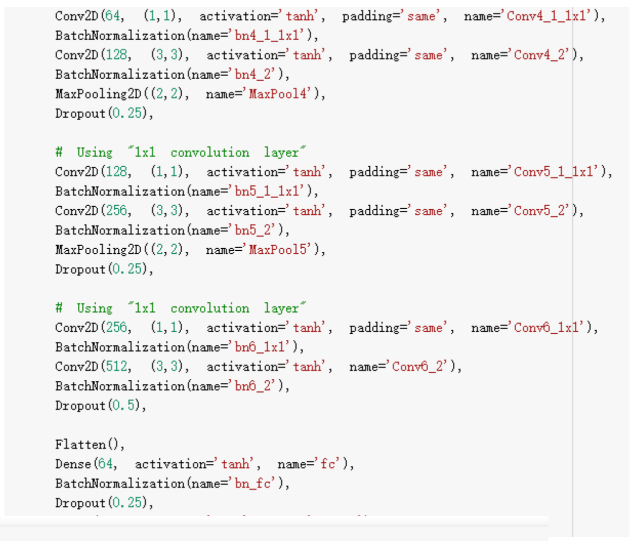
```
[100] # Score trained model.
      loss, acc = model.evaluate(x_test, y_test, verbose=1)
      print('Test loss:', loss)
      print('Test accuracy:', acc)

      20/20 [==============================] - 1s 62ms/step - loss: 0.6334 - accuracy: 0.8333
      Test loss: 0.6333690881729126
      Test accuracy: 0.8333333134651184
```

（3）將 Activation 設為 Tanh，並取得 Tanh 之 test accuracy 約為

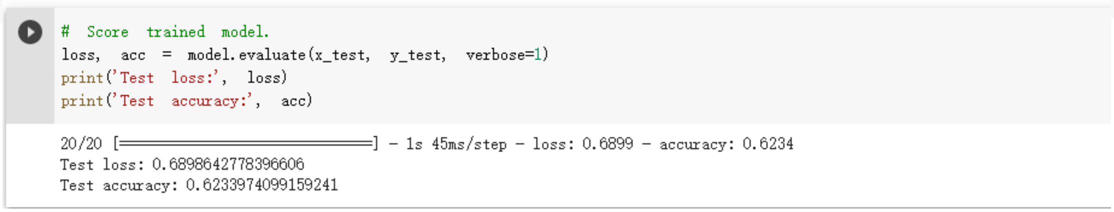
62.4%。



```
98]  model = Sequential([
         Conv2D(32, (5,5), activation='tanh', padding='same',
                input_shape=(224,224,3), name='Conv1_1'),
         BatchNormalization(name='bn1_1'),
         Conv2D(32, (5,5), activation='tanh', padding='same', name='Conv1_2'),
         BatchNormalization(name='bn1_2'),
         Conv2D(32, (5,5), activation='tanh', padding='same', name='Conv1_3'),
         BatchNormalization(name='bn1_3'),
         MaxPooling2D((2,2), name='MaxPool1'),
         Dropout(0.25),

         Conv2D(48, (3,3), activation='tanh', padding='same', name='Conv2_1'),
         BatchNormalization(name='bn2_1'),
         Conv2D(48, (3,3), activation='tanh', padding='same', name='Conv2_2'),
         BatchNormalization(name='bn2_2'),
         Conv2D(48, (3,3), activation='tanh', padding='same', name='Conv2_3'),
         BatchNormalization(name='bn2_3'),
         MaxPooling2D((2,2), name='MaxPool2'),
         Dropout(0.25),

         Conv2D(64, (3,3), activation='tanh', padding='same', name='Conv3_1'),
         BatchNormalization(name='bn3_1'),
         Conv2D(64, (3,3), activation='tanh', padding='same', name='Conv3_2'),
         BatchNormalization(name='bn3_2'),
         Conv2D(64, (3,3), activation='tanh', padding='same', name='Conv3_3'),
         BatchNormalization(name='bn3_3'),
         MaxPooling2D((2,2), name='MaxPool3'),
```



