DeepLearning_Fall2023_HW6

November 11, 2023

1 Deep Learning Homework 6 (Spring 2023)

This code is provided for Deep Learning class (601.482/682) Homework 6. For ease of implementation, we recommend working entire in Google Colaboratory.

 Modifications made by Hongtao Wu, Suzanna Sia, Hao Ding, Keith Harrigian, and Yiqing Shen.

1.0.1 Imports

[2]:
```python
## Mount Google Drive Data (If using Google Colaboratory)
try:
    from google.colab import drive
    drive.mount('/content/gdrive')
except:
    print("Mounting Failed.")
```

```
Mounted at /content/gdrive
```

[ ]:
```python
## Standard Library
import os
import json

## External Libraries
import numpy as np
import torch
import torch.nn as nn
from torchvision import transforms
from torch.autograd import Variable
import torch.nn.functional as functional
from torch.utils.data import Dataset, DataLoader
from skimage import io
import matplotlib.pyplot as plt
```

2 Problem 1: Unsupervised Pre-training

2.0.1 Training Hyperparameters

These are recommended hyperparameters - please feel free to use what works for you. Batch size can be changed if it does not match your memory, please state your batch step_size in your report.

Dataset is available at: https://livejohnshopkins-my.sharepoint.com/:u:/g/personal/yshen92_jh_edu/EcTxWAXs pEExyMg

[ ]:
```
## Batch Size
train_batch_size = 10
validation_batch_size = 10

## Learning Rate
learning_rate = 0.001

# Epochs (Consider setting high and implementing early stopping)
num_epochs = 100
```

2.0.2 Data Paths

[ ]:
```
# General Data Directory ##TODO: Please fill in the appropriate directory
data_dir = "/content/gdrive/MyDrive/Colab Notebooks/MLDL_HW6/
 ↪DeepLearning_Fall2023_HW6_data/HW6_data"

## Segmentation + Colorization Paths
segmentation_data_dir = f"{data_dir}/segmentation/"
colorization_data_dir = f"{data_dir}/colorization/"

# Mask JSON
mask_json = f"{data_dir}/mapping.json"
```

2.0.3 Data Loaders

We have provided you with some preprocessing code for the images but you should feel free to modify the class however you please to support your training schema. In the very least, you will have to modify the dataloader to support loading of the colorization dataset.

[ ]:
```
## Image Transforms
img_transform = transforms.Compose([
        transforms.ToTensor(),
])

## Image Dataloader
class ImageDataset(Dataset):

    """
    ImageDataset
```

```
    """

    def __init__(self,
                 input_dir,
                 op,
                 mask_json_path,
                 transforms=None):
        """
        ##TODO: Add support for colorization dataset

        Args:
            input_dir (str): Path to either colorization or segmentation␣
↪directory
            op (str): One of "train", "val", or "test" signifying the desired␣
↪split
            mask_json_path (str): Path to mapping.json file
            transforms (list or None): Image transformations to apply upon␣
↪loading.
        """
        self.transform = transforms
        self.op = op
        with open(mask_json_path, 'r') as f:
            self.mask = json.load(f)
        self.mask_num = len(self.mask)  # There are 6 categories: grey, dark␣
↪grey, and black
        self.mask_value = [value for value in self.mask.values()]
        self.mask_value.sort()
        try:
            if self.op == 'train':
                self.data_dir = os.path.join(input_dir, 'train')
            elif self.op == 'val':
                self.data_dir = os.path.join(input_dir, 'validation')
            elif self.op == 'test':
                self.data_dir = os.path.join(input_dir, 'test')
        except ValueError:
            print('op should be either train, val or test!')

    def __len__(self):
        """

        """
        return len(next(os.walk(self.data_dir))[1])

    def __getitem__(self,
                    idx):
        """
```

```
        """
        ## Load Image and Parse Properties
        img_name = str(idx) + '_input.jpg'
        mask_name = str(idx) + '_mask.png'
        img = io.imread(os.path.join(self.data_dir, str(idx), img_name))
        mask = io.imread(os.path.join(self.data_dir, str(idx), mask_name))
        if len(mask.shape) == 2:
            h, w  = mask.shape
        elif len(mask.shape) == 3:
            h, w, c = mask.shape
        ## Convert grey-scale label to one-hot encoding
        new_mask = np.zeros((h, w, self.mask_num))
        for idx in range(self.mask_num):
            #if the mask has 3 dimension use this code
            new_mask[:, :, idx] = mask[:,:,0] == self.mask_value[idx]
            #if the mask has 1 dimension use the code below
            #new_mask[:, :, idx] = mask == self.mask_value[idx]
        ## Transform image and mask
        if self.transform:
            img, mask = self.img_transform(img, new_mask)
        # ## Use dictionary to output
        # sample = {'img': img, 'mask': mask}
        # return sample
        return img, mask

    def img_transform(self,
                      img,
                      mask):
        """

        """
        ## Apply Transformations to Image and Mask
        img = self.transform(img)
        mask = self.transform(mask)
        return img, mask
```

2.1 Model Architecture

Finish building the U-net architecture below.

[ ]:
```
## Functions for adding the convolution layer
def add_conv_stage(dim_in,
                   dim_out,
                   kernel_size=3,
                   stride=1,
                   padding=1,
                   bias=True,
```

```
                   useBN=True):
    """

    """
    # Use batch normalization
    if useBN:
        return nn.Sequential(
          nn.Conv2d(dim_in, dim_out, kernel_size=kernel_size, stride=stride,␣
 ↪padding=padding, bias=bias),
          nn.BatchNorm2d(dim_out),
          nn.LeakyReLU(0.1),
          nn.Conv2d(dim_out, dim_out, kernel_size=kernel_size, stride=stride,␣
 ↪padding=padding, bias=bias),
          nn.BatchNorm2d(dim_out),
          nn.LeakyReLU(0.1)
        )
    # No batch normalization
    else:
        return nn.Sequential(
          nn.Conv2d(dim_in, dim_out, kernel_size=kernel_size, stride=stride,␣
 ↪padding=padding, bias=bias),
          nn.ReLU(),
          nn.Conv2d(dim_out, dim_out, kernel_size=kernel_size, stride=stride,␣
 ↪padding=padding, bias=bias),
          nn.ReLU()
        )

## Upsampling
def upsample(ch_coarse,
             ch_fine):
    """

    """
    return nn.Sequential(
                    nn.ConvTranspose2d(ch_coarse, ch_fine, 4, 2, 1, bias=False),
                    nn.ReLU())


# U-Net
class UNET(nn.Module):

    """

    """
    def __init__(self, n_classes, useBN=True):
        """
        Args:
```

```
            n_classes (int): Number of classes
            useBN (bool): Turn Batch Norm on or off. (Hint: Using BatchNorm␣
↪might help you achieve better performance.)
        """
        super(UNET, self).__init__()
        # Downgrade stages
        self.conv1 = add_conv_stage(3, 32, useBN=useBN)
        self.conv2 = add_conv_stage(32, 64, useBN=useBN)
        self.conv3 = add_conv_stage(64, 128, useBN=useBN)
        self.conv4 = add_conv_stage(128, 256, useBN=useBN)
        # Upgrade stages
        self.conv3m = add_conv_stage(256, 128, useBN=useBN)
        self.conv2m = add_conv_stage(128,  64, useBN=useBN)
        self.conv1m = add_conv_stage( 64,  32, useBN=useBN)
        # Maxpool
        self.max_pool = nn.MaxPool2d(2)
        # Upsample layers
        self.upsample43 = upsample(256, 128)
        self.upsample32 = upsample(128,  64)
        self.upsample21 = upsample(64 ,  32)
        # weight initialization
        # You can have your own weight intialization. This is just an example.
        for m in self.modules():
            if isinstance(m, nn.Conv2d) or isinstance(m, nn.ConvTranspose2d):
                if m.bias is not None:
                    m.bias.data.zero_()
        #TODO: Design your last layer & activations
        self.out = nn.Conv2d(32,n_classes, kernel_size = 1, stride = 1, padding␣
↪= 0, bias = True)
        self.softmax = nn.Softmax()

    def forward(self, x):
        """
        Forward pass
        """
        conv1_out = self.conv1(x)
        conv2_out = self.conv2(self.max_pool(conv1_out))
        conv3_out = self.conv3(self.max_pool(conv2_out))
        conv4_out = self.conv4(self.max_pool(conv3_out))

        conv4m_out_ = torch.cat((self.upsample43(conv4_out), conv3_out), 1)
        conv3m_out  = self.conv3m(conv4m_out_)

        conv3m_out_ = torch.cat((self.upsample32(conv3m_out), conv2_out), 1)
        conv2m_out  = self.conv2m(conv3m_out_)

        conv2m_out_ = torch.cat((self.upsample21(conv2m_out), conv1_out), 1)
```

```
        conv1m_out  = self.conv1m(conv2m_out_)

        #TODO: Design your last layer & activations
        out = self.softmax(self.out(conv1m_out))

        return out
```

2.1.1 DICE Score and DICE Loss

Finish implementing the DICE score function below and then write a Dice Loss function that you can use to update your model weights.

[ ]:
```
##TODO: Finish implementing the multi-class DICE score function
def dice_score_image(prediction, target, n_classes):
    '''
      computer the mean dice score for a single image

      Reminders: A false positive is a result that indicates a given condition␣
 ↪exists, when it does not
               A false negative is a test result that indicates that a␣
 ↪condition does not hold, while in fact it does
      Args:
          prediction (tensor): predictied labels of the image
          target (tensor): ground truth of the image
          n_classes (int): number of classes

      Returns:
          m_dice (float): Mean dice score over classes
    '''
    ## Should test image one by one
    assert prediction.shape[0] == 1 #This line can not be deleted
    ## TODO: Compute Dice Score for Each Class. Compute Mean Dice Score over␣
 ↪Classes.
    dice_classes = np.zeros(n_classes)
    for cl in range(n_classes):
        pred = (prediction[0] == cl).float()
        label = target[0, cl, :, :]

        TP = (pred * label).sum()
        FP = (pred * (1 - label)).sum()
        FN = ((1 - pred) * label).sum()
        #When there is no ground truth of the class in this image
        #Give 1 dice score if False Positive pixel number is 0,
        #give 0 dice score if False Positive pixel number is not 0 (> 0).
        if TP == 0 and FN == 0:
            if FP == 0:
              dice_classes[cl] = 1
```

```
            elif FP > 0:
              dice_classes[cl] = 0
        else:
          dice_classes[cl] = (2 * TP) / (2*TP + FP + FN)
    return dice_classes.mean()



def dice_score_dataset(model, dataloader, num_classes, use_gpu=False):
    """
    Compute the mean dice score on a set of data.

    Note that multiclass dice score can be defined as the mean over classes of␣
 ↪binary
    dice score. Dice score is computed per image. Mean dice score over the␣
 ↪dataset is the dice
    score averaged across all images.

    Reminders: A false positive is a result that indicates a given condition␣
 ↪exists, when it does not
               A false negative is a test result that indicates that a␣
 ↪condition does not hold, while in fact it does

    Args:
        model (UNET class): Your trained model
        dataloader (DataLoader): Dataset for evaluation
        num_classes (int): Number of classes

    Returns:
        m_dice (float): Mean dice score over the input dataset
    """
    ## Number of Batches and Cache over Dataset
    n_batches = len(dataloader)
    scores = np.zeros(n_batches)
    ## Evaluate
    model.eval()
    idx = 0
    for data in dataloader:
        ## Format Data
        img, target = data
        if use_gpu:
            img = img.cuda()
            target = target.cuda()
        ## Make Predictions
        out = model(img)
        n_classes = out.shape[1]
        prediction = torch.argmax(out, dim = 1)
```

```
        scores[idx] = dice_score_image(prediction, target, n_classes)
        idx += 1
    ## Average Dice Score Over Images
    m_dice = scores.mean()
    return m_dice


## TODO: Implement DICE loss,
#  It should conform to to how we computer the dice score.
class DICELoss(nn.Module):
    def __init__(self, num_classes):
      super(DICELoss, self).__init__()
      self.num_classes = num_classes
    def forward(self, input, target):
      intersection = 0
      pred_sum = 0
      label_sum = 0
      for i in range(input.shape[0]):
        for cl in range(self.num_classes):
          pred = input[i, cl, :, :]
          label = target[i, cl, :, :]
          intersection += (pred * label).sum()
          pred_sum += (pred * pred).sum()
          label_sum += (label * label).sum()
      total_loss = 1 - (2 * intersection)/(pred_sum + label_sum)
      return total_loss
```

