Computer Vision HW2 Report

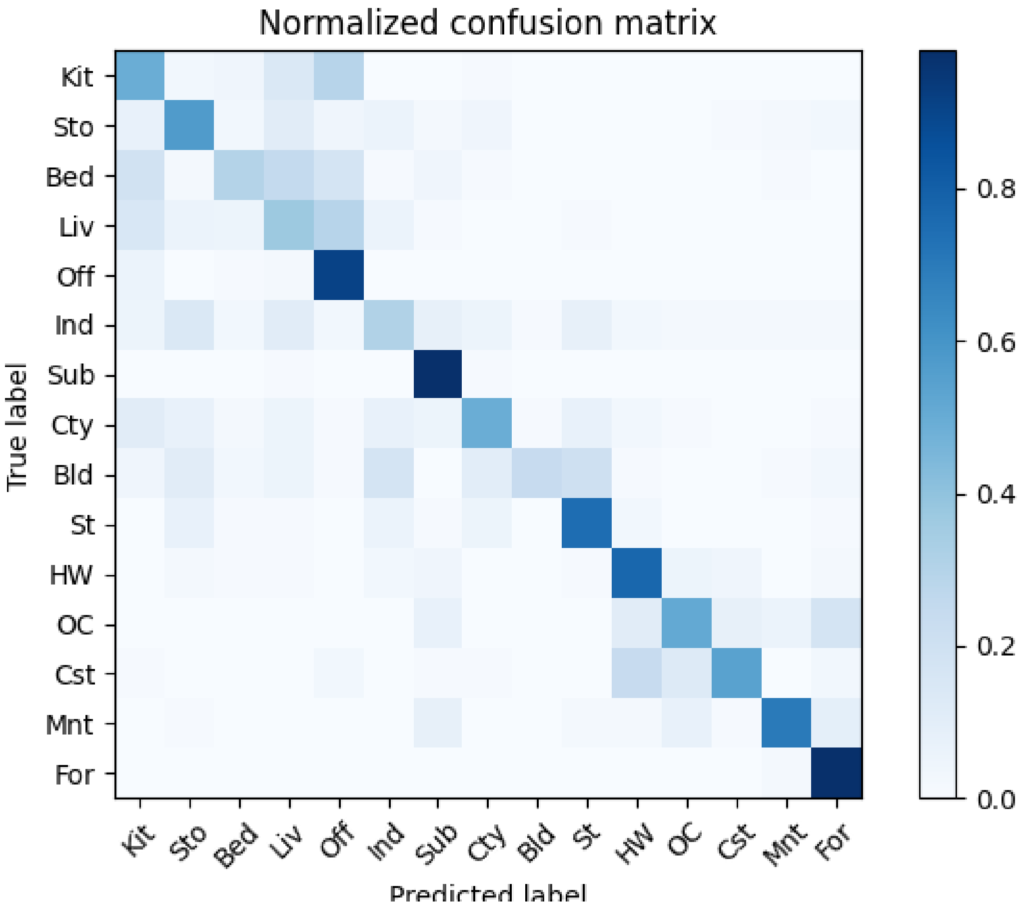
Student ID: R012323007
Name: 廖明祐

Part 1. (10%)

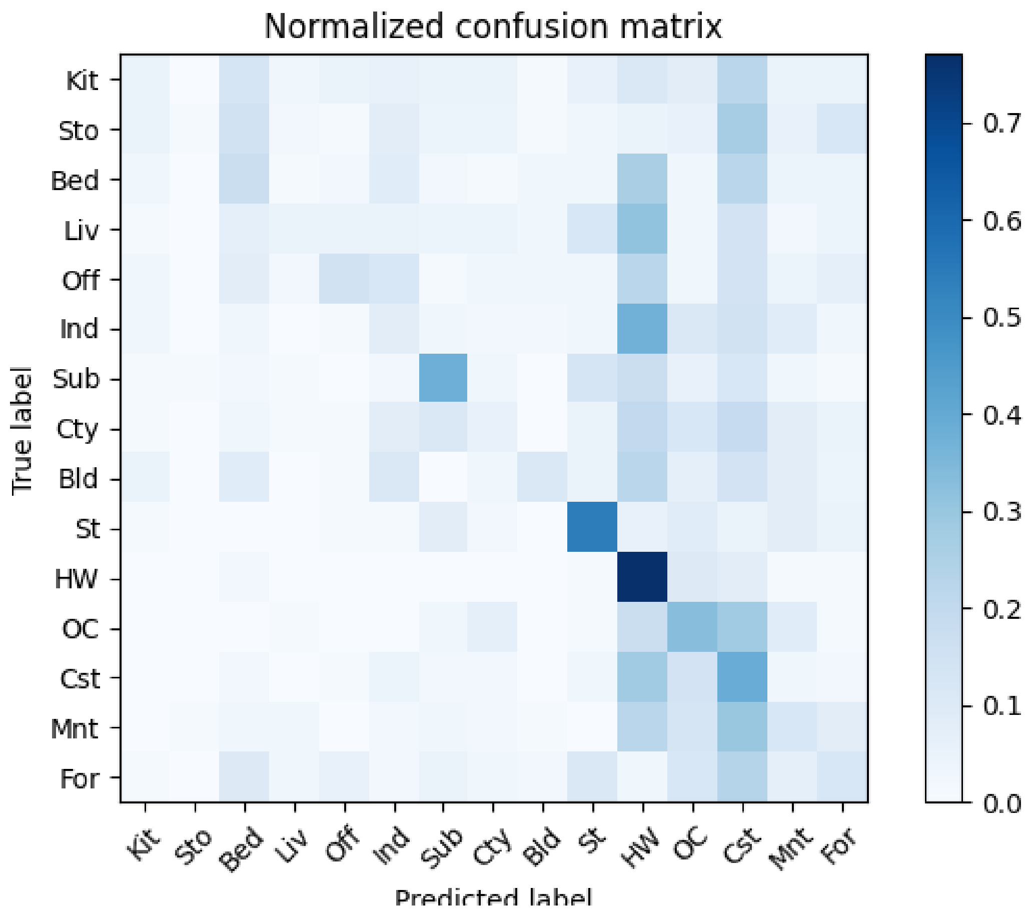
• Plot confusion matrix of two settings. (i.e. Bag of sift and tiny image) (5%)

