## Lab 3: Gesture Recognition using Convolutional Neural Networks

In this lab you will train a convolutional neural network to make classifications on different hand gestures. By the end of the lab, you should be able to:

1. Load and split data for training, validation and testing
2. Train a Convolutional Neural Network
3. Apply transfer learning to improve your model

Note that for this lab we will not be providing you with any starter code. You should be able to take the code used in previous labs, tutorials and lectures and modify it accordingly to complete the tasks outlined below.

### What to submit

Submit a PDF file containing all your code, outputs, and write-up from parts 1-5. You can produce a PDF of your Google Colab file by going to **File > Print** and then save as PDF. The Colab instructions has more information. Make sure to review the PDF submission to ensure that your answers are easy to read. Make sure that your text is not cut off at the margins.

**Do not submit any other files produced by your code.**

Include a link to your colab file in your submission.

Please use Google Colab to complete this assignment. If you want to use Jupyter Notebook, please complete the assignment and upload your Jupyter Notebook file to Google Colab for submission.

### Colab Link

Include a link to your colab file here

Colab Link: [https://drive.google.com/file/d/1a485nluGKhZ8GMlCVT0a4Nd7PlmghprS/view?usp=sharing](https://drive.google.com/file/d/1a485nluGKhZ8GMlCVT0a4Nd7PlmghprS/view?usp=sharing)

### Dataset

American Sign Language (ASL) is a complete, complex language that employs signs made by moving the hands combined with facial expressions and postures of the body. It is the primary language of many North Americans who are deaf and is one of several communication options used by people who are deaf or hard-of-hearing. The hand gestures representing English alphabet are shown below. This lab focuses on classifying a subset of these hand gesture images using convolutional neural networks. Specifically, given an image of a hand showing one of the letters A-I, we want to detect which letter is being represented.


## Part B. Building a CNN [50 pt]

For this lab, we are not going to give you any starter code. You will be writing a convolutional neural network from scratch. You are welcome to use any code from previous labs, lectures and tutorials. You should also write your own code.

You may use the PyTorch documentation freely. You might also find online tutorials helpful. However, all code that you submit must be your own.

Make sure that your code is vectorized, and does not contain obvious inefficiencies (for example, unecessary for loops, or unnecessary calls to unsqueeze()). Ensure enough comments are included in the code so that your TA can understand what you are doing. It is your responsibility to show that you understand what you write.

**This is much more challenging and time-consuming than the previous labs.** Make sure that you give yourself plenty of time by starting early.

## 1. Data Loading and Splitting [5 pt]

Download the anonymized data provided on Quercus. To allow you to get a heads start on this project we will provide you with sample data from previous years. Split the data into training, validation, and test sets.

Note: Data splitting is not as trivial in this lab. We want our test set to closely resemble the setting in which our model will be used. In particular, our test set should contain hands that are never seen in training!

Explain how you split the data, either by describing what you did, or by showing the code that you used. Justify your choice of splitting strategy. How many training, validation, and test images do you have?

For loading the data, you can use plt.imread as in Lab 1, or any other method that you choose. You may find torchvision.datasets.ImageFolder helpful. (see https://pytorch.org/docs/stable/torchvision/datasets.html?highlight=image%20folder#torchvision.datasets.ImageFolder )

```
import numpy as np
import time
import torch
import os
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import torchvision
from torch.utils.data.sampler import SubsetRandomSampler
from tqdm.auto import tqdm
import torchvision.transforms as transforms
from torchvision.datasets import ImageFolder
import matplotlib.pyplot as plt
```

```
#mount googledrive
from google.colab import drive
drive.mount('/content/gdrive')
```

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

The data sets which is constructed with 9 folders which each contains around 800+ sets of images. I think most of the data should be used for image training instead of model testing and parameter tuning whiling still leaving enough for these two. Hence, I choose 60% of the total data goes to training set, 20% goes to both validation set and testing set.