2.2 Training Procedure (Segmentation)

[ ]:
```
## Initialize your unet
n_classes = 6
model = UNET(n_classes)

## Initialize Dataloaders
train_dataset=ImageDataset(input_dir=segmentation_data_dir, op="train",␣
 ↪mask_json_path=mask_json, transforms=img_transform)
validation_dataset=ImageDataset(input_dir=segmentation_data_dir, op="val",␣
 ↪mask_json_path=mask_json, transforms=img_transform)
test_dataset=ImageDataset(input_dir=segmentation_data_dir, op="test",␣
 ↪mask_json_path=mask_json, transforms=img_transform)
train_dataloader = DataLoader(train_dataset, batch_size=train_batch_size,␣
 ↪shuffle=True)
validation_dataloader = DataLoader(validation_dataset,␣
 ↪batch_size=validation_batch_size, shuffle=False)
test_dataloader = DataLoader(test_dataset, batch_size=1, shuffle=False)
## Initialize Optimizer and Learning Rate Scheduler
```

```
optimizer = torch.optim.Adam(model.parameters(),lr=learning_rate)
scheduler = torch.optim.lr_scheduler.StepLR(optimizer, step_size=10, gamma=0.1)
criterion = DICELoss(n_classes)
model = model.cuda()

# Define lists to store training and validation losses
train_losses = []
val_losses = []
test_score = []

print("Start Training...")
for epoch in range(num_epochs):
    ########################### Training #####################################
    print("\nEPOCH " +str(epoch+1)+" of "+str(num_epochs)+"\n")
    # TODO: Design your own training section
    model.train()
    train_loss = 0.0

    # Iterate through the training data
    for inputs, labels in train_dataloader:
      inputs = inputs.cuda()
      labels = labels.cuda()
      output = model.forward(inputs)
      loss = criterion.forward(output, labels)

      optimizer.zero_grad()
      loss.backward()
      optimizer.step()

      train_loss += loss.item()

    avg_train_loss = train_loss / len(train_dataloader)
    train_losses.append(avg_train_loss)

    ########################### Validation #####################################
    # TODO: Design your own validation section
    model.eval()
    val_loss = 0.0
    with torch.no_grad():
      for inputs, labels in validation_dataloader:
        inputs = inputs.cuda()
        labels = labels.cuda()
        output = model(inputs)
        loss = criterion.forward(output, labels)
        val_loss += loss.item()

    avg_val_loss = val_loss / len(validation_dataloader)
```

```
    val_losses.append(avg_val_loss)
    test_score_i = dice_score_dataset(model, test_dataloader, n_classes,␣
↪use_gpu=gpu_bool)
    test_score.append(test_score_i)
    scheduler.step()

    print(f'Epoch [{epoch+1}/{num_epochs}], Train Loss: {avg_train_loss:.4f},␣
↪Val Loss: {avg_val_loss:.4f}')
    print(f'Test Score: {test_score_i:.4f}')
```

```
Start Training…

EPOCH 1 of 100


/usr/local/lib/python3.10/dist-packages/torch/nn/modules/module.py:1518:
UserWarning: Implicit dimension choice for softmax has been deprecated. Change
the call to include dim=X as an argument.
  return self._call_impl(*args, **kwargs)

Epoch [1/100], Train Loss: 0.3988, Val Loss: 0.2168
Test Score: 0.5909

EPOCH 2 of 100

Epoch [2/100], Train Loss: 0.2262, Val Loss: 0.1446
Test Score: 0.6099

EPOCH 3 of 100

Epoch [3/100], Train Loss: 0.1499, Val Loss: 0.1124
Test Score: 0.5028

EPOCH 4 of 100

Epoch [4/100], Train Loss: 0.1098, Val Loss: 0.1014
Test Score: 0.5022

EPOCH 5 of 100

Epoch [5/100], Train Loss: 0.0947, Val Loss: 0.1183
Test Score: 0.5234

EPOCH 6 of 100

Epoch [6/100], Train Loss: 0.0824, Val Loss: 0.0766
Test Score: 0.4657
```

```
EPOCH 7 of 100

Epoch [7/100], Train Loss: 0.0756, Val Loss: 0.1432
Test Score: 0.3881

EPOCH 8 of 100

Epoch [8/100], Train Loss: 0.0725, Val Loss: 0.0766
Test Score: 0.5347

EPOCH 9 of 100

Epoch [9/100], Train Loss: 0.0698, Val Loss: 0.0696
Test Score: 0.5196

EPOCH 10 of 100

Epoch [10/100], Train Loss: 0.0650, Val Loss: 0.0701
Test Score: 0.5394

EPOCH 11 of 100

Epoch [11/100], Train Loss: 0.0599, Val Loss: 0.0613
Test Score: 0.5804

EPOCH 12 of 100

Epoch [12/100], Train Loss: 0.0593, Val Loss: 0.0591
Test Score: 0.5667

EPOCH 13 of 100

Epoch [13/100], Train Loss: 0.0575, Val Loss: 0.0580
Test Score: 0.6237

EPOCH 14 of 100

Epoch [14/100], Train Loss: 0.0572, Val Loss: 0.0571
Test Score: 0.6174

EPOCH 15 of 100

Epoch [15/100], Train Loss: 0.0549, Val Loss: 0.0566
Test Score: 0.6213

EPOCH 16 of 100

Epoch [16/100], Train Loss: 0.0574, Val Loss: 0.0581
```

```
Test Score: 0.6246

EPOCH 17 of 100

Epoch [17/100], Train Loss: 0.0554, Val Loss: 0.0550
Test Score: 0.6139

EPOCH 18 of 100

Epoch [18/100], Train Loss: 0.0543, Val Loss: 0.0549
Test Score: 0.6104

EPOCH 19 of 100

Epoch [19/100], Train Loss: 0.0534, Val Loss: 0.0578
Test Score: 0.6248

EPOCH 20 of 100

Epoch [20/100], Train Loss: 0.0535, Val Loss: 0.0541
Test Score: 0.6440

EPOCH 21 of 100

Epoch [21/100], Train Loss: 0.0500, Val Loss: 0.0524
Test Score: 0.6092

EPOCH 22 of 100

Epoch [22/100], Train Loss: 0.0506, Val Loss: 0.0522
Test Score: 0.6168

EPOCH 23 of 100

Epoch [23/100], Train Loss: 0.0506, Val Loss: 0.0524
Test Score: 0.6118

EPOCH 24 of 100

Epoch [24/100], Train Loss: 0.0512, Val Loss: 0.0524
Test Score: 0.6090

EPOCH 25 of 100

Epoch [25/100], Train Loss: 0.0519, Val Loss: 0.0522
Test Score: 0.6073

EPOCH 26 of 100
```

```
Epoch [26/100], Train Loss: 0.0517, Val Loss: 0.0522
Test Score: 0.6151

EPOCH 27 of 100

Epoch [27/100], Train Loss: 0.0492, Val Loss: 0.0522
Test Score: 0.6126

EPOCH 28 of 100

Epoch [28/100], Train Loss: 0.0525, Val Loss: 0.0521
Test Score: 0.6336

EPOCH 29 of 100

Epoch [29/100], Train Loss: 0.0493, Val Loss: 0.0517
Test Score: 0.6029

EPOCH 30 of 100

Epoch [30/100], Train Loss: 0.0505, Val Loss: 0.0519
Test Score: 0.6064

EPOCH 31 of 100

Epoch [31/100], Train Loss: 0.0493, Val Loss: 0.0517
Test Score: 0.6055

EPOCH 32 of 100

Epoch [32/100], Train Loss: 0.0491, Val Loss: 0.0521
Test Score: 0.6006

EPOCH 33 of 100

Epoch [33/100], Train Loss: 0.0510, Val Loss: 0.0520
Test Score: 0.6035

EPOCH 34 of 100

Epoch [34/100], Train Loss: 0.0491, Val Loss: 0.0520
Test Score: 0.6163

EPOCH 35 of 100

Epoch [35/100], Train Loss: 0.0495, Val Loss: 0.0519
Test Score: 0.6002
```

```
EPOCH 36 of 100

Epoch [36/100], Train Loss: 0.0520, Val Loss: 0.0516
Test Score: 0.6207

EPOCH 37 of 100

Epoch [37/100], Train Loss: 0.0504, Val Loss: 0.0517
Test Score: 0.6203

EPOCH 38 of 100

Epoch [38/100], Train Loss: 0.0512, Val Loss: 0.0517
Test Score: 0.6033

EPOCH 39 of 100

Epoch [39/100], Train Loss: 0.0517, Val Loss: 0.0517
Test Score: 0.6101

EPOCH 40 of 100

Epoch [40/100], Train Loss: 0.0504, Val Loss: 0.0518
Test Score: 0.5999

EPOCH 41 of 100

Epoch [41/100], Train Loss: 0.0510, Val Loss: 0.0519
Test Score: 0.6155

EPOCH 42 of 100

Epoch [42/100], Train Loss: 0.0497, Val Loss: 0.0515
Test Score: 0.6091

EPOCH 43 of 100

Epoch [43/100], Train Loss: 0.0501, Val Loss: 0.0521
Test Score: 0.5959

EPOCH 44 of 100

Epoch [44/100], Train Loss: 0.0508, Val Loss: 0.0521
Test Score: 0.6036

EPOCH 45 of 100
```

```
Epoch [45/100], Train Loss: 0.0494, Val Loss: 0.0517
Test Score: 0.5968

EPOCH 46 of 100

Epoch [46/100], Train Loss: 0.0503, Val Loss: 0.0518
Test Score: 0.5967

EPOCH 47 of 100

Epoch [47/100], Train Loss: 0.0504, Val Loss: 0.0517
Test Score: 0.6138

EPOCH 48 of 100

Epoch [48/100], Train Loss: 0.0503, Val Loss: 0.0518
Test Score: 0.6032

EPOCH 49 of 100

Epoch [49/100], Train Loss: 0.0492, Val Loss: 0.0517
Test Score: 0.6034

EPOCH 50 of 100

Epoch [50/100], Train Loss: 0.0492, Val Loss: 0.0519
Test Score: 0.6073

EPOCH 51 of 100

Epoch [51/100], Train Loss: 0.0507, Val Loss: 0.0518
Test Score: 0.5897

EPOCH 52 of 100

Epoch [52/100], Train Loss: 0.0490, Val Loss: 0.0518
Test Score: 0.6003

EPOCH 53 of 100

Epoch [53/100], Train Loss: 0.0504, Val Loss: 0.0516
Test Score: 0.6128

EPOCH 54 of 100

Epoch [54/100], Train Loss: 0.0497, Val Loss: 0.0517
Test Score: 0.6129
```

```
EPOCH 55 of 100

Epoch [55/100], Train Loss: 0.0509, Val Loss: 0.0517
Test Score: 0.6064

EPOCH 56 of 100

Epoch [56/100], Train Loss: 0.0503, Val Loss: 0.0516
Test Score: 0.6030

EPOCH 57 of 100

Epoch [57/100], Train Loss: 0.0506, Val Loss: 0.0517
Test Score: 0.6030

EPOCH 58 of 100

Epoch [58/100], Train Loss: 0.0500, Val Loss: 0.0517
Test Score: 0.6060

EPOCH 59 of 100

Epoch [59/100], Train Loss: 0.0517, Val Loss: 0.0516
Test Score: 0.6092

EPOCH 60 of 100

Epoch [60/100], Train Loss: 0.0502, Val Loss: 0.0516
Test Score: 0.6093

EPOCH 61 of 100

Epoch [61/100], Train Loss: 0.0497, Val Loss: 0.0515
Test Score: 0.6122

EPOCH 62 of 100

Epoch [62/100], Train Loss: 0.0500, Val Loss: 0.0518
Test Score: 0.6133

EPOCH 63 of 100

Epoch [63/100], Train Loss: 0.0498, Val Loss: 0.0519
Test Score: 0.5969

EPOCH 64 of 100

Epoch [64/100], Train Loss: 0.0504, Val Loss: 0.0518
```

```
Test Score: 0.6036

EPOCH 65 of 100

Epoch [65/100], Train Loss: 0.0500, Val Loss: 0.0519
Test Score: 0.6131

EPOCH 66 of 100

Epoch [66/100], Train Loss: 0.0489, Val Loss: 0.0518
Test Score: 0.6069

EPOCH 67 of 100

Epoch [67/100], Train Loss: 0.0491, Val Loss: 0.0518
Test Score: 0.6035

EPOCH 68 of 100

Epoch [68/100], Train Loss: 0.0504, Val Loss: 0.0517
Test Score: 0.6063

EPOCH 69 of 100

Epoch [69/100], Train Loss: 0.0508, Val Loss: 0.0519
Test Score: 0.5964

EPOCH 70 of 100

Epoch [70/100], Train Loss: 0.0496, Val Loss: 0.0516
Test Score: 0.6061

EPOCH 71 of 100

Epoch [71/100], Train Loss: 0.0498, Val Loss: 0.0517
Test Score: 0.5927

EPOCH 72 of 100

Epoch [72/100], Train Loss: 0.0488, Val Loss: 0.0518
Test Score: 0.6033

EPOCH 73 of 100

Epoch [73/100], Train Loss: 0.0505, Val Loss: 0.0519
Test Score: 0.6311

EPOCH 74 of 100
```

```
Epoch [74/100], Train Loss: 0.0498, Val Loss: 0.0519
Test Score: 0.6003

EPOCH 75 of 100

Epoch [75/100], Train Loss: 0.0500, Val Loss: 0.0519
Test Score: 0.5967

EPOCH 76 of 100

Epoch [76/100], Train Loss: 0.0510, Val Loss: 0.0518
Test Score: 0.6031

EPOCH 77 of 100

Epoch [77/100], Train Loss: 0.0521, Val Loss: 0.0517
Test Score: 0.6031

EPOCH 78 of 100

Epoch [78/100], Train Loss: 0.0506, Val Loss: 0.0520
Test Score: 0.6076

EPOCH 79 of 100

Epoch [79/100], Train Loss: 0.0494, Val Loss: 0.0519
Test Score: 0.6005

EPOCH 80 of 100

Epoch [80/100], Train Loss: 0.0519, Val Loss: 0.0516
Test Score: 0.6126

EPOCH 81 of 100

Epoch [81/100], Train Loss: 0.0505, Val Loss: 0.0519
Test Score: 0.6056

EPOCH 82 of 100

Epoch [82/100], Train Loss: 0.0493, Val Loss: 0.0518
Test Score: 0.6069

EPOCH 83 of 100

Epoch [83/100], Train Loss: 0.0512, Val Loss: 0.0517
Test Score: 0.6065
```

```
EPOCH 84 of 100

Epoch [84/100], Train Loss: 0.0507, Val Loss: 0.0517
Test Score: 0.6032

EPOCH 85 of 100

Epoch [85/100], Train Loss: 0.0507, Val Loss: 0.0517
Test Score: 0.6037

EPOCH 86 of 100

Epoch [86/100], Train Loss: 0.0504, Val Loss: 0.0519
Test Score: 0.6106

EPOCH 87 of 100

Epoch [87/100], Train Loss: 0.0503, Val Loss: 0.0519
Test Score: 0.6068

EPOCH 88 of 100

Epoch [88/100], Train Loss: 0.0499, Val Loss: 0.0523
Test Score: 0.6107

EPOCH 89 of 100

Epoch [89/100], Train Loss: 0.0494, Val Loss: 0.0516
Test Score: 0.6187

EPOCH 90 of 100

Epoch [90/100], Train Loss: 0.0499, Val Loss: 0.0517
Test Score: 0.6035

EPOCH 91 of 100

Epoch [91/100], Train Loss: 0.0503, Val Loss: 0.0516
Test Score: 0.6124

EPOCH 92 of 100

Epoch [92/100], Train Loss: 0.0500, Val Loss: 0.0516
Test Score: 0.5962

EPOCH 93 of 100
```

