自然圖像辨識

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探討CNN圖像辨識的深淺層數差異

製作動機

使用工具

- 模型架構採用 CNN
- 使用 Google Colab 實作
- 資料集來自 Kaggle

實作目錄

模型建立

```
[ ]
model = Sequential()

model.add(Conv2D(64, (3, 3), padding='same',input_shape=x_train.shape[1:]))
model.add(Activation('relu'))
model.add(BatchNormalization())

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model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(BatchNormalization())
model.add(Dropout(0.35))

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model.add(Conv2D(64, (3, 3), padding='same'))
model.add(Activation('relu'))
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model.add(Flatten())
model.add(Dropout(0.5))
model.add(Dense(512))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Dense(8))
model.add(Activation('softmax'))

model.summary()
```

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```

```
[ ]  model.compile(
         loss='categorical_crossentropy',
         optimizer='adam',
         metrics=['accuracy'])
```

訓練模型

```
[ ]  1 EPOCHS=25
     2 history = model.fit(x_train, y_train, epochs=EPOCHS, validation_split=0.2)
     3 model.save(drive_path + "5model_" + str(EPOCHS) + ".h5")
```

```
[ ]  1 EPOCHS=100
     2 history = model.fit(x_train, y_train, epochs=EPOCHS, validation_split=0.2)
     3 model.save(drive_path + "5model_" + str(EPOCHS) + ".h5")
```

```
[ ]  1 EPOCHS=25
     2 history = model.fit(x_train, y_train, epochs=EPOCHS, validation_split=0.2)
     3 model.save(drive_path + "9model_" + str(EPOCHS) + ".h5")
```

