Lab3: Diabetic Retinopathy Detection

Lab Objective:

In this lab, you will need to analysis diabetic retinopathy (糖尿病所引發視網膜病變) in the following three steps. First, you need to write your own custom DataLoader through PyTorch framework. Second, you need to classify diabetic retinopathy grading via the ResNet architecture [1]. Finally, you have to calculate the confusion matrix to evaluate the performance.

Important Date:

1. Experiment Report Submission Deadline: 4/21 (Tue) 12:00
2. Demo date: 4/18 (Tue)

Turn in:

1. Experiment Report (.pdf)
2. Source code

Notice: zip all files in one file and name it like「DLP_LAB3_your studentID_name.zip」, ex: 「DLP_LAB3_0760447_李孟陽.zip」

Requirements:

1. Implement the **ResNet18、ResNet50** architecture and **load parameters** from a pretrained model
2. Compare and **visualize** the accuracy trend between the **pretrained model and without pretraining** in same architectures, you need to plot each epoch **accuracy (not loss)** during training phase and testing phase.
3. Implement your own custom **DataLoader**
4. Calculate the **confusion matrix** and plotting

Dataset- Diabetic Retinopathy Detection (kaggle):

Diabetic retinopathy is the leading cause of blindness in the working-age population of the developed world. It is estimated to affect over 93 million people. This dataset provided with a large set of high-resolution retina images taken under a variety of imaging conditions. ***Format: .jpeg***

Reference :

https://www.kaggle.com/c/diabetic-retinopathy-detection#description

Implementation Details:

- **Prepare Data**

  The dataset contains 35124 images, we divided dataset into 28,099 training data and 7025 testing data. The image resolution is 512x512 and has been preprocessed.

  Download link:
  https://drive.google.com/open?id=1RTmrk7Qu9IBjQYLczaYKOvXaHWBS0o72

- **Custom Dataloader**
  - This is the skeleton that you have to fill to have a custom dataset, refer to "dataloader.py"

```
class RetinopathyLoader(data.Dataset):
    def __init__(self, root, mode):
        """
        Args:
            root (string): Root path of the dataset.
            mode : Indicate procedure status(training or testing)

            self.img_name (string list): String list that store all image names.
            self.label (int or float list): Numerical list that store all ground truth label values.
        """
        self.root = root
        self.img_name, self.label = getData(mode)
        self.mode = mode
        print("> Found %d images..." % (len(self.img_name)))

    def __len__(self):
        """'return the size of dataset"""
        return len(self.img_name)

    def __getitem__(self, index):
        """something you should implement here"""

        """
           step1. Get the image path from 'self.img_name' and load it.
                  hint : path = root + self.img_name[index] + '.jpeg'

           step2. Get the ground truth label from self.label

           step3. Transform the .jpeg rgb images during the training phase, such as resizing, random flipping,
                  rotation, cropping, normalization etc. But at the beginning, I suggest you follow the hints.

                  In the testing phase, if you have a normalization process during the training phase, you only need
                  to normalize the data.

                  hints : Convert the pixel value to [0, 1]
                          Transpose the image shape from [H, W, C] to [C, H, W]

           step4. Return processed image and label
        """

        return img, label
```

  - The `__init__` function is where the initial logic happens like reading a csv, assigning transforms etc.

  - The `__getitem__` function returns the data and labels and you can process the data like loading image, preprocessing, transforming image before returns.

  - The index parameter where in the `__getitem__` function, it is the nth data/image you are going to return.

  - Reference:
    https://pytorch.org/tutorials/beginner/data_loading_tutorial.html
    https://github.com/utkuozbulak/pytorch-custom-dataset-examples

- You can use getData function to read all images name and ground truth.

```
def getData(mode):
    if mode == 'train':
        img = pd.read_csv('train_img.csv')
        label = pd.read_csv('train_label.csv')
        return np.squeeze(img.values), np.squeeze(label.values)
    else:
        img = pd.read_csv('test_img.csv')
        label = pd.read_csv('test_label.csv')
        return np.squeeze(img.values), np.squeeze(label.values)
```

ResNet

ResNet (Residual Network) is the Winner of ILSVRC 2015 in image classification, detection, and localization, as well as Winner of MS COCO 2015 detection, and segmentation [2].

- **Degradation problem:** the network depth increasing, accuracy gets saturated (which might be unsurprising) and then degrades rapidly. Not overfitting, it's the vanishing/ exploding gradient problem.

