Computer Vision HW2 Report

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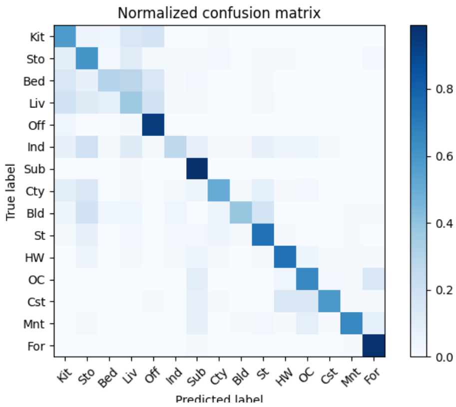
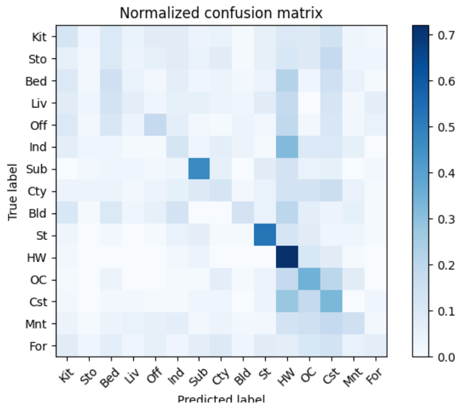
Part 1. (10%)

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

Ans:

<table>
<tr><th></th><th>Bag of sift</th><th>Tiny image</th></tr>
<tr><td>Accuracy</td><td>62.20%</td><td>23.53%</td></tr>
<tr><td>Confusion matrix</td><td>
</td><td>
</td></tr>
</table>

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

Ans:

以 accuracy 而言，bag of sift 的 accuracy 明顯高過於 tiny image。從 confusion matrix 來看，bag of sift 大多的類別都能做出相對正確的分類預測，而 tiny image 除了在 suburb、highway 和 street 類別有較高的準確率，其他類別則容易出現分類錯誤。

之所以 bag of sift 的表現可以優於 tiny image，是因為 bag of words 模型會將圖片特徵擷取初並加以分群，因此在找相近鄰居時，可以使用更精確的細部特徵去計算特徵之間的距離，而非使用整張圖片去計算距離。

Part 2. (25%)

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

Ans:

	MyNet	ResNet18
Accuracy	84.48%	89.76%

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

Ans:

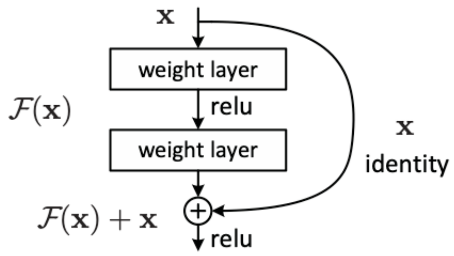
<table>
<tr><th></th><th>Mynet</th></tr>
<tr><td>Number of parameters</td><td>9444490</td></tr>
<tr><td>Model architecture</td><td><pre>
MyNet(
  (conv1): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): GELU()
    (3): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (5): GELU()
    (6): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
)
  (conv2): Sequential(
    (0): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): GELU()
    (3): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (5): GELU()
    (6): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
)
  (conv3): Sequential(
    (0): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): GELU()
    (3): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (5): GELU()
    (6): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
)
  (conv4): Sequential(
    (0): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): GELU()
    (3): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (5): GELU()
    (6): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
)
  (conv5): Sequential(
    (0): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): GELU()
    (3): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (5): GELU()
    (6): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
)
  (avgpool): AvgPool2d(kernel_size=1, stride=1, padding=0)
  (fc): Sequential(
    (0): Linear(in_features=512, out_features=64, bias=True)
    (1): BatchNorm1d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): GELU()
    (3): Linear(in_features=64, out_features=10, bias=True)
)
)
</pre></td></tr>
</table>

	ResNet18
Number of parameters	11202442

Model architecture	See code below

```
ResNet18(
  (resnet): ResNet(
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (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))
    (conv1): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (maxpool): Identity()
    (fc): Sequential(
      (0): Linear(in_features=512, out_features=64, bias=True)
      (1): BatchNorm1d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): GELU()
      (3): Linear(in_features=64, out_features=10, bias=True)
    )
  )
)
```