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     1 EPOCHS=100
     2 history = model.fit(x_train, y_train, epochs=EPOCHS, validation_split=0.2)
     3 model.save(drive_path + "9model_" + str(EPOCHS) + ".h5")
Epoch 7/100
```
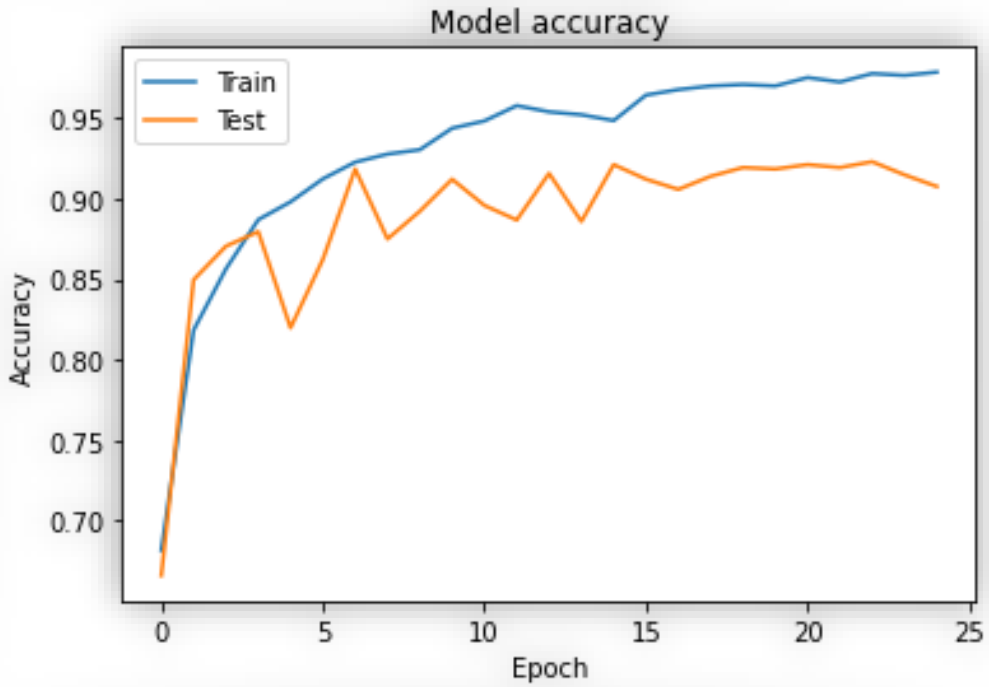
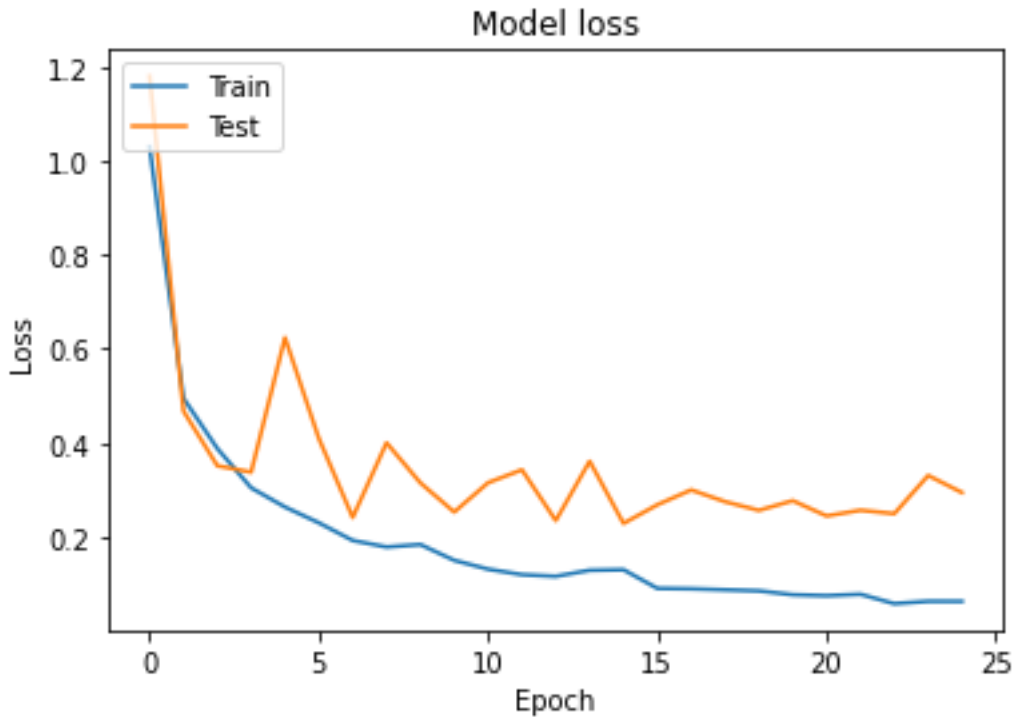

訓練曲線

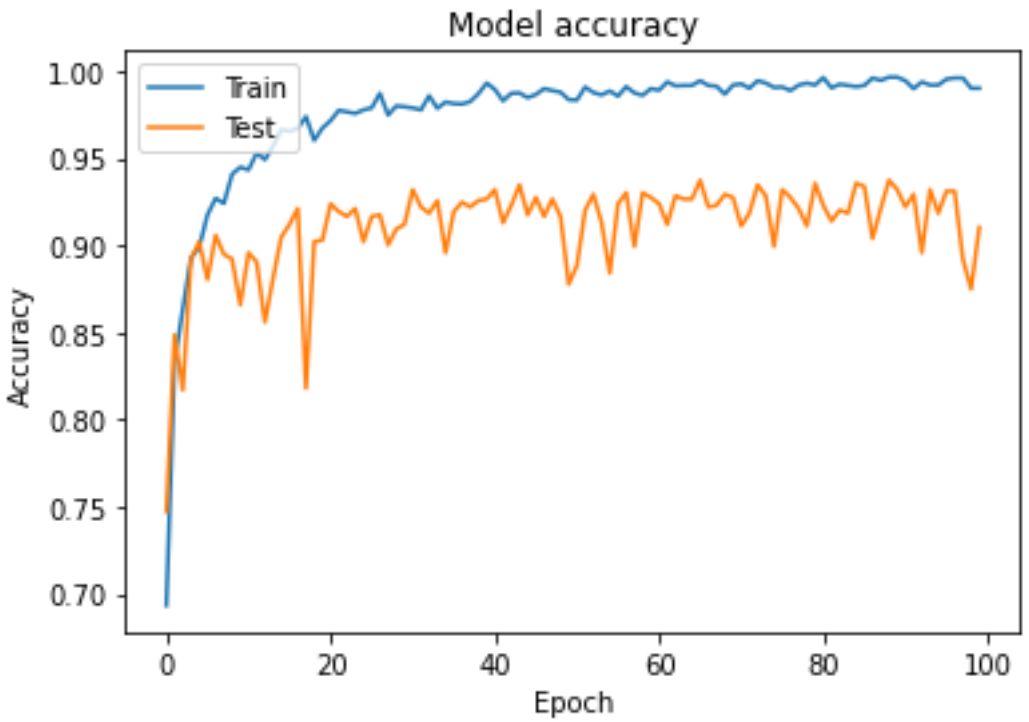
```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model  accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train',  'Test'],  loc='upper  left')
plt.show()