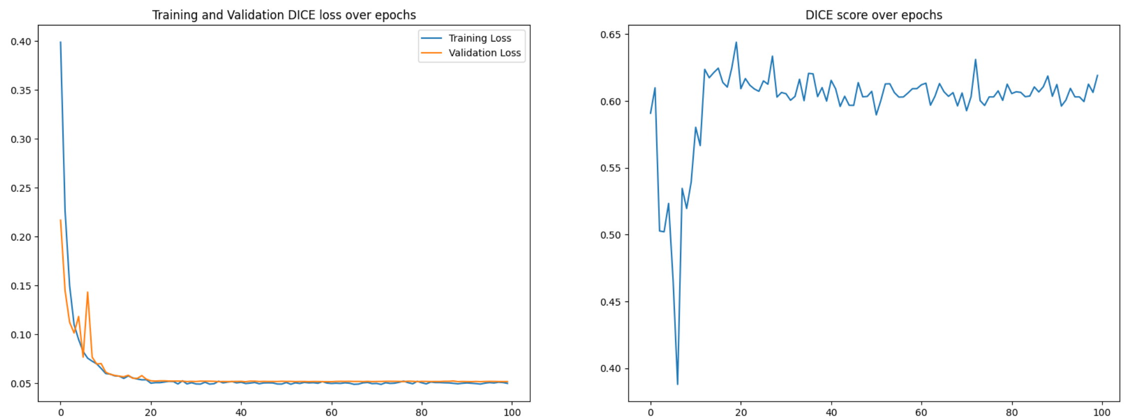
```
Epoch [93/100], Train Loss: 0.0496, Val Loss: 0.0518
Test Score: 0.6007

EPOCH 94 of 100

Epoch [94/100], Train Loss: 0.0492, Val Loss: 0.0516
Test Score: 0.6095

EPOCH 95 of 100

Epoch [95/100], Train Loss: 0.0501, Val Loss: 0.0517
Test Score: 0.6031

EPOCH 96 of 100

Epoch [96/100], Train Loss: 0.0507, Val Loss: 0.0518
Test Score: 0.6031

EPOCH 97 of 100

Epoch [97/100], Train Loss: 0.0502, Val Loss: 0.0518
Test Score: 0.5996

EPOCH 98 of 100

Epoch [98/100], Train Loss: 0.0511, Val Loss: 0.0517
Test Score: 0.6126

EPOCH 99 of 100

Epoch [99/100], Train Loss: 0.0507, Val Loss: 0.0516
Test Score: 0.6065

EPOCH 100 of 100

Epoch [100/100], Train Loss: 0.0498, Val Loss: 0.0516
Test Score: 0.6192
```

[ ]:
```
max_score = max(test_score)
max_score_idx = test_score.index(max_score)
print(f'At Epoch {max_score_idx}, Test DICE score reaches its max as: 
 ↪{max_score:.4f}')
```

```
At Epoch 19, Test DICE score reaches its max as: 0.6440
```

[ ]:
```
# Graph
fig, axs = plt.subplots(1, 2,figsize=(20, 7))
```

```
axs[0].plot(range(num_epochs), train_losses)
axs[0].plot(range(num_epochs), val_losses)
axs[0].legend(['Training Loss', 'Validation Loss'])
axs[0].set_title('Training and Validation DICE loss over epochs')

axs[1].plot(range(num_epochs), test_score)
axs[1].set_title('DICE score over epochs')

plt.show()
```



2.3 Data Augmentation

[ ]:
```
## Augmented Image Transforms
augmented_transform = transforms.Compose([
        transforms.ToTensor(),
        transforms.RandomHorizontalFlip(),
        transforms.RandomVerticalFlip(),
])
```