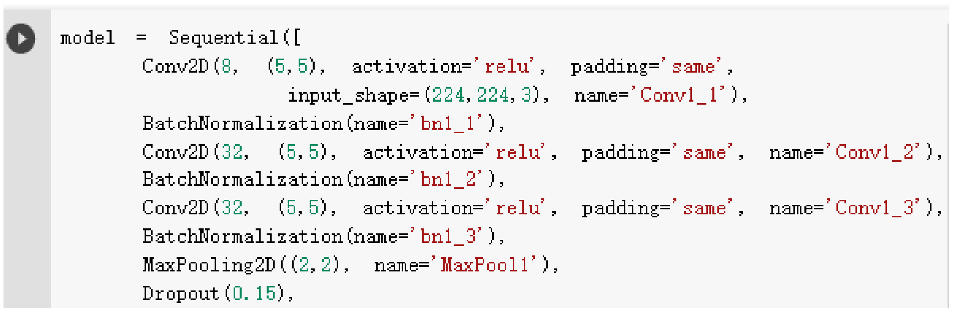
```
Conv2D(64, (1,1), activation='tanh', padding='same', name='Conv4_1_1x1'),
BatchNormalization(name='bn4_1_1x1'),
Conv2D(128, (3,3), activation='tanh', padding='same', name='Conv4_2'),
BatchNormalization(name='bn4_2'),
MaxPooling2D((2,2), name='MaxPool4'),
Dropout(0.25),

# Using "1x1 convolution layer"
Conv2D(128, (1,1), activation='tanh', padding='same', name='Conv5_1_1x1'),
BatchNormalization(name='bn5_1_1x1'),
Conv2D(256, (3,3), activation='tanh', padding='same', name='Conv5_2'),
BatchNormalization(name='bn5_2'),
MaxPooling2D((2,2), name='MaxPool5'),
Dropout(0.25),

# Using "1x1 convolution layer"
Conv2D(256, (1,1), activation='tanh', padding='same', name='Conv6_1x1'),
BatchNormalization(name='bn6_1x1'),
Conv2D(512, (3,3), activation='tanh', name='Conv6_2'),
BatchNormalization(name='bn6_2'),
Dropout(0.5),

Flatten(),
Dense(64, activation='tanh', name='fc'),
BatchNormalization(name='bn_fc'),
Dropout(0.25),
```



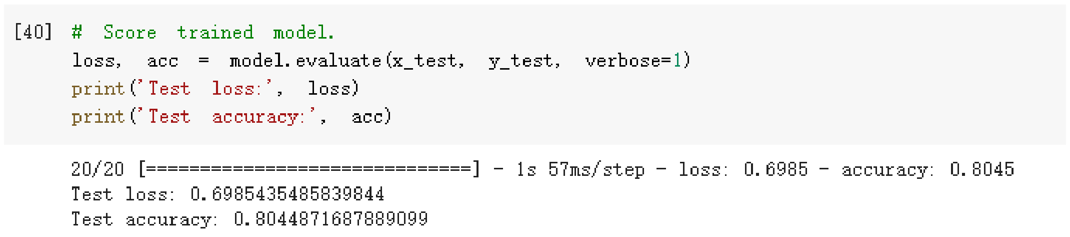
```
# Score trained model.
loss, acc = model.evaluate(x_test, y_test, verbose=1)
print('Test loss:', loss)
print('Test accuracy:', acc)

20/20 [==============================] - 1s 45ms/step - loss: 0.6899 - accuracy: 0.6234
Test loss: 0.6898642778396606
Test accuracy: 0.6233974099159241
```

2. 調整 Filters 參數，並分別取得各 Filters 之 test accuracy。

(1) 將 Filters 設為 8，並取得其 test accuracy 約為 80.4%。

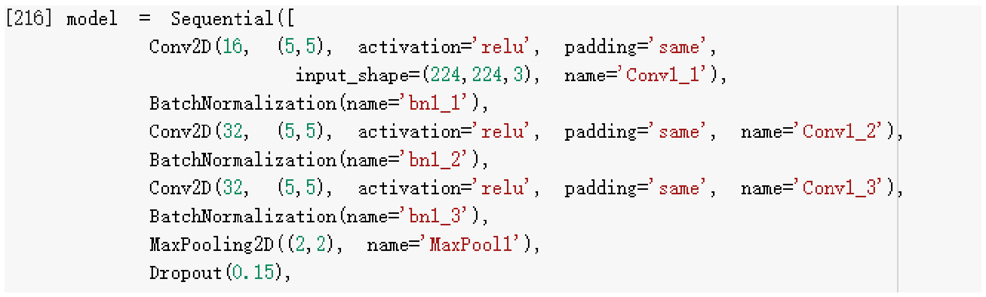


```
model = Sequential([
    Conv2D(8, (5,5), activation='relu', padding='same',
            input_shape=(224,224,3), name='Conv1_1'),
    BatchNormalization(name='bn1_1'),
    Conv2D(32, (5,5), activation='relu', padding='same', name='Conv1_2'),
    BatchNormalization(name='bn1_2'),
    Conv2D(32, (5,5), activation='relu', padding='same', name='Conv1_3'),
    BatchNormalization(name='bn1_3'),
    MaxPooling2D((2,2), name='MaxPool1'),
    Dropout(0.15),
```