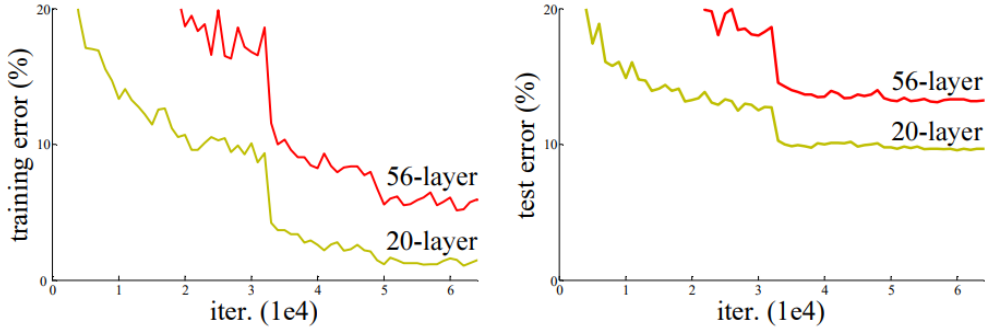
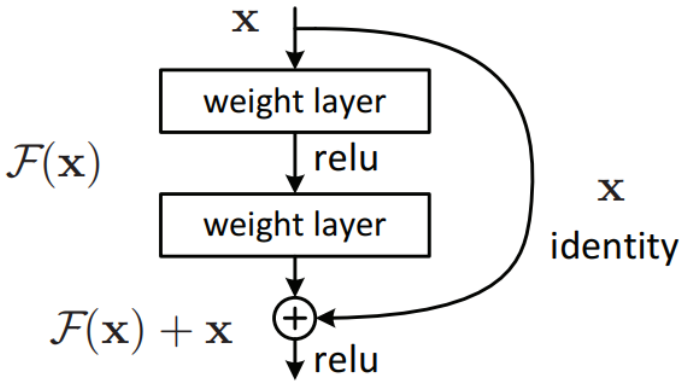


Figure. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error.

- **Skip/Shortcut connection:** to solve the problem of vanishing/exploding gradients, a skip / shortcut connection is added to add the input x to the output after few weight layers as below [2]



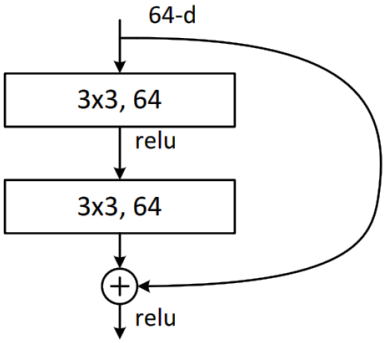
- Why ResNet can avoid vanishing gradient problem??

$$\mathbf{x}_L = \mathbf{x}_l + \sum_{i=l}^{L-1} \mathcal{F}(\mathbf{x}_i, \mathcal{W}_i),$$

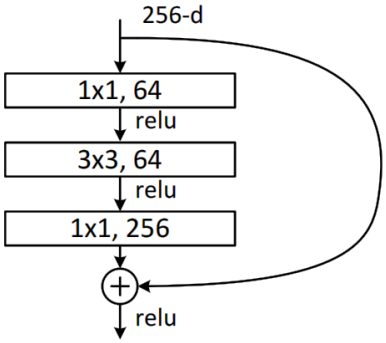
$$\frac{\partial \mathcal{E}}{\partial \mathbf{x}_l} = \frac{\partial \mathcal{E}}{\partial \mathbf{x}_L}\frac{\partial \mathbf{x}_L}{\partial \mathbf{x}_l} = \frac{\partial \mathcal{E}}{\partial \mathbf{x}_L}\left(1 + \frac{\partial}{\partial \mathbf{x}_l}\sum_{i=l}^{L-1}\mathcal{F}(\mathbf{x}_i, \mathcal{W}_i)\right).$$

- Building residual basic block and bottleneck block:

Basic block

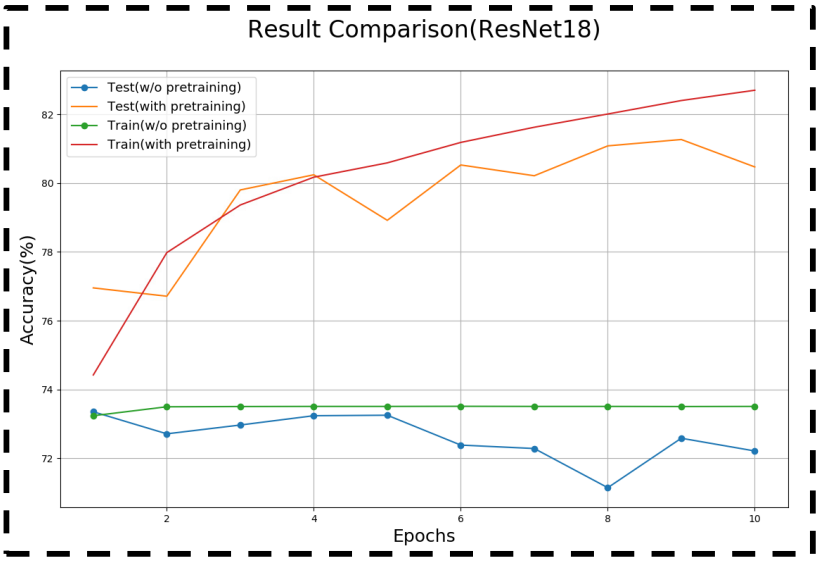


Bottleneck block



- Using pretrained model and reinitialize the specific layers **https://pytorch.org/tutorials/beginner/finetuning_torchvision_models_tutorial.html**

- Your visualization figure of accuracy should like example as below.