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model  loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train',  'Test'],  loc='upper  left')
plt.show()
```

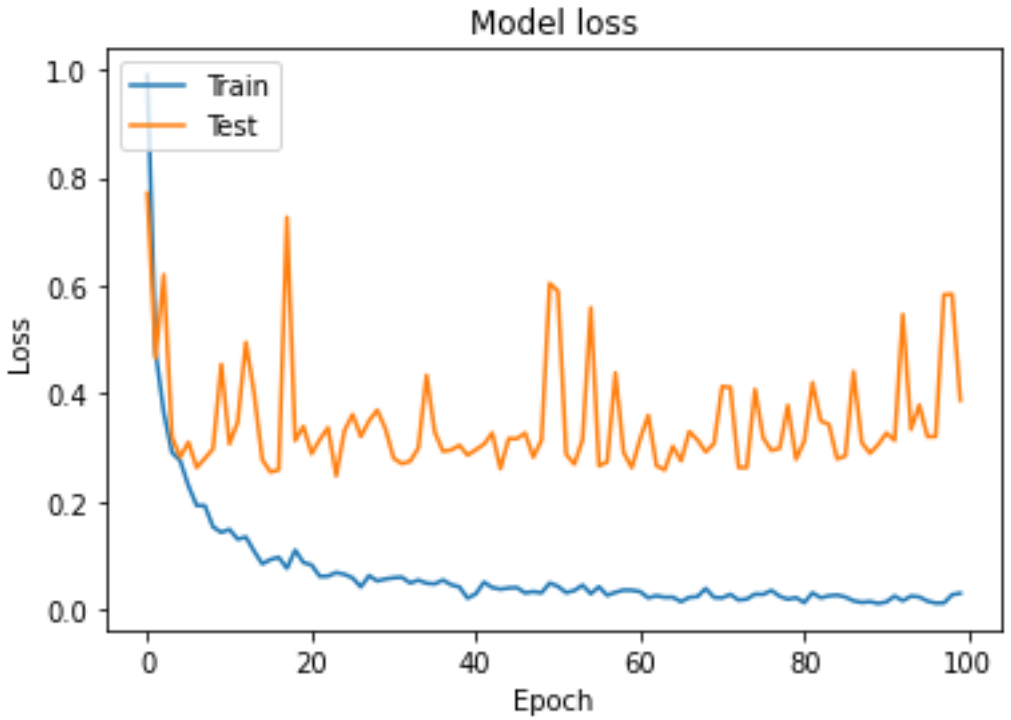
訓練曲線（5層CNN網路 訓練25圈）