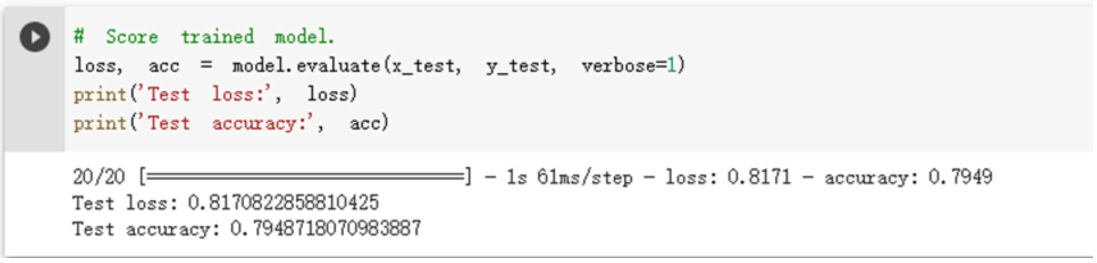


```
[40] # Score trained model.
     loss, acc = model.evaluate(x_test, y_test, verbose=1)
     print('Test loss:', loss)
     print('Test accuracy:', acc)

     20/20 [==============================] - 1s 57ms/step - loss: 0.6985 - accuracy: 0.8045
     Test loss: 0.6985435485839844
     Test accuracy: 0.8044871687889099
```

(2) 將 Filters 設為 16，並取得其 test accuracy 約為 76%。

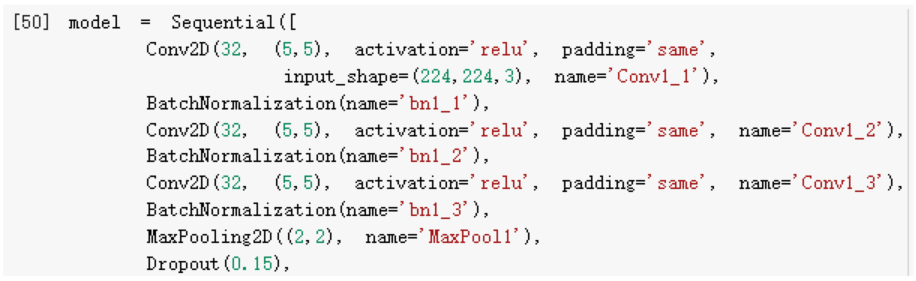


```
[216] model = Sequential([
          Conv2D(16, (5,5), activation='relu', padding='same',
                  input_shape=(224,224,3), name='Conv1_1'),
          BatchNormalization(name='bn1_1'),
          Conv2D(32, (5,5), activation='relu', padding='same', name='Conv1_2'),
          BatchNormalization(name='bn1_2'),
          Conv2D(32, (5,5), activation='relu', padding='same', name='Conv1_3'),
          BatchNormalization(name='bn1_3'),
          MaxPooling2D((2,2), name='MaxPool1'),
          Dropout(0.15),
```

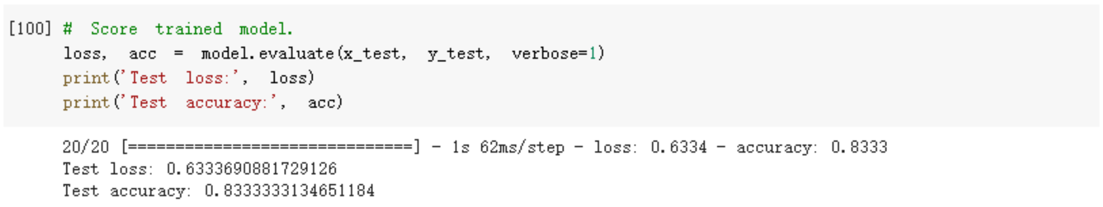


```
# Score trained model.
loss, acc = model.evaluate(x_test, y_test, verbose=1)
print('Test loss:', loss)
print('Test accuracy:', acc)

20/20 [==============================] - 1s 61ms/step - loss: 0.8171 - accuracy: 0.7949
Test loss: 0.8170822858810425
Test accuracy: 0.7948718070983887
```

（3）將 Filters 設為 32，並取得其 test accuracy 約為 83.3%。

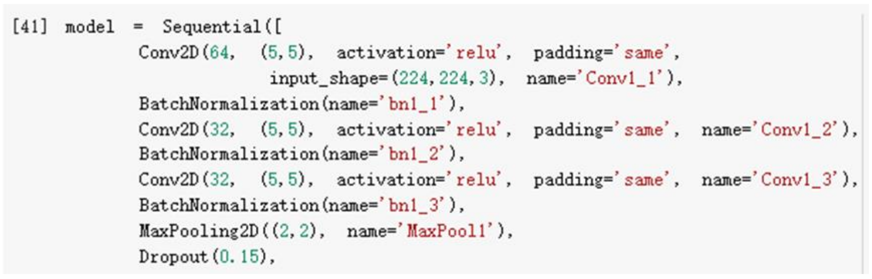


```
[50] model = Sequential([
            Conv2D(32, (5,5), activation='relu', padding='same',
                        input_shape=(224,224,3), name='Conv1_1'),
            BatchNormalization(name='bn1_1'),
            Conv2D(32, (5,5), activation='relu', padding='same', name='Conv1_2'),
            BatchNormalization(name='bn1_2'),
            Conv2D(32, (5,5), activation='relu', padding='same', name='Conv1_3'),
            BatchNormalization(name='bn1_3'),
            MaxPooling2D((2,2), name='MaxPool1'),
            Dropout(0.15),
```