- **Confusion matrix**

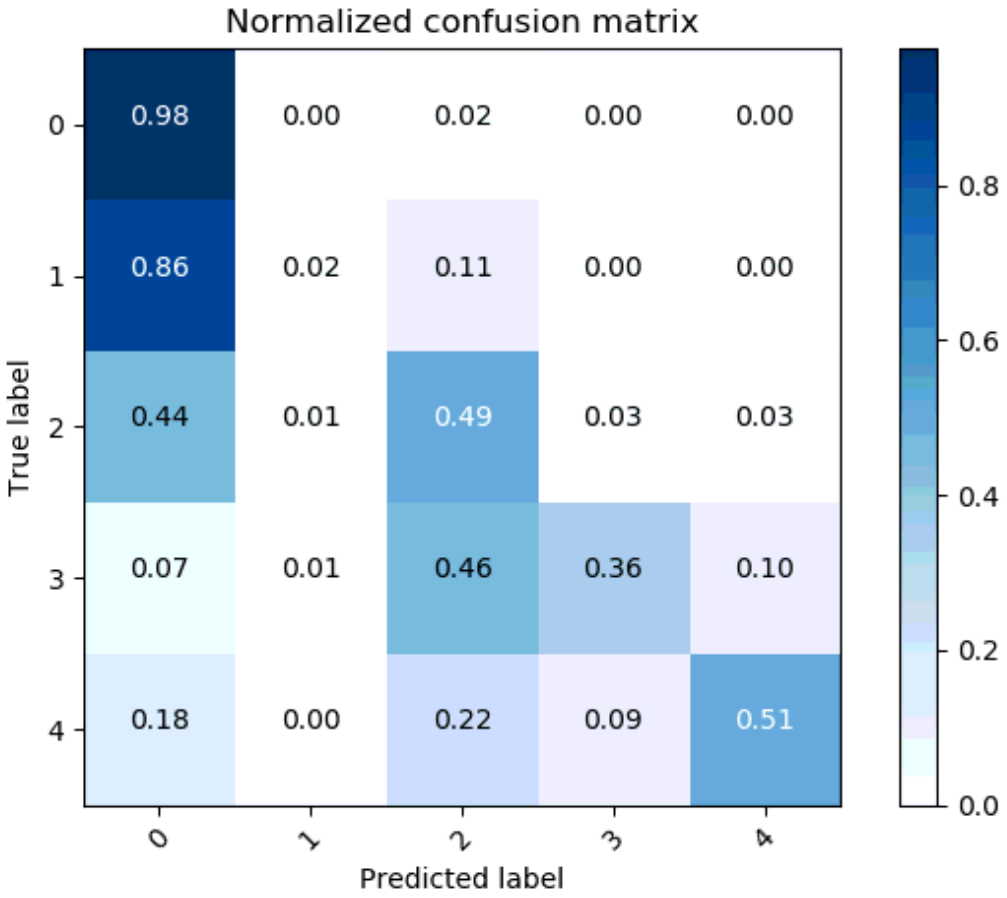
  A confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data for which the true values are known. It is extremely useful for measuring Recall, Precision, Specificity, Accuracy and most importantly AUC-ROC curve [3].

  - **Sample code:**

    You can use the following example and library to conduct this section.

    https://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html#sphx-glr-auto-examples-model-selection-plot-confusion-matrix-py

  - The confusion matrix will be similar as the following example:



- **Hyper Parameters**

  Batch size= 4 Learning rate = 1e-3
  Epochs = 10(resnet18), 5(resnet50)
  Optimizer: SGD momentum = 0.9 weight_decay = 5e-4
  Loss function: torch.nn.CrossEntropyLoss()

  You can adjust the hyper-parameters according to your own ideas.

Report Spec

1. Introduction (20%)
2. Experiment setups (30%)
   A. The details of your model (ResNet)
   B. The details of your Dataloader
   C. Describing your evaluation through the confusion matrix
3. Experimental results (30%)
   A. The highest testing accuracy
      - Screenshot
      - Anything you want to present
   B. Comparison figures
      - Plotting the comparison figures
        (RseNet18/50, with/without pretraining)
4. Discussion (20%)
   A. Anything you want to share

---- Criterion of result (40%) ----

Accuracy > = 82% = 100 pts
Accuracy 80~82% = 90 pts
Accuracy 75~80% = 80 pts
Accuracy < 75% = 70 pts

Score: 40% experimental results + 60% (report+ demo score)
P.S If the zip file name or the report spec have format error, it will be penalty (-5).

In demo phase, you need to load trained model and evaluate.

Reference:

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

[2] Review: ResNet
https://towardsdatascience.com/review-resnet-winner-of-ilsvrc-2015-image-classification-localization-detection-e39402bfa5d8

[3] Understanding Confusion Matrix
https://towardsdatascience.com/understanding-confusion-matrix-a9ad42dcfd62

[4] Confusion Matrix
http://www2.cs.uregina.ca/~dbd/cs831/notes/confusion_matrix/confusion_matrix.html