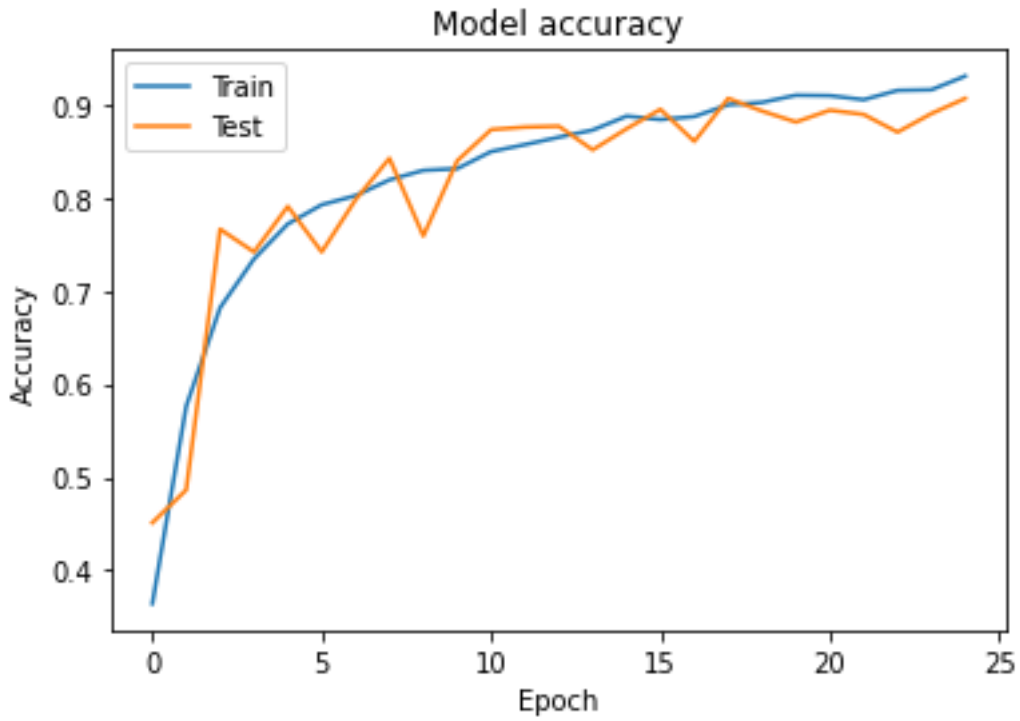


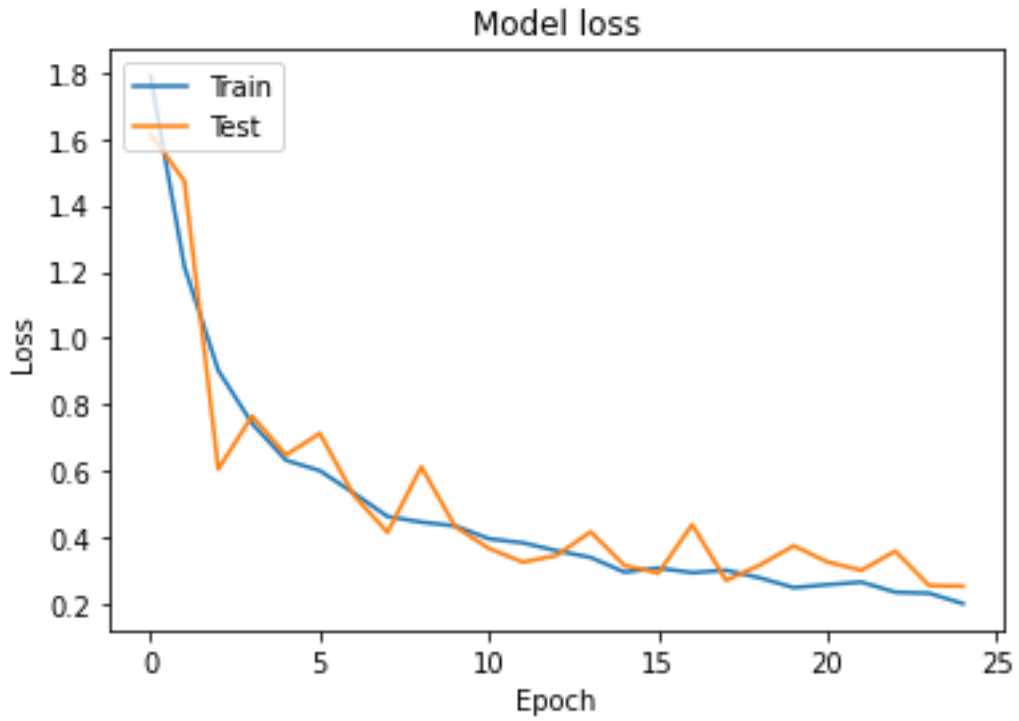
訓練曲線（5層CNN網路 訓練100圈）



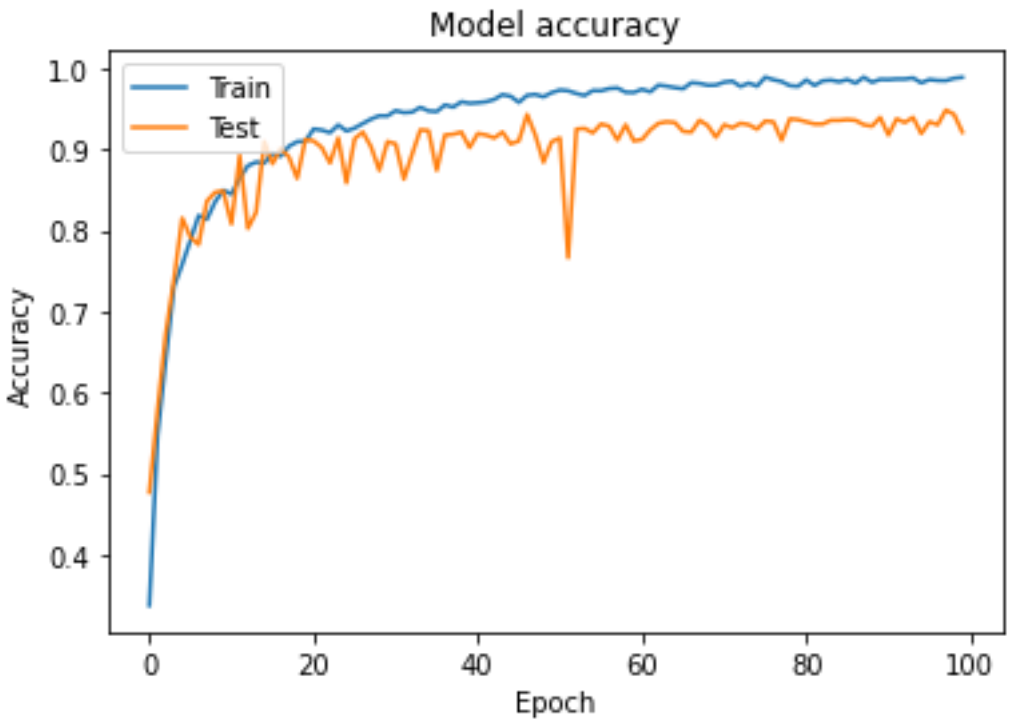


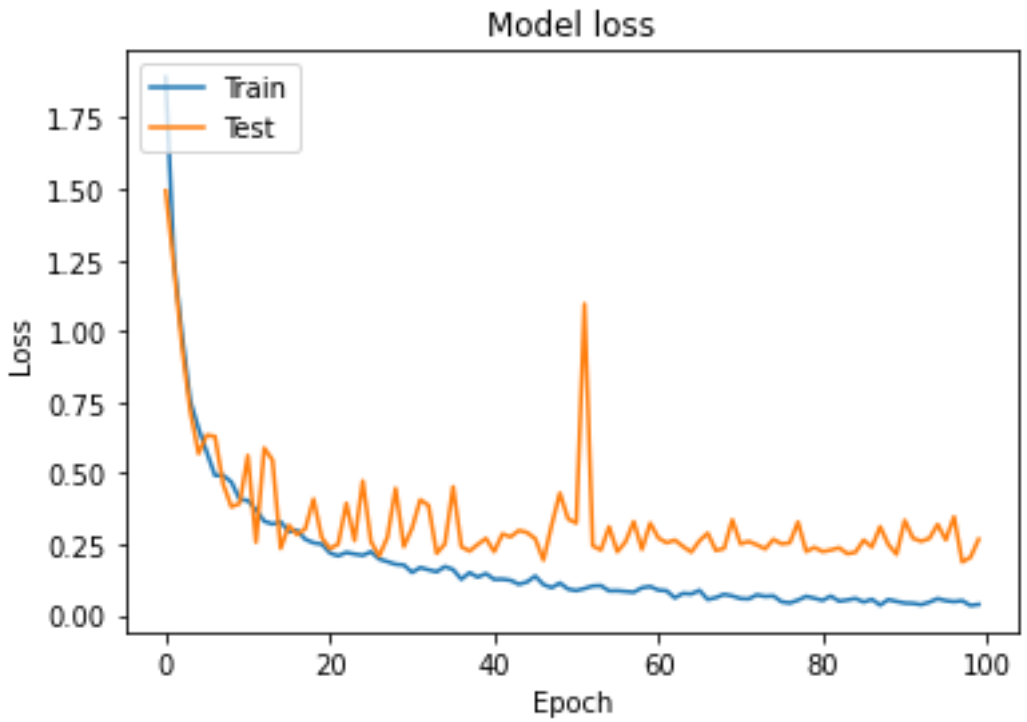
訓練曲線（9層CNN網路 訓練25圈）





訓練曲線（9層CNN網路 訓練100圈）





準確率與損失率