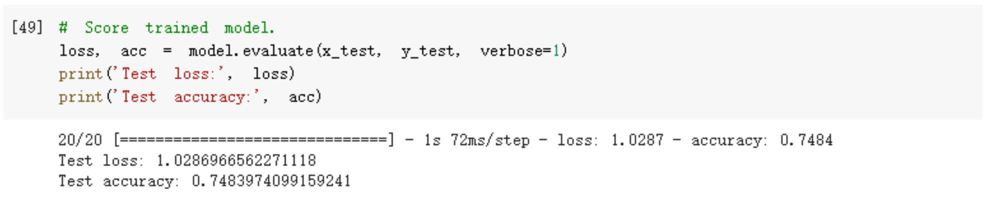


```
[100] # Score trained model.
      loss, acc = model.evaluate(x_test, y_test, verbose=1)
      print('Test loss:', loss)
      print('Test accuracy:', acc)

      20/20 [==============================] - 1s 62ms/step - loss: 0.6334 - accuracy: 0.8333
      Test loss: 0.6333690881729126
      Test accuracy: 0.8333333134651184
```

（4)將 Filters 設為 64，並取得其 test accuracy 約為 74.8%。



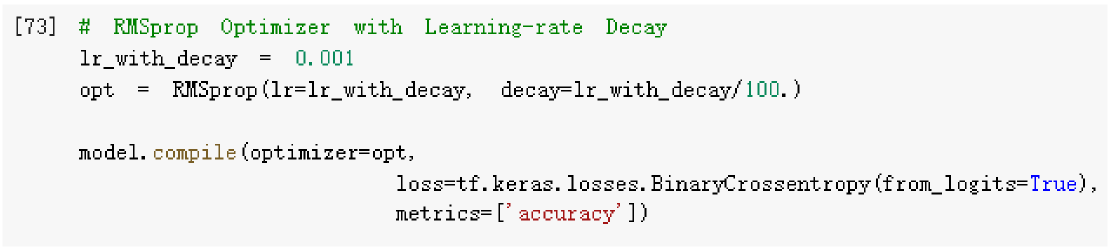
```
[41] model = Sequential([
            Conv2D(64, (5,5), activation='relu', padding='same',
                        input_shape=(224,224,3), name='Conv1_1'),
            BatchNormalization(name='bn1_1'),
            Conv2D(32, (5,5), activation='relu', padding='same', name='Conv1_2'),
            BatchNormalization(name='bn1_2'),
            Conv2D(32, (5,5), activation='relu', padding='same', name='Conv1_3'),
            BatchNormalization(name='bn1_3'),
            MaxPooling2D((2,2), name='MaxPool1'),
            Dropout(0.15),
```



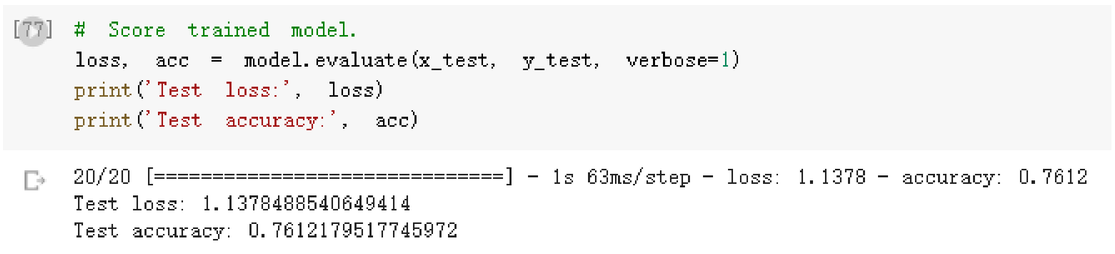
```
[49] # Score trained model.
     loss, acc = model.evaluate(x_test, y_test, verbose=1)
     print('Test loss:', loss)
     print('Test accuracy:', acc)

     20/20 [==============================] - 1s 72ms/step - loss: 1.0287 - accuracy: 0.7484
     Test loss: 1.0286966562271118
     Test accuracy: 0.7483974099159241
```