[ ]:
```
## Initialize your unet
n_classes = 6
model = UNET(n_classes)

## Initialize Dataloaders
train_dataset=ImageDataset(input_dir=segmentation_data_dir, op="train",
 ↪mask_json_path=mask_json, transforms=augmented_transform)
validation_dataset=ImageDataset(input_dir=segmentation_data_dir, op="val",
 ↪mask_json_path=mask_json, transforms=img_transform)
test_dataset=ImageDataset(input_dir=segmentation_data_dir, op="test",
 ↪mask_json_path=mask_json, transforms=img_transform)
```

```python
train_dataloader = DataLoader(train_dataset, batch_size=train_batch_size,␣
↪shuffle=True)
validation_dataloader = DataLoader(validation_dataset,␣
↪batch_size=validation_batch_size, shuffle=False)
test_dataloader = DataLoader(test_dataset, batch_size=1, shuffle=False)
## Initialize Optimizer and Learning Rate Scheduler
optimizer = torch.optim.Adam(model.parameters(),lr=learning_rate)
scheduler = torch.optim.lr_scheduler.StepLR(optimizer, step_size=10, gamma=0.1)
criterion = DICELoss(n_classes)
model = model.cuda()

# Define lists to store training and validation losses
train_losses = []
val_losses = []
test_score = []

print("Start Training...")
for epoch in range(num_epochs):
    ########################### Training ####################################
    print("\nEPOCH " +str(epoch+1)+" of "+str(num_epochs)+"\n")
    # TODO: Design your own training section
    model.train()
    train_loss = 0.0

    # Iterate through the training data
    for inputs, labels in train_dataloader:
      # Forward pass
      inputs = inputs.cuda()
      labels = labels.cuda()
      output = model.forward(inputs)

      # Compute loss
      loss = criterion.forward(output, labels)

      # Backpropagation
      optimizer.zero_grad()  # Zero the gradients
      loss.backward()
      optimizer.step()

    # Update running training loss
      train_loss += loss.item()

    # Compute average training loss for the epoch
    avg_train_loss = train_loss / len(train_dataloader)
    train_losses.append(avg_train_loss)

    ########################### Validation #####################################
```

```
    # TODO: Design your own validation section
    model.eval()
    val_loss = 0.0
    with torch.no_grad():
      for inputs, labels in validation_dataloader:
        if gpu_bool:
          inputs = inputs.cuda()
          labels = labels.cuda()
        output = model(inputs)
        loss = criterion.forward(output, labels)
        val_loss += loss.item()

    avg_val_loss = val_loss / len(validation_dataloader)
    val_losses.append(avg_val_loss)

    ########################### Test ######################################
    test_score_i = dice_score_dataset(model, test_dataloader, n_classes,␣
↪use_gpu=gpu_bool)
    test_score.append(test_score_i)
    scheduler.step()

    print(f'Epoch [{epoch+1}/{num_epochs}], Train Loss: {avg_train_loss:.4f},␣
↪Val Loss: {avg_val_loss:.4f}')
    print(f'Test Score: {test_score_i:.4f}')
```

```
Start Training…

EPOCH 1 of 100

Epoch [1/100], Train Loss: 0.5144, Val Loss: 0.3952
Test Score: 0.3992

EPOCH 2 of 100

Epoch [2/100], Train Loss: 0.3254, Val Loss: 0.3205
Test Score: 0.2604

EPOCH 3 of 100

Epoch [3/100], Train Loss: 0.2249, Val Loss: 0.2182
Test Score: 0.5009

EPOCH 4 of 100

Epoch [4/100], Train Loss: 0.1820, Val Loss: 0.1834
Test Score: 0.5757
```

```
EPOCH 5 of 100

Epoch [5/100], Train Loss: 0.1600, Val Loss: 0.1823
Test Score: 0.3985

EPOCH 6 of 100

Epoch [6/100], Train Loss: 0.1547, Val Loss: 0.1637
Test Score: 0.6829

EPOCH 7 of 100

Epoch [7/100], Train Loss: 0.1480, Val Loss: 0.1847
Test Score: 0.5854

EPOCH 8 of 100

Epoch [8/100], Train Loss: 0.1455, Val Loss: 0.1583
Test Score: 0.6540

EPOCH 9 of 100

Epoch [9/100], Train Loss: 0.1440, Val Loss: 0.1566
Test Score: 0.6669

EPOCH 10 of 100

Epoch [10/100], Train Loss: 0.1421, Val Loss: 0.1551
Test Score: 0.6559

EPOCH 11 of 100

Epoch [11/100], Train Loss: 0.1406, Val Loss: 0.1518
Test Score: 0.6799

EPOCH 12 of 100

Epoch [12/100], Train Loss: 0.1410, Val Loss: 0.1542
Test Score: 0.6701

EPOCH 13 of 100

Epoch [13/100], Train Loss: 0.1406, Val Loss: 0.1553
Test Score: 0.6701

EPOCH 14 of 100

Epoch [14/100], Train Loss: 0.1391, Val Loss: 0.1520
```

```
Test Score: 0.6600

EPOCH 15 of 100

Epoch [15/100], Train Loss: 0.1411, Val Loss: 0.1574
Test Score: 0.6703

EPOCH 16 of 100

Epoch [16/100], Train Loss: 0.1394, Val Loss: 0.1548
Test Score: 0.6677

EPOCH 17 of 100

Epoch [17/100], Train Loss: 0.1405, Val Loss: 0.1509
Test Score: 0.6734

EPOCH 18 of 100

Epoch [18/100], Train Loss: 0.1376, Val Loss: 0.1555
Test Score: 0.6511

EPOCH 19 of 100

Epoch [19/100], Train Loss: 0.1415, Val Loss: 0.1554
Test Score: 0.6798

EPOCH 20 of 100

Epoch [20/100], Train Loss: 0.1419, Val Loss: 0.1535
Test Score: 0.6235

EPOCH 21 of 100

Epoch [21/100], Train Loss: 0.1404, Val Loss: 0.1539
Test Score: 0.6333

EPOCH 22 of 100

Epoch [22/100], Train Loss: 0.1391, Val Loss: 0.1536
Test Score: 0.6467

EPOCH 23 of 100

Epoch [23/100], Train Loss: 0.1399, Val Loss: 0.1486
Test Score: 0.6483

EPOCH 24 of 100
```

```
Epoch [24/100], Train Loss: 0.1394, Val Loss: 0.1604
Test Score: 0.6679

EPOCH 25 of 100

Epoch [25/100], Train Loss: 0.1410, Val Loss: 0.1508
Test Score: 0.6680

EPOCH 26 of 100

Epoch [26/100], Train Loss: 0.1404, Val Loss: 0.1492
Test Score: 0.6580

EPOCH 27 of 100

Epoch [27/100], Train Loss: 0.1385, Val Loss: 0.1520
Test Score: 0.6566

EPOCH 28 of 100

Epoch [28/100], Train Loss: 0.1395, Val Loss: 0.1549
Test Score: 0.6643

EPOCH 29 of 100

Epoch [29/100], Train Loss: 0.1402, Val Loss: 0.1514
Test Score: 0.6641

EPOCH 30 of 100

Epoch [30/100], Train Loss: 0.1392, Val Loss: 0.1567
Test Score: 0.6673

EPOCH 31 of 100

Epoch [31/100], Train Loss: 0.1393, Val Loss: 0.1559
Test Score: 0.6536

EPOCH 32 of 100

Epoch [32/100], Train Loss: 0.1406, Val Loss: 0.1524
Test Score: 0.6635

EPOCH 33 of 100

Epoch [33/100], Train Loss: 0.1373, Val Loss: 0.1540
Test Score: 0.6704
```

```
EPOCH 34 of 100

Epoch [34/100], Train Loss: 0.1403, Val Loss: 0.1515
Test Score: 0.6732

EPOCH 35 of 100

Epoch [35/100], Train Loss: 0.1398, Val Loss: 0.1504
Test Score: 0.6767

EPOCH 36 of 100

Epoch [36/100], Train Loss: 0.1394, Val Loss: 0.1508
Test Score: 0.6602

EPOCH 37 of 100

Epoch [37/100], Train Loss: 0.1387, Val Loss: 0.1566
Test Score: 0.6700

EPOCH 38 of 100

Epoch [38/100], Train Loss: 0.1378, Val Loss: 0.1513
Test Score: 0.6673

EPOCH 39 of 100

Epoch [39/100], Train Loss: 0.1391, Val Loss: 0.1492
Test Score: 0.6701

EPOCH 40 of 100

Epoch [40/100], Train Loss: 0.1400, Val Loss: 0.1471
Test Score: 0.6665

EPOCH 41 of 100

Epoch [41/100], Train Loss: 0.1400, Val Loss: 0.1502
Test Score: 0.6666

EPOCH 42 of 100

Epoch [42/100], Train Loss: 0.1390, Val Loss: 0.1584
Test Score: 0.6598

EPOCH 43 of 100
```

```
Epoch [43/100], Train Loss: 0.1407, Val Loss: 0.1563
Test Score: 0.6697

EPOCH 44 of 100

Epoch [44/100], Train Loss: 0.1399, Val Loss: 0.1576
Test Score: 0.6644

EPOCH 45 of 100

Epoch [45/100], Train Loss: 0.1407, Val Loss: 0.1572
Test Score: 0.6698

EPOCH 46 of 100

Epoch [46/100], Train Loss: 0.1395, Val Loss: 0.1528
Test Score: 0.6636

EPOCH 47 of 100

Epoch [47/100], Train Loss: 0.1381, Val Loss: 0.1553
Test Score: 0.6705

EPOCH 48 of 100

Epoch [48/100], Train Loss: 0.1390, Val Loss: 0.1507
Test Score: 0.6675

EPOCH 49 of 100

Epoch [49/100], Train Loss: 0.1391, Val Loss: 0.1515
Test Score: 0.6636

EPOCH 50 of 100

Epoch [50/100], Train Loss: 0.1391, Val Loss: 0.1516
Test Score: 0.6669

EPOCH 51 of 100

Epoch [51/100], Train Loss: 0.1384, Val Loss: 0.1549
Test Score: 0.6653

EPOCH 52 of 100

Epoch [52/100], Train Loss: 0.1398, Val Loss: 0.1525
Test Score: 0.6634
```

```
EPOCH 53 of 100

Epoch [53/100], Train Loss: 0.1402, Val Loss: 0.1559
Test Score: 0.6641

EPOCH 54 of 100

Epoch [54/100], Train Loss: 0.1392, Val Loss: 0.1510
Test Score: 0.6606

EPOCH 55 of 100

Epoch [55/100], Train Loss: 0.1386, Val Loss: 0.1508
Test Score: 0.6715

EPOCH 56 of 100

Epoch [56/100], Train Loss: 0.1395, Val Loss: 0.1475
Test Score: 0.6668

EPOCH 57 of 100

Epoch [57/100], Train Loss: 0.1377, Val Loss: 0.1540
Test Score: 0.6580

EPOCH 58 of 100

Epoch [58/100], Train Loss: 0.1399, Val Loss: 0.1584
Test Score: 0.6643

EPOCH 59 of 100

Epoch [59/100], Train Loss: 0.1383, Val Loss: 0.1559
Test Score: 0.6629

EPOCH 60 of 100

Epoch [60/100], Train Loss: 0.1372, Val Loss: 0.1537
Test Score: 0.6566

EPOCH 61 of 100

Epoch [61/100], Train Loss: 0.1401, Val Loss: 0.1567
Test Score: 0.6570

EPOCH 62 of 100

Epoch [62/100], Train Loss: 0.1400, Val Loss: 0.1546
```

```
Test Score: 0.6709

EPOCH 63 of 100

Epoch [63/100], Train Loss: 0.1398, Val Loss: 0.1536
Test Score: 0.6732

EPOCH 64 of 100

Epoch [64/100], Train Loss: 0.1411, Val Loss: 0.1531
Test Score: 0.6607

EPOCH 65 of 100

Epoch [65/100], Train Loss: 0.1378, Val Loss: 0.1501
Test Score: 0.6703

EPOCH 66 of 100

Epoch [66/100], Train Loss: 0.1383, Val Loss: 0.1531
Test Score: 0.6677

EPOCH 67 of 100

Epoch [67/100], Train Loss: 0.1385, Val Loss: 0.1567
Test Score: 0.6700

EPOCH 68 of 100

Epoch [68/100], Train Loss: 0.1385, Val Loss: 0.1506
Test Score: 0.6638

EPOCH 69 of 100

Epoch [69/100], Train Loss: 0.1403, Val Loss: 0.1521
Test Score: 0.6678

EPOCH 70 of 100

Epoch [70/100], Train Loss: 0.1395, Val Loss: 0.1505
Test Score: 0.6603

EPOCH 71 of 100

Epoch [71/100], Train Loss: 0.1380, Val Loss: 0.1543
Test Score: 0.6596

EPOCH 72 of 100
```

```
Epoch [72/100], Train Loss: 0.1396, Val Loss: 0.1556
Test Score: 0.6636

EPOCH 73 of 100

Epoch [73/100], Train Loss: 0.1384, Val Loss: 0.1587
Test Score: 0.6675

EPOCH 74 of 100

Epoch [74/100], Train Loss: 0.1374, Val Loss: 0.1495
Test Score: 0.6533

EPOCH 75 of 100

Epoch [75/100], Train Loss: 0.1387, Val Loss: 0.1508
Test Score: 0.6669

EPOCH 76 of 100

Epoch [76/100], Train Loss: 0.1403, Val Loss: 0.1502
Test Score: 0.6702

EPOCH 77 of 100

Epoch [77/100], Train Loss: 0.1405, Val Loss: 0.1523
Test Score: 0.6467

EPOCH 78 of 100

Epoch [78/100], Train Loss: 0.1384, Val Loss: 0.1482
Test Score: 0.6610

EPOCH 79 of 100

Epoch [79/100], Train Loss: 0.1393, Val Loss: 0.1573
Test Score: 0.6650

EPOCH 80 of 100

Epoch [80/100], Train Loss: 0.1385, Val Loss: 0.1554
Test Score: 0.6576

EPOCH 81 of 100

Epoch [81/100], Train Loss: 0.1386, Val Loss: 0.1518
Test Score: 0.6704
```

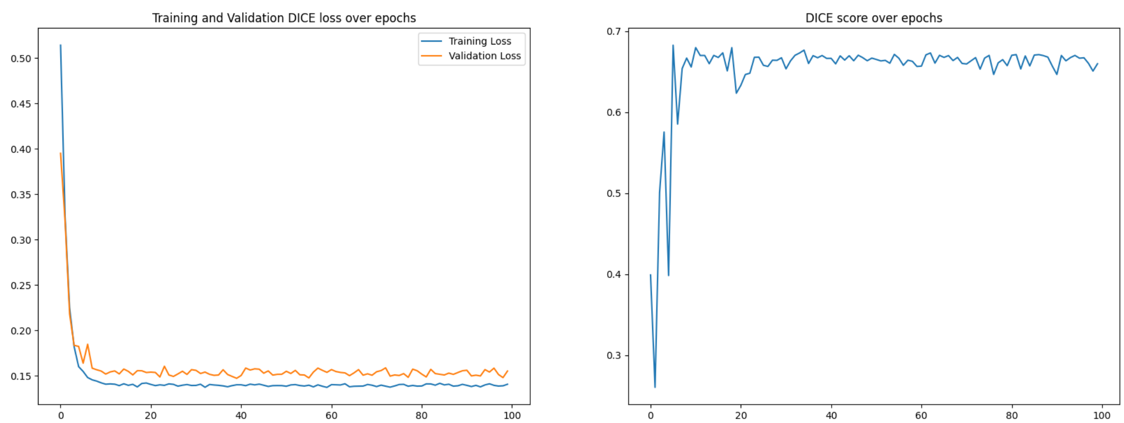
```
EPOCH 82 of 100

Epoch [82/100], Train Loss: 0.1410, Val Loss: 0.1486
Test Score: 0.6712

EPOCH 83 of 100

Epoch [83/100], Train Loss: 0.1409, Val Loss: 0.1570
Test Score: 0.6535

EPOCH 84 of 100

Epoch [84/100], Train Loss: 0.1395, Val Loss: 0.1523
Test Score: 0.6696

EPOCH 85 of 100

Epoch [85/100], Train Loss: 0.1416, Val Loss: 0.1516
Test Score: 0.6572

EPOCH 86 of 100

Epoch [86/100], Train Loss: 0.1398, Val Loss: 0.1508
Test Score: 0.6706

EPOCH 87 of 100

Epoch [87/100], Train Loss: 0.1406, Val Loss: 0.1528
Test Score: 0.6712

EPOCH 88 of 100

Epoch [88/100], Train Loss: 0.1385, Val Loss: 0.1515
Test Score: 0.6700

EPOCH 89 of 100

Epoch [89/100], Train Loss: 0.1389, Val Loss: 0.1535
Test Score: 0.6681

EPOCH 90 of 100

Epoch [90/100], Train Loss: 0.1404, Val Loss: 0.1554
Test Score: 0.6569

EPOCH 91 of 100
```

```
Epoch [91/100], Train Loss: 0.1394, Val Loss: 0.1560
Test Score: 0.6467

EPOCH 92 of 100

Epoch [92/100], Train Loss: 0.1380, Val Loss: 0.1498
Test Score: 0.6702

EPOCH 93 of 100

Epoch [93/100], Train Loss: 0.1394, Val Loss: 0.1506
Test Score: 0.6635

EPOCH 94 of 100

Epoch [94/100], Train Loss: 0.1377, Val Loss: 0.1497
Test Score: 0.6675

EPOCH 95 of 100

Epoch [95/100], Train Loss: 0.1398, Val Loss: 0.1567
Test Score: 0.6702

EPOCH 96 of 100

Epoch [96/100], Train Loss: 0.1411, Val Loss: 0.1540
Test Score: 0.6668

EPOCH 97 of 100

Epoch [97/100], Train Loss: 0.1394, Val Loss: 0.1583
Test Score: 0.6673

EPOCH 98 of 100

Epoch [98/100], Train Loss: 0.1386, Val Loss: 0.1513
Test Score: 0.6604

EPOCH 99 of 100

Epoch [99/100], Train Loss: 0.1389, Val Loss: 0.1479
Test Score: 0.6509

EPOCH 100 of 100

Epoch [100/100], Train Loss: 0.1406, Val Loss: 0.1552
Test Score: 0.6599
```