```
1 print("train")
2 train_loss_acc  =  model.evaluate(x_train,  y_train)
3 print("test")
4 test_loss_acc  =  model.evaluate(x_test,  y_test)
```

```
train
173/173 [==============================] - 2s 9ms/step - loss: 0.0860 - accuracy: 0.9714
test
44/44 [==============================] - 0s 10ms/step - loss: 0.3227 - accuracy: 0.8993
```

5層CNN網路 訓練25圈

```
train
173/173 [==============================] - 2s 12ms/step - loss: 0.1068 - accuracy: 0.9735
test
44/44 [==============================] - 1s 14ms/step - loss: 0.3456 - accuracy: 0.9188
```

5層CNN網路 訓練100圈

```
train
173/173 [==============================] - 2s 10ms/step - loss: 0.1319 - accuracy: 0.9514
test
44/44 [==============================] - 1s 12ms/step - loss: 0.2157 - accuracy: 0.9174
```

9層CNN網路 訓練25圈

```
train
173/173 [==============================] - 3s 15ms/step - loss: 0.0703 - accuracy: 0.9779
test
44/44 [==============================] - 1s 19ms/step - loss: 0.2819 - accuracy: 0.9268
```

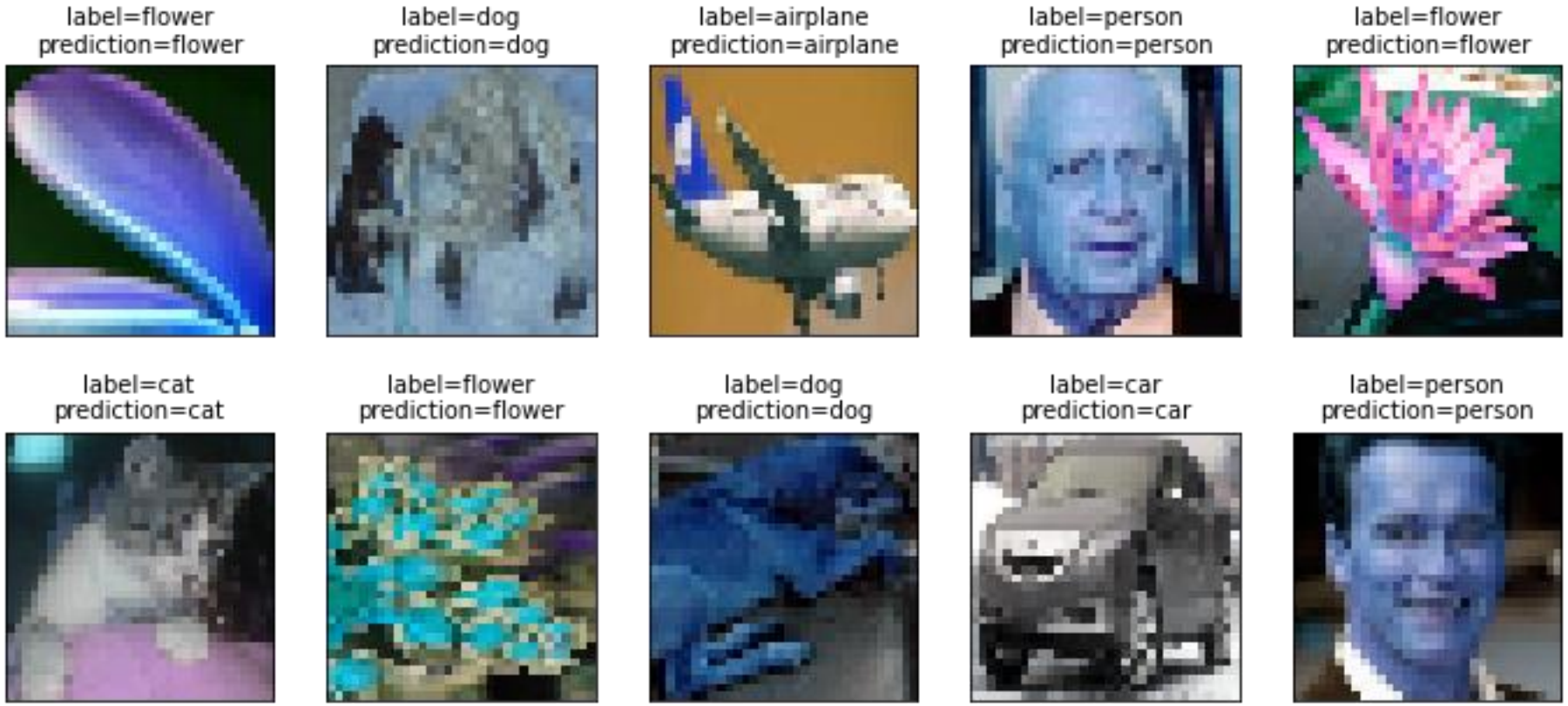