3. 調整 Learning Rate 參數，並分別取得各 Learning Rate 之 test accuracy。

（1）將 Learning Rate 設為 0.001%，並取得其 test accuracy 約為 80%。

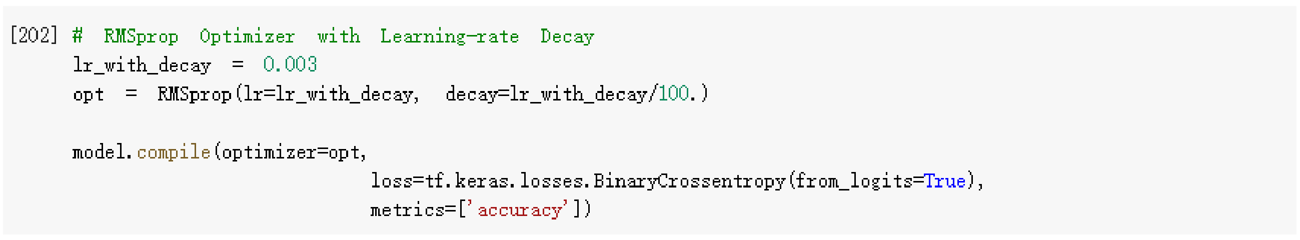


```
[73] # RMSprop Optimizer with Learning-rate Decay
     lr_with_decay = 0.001
     opt = RMSprop(lr=lr_with_decay, decay=lr_with_decay/100.)

     model.compile(optimizer=opt,
                           loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
                           metrics=['accuracy'])
```

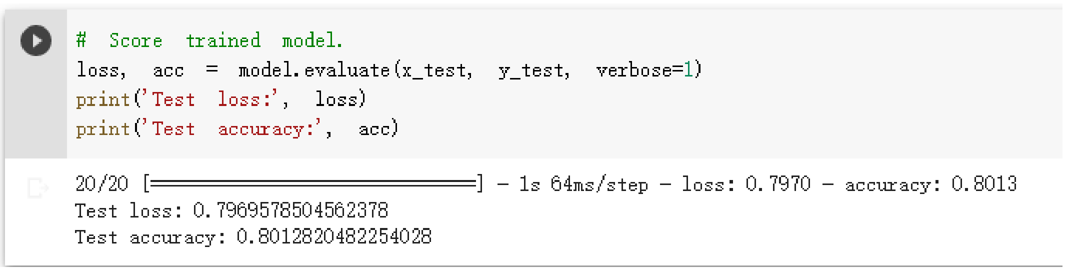


```
[77] # Score trained model.
     loss, acc = model.evaluate(x_test, y_test, verbose=1)
     print('Test loss:', loss)
     print('Test accuracy:', acc)

     20/20 [==============================] - 1s 63ms/step - loss: 1.1378 - accuracy: 0.7612
     Test loss: 1.1378488540649414
     Test accuracy: 0.7612179517745972
```

（2）將 Learning Rate 設為 0.003%，並取得其 test accuracy 約為 80%。

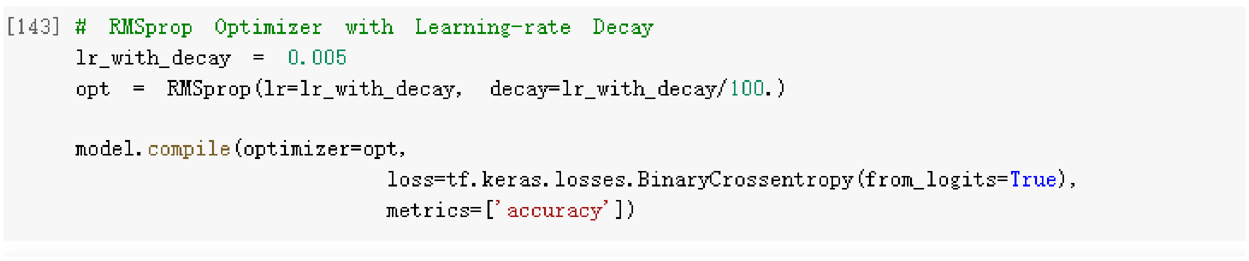


```
[202] # RMSprop Optimizer with Learning-rate Decay
      lr_with_decay = 0.003
      opt = RMSprop(lr=lr_with_decay, decay=lr_with_decay/100.)

      model.compile(optimizer=opt,
                    loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
                    metrics=['accuracy'])
```