[ ]:
```
max_score = max(test_score)
max_score_idx = test_score.index(max_score)
print(f'At Epoch {max_score_idx}, Test DICE score reaches its max as:␣
  ↪{max_score:.4f}')
```

```
At Epoch 75, Test DICE score reaches its max as: 0.6831
```

[ ]:
```
# Graph
fig, axs = plt.subplots(1, 2,figsize=(20, 7))

axs[0].plot(range(num_epochs), train_losses)
axs[0].plot(range(num_epochs), val_losses)
axs[0].legend(['Training Loss', 'Validation Loss'])
axs[0].set_title('Training and Validation DICE loss over epochs')

axs[1].plot(range(num_epochs), test_score)
axs[1].set_title('DICE score over epochs')

plt.show()
```



2.4 Training Procedure: Colorization Pre-training

Complete the rest of this problem in the cells below.

[ ]:
```
## Batch Size
train_batch_size = 10
validation_batch_size = 10

## Learning Rate|
learning_rate = 0.001

# Epochs (Consider setting high and implementing early stopping)
num_epochs = 50
```

```
[ ]: ## Augmented Image Transforms
augmented_transform = transforms.Compose([
        transforms.ToTensor(),
        transforms.RandomHorizontalFlip(),
        transforms.RandomVerticalFlip(),
])
## Image Dataloader
class ColorDataset(Dataset):

    """
    ImageDataset
    """

    def __init__(self,
                 input_dir,
                 op,
                 transforms=None):
        """
        ##TODO: Add support for colorization dataset

        Args:
            input_dir (str): Path to either colorization or segmentation␣
 ↪directory
            op (str): One of "train", "val", or "test" signifying the desired␣
 ↪split
            transforms (list or None): Image transformations to apply upon␣
 ↪loading.
        """
        self.transform = transforms
        self.op = op
        # Get directories
        try:
            if self.op == 'train':
                self.data_dir = os.path.join(input_dir, 'train_cor')
            elif self.op == 'val':
                self.data_dir = os.path.join(input_dir, 'validation_cor')
        except ValueError:
            print('op should be either train or val!')

    def __len__(self):
        """

        """
        return len(next(os.walk(self.data_dir))[1])-1

    def __getitem__(self,
                    idx):
```

```
        """

        """
        ## Load Image and Parse Properties
        idx = idx + 1
        img_name = str(idx) + '_gray.jpg'
        mask_name = str(idx) + '_input.jpg'
        img = io.imread(os.path.join(self.data_dir, str(idx), img_name))
        mask = io.imread(os.path.join(self.data_dir, str(idx), mask_name))
        if self.transform:
            img, mask = self.img_transform(img, mask)
        return img, mask

    def img_transform(self,
                      img,
                      mask):
        """

        """
        ## Apply Transformations to Image and Mask
        img = self.transform(img)
        mask = self.transform(mask)
        img = img.repeat(3,1,1)
        return img, mask
```

[ ]:
```
## Initialize your unet
n_classes = 3
model = UNET(n_classes)

## Initialize Dataloaders
train_dataset=ColorDataset(input_dir=colorization_data_dir, op="train",␣
 ↪transforms=augmented_transform)
validation_dataset=ColorDataset(input_dir=colorization_data_dir, op="val",␣
 ↪transforms=img_transform)
train_dataloader = DataLoader(train_dataset, batch_size=train_batch_size,␣
 ↪shuffle=True)
validation_dataloader = DataLoader(validation_dataset,␣
 ↪batch_size=validation_batch_size, shuffle=False)
## Initialize Optimizer and Learning Rate Scheduler
optimizer = torch.optim.Adam(model.parameters(),lr=learning_rate)
scheduler = torch.optim.lr_scheduler.StepLR(optimizer, step_size=10, gamma=0.1)
criterion = nn.MSELoss()
gpu_bool = torch.cuda.is_available()
if gpu_bool:
  model = model.cuda()

# Define lists to store training and validation losses
```

```python
train_losses = []
val_losses = []

print("Start Training...")
for epoch in range(num_epochs):
    ########################### Training #####################################
    print("\nEPOCH " +str(epoch+1)+" of "+str(num_epochs)+"\n")
    # TODO: Design your own training section
    model.train()
    train_loss = 0.0

    # Iterate through the training data
    for inputs, labels in train_dataloader:

      # Forward pass
      if gpu_bool:
        inputs = inputs.cuda()
        labels = labels.cuda()
      output = model.forward(inputs)

      # Compute loss
      loss = criterion.forward(output, labels)

      # Backpropagation
      optimizer.zero_grad()  # Zero the gradients
      loss.backward()
      optimizer.step()

      # Update running training loss
      train_loss += loss.item()

    # Compute average training loss for the epoch
    avg_train_loss = train_loss / len(train_dataloader)
    train_losses.append(avg_train_loss)

    ########################### Validation ###################################
    # TODO: Design your own validation section
    model.eval()
    val_loss = 0.0
    with torch.no_grad():
      for inputs, labels in validation_dataloader:
        if gpu_bool:
          inputs = inputs.cuda()
          labels = labels.cuda()
        output = model(inputs)
        loss = criterion.forward(output, labels)
        val_loss += loss.item()
```

```python
    avg_val_loss = val_loss / len(validation_dataloader)
    val_losses.append(avg_val_loss)
    scheduler.step()

    print(f'Epoch [{epoch+1}/{num_epochs}], Train Loss: {avg_train_loss:.4f},␣
↪Val Loss: {avg_val_loss:.4f}')
```

```
Start Training…

EPOCH 1 of 50

Epoch [1/50], Train Loss: 0.0356, Val Loss: 0.0290

EPOCH 2 of 50

Epoch [2/50], Train Loss: 0.0353, Val Loss: 0.0286

EPOCH 3 of 50

Epoch [3/50], Train Loss: 0.0353, Val Loss: 0.0287

EPOCH 4 of 50

Epoch [4/50], Train Loss: 0.0353, Val Loss: 0.0290

EPOCH 5 of 50

Epoch [5/50], Train Loss: 0.0352, Val Loss: 0.0294

EPOCH 6 of 50

Epoch [6/50], Train Loss: 0.0352, Val Loss: 0.0288

EPOCH 7 of 50

Epoch [7/50], Train Loss: 0.0352, Val Loss: 0.0288

EPOCH 8 of 50

Epoch [8/50], Train Loss: 0.0352, Val Loss: 0.0288

EPOCH 9 of 50

Epoch [9/50], Train Loss: 0.0352, Val Loss: 0.0287

EPOCH 10 of 50
```

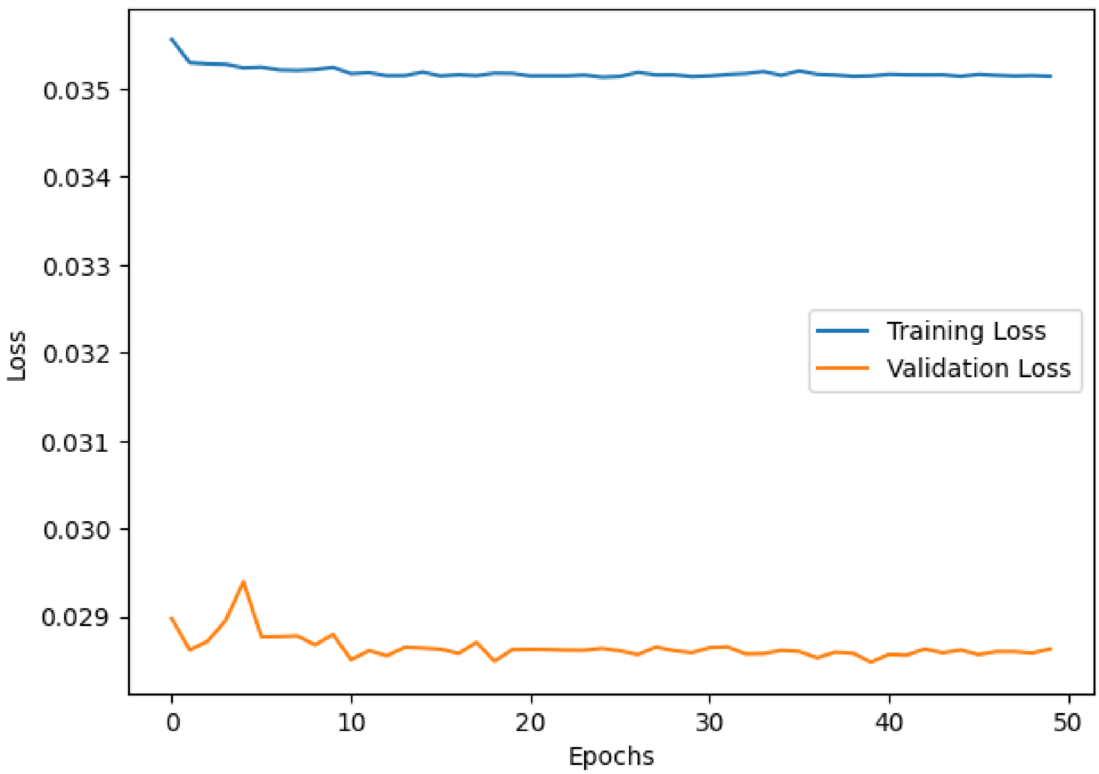
```
Epoch [10/50], Train Loss: 0.0352, Val Loss: 0.0288

EPOCH 11 of 50

Epoch [11/50], Train Loss: 0.0352, Val Loss: 0.0285

EPOCH 12 of 50

Epoch [12/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 13 of 50

Epoch [13/50], Train Loss: 0.0351, Val Loss: 0.0286

EPOCH 14 of 50

Epoch [14/50], Train Loss: 0.0351, Val Loss: 0.0286

EPOCH 15 of 50

Epoch [15/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 16 of 50

Epoch [16/50], Train Loss: 0.0351, Val Loss: 0.0286

EPOCH 17 of 50

Epoch [17/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 18 of 50

Epoch [18/50], Train Loss: 0.0351, Val Loss: 0.0287

EPOCH 19 of 50

Epoch [19/50], Train Loss: 0.0352, Val Loss: 0.0285

EPOCH 20 of 50

Epoch [20/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 21 of 50

Epoch [21/50], Train Loss: 0.0351, Val Loss: 0.0286

EPOCH 22 of 50
```

```
Epoch [22/50], Train Loss: 0.0351, Val Loss: 0.0286

EPOCH 23 of 50

Epoch [23/50], Train Loss: 0.0351, Val Loss: 0.0286

EPOCH 24 of 50

Epoch [24/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 25 of 50

Epoch [25/50], Train Loss: 0.0351, Val Loss: 0.0286

EPOCH 26 of 50

Epoch [26/50], Train Loss: 0.0351, Val Loss: 0.0286

EPOCH 27 of 50

Epoch [27/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 28 of 50

Epoch [28/50], Train Loss: 0.0352, Val Loss: 0.0287

EPOCH 29 of 50

Epoch [29/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 30 of 50

Epoch [30/50], Train Loss: 0.0351, Val Loss: 0.0286

EPOCH 31 of 50

Epoch [31/50], Train Loss: 0.0351, Val Loss: 0.0286

EPOCH 32 of 50

Epoch [32/50], Train Loss: 0.0352, Val Loss: 0.0287

EPOCH 33 of 50

Epoch [33/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 34 of 50
```

```
Epoch [34/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 35 of 50

Epoch [35/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 36 of 50

Epoch [36/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 37 of 50

Epoch [37/50], Train Loss: 0.0352, Val Loss: 0.0285

EPOCH 38 of 50

Epoch [38/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 39 of 50

Epoch [39/50], Train Loss: 0.0351, Val Loss: 0.0286

EPOCH 40 of 50

Epoch [40/50], Train Loss: 0.0351, Val Loss: 0.0285

EPOCH 41 of 50

Epoch [41/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 42 of 50

Epoch [42/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 43 of 50

Epoch [43/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 44 of 50

Epoch [44/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 45 of 50

Epoch [45/50], Train Loss: 0.0351, Val Loss: 0.0286

EPOCH 46 of 50
```

```
Epoch [46/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 47 of 50

Epoch [47/50], Train Loss: 0.0352, Val Loss: 0.0286

EPOCH 48 of 50

Epoch [48/50], Train Loss: 0.0351, Val Loss: 0.0286

EPOCH 49 of 50

Epoch [49/50], Train Loss: 0.0351, Val Loss: 0.0286

EPOCH 50 of 50

Epoch [50/50], Train Loss: 0.0351, Val Loss: 0.0286
```