Ans:

Bag of sift:



Tiny image:



• Compare the results/accuracy of both settings and explain the result. (5%)

Ans:

1.Feature: tiny_image, Classifier: nearest_neighbor, Accuracy = 0.222

2. Feature: bag_of_sift, Classifier: nearest_neighbor, Accuracy = 0.594

從 confusion matrix 來看，使用 Bag of sift 方式的大部分的種類都能正確分類，因此對角線顏色很深。使用 tiny image 則是將很多圖片歸類為 St、HW、OC、Cst 三類，所以造成 Accuracy 很低。

Part 2. (25%)

• Report accuracy of both models on the validation set. (2%)

Ans:

Using resnet18, accuracy is 0.888 on validation set.

Using mynet, accuracy is 0.6262 on validation set.

• Print the network architecture & number of parameters of both models. What is the main difference between ResNet and other CNN architectures? (5%)

Ans:

ResNet:

```
ResNet18(
  (resnet): ResNet(
    (conv1): Conv2d(3, 64, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (maxpool): Identity()
    (layer1): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (1): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (layer2): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
```

```
(layer3): Sequential(
  (0): BasicBlock(
    (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (downsample): Sequential(
      (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (1): BasicBlock(
    (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
)
(layer4): Sequential(
  (0): BasicBlock(
    (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (downsample): Sequential(
      (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (1): BasicBlock(
    (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
)
(avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
(fc): Linear(in_features=512, out_features=10, bias=True)
```

```
    )
)
```

MyNet:

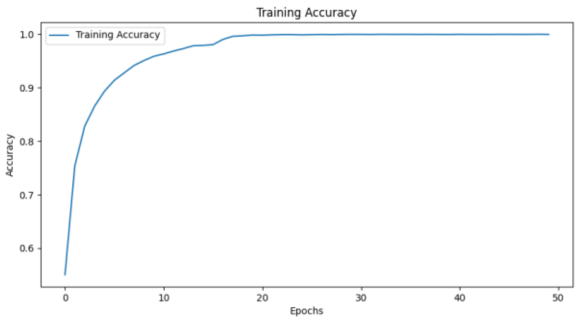
```
MyNet(
    (conv1): Sequential(
        (0): Conv2d(3, 6, kernel_size=(5, 5), stride=(1, 1))
        (1): ReLU()
        (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    )
    (conv2): Sequential(
        (0): Conv2d(6, 16, kernel_size=(5, 5), stride=(1, 1))
        (1): ReLU()
        (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    )
    (fc1): Sequential(
        (0): Linear(in_features=400, out_features=120, bias=True)
        (1): ReLU()
    )
    (fc2): Sequential(
        (0): Linear(in_features=120, out_features=84, bias=True)
        (1): ReLU()
    )
    (fc3): Linear(in_features=84, out_features=10, bias=True)
)
```

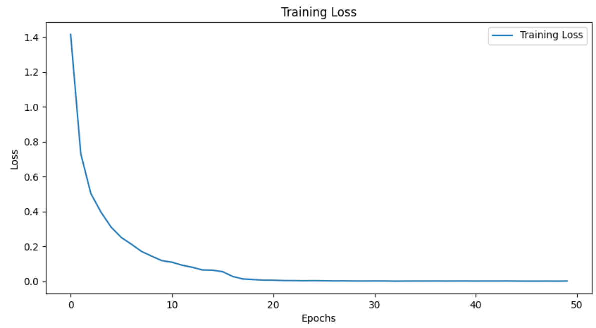
Resnet和一般CNN模型的差別在於，再Resnet的模型中，他有直通網路，直通網路的好處在於，他和卷基層相加時，模型只需要學習 residual，就可以解決CNN會遇到的梯度問題。即使Resnet有很多層，讓模型變得很重，但因為直通網路的加成，就讓Resnet可以訓練得不錯。