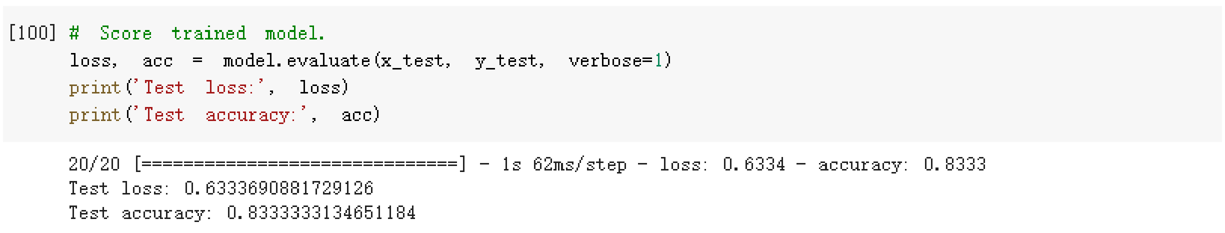


```
# Score trained model.
loss, acc = model.evaluate(x_test, y_test, verbose=1)
print('Test loss:', loss)
print('Test accuracy:', acc)

20/20 [==============================] - 1s 64ms/step - loss: 0.7970 - accuracy: 0.8013
Test loss: 0.7969578504562378
Test accuracy: 0.8012820482254028
```

（3）將 Learning Rate 設為 0.005%，並取得其 test accuracy 約為 83.3%。

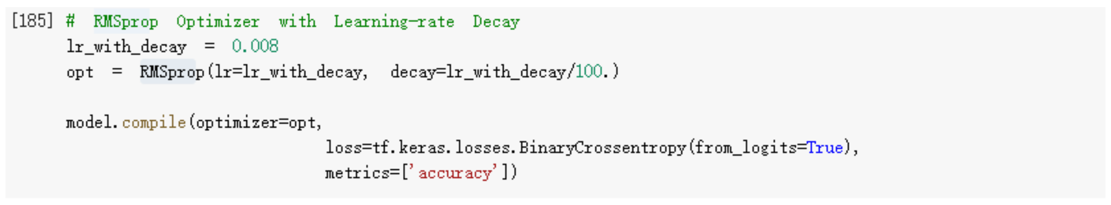


```
[143] # RMSprop Optimizer with Learning-rate Decay
      lr_with_decay = 0.005
      opt = RMSprop(lr=lr_with_decay, decay=lr_with_decay/100.)

      model.compile(optimizer=opt,
                    loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
                    metrics=['accuracy'])
```

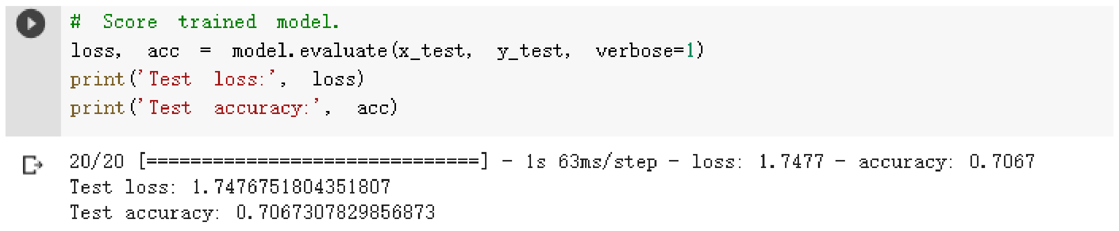


```
[100] # Score trained model.
      loss, acc = model.evaluate(x_test, y_test, verbose=1)
      print('Test loss:', loss)
      print('Test accuracy:', acc)

      20/20 [==============================] - 1s 62ms/step - loss: 0.6334 - accuracy: 0.8333
      Test loss: 0.6333690881729126
      Test accuracy: 0.8333333134651184
```

（4）將 Learning Rate 設為 0.008%，並取得其 test accuracy 約為 75%。



```
[185] # RMSprop Optimizer with Learning-rate Decay
      lr_with_decay = 0.008
      opt = RMSprop(lr=lr_with_decay, decay=lr_with_decay/100.)

      model.compile(optimizer=opt,
                    loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
                    metrics=['accuracy'])
```

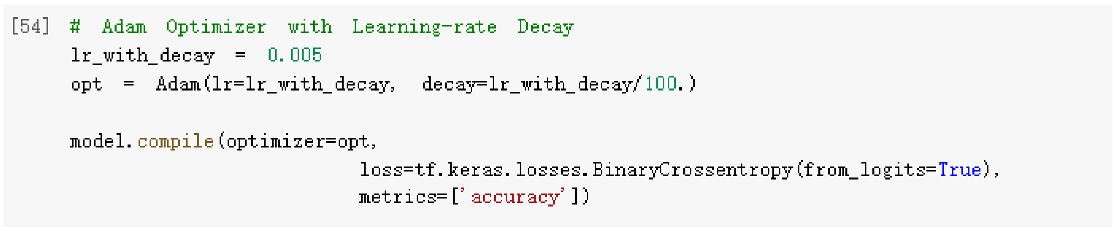


```
# Score trained model.
loss, acc = model.evaluate(x_test, y_test, verbose=1)
print('Test loss:', loss)
print('Test accuracy:', acc)
```