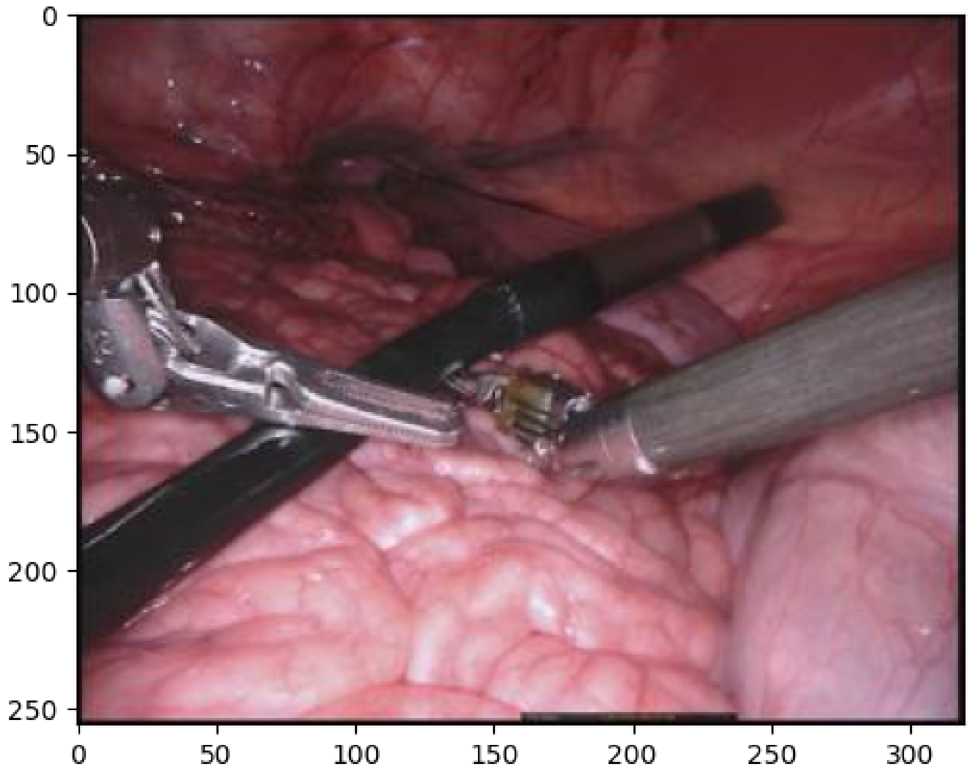
[ ]:
```
fig = plt.figure(figsize=(7, 5)) # create the canvas for plotting
ax = plt.subplot()
ax.plot(train_losses, label = "Training Loss")
ax.plot(val_losses, label = "Validation Loss")
handles, labels = ax.get_legend_handles_labels()

ax.set_ylabel("Loss")
ax.set_xlabel("Epochs")
ax.legend(handles, labels)

plt.show()
```

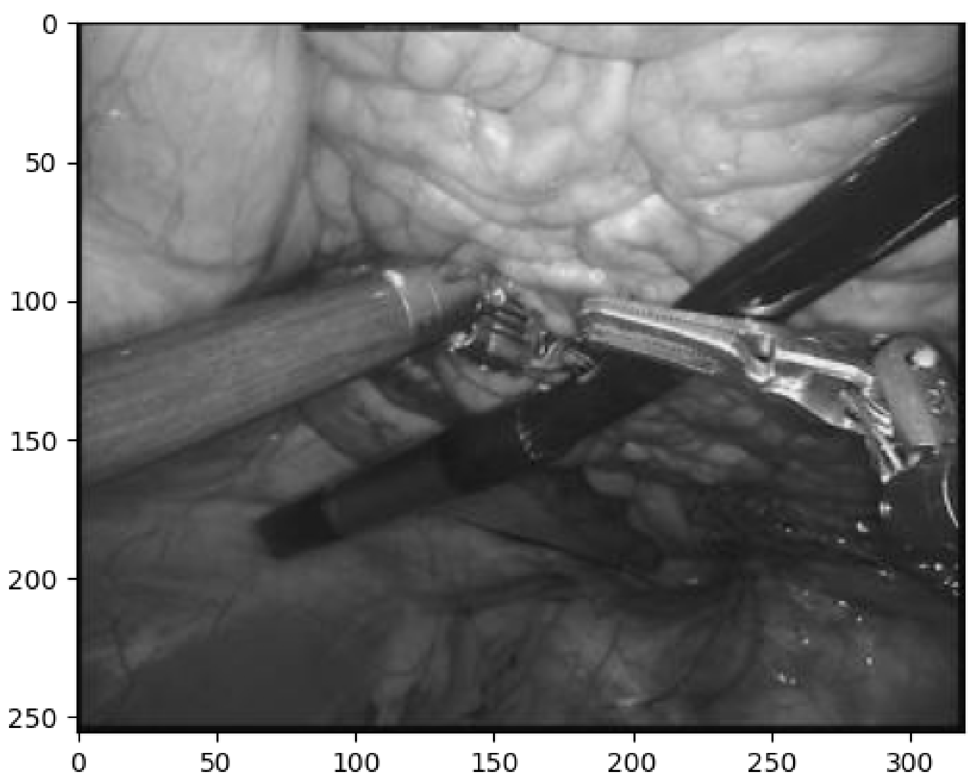


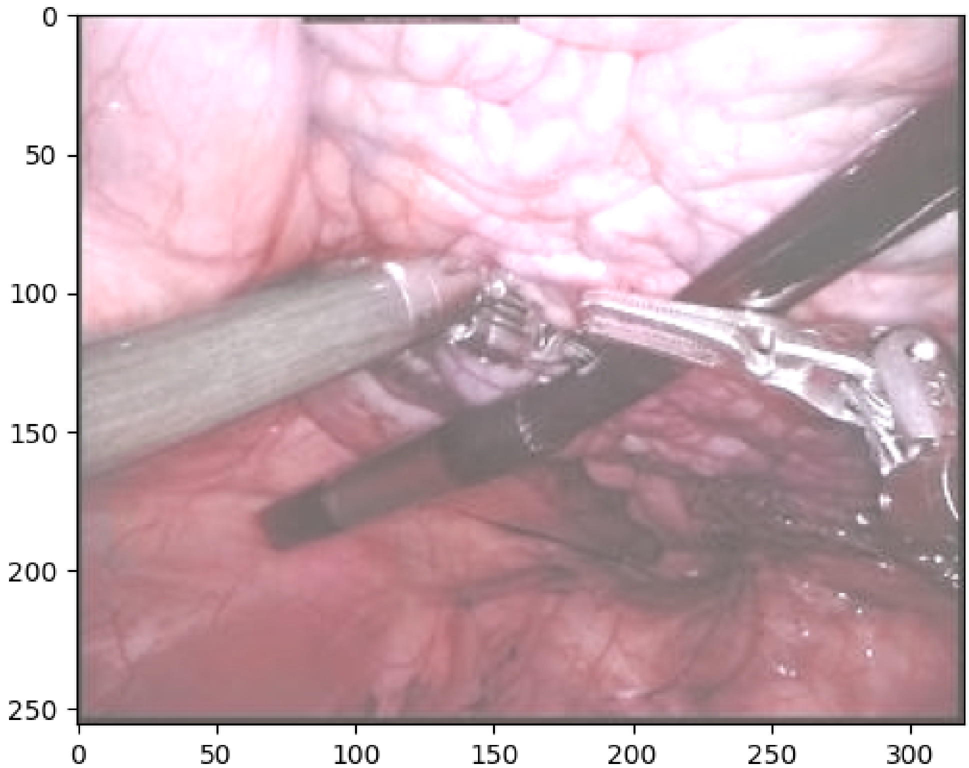
[ ]:
```
torch.save(model.state_dict(), f'{data_dir}/color_pretrained.dict')
model = UNET(3)
model.load_state_dict(torch.load(f'{data_dir}/color_pretrained.dict',␣
 ↪map_location=torch.device('cpu')))
train_dataset=ColorDataset(input_dir=colorization_data_dir, op="train",␣
 ↪transforms=img_transform)
```

[ ]:
```
model.eval()
plt.figure()
img, label = train_dataset[2]
plt.imshow(label.cpu().permute(1,2,0).numpy())
plt.figure()
img, label = train_dataset[2]
plt.imshow(img.cpu().permute(1,2,0).numpy())
with torch.no_grad():
  plt.figure()

  plt.imshow(img.cpu().permute(1,2,0).numpy()+model(torch.unsqueeze(img,0)).
 ↪squeeze().permute(1, 2, 0).cpu().numpy())
```

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with
RGB data ([0..1] for floats or [0..255] for integers).
```


0
50
100
150
200
250
0
50
100
150
200
250
300


0
50
100
150
200
250
0
50
100
150
200
250
300



2.5 Use Color Pretrained Model on Segmentation dataset

[ ]:
```
n_classes = 6
model.out_layer = nn.Conv2d(32, n_classes, kernel_size = 1, stride = 1, padding␣
 ↪= 0, bias = True)
## Batch Size
train_batch_size = 10
validation_batch_size = 10

## Learning Rate|
learning_rate = 0.001

# Epochs (Consider setting high and implementing early stopping)
num_epochs = 100
```

[ ]:
```
## Initialize your unet
n_classes = 6
model = UNET(n_classes)
```

```python
## Initialize Dataloaders
train_dataset=ImageDataset(input_dir=segmentation_data_dir, op="train", mask_json_path=mask_json, transforms=augmented_transform)
validation_dataset=ImageDataset(input_dir=segmentation_data_dir, op="val", mask_json_path=mask_json, transforms=img_transform)
test_dataset=ImageDataset(input_dir=segmentation_data_dir, op="test", mask_json_path=mask_json, transforms=img_transform)
train_dataloader = DataLoader(train_dataset, batch_size=train_batch_size, shuffle=True)
validation_dataloader = DataLoader(validation_dataset, batch_size=validation_batch_size, shuffle=False)
test_dataloader = DataLoader(test_dataset, batch_size=1, shuffle=False)
## Initialize Optimizer and Learning Rate Scheduler
optimizer = torch.optim.Adam(model.parameters(),lr=learning_rate)
scheduler = torch.optim.lr_scheduler.StepLR(optimizer, step_size=10, gamma=0.1)
loss_func = DICELoss(n_classes)
model = model.cuda()

