Computer Vision HW2 Report

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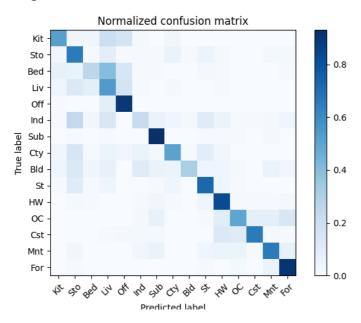
Name: 李品樺

Part 1. (10%)

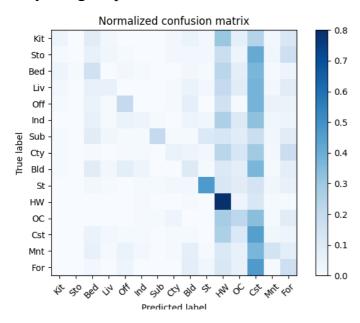
 \bullet Plot confusion matrix of two settings. (i.e. Bag of sift and tiny image representation) (5%)

Ans:

• Bag of sift



• Tiny image representation



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

Performance

Type	Bag of sift	Tiny image
Accuracy	60.93%	20.73%

Experiment setting

For tiny image, we resize the image to 8*8. When the tiny image size is smaller, the performance is usually better. For Bag of sift, there are several hyperparameters to choose from in dsift. We set the function as below in get bags of sift.py.

dsift(img, step = [3, 3], window_size=4, fast=True)

In the KNN classifier, we choose k as 5, and use cdist from scipy.spatial.distance with metric 'cityblock'. Then, we utilize the function, np.argsort(), to sort the distancesfrom smallest to largest. Finally, we can compute the mode to get the predicted result. From the confusion matrix of tiny image representation above, we can find out that several columns of the class are darker. The tiny image feature tends to guess the image these classes.

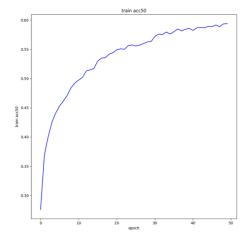
Part 2. (35%)

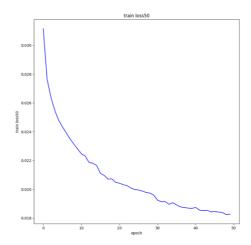
• Compare the performance on residual networks and LeNet. Plot the learning curve (loss and accuracy) on both training and validation sets for both 2 schemes. 8 plots in total. (20%)

Ans:

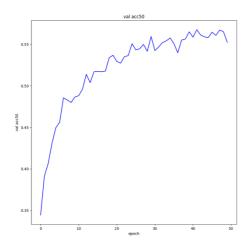
- The performance of MyResnet is clearly better than LeNet as the images show. The residual net can reach about 79% on validation set but LeNet only reaches 57%.
- LeNet

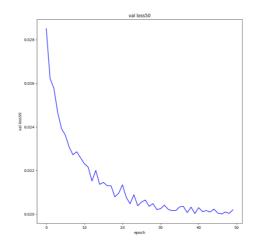
■ Train





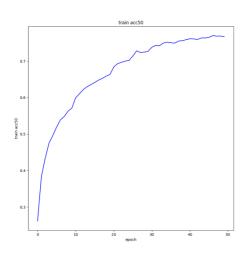
■ Validation

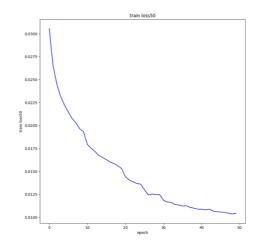




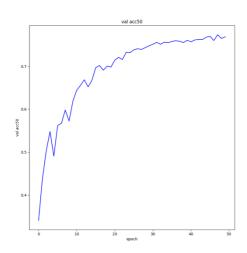
MyResnet

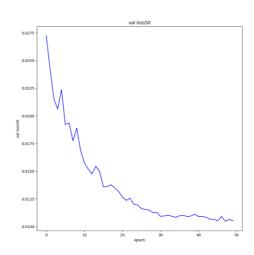
■ Train





■ Validation





 \bullet Attach basic information of the model you use including model architecture and number of the parameters. (5%)

Ans:

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Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 64, 32, 32]	1,792
Conv2d-2 BatchNorm2d-3	[-1, 64, 32, 32] [-1, 64, 32, 32]	36,928 128
ReLU-4	[-1, 64, 32, 32]	0
Conv2d-5	[-1, 64, 32, 32]	4,160
ReLU-6 residual block-7	[-1, 64, 32, 32] [-1, 64, 32, 32]	0
Conv2d-8	[-1, 128, 32, 32]	73,856
MaxPool2d-9	[-1, 128, 16, 16]	0
BatchNorm2d-10	[-1, 128, 16, 16]	256
ReLU-11 Conv2d-12	[-1, 128, 16, 16] [-1, 128, 16, 16]	0 147,584
BatchNorm2d-13	[-1, 128, 16, 16]	256
ReLU-14	[-1, 128, 16, 16]	0
Conv2d-15 ReLU-16	[-1, 128, 16, 16] [-1, 128, 16, 16]	16,512 0
residual_block-17	[-1, 128, 16, 16]	0
Conv2d-18	[-1, 128, 16, 16]	147,584
BatchNorm2d-19 ReLU-20	[-1, 128, 16, 16]	256 0
Conv2d-21	[-1, 128, 16, 16] [-1, 256, 16, 16]	295,168
BatchNorm2d-22	[-1, 256, 16, 16]	512
ReLU-23	[-1, 256, 16, 16]	0
Conv2d-24 ReLU-25	[-1, 128, 16, 16] [-1, 128, 16, 16]	32,896 0
residual_block-26	[-1, 128, 16, 16]	0
Dropout-27	[-1, 128, 16, 16]	0
Conv2d-28 MaxPool2d-29	[-1, 256, 16, 16] [-1, 256, 8, 8]	295,168 0
BatchNorm2d-30	[-1, 256, 8, 8]	512
ReLU-31	[-1, 256, 8, 8]	0
Conv2d-32	[-1, 256, 8, 8]	590,080
BatchNorm2d-33 ReLU-34	[-1, 256, 8, 8] [-1, 256, 8, 8]	512 0
Conv2d-35	[-1, 256, 8, 8]	65,792
ReLU-36	[-1, 256, 8, 8]	0
residual_block-37 Dropout-38	[-1, 256, 8, 8] [-1, 256, 8, 8]	0
Conv2d-39	[-1, 256, 8, 8]	590,080
MaxPool2d-40	[-1, 256, 4, 4]	0
BatchNorm2d-41	[-1, 256, 4, 4]	512
ReLU-42 Conv2d-43	[-1, 256, 4, 4] [-1, 256, 4, 4]	0 590,080
BatchNorm2d-44	[-1, 256, 4, 4]	512
ReLU-45	[-1, 256, 4, 4]	0 65 703
Conv2d-46 ReLU-47	[-1, 256, 4, 4] [-1, 256, 4, 4]	65,792 0
residual_block-48	[-1, 256, 4, 4]	0
Dropout-49	[-1, 256, 4, 4]	0
AdaptiveAvgPool2d-50	[-1, 256, 1, 1]	0
Linear-51 ReLU-52	[-1, 128] [-1, 128]	32,896 0
Dropout-53	[-1, 128]	0
Linear-54	[-1, 10]	1,290
Total params: 2,991,114 Trainable params: 2,991, Non-trainable params: 0		
Input size (MB): 0.01 Forward/backward pass size (MB): 11.41 Estimated Total Size (MB		

• Briefly describe what method do you apply? (e.g. data augmentation, model architecture, loss function, semi-supervised etc.) (10%)
Ans:

For training set, we use the following data augmentation:

The model architecture is composed of 5 modules, each module includes a CNN layer follows by a residual block. Some dropout layers are added after the block to prevent overfitting. After the 5 modules, we use an average pooling layer then flatten the result. Finally, the flattened vector is fed into the classifier that output a 10-dimension logit that represents each class. We choose Adam as optimizer with step learning rate scheduler and gamma equals to 0.6 on epoch 10, 20, 25 30. Using cross entropy as loss function, and implemented the method mentioned above, we train for 50 epochs. The accuracy on the public testing set can reach about 84.22%.