9層CNN網路 訓練100圈

預測結果

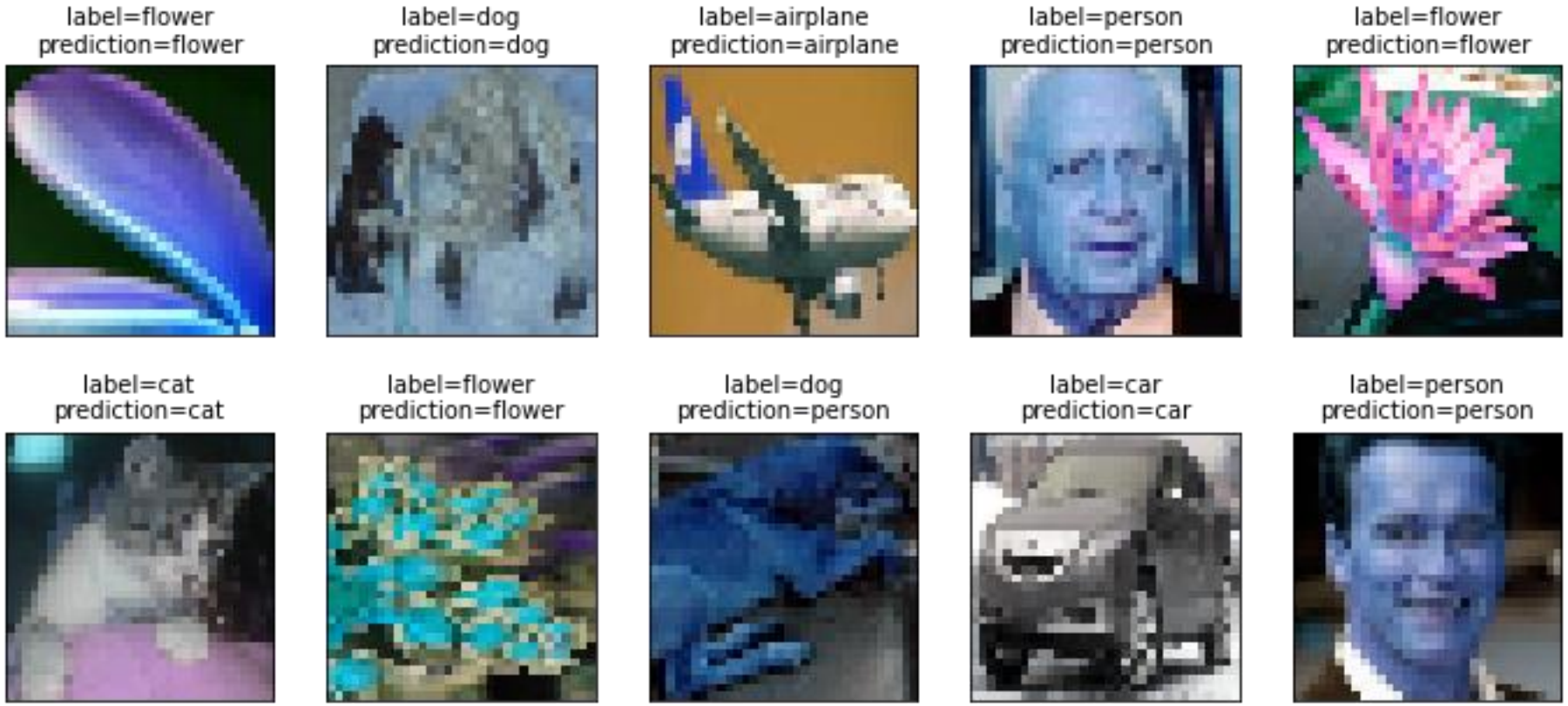
```
[ ]
def plot_images_labels_prediction(images,labels,prediction,idx,num=10):
        fig = plt.gcf()
        fig.set_size_inches(12,14)                          #設定影像的大小
        if num>25 : num =25                                          #設定顯示最大項數
        for i in range(0,num):                                  #for回圈畫出num個數字影像
                ax=plt.subplot(5,5,i+1)
                ax.imshow(images[idx],cmap='binary')          #建立subgraph子圖形為五行五列
                for j in range(0, len(labels[i])):
                    if labels[i][j] == 1:
                        break
                title = "label="+label_dict[j]+"\n"             #設定子圖形title，顯示標簽欄位
                for k in range(0, len(prediction[i])):
                    if prediction[i][k] == 1:
                        break
                if len(prediction)>0:                                  #如果傳入了預測結果
                        title+="prediction="+label_dict[k]    #標題