# Define lists to store training and validation losses
train_losses = []
val_losses = []
test_score = []

print("Start Training...")
for epoch in range(num_epochs):
    ########################### Training #####################################
    print("\nEPOCH " +str(epoch+1)+" of "+str(num_epochs)+"\n")
    # TODO: Design your own training section
    model.train()
    train_loss = 0.0

    # Iterate through the training data
    for inputs, labels in train_dataloader:
        inputs = inputs.cuda()
        labels = labels.cuda()
        output = model.forward(inputs)

        loss = loss_func.forward(output, labels)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

      # Update running training loss
        train_loss += loss.item()

    # Compute average training loss for the epoch
    train_loss = train_loss / len(train_dataloader)
```

```
    train_losses.append(train_loss)

    ########################### Validation ####################################
    # TODO: Design your own validation section
    model.eval()
    val_loss = 0.0
    with torch.no_grad():
      for inputs, labels in validation_dataloader:
        inputs = inputs.cuda()
        labels = labels.cuda()
        output = model(inputs)
        loss = criterion.forward(output, labels)
        val_loss += loss.item()

    val_loss = val_loss / len(validation_dataloader)
    val_losses.append(val_loss)
    test_score_i = dice_score_dataset(model, test_dataloader, n_classes,␣
↪use_gpu=gpu_bool)
    test_score.append(test_score_i)
    scheduler.step()

    print(f'Epoch [{epoch+1}/{num_epochs}], Train Loss: {avg_train_loss:.4f},␣
↪Val Loss: {avg_val_loss:.4f}')
    print(f'Test Score: {test_score_i:.4f}')
```

```
Start Training…

EPOCH 1 of 100

Epoch [1/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.3601

EPOCH 2 of 100

Epoch [2/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.3434

EPOCH 3 of 100

Epoch [3/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.3954

EPOCH 4 of 100

Epoch [4/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.5849
```

```
EPOCH 5 of 100

Epoch [5/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6144

EPOCH 6 of 100

Epoch [6/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.5524

EPOCH 7 of 100

Epoch [7/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.3340

EPOCH 8 of 100

Epoch [8/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.5642

EPOCH 9 of 100

Epoch [9/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.5727

EPOCH 10 of 100

Epoch [10/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6628

EPOCH 11 of 100

Epoch [11/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6200

EPOCH 12 of 100

Epoch [12/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6557

EPOCH 13 of 100

Epoch [13/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6778

EPOCH 14 of 100

Epoch [14/100], Train Loss: 0.0351, Val Loss: 0.0286
```

```
Test Score: 0.6730

EPOCH 15 of 100

Epoch [15/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6733

EPOCH 16 of 100

Epoch [16/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6765

EPOCH 17 of 100

Epoch [17/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6721

EPOCH 18 of 100

Epoch [18/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6697

EPOCH 19 of 100

Epoch [19/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6769

EPOCH 20 of 100

Epoch [20/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6777

EPOCH 21 of 100

Epoch [21/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6782

EPOCH 22 of 100

Epoch [22/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6765

EPOCH 23 of 100

Epoch [23/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6746

EPOCH 24 of 100
```

```
Epoch [24/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6771

EPOCH 25 of 100

Epoch [25/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6812

EPOCH 26 of 100

Epoch [26/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6760

EPOCH 27 of 100

Epoch [27/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6774

EPOCH 28 of 100

Epoch [28/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6812

EPOCH 29 of 100

Epoch [29/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6761

EPOCH 30 of 100

Epoch [30/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6809

EPOCH 31 of 100

Epoch [31/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6782

EPOCH 32 of 100

Epoch [32/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6733

EPOCH 33 of 100

Epoch [33/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6788
```

```
EPOCH 34 of 100

Epoch [34/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6773

EPOCH 35 of 100

Epoch [35/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6741

EPOCH 36 of 100

Epoch [36/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6798

EPOCH 37 of 100

Epoch [37/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6761

EPOCH 38 of 100

Epoch [38/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6798

EPOCH 39 of 100

Epoch [39/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6774

EPOCH 40 of 100

Epoch [40/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6749

EPOCH 41 of 100

Epoch [41/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6774

EPOCH 42 of 100

Epoch [42/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6776

EPOCH 43 of 100
```

```
Epoch [43/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6734

EPOCH 44 of 100

Epoch [44/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6811

EPOCH 45 of 100

Epoch [45/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6811

EPOCH 46 of 100

Epoch [46/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6778

EPOCH 47 of 100

Epoch [47/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6782

EPOCH 48 of 100

Epoch [48/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6792

EPOCH 49 of 100

Epoch [49/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6740

EPOCH 50 of 100

Epoch [50/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6734

EPOCH 51 of 100

Epoch [51/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6779

EPOCH 52 of 100

Epoch [52/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6815
```

```
EPOCH 53 of 100

Epoch [53/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6800

EPOCH 54 of 100

Epoch [54/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6765

EPOCH 55 of 100

Epoch [55/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6795

EPOCH 56 of 100

Epoch [56/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6814

EPOCH 57 of 100

Epoch [57/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6799

EPOCH 58 of 100

Epoch [58/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6794

EPOCH 59 of 100

Epoch [59/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6782

EPOCH 60 of 100

Epoch [60/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6794

EPOCH 61 of 100

Epoch [61/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6767

EPOCH 62 of 100

Epoch [62/100], Train Loss: 0.0351, Val Loss: 0.0286
```

```
Test Score: 0.6727

EPOCH 63 of 100

Epoch [63/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6782

EPOCH 64 of 100

Epoch [64/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6788

EPOCH 65 of 100

Epoch [65/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6777

EPOCH 66 of 100

Epoch [66/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6815

EPOCH 67 of 100

Epoch [67/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6771

EPOCH 68 of 100

Epoch [68/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6766

EPOCH 69 of 100

Epoch [69/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6798

EPOCH 70 of 100

Epoch [70/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6804

EPOCH 71 of 100

Epoch [71/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6800

EPOCH 72 of 100
```

```
Epoch [72/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6816

EPOCH 73 of 100

Epoch [73/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6780

EPOCH 74 of 100

Epoch [74/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6761

EPOCH 75 of 100

Epoch [75/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6783

EPOCH 76 of 100

Epoch [76/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6831

EPOCH 77 of 100

Epoch [77/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6766

EPOCH 78 of 100

Epoch [78/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6761

EPOCH 79 of 100

Epoch [79/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6769

EPOCH 80 of 100

Epoch [80/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6782

EPOCH 81 of 100

Epoch [81/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6814
```

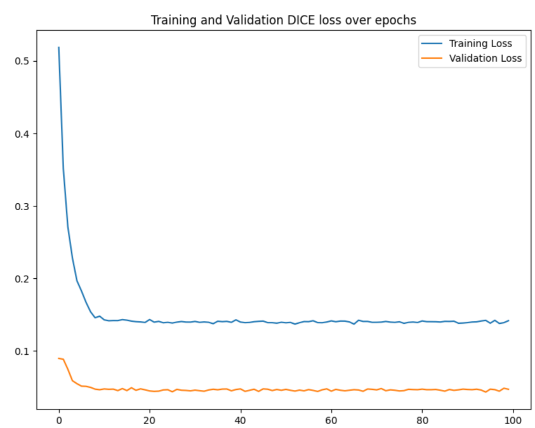
```
EPOCH 82 of 100

Epoch [82/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6788

EPOCH 83 of 100

Epoch [83/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6813

EPOCH 84 of 100

Epoch [84/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6817

EPOCH 85 of 100

Epoch [85/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6771

EPOCH 86 of 100

Epoch [86/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6820

EPOCH 87 of 100

Epoch [87/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6809

EPOCH 88 of 100

Epoch [88/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6790

EPOCH 89 of 100

Epoch [89/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6811

EPOCH 90 of 100

Epoch [90/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6774

EPOCH 91 of 100
```

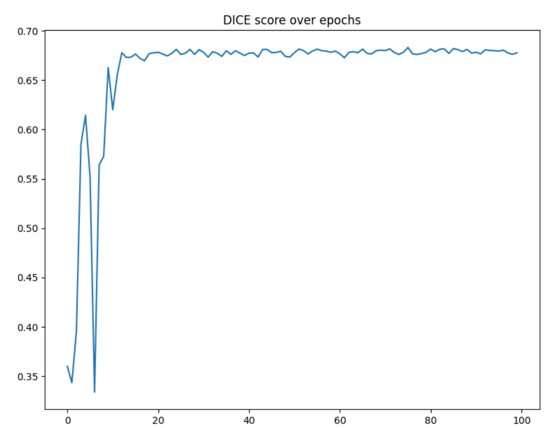
```
Epoch [91/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6783

EPOCH 92 of 100

Epoch [92/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6766

EPOCH 93 of 100

Epoch [93/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6807

EPOCH 94 of 100

Epoch [94/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6801

EPOCH 95 of 100

Epoch [95/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6799

EPOCH 96 of 100

Epoch [96/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6794

EPOCH 97 of 100

Epoch [97/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6804

EPOCH 98 of 100

Epoch [98/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6775

EPOCH 99 of 100

Epoch [99/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6762

EPOCH 100 of 100

Epoch [100/100], Train Loss: 0.0351, Val Loss: 0.0286
Test Score: 0.6777
```

[ ]:
```
max_score = max(test_score)
max_score_idx = test_score.index(max_score)
print(f'At Epoch {max_score_idx}, Test DICE score reaches its max as:␣
↪{max_score:.4f}')
```

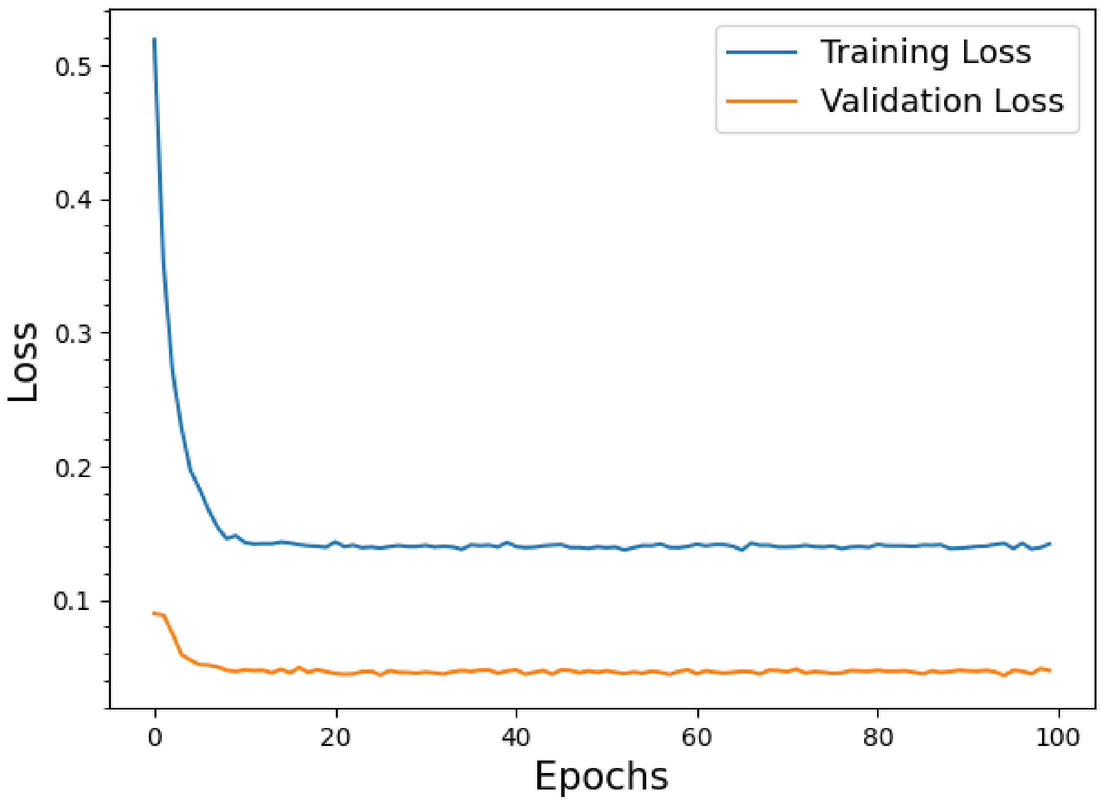
```
At Epoch 75, Test DICE score reaches its max as: 0.6831
```

[ ]:
```
# Graph
fig, axs = plt.subplots(1, 2,figsize=(20, 7))

axs[0].plot(range(num_epochs), train_losses)
axs[0].plot(range(num_epochs), val_losses)
axs[0].legend(['Training Loss', 'Validation Loss'])
axs[0].set_title('Training and Validation DICE loss over epochs')

axs[1].plot(range(num_epochs), test_score)
axs[1].set_title('DICE score over epochs')

plt.show()
```





[ ]:
```
fig = plt.figure() # create the canvas for plotting
ax = plt.subplot()
ax.plot(train_losses, label = "Training Loss")
ax.plot(val_losses, label = "Validation Loss")
handles, labels = ax.get_legend_handles_labels()

ax.set_ylabel("Loss")
ax.set_xlabel("Epochs")
ax.legend(handles, labels)

plt.show()
```



3 Problem 2: Transfer Learning

3.0.1 Imports

[47]:
```
## Import VGG and FashionMNIST
from torchvision.models import vgg16
from torchvision.datasets import FashionMNIST
```

3.0.2 Data Loading

[48]:
```
## Specify Batch Size
train_batch_size = 32
test_batch_size = 32