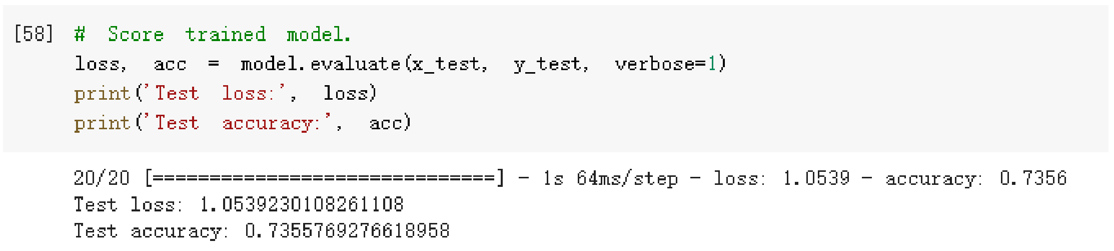
```
20/20 [==============================] - 1s 63ms/step - loss: 1.7477 - accuracy: 0.7067
Test loss: 1.7476751804351807
Test accuracy: 0.7067307829856873
```

4. 調整 Optimizer 參數，並分別取得各 Optimizer 之 test accuracy。

（1）將 Optimizer 設為 Adam，並取得其 test accuracy 約為 73.5%

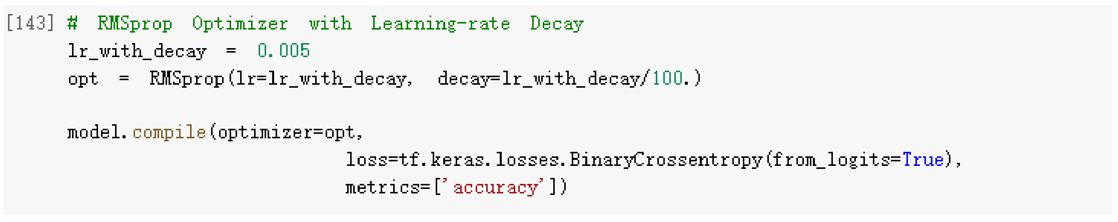


```
[54] # Adam Optimizer with Learning-rate Decay
     lr_with_decay = 0.005
     opt = Adam(lr=lr_with_decay, decay=lr_with_decay/100.)

     model.compile(optimizer=opt,
                   loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
                   metrics=['accuracy'])
```

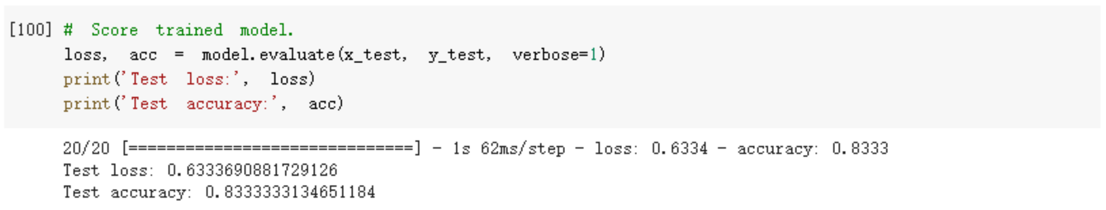


```
[58] # Score trained model.
     loss, acc = model.evaluate(x_test, y_test, verbose=1)
     print('Test loss:', loss)
     print('Test accuracy:', acc)

     20/20 [==============================] - 1s 64ms/step - loss: 1.0539 - accuracy: 0.7356
     Test loss: 1.0539230108261108
     Test accuracy: 0.7355769276618958
```