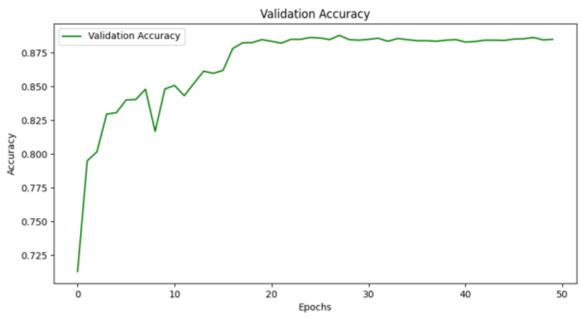
• Plot four learning curves (loss & accuracy) of the training process (train/validation) for both models. Total 8 plots. (8%)

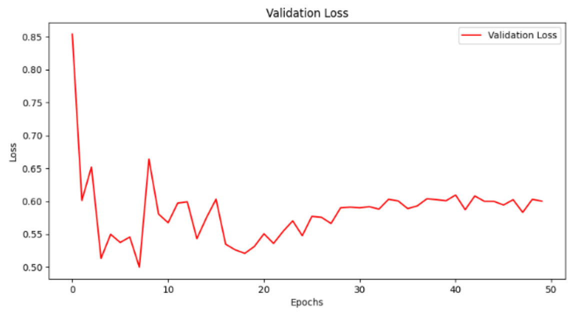
Ans:

Resnet:

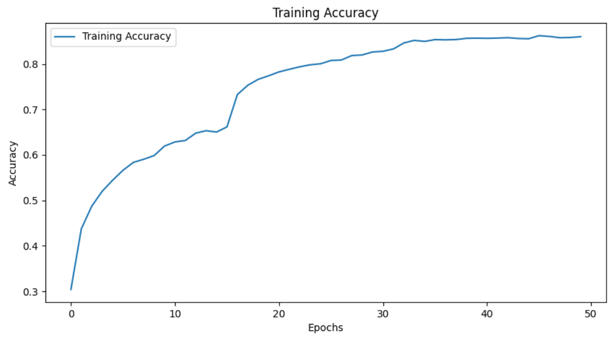


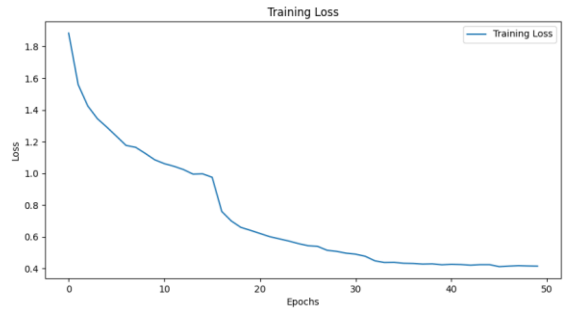


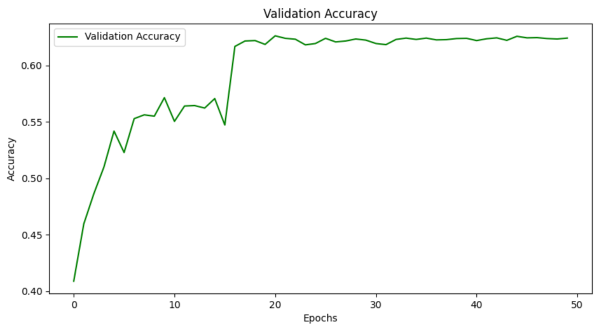


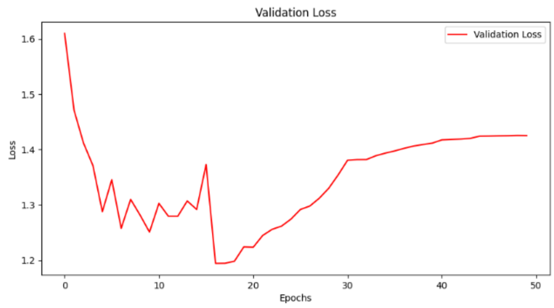


Mynet:









• Briefly describe what method do you apply on your best model? (e.g. data augmentation, model architecture, loss function, etc) (10%)

Ans:

以下是我增加 Accuracy 的方法:

1. 我在 data augmentation 上採用 transforms.RandomHorizontalFlip 的方式來實作，發現這樣的方式可以降低 over fitting 的問題。

2. Model 的話，我採用題目給的 Hint 實作，將 resnet18 第一個捲基層的 kernel size 改成 3*3 並把 maxpool 層換成 Identity。