## Specify Image Transforms
img_transform = transforms.Compose([
    transforms.Resize((224,224)),
    transforms.Grayscale(3),
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
```

```python
])

## Download Datasets
train_data = FashionMNIST('./data', transform=img_transform, download=True,␣
↪train=True)
test_data = FashionMNIST('./data', transform=img_transform, download=True,␣
↪train=False)

## Initialize Dataloaders
training_dataloader = DataLoader(train_data, batch_size=train_batch_size,␣
↪shuffle=True)
test_dataloader = DataLoader(test_data, batch_size=test_batch_size,␣
↪shuffle=False)
```

```
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-
images-idx3-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-
images-idx3-ubyte.gz to ./data/FashionMNIST/raw/train-images-idx3-ubyte.gz

100%|      | 26421880/26421880 [00:01<00:00, 18023259.01it/s]

Extracting ./data/FashionMNIST/raw/train-images-idx3-ubyte.gz to
./data/FashionMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-
labels-idx1-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-
labels-idx1-ubyte.gz to ./data/FashionMNIST/raw/train-labels-idx1-ubyte.gz

100%|      | 29515/29515 [00:00<00:00, 305220.98it/s]

Extracting ./data/FashionMNIST/raw/train-labels-idx1-ubyte.gz to
./data/FashionMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-
central-1.amazonaws.com/t10k-images-idx3-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-
central-1.amazonaws.com/t10k-images-idx3-ubyte.gz to
./data/FashionMNIST/raw/t10k-images-idx3-ubyte.gz

100%|      | 4422102/4422102 [00:00<00:00, 5588060.85it/s]

Extracting ./data/FashionMNIST/raw/t10k-images-idx3-ubyte.gz to
./data/FashionMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-
central-1.amazonaws.com/t10k-labels-idx1-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-
central-1.amazonaws.com/t10k-labels-idx1-ubyte.gz to
./data/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz
```

```
100%|          | 5148/5148 [00:00<00:00, 20466613.26it/s]

Extracting ./data/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz to
./data/FashionMNIST/raw
```

3.0.3 Model Initialization and Training/Fine-tuning

Complete the rest of the assignment in the notebook below.

[57]:
```python
model = vgg16(pretrained=False)
model.classifier[-1] = nn.Linear(in_features=4096, out_features=10)
model = model.cuda()

def initialize_weights(m):
  """
  Initialize the weights and biases of the model.
  """
  if isinstance(m, nn.Conv2d) or isinstance(m, nn.Linear):
      torch.nn.init.kaiming_uniform_(m.weight)
      torch.nn.init.uniform_(m.bias)

model.apply(initialize_weights)
```

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223:
UserWarning: Arguments other than a weight enum or `None` for 'weights' are
deprecated since 0.13 and may be removed in the future. The current behavior is
equivalent to passing `weights=None`.
  warnings.warn(msg)
```

[57]:
```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
```

```
    (13): ReLU(inplace=True)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace=True)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace=True)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace=True)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU(inplace=True)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU(inplace=True)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (27): ReLU(inplace=True)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (29): ReLU(inplace=True)
    (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(7, 7))
  (classifier): Sequential(
    (0): Linear(in_features=25088, out_features=4096, bias=True)
    (1): ReLU(inplace=True)
    (2): Dropout(p=0.5, inplace=False)
    (3): Linear(in_features=4096, out_features=4096, bias=True)
    (4): ReLU(inplace=True)
    (5): Dropout(p=0.5, inplace=False)
    (6): Linear(in_features=4096, out_features=10, bias=True)
  )
)
```

[ ]:
```
model = model.cuda()

criterion = nn.CrossEntropyLoss()
lr = 0.001
optimizer = torch.optim.SGD(model.parameters(), lr = lr)
num_epochs = 10

# Define lists to store training and validation losses
train_losses = []
accuracy = []

print("Start Training...")
for epoch in range(num_epochs):
```

```python
########################### Training ######################################
print("\nEPOCH " +str(epoch+1)+" of "+str(num_epochs)+"\n")
# TODO: Design your own training section
model.train()
train_loss = 0.0

# Iterate through the training data
for inputs, labels in training_dataloader:
  inputs = inputs.cuda()
  labels = labels.cuda()
  output = model.forward(inputs)
  loss = criterion(output, labels)

  optimizer.zero_grad()
  loss.backward()
  optimizer.step()

  train_loss += loss.item()

# Compute average training loss for the epoch
avg_train_loss = train_loss / len(training_dataloader)
train_losses.append(avg_train_loss)
print(f'Epoch [{epoch+1}/{num_epochs}], Train Loss: {avg_train_loss:.4f}')


########################### Test ######################################
# TODO: Design your own Test section
model.eval()
test_loss = 0.0
test_correct = 0
with torch.no_grad():
    for inputs, labels in test_dataloader:
      if gpu_bool:
        inputs = inputs.cuda()
        labels = labels.cuda()
      output = model(inputs)
      loss = criterion(output, labels)
      test_loss += loss.item()
      predict = output.argmax(axis=1)
      test_correct += (predict == labels).float().sum()

avg_test_loss = test_loss / len(test_dataloader.dataset)
test_accuracy = test_correct / len(test_dataloader.dataset)
accuracy.append(test_accuracy.item())
print(f'Test Loss: {avg_test_loss:.4f}')
print(f'Test Accuracy: {test_accuracy:.4f}')
```

```
Start Training…

EPOCH 1 of 10

Epoch [1/10], Train Loss: 1.0280
Test Loss: 0.0139
Test Accuracy: 0.8349

EPOCH 2 of 10

Epoch [2/10], Train Loss: 0.5088
Test Loss: 0.0122
Test Accuracy: 0.8634

EPOCH 3 of 10

Epoch [3/10], Train Loss: 0.4306
Test Loss: 0.0110
Test Accuracy: 0.8715

EPOCH 4 of 10
```

[ ]:

```
fig = plt.figure(figsize=(7, 5)) # create the canvas for plotting
ax = plt.subplot()
ax.plot(train_losses, label = "Training Loss")
ax.plot(accuracy, label = "Test Accuracy")
handles, labels = ax.get_legend_handles_labels()
ax.set_xlabel("Epochs")
ax.legend(handles, labels)
```

3.0.4 Using Pretrained VGG16

[56]:

```
model = vgg16(pretrained = True)
model.classifier[-1] = nn.Linear(in_features=4096, out_features=10)
for param in model.parameters():
    param.requires_grad = False
for param in model.classifier[-1].parameters():
    param.requires_grad = True
initialize_weights(model.classifier[-1])
```

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208:
UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may be
removed in the future, please use 'weights' instead.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223:
UserWarning: Arguments other than a weight enum or `None` for 'weights' are
```

```
deprecated since 0.13 and may be removed in the future. The current behavior is
equivalent to passing `weights=VGG16_Weights.IMAGENET1K_V1`. You can also use
`weights=VGG16_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to
/root/.cache/torch/hub/checkpoints/vgg16-397923af.pth
100%|      | 528M/528M [00:10<00:00, 50.3MB/s]
```

[ ]:
```python
model = model.cuda()

criterion = nn.CrossEntropyLoss()
lr = 0.001
optimizer = torch.optim.SGD(model.parameters(), lr = lr)
num_epochs = 10

# Define lists to store training and validation losses
train_losses = []
accuracy = []

print("Start Training...")
for epoch in range(num_epochs):
    ########################### Training #####################################
    print("\nEPOCH " +str(epoch+1)+" of "+str(num_epochs)+"\n")
    # TODO: Design your own training section
    model.train()
    train_loss = 0.0

    # Iterate through the training data
    for inputs, labels in training_dataloader:
      inputs = inputs.cuda()
      labels = labels.cuda()
      output = model.forward(inputs)
      loss = criterion(output, labels)

      # Backpropagation
      optimizer.zero_grad()
      loss.backward()
      optimizer.step()

      train_loss += loss.item()

    # Compute average training loss for the epoch
    avg_train_loss = train_loss / len(training_dataloader)
    train_losses.append(avg_train_loss)
    print(f'Epoch [{epoch+1}/{num_epochs}], Train Loss: {avg_train_loss:.4f}')
```

```python
########################### Test #####################################
# TODO: Design your own Test section
model.eval()
test_loss = 0.0
test_correct = 0
with torch.no_grad():
    for inputs, labels in test_dataloader:
      inputs = inputs.cuda()
      labels = labels.cuda()
      output = model(inputs)
      loss = criterion(output, labels)
      test_loss += loss.item()
      predict = output.argmax(axis=1)
      test_correct += (predict == labels).float().sum()

avg_test_loss = test_loss / len(test_dataloader.dataset)
test_accuracy = test_correct / len(test_dataloader.dataset)
accuracy.append(test_accuracy.item())
print(f'Test Loss: {avg_test_loss:.4f}')
print(f'Test Accuracy: {test_accuracy:.4f}')
```

```
Start Training…

EPOCH 1 of 10

Epoch [1/10], Train Loss: 0.9955
Test Loss: 0.0190
Test Accuracy: 0.7926

EPOCH 2 of 10

Epoch [2/10], Train Loss: 0.6827
Test Loss: 0.0173
Test Accuracy: 0.8063

EPOCH 3 of 10

Epoch [3/10], Train Loss: 0.6283
Test Loss: 0.0165
Test Accuracy: 0.8137

EPOCH 4 of 10

Epoch [4/10], Train Loss: 0.5976
Test Loss: 0.0160
Test Accuracy: 0.8193
```

```
EPOCH 5 of 10

Epoch [5/10], Train Loss: 0.5803
Test Loss: 0.0156
Test Accuracy: 0.8246

EPOCH 6 of 10

Epoch [6/10], Train Loss: 0.5627
Test Loss: 0.0153
Test Accuracy: 0.8271

EPOCH 7 of 10

Epoch [7/10], Train Loss: 0.5528
Test Loss: 0.0150
Test Accuracy: 0.8298

EPOCH 8 of 10

Epoch [8/10], Train Loss: 0.5411
Test Loss: 0.0148
Test Accuracy: 0.8305

EPOCH 9 of 10

Epoch [9/10], Train Loss: 0.5362
Test Loss: 0.0146
Test Accuracy: 0.8362

EPOCH 10 of 10

Epoch [10/10], Train Loss: 0.5284
Test Loss: 0.0145
Test Accuracy: 0.8367
```

[55]:

```
print(train_losses)
```

```
[1.0672889280001323, 0.5154962116916975]
```

[ ]:

```
fig = plt.figure() # create the canvas for plotting
ax = plt.subplot()
ax.plot(train_losses, label = "Training Loss")
ax.plot(accuracy, label = "Test Accuracy")
handles, labels = ax.get_legend_handles_labels()
ax.set_xlabel("Epochs")
ax.legend(handles, labels)
```

```
[ ]: <matplotlib.legend.Legend at 0x7fad7b5d3a90>
```