（2）將 Optimizer 設為 RMSprop，並取得其 test accuracy 約為 83.3%

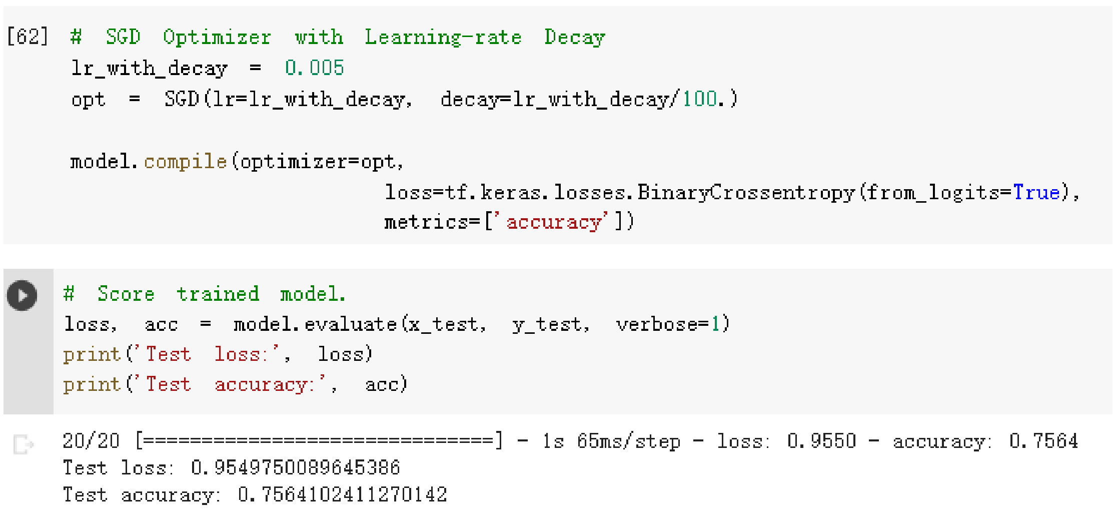


```
[143] # RMSprop Optimizer with Learning-rate Decay
      lr_with_decay = 0.005
      opt = RMSprop(lr=lr_with_decay, decay=lr_with_decay/100.)

      model.compile(optimizer=opt,
                    loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
                    metrics=['accuracy'])
```



```
[100] # Score trained model.
      loss, acc = model.evaluate(x_test, y_test, verbose=1)
      print('Test loss:', loss)
      print('Test accuracy:', acc)

      20/20 [==============================] - 1s 62ms/step - loss: 0.6334 - accuracy: 0.8333
      Test loss: 0.6333690881729126
      Test accuracy: 0.8333333134651184
```

（3）將 Optimizer 設為 SGD，並取得其 test accuracy 約為 75.6%



```
[62] #  SGD  Optimizer  with  Learning-rate  Decay
     lr_with_decay  =  0.005
     opt  =  SGD(lr=lr_with_decay,  decay=lr_with_decay/100.)

     model.compile(optimizer=opt,
                               loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
                               metrics=['accuracy'])
```

```
#  Score  trained  model.
loss,  acc  =  model.evaluate(x_test,  y_test,  verbose=1)
print('Test  loss:',  loss)
print('Test  accuracy:',  acc)
```

```
20/20 [==============================] - 1s 65ms/step - loss: 0.9550 - accuracy: 0.7564
Test loss: 0.9549750089645386
Test accuracy: 0.7564102411270142
```

本組將各參數調整彙整為下表，由下表可知，Activation 若採用 Relu 其 test accuracy 較高，Filters 若採用 32 其 test accuracy 較高，Learning Rate 若採用 0.005 其 test accuracy 較高；Optimizer 若採用 RMSprop 其 test accuracy 較高，因此本組將採用以上 test accuracy 較高之參數。

Activation		Filters		Learning Rate		Optimizer	
參數	Test accuracy	參數	Test accuracy	參數	Test accuracy	參數	Test accuracy
Sigmoid	62.5%	8	80.4%	0.001	64%	Adam	73.5%
Relu	83.3%	16	76%	0.003	80%	RMSprop	83.3%
Tanh	62.4%	32	83.3%	0.005	83.3%	SGD	75.6%
		64	74.8%	0.008	75%		

五、結論與未來展望

1. 結論

本研究透過 CNN 建構透過胸腔 X-光片影像進行肺炎偵測之技術，節省人工辨識所浪費之時間以及降低人工因疲勞辨識的錯誤率，本研究透過多次超參數的調整可使準確率的提升，透過混淆矩陣所得知的結果可知，未得病之病患 X 光片被判讀成有肺炎之案例較多，因以此方向進行改善，避免病患恐慌。且因兩種 X 光片的照片張數較少且不平均，而這樣會導致病徵模型學習的次數較少，導致分類預測不準確。除此之外，這次訓練模型的過程，每次修改只能變動一個指標，因此沒辦法將所有可能優化模型的狀況皆跑過一 次，因此這次所得到的結論只是根據所有試過的模型當中，所推得的結果，並不是所有可能組合當中最好的結果。

2. 未來展望：

目前的研究結果準確率仍無法達到 0.9 的高準確度，因此可以藉由下面的幾種方式繼續優化此模型，來加強 CNN 模型準確率，甚至提高訓練效率。

(1) 增加圖片張數較少的 X 光片數量，讓兩種分類結果都有被完整訓練。

(2) 因資料集有限，因此我們可透過 DCGAN，DCGAN 主要是利用反卷積網路(Deconvolution network)反覆生成圖像，再將生成圖像放入 GAN 模型中執行，不斷訓練，最後產出多個圖像以增加資料集。

參考文獻：

https://docs.scipy.org/doc/numpy/reference/generated/numpy.dstack.html

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https://www.kaggle.com/calexhu/data-preprocessing-for-pneumonia-detection

https://www.kaggle.com/madz2000/pneumonia-detection-using-cnn-92-6-accuracy