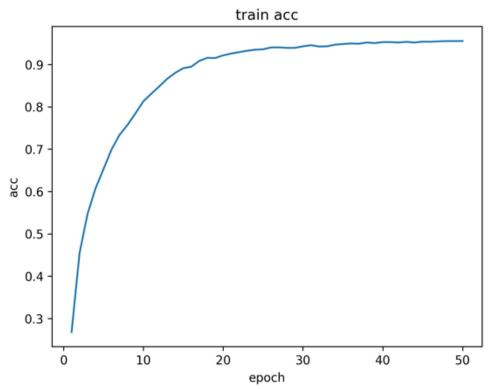
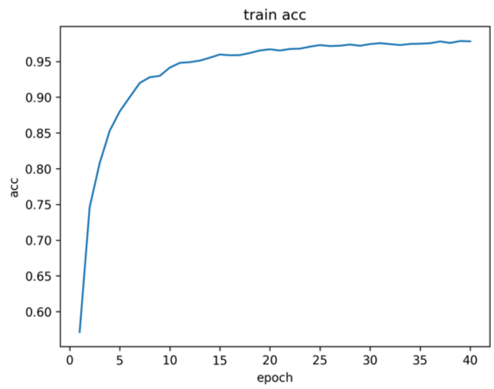
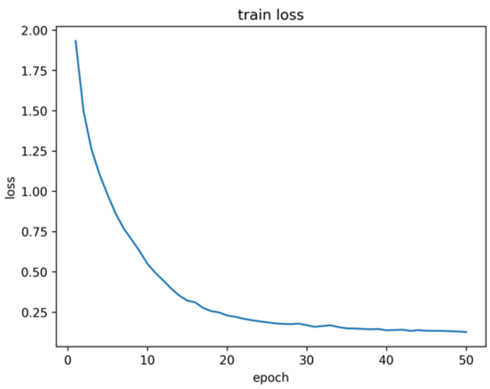
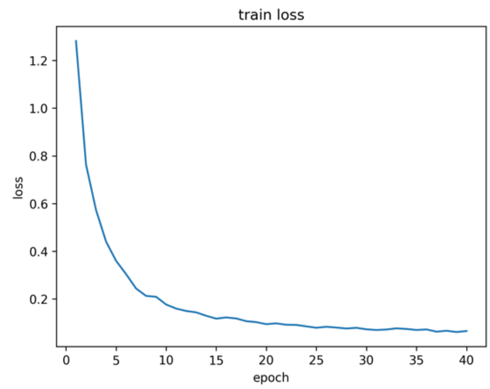
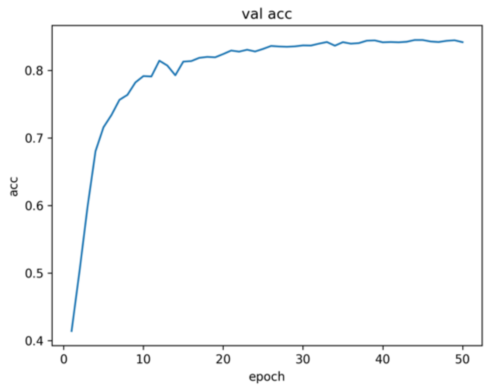
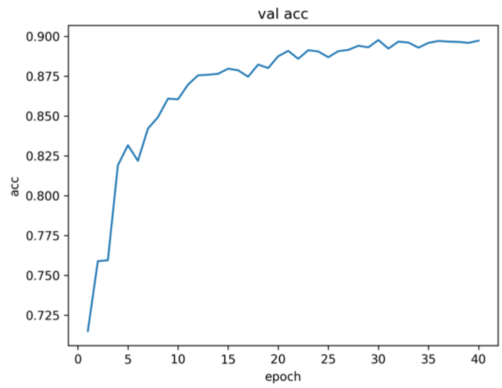
ResNet 與一般 CNN 模型相比，加入了 residual learning 的機制，也就是將前面數層的輸出和當前輸出做加法，形成一個 building，如下圖所示。此機制有效避免了梯度消失的問題，使得深層神經網路可以容易訓練。

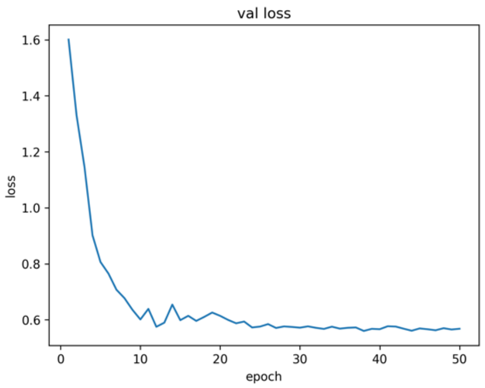
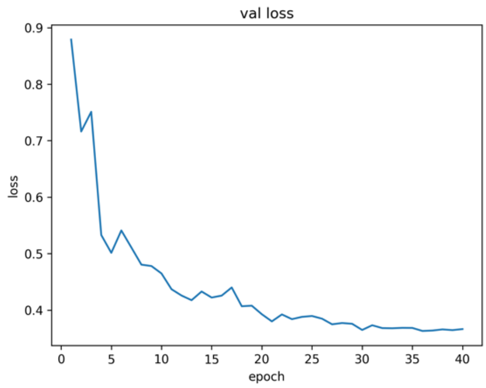


He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.

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

Ans:

	MyNet	ResNet18
Training accuracy		
Training loss		
Validation accuracy		

Validation loss		

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

Ans:

1. Data augmentation

   使用 AutoAugment 中的 CIFAR10 policy。概略而言，AutoAugment 是在各種資料集上搜尋出能夠最佳化 validation accuracy 的 augmentation 方法，而 Pytorch 使用的 AutoAugment 則是根據論文的成果去整理出 sub-policies。

2. Model architecture

   ✓ MyNet：主要使用 VGG-13 的架構，並修改 activation layer 的 function，以及最後 fully-connected layer 的架構。

   ✓ ResNet18：參考投影片建議，將 conv1 的 kernel size 改為 3x3，並將 maxpool 改為 identity，最後修改 fully-connected layer 的架構，而非直接對應到 number of class。

3. Optimizer

   在 Adam optimizer 中加入 weight decay 參數。

4. Scheduler

   改用 StepLR 而非原本的 MultiStepLR，每一個 epoch 即下降小幅度的 learning rate，以避免 accuracy 或 loss curve 過於波動或困於 local optima 中，以達到較好的 accuracy。