                ax.set_title(title,fontsize=10)               #設定子圖形的標題
                ax.set_xticks([]);ax.set_yticks([])         #設定不顯示刻度
                idx+=1                                                                  #讀取下一項
        plt.show()

label_dict={0:"airplane",1:"car",2:"cat",3:"dog",4:"flower",5:"fruit",6:"motorbike",7:"person"}
```

```
[ ]
predictions = (model.predict(x_test) > 0.5).astype("int32")
plot_images_labels_prediction(x_test,y_test,predictions,0,10)
```

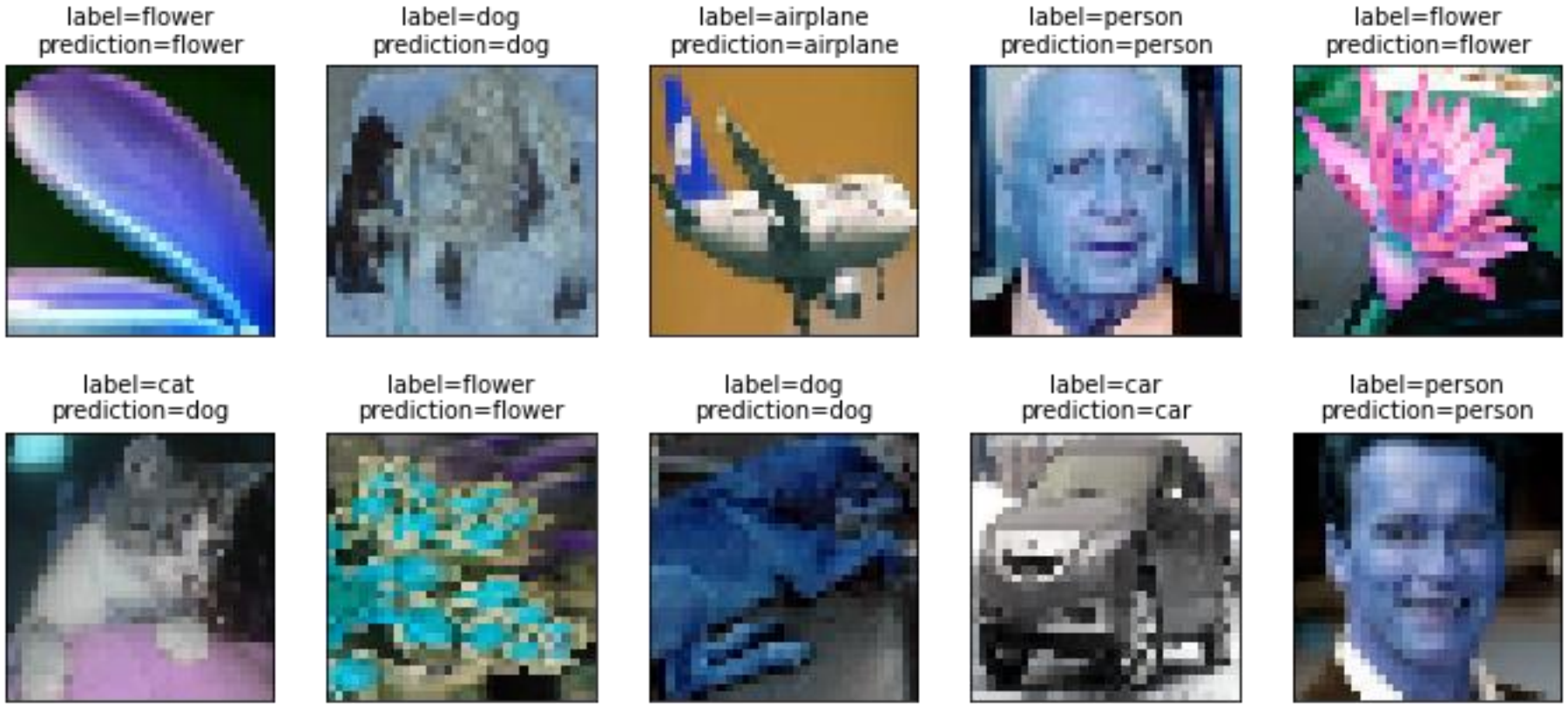
預測結果（5層CNN網路 訓練25圈）



預測結果（5層CNN網路 訓練100圈）



預測結果（9層CNN網路 訓練25圈）



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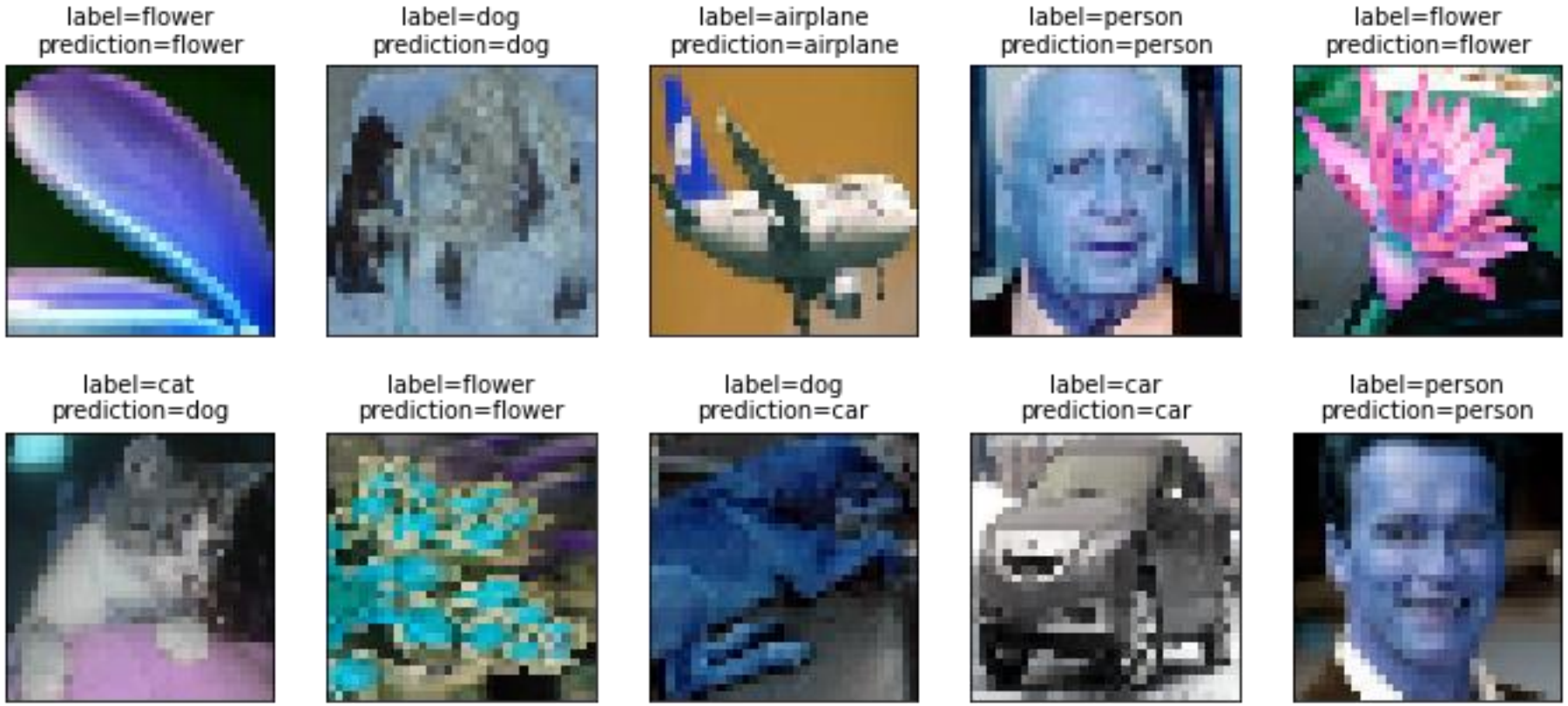

結論

測試過相同圈數與不同層數的比較後，我們認為較多層的CNN模型能夠提高準確率。同時發現到在卷基層較多時，8種類別中僅在貓狗辨識的部分出錯，其餘6種類別的辨識效果良好，我們認為是由於增加了池化層後減少了特徵擷取，因此對於較接近的物件上特徵數不足而造成了辨識的困難。

分工表

大家一起做

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