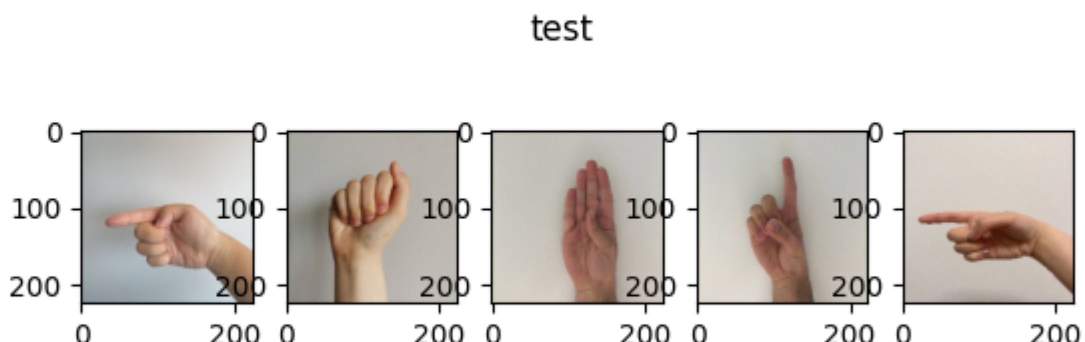
For lab2

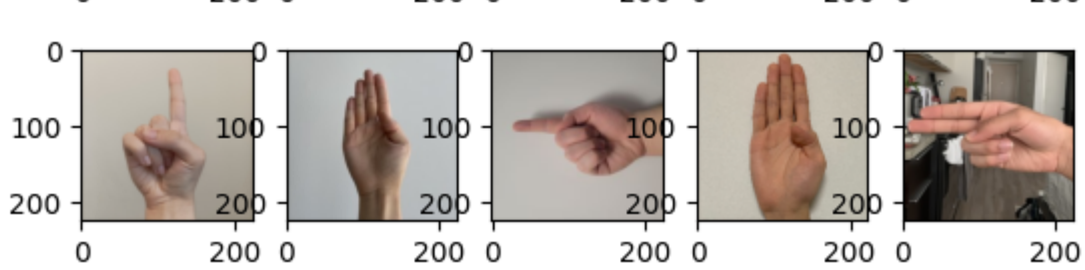
```
#adapt
def get_data_loader(data_folder, class_num, batch_size):
    """ Loads images of cats and dogs, splits the data into training, validation
    and testing datasets. Returns data loaders for the three preprocessed datasets.

    Args:
        target_classes: A list of strings denoting the name of the desired
                        classes. Should be a subset of the argument 'classes'
        batch_size: A int representing the number of samples per batch

    Returns:
        train_loader: iterable training dataset organized according to batch size
        val_loader: iterable validation dataset organized according to batch size
        test_loader: iterable testing dataset organized according to batch size
    """

    train_indices, val_indices, test_indices = [], [], []
    count = 0
    for i in class_num:
        train_indices.extend(list(range(count, count + int(i * 0.6))))    # 60% for training
        val_indices.extend(list(range(count + int(i * 0.6), count + int(i * 0.8))))  # 20% for validation
        test_indices.extend(list(range(count + int(i * 0.8), count + i)))  # 20% for testing
        count += i

    np.random.seed(1234)
```

```
    np.random.shuffle(train_indices)

    train_sampler = SubsetRandomSampler(train_indices)
    train_loader = torch.utils.data.DataLoader(data_folder, batch_size=batch_size, num_workers=1, sampler=train_sampler)

    val_sampler = SubsetRandomSampler(val_indices)
    val_loader = torch.utils.data.DataLoader(data_folder, batch_size=batch_size, num_workers=1, sampler=val_sampler)

    test_sampler = SubsetRandomSampler(test_indices)
    test_loader = torch.utils.data.DataLoader(data_folder, batch_size=batch_size, num_workers=1, sampler=test_sampler)

    print("60% traing 20% test and val")

    return train_loader, val_loader, test_loader

def get_class_num(directory):
    total = 0
    count_list = []
    for folder in os.listdir(directory):
        count = 0
        f_path = os.path.join(directory, folder)
        for file in os.listdir(f_path):
            count += 1

        print(folder, " ", count)
        total += count
        count_list.append(count)

    print("Total: ", total)
    return count_list
```

```
data_path = "/content/gdrive/MyDrive/here/Lab3_Gestures_Summer"

# The output of torchvision datasets are PILImage images of range [0, 1].
# We transform them to Tensors of normalized range [-1, 1].
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
data_folder = ImageFolder(data_path, transform=transform)

class_num = get_class_num(data_path)
train_loader, val_loader, test_loader = get_data_loader(data_folder, class_num, 1) #batch = 1 for eas

plt.figure()
k = 0
for images, labels in test_loader:
    image = images[0]
    img = np.transpose(image, [1, 2, 0])
    # normalize pixel to [0, 1]
    img = img / 2 + 0.5
    plt.subplot(3, 5, k + 1)
    plt.suptitle("test")
    plt.imshow(img)
    #print(first 10)
    k += 1
    if k > 9:
        break
```

```
F   236
B   247
C   245
D   247
E   247
G   250
I   249
H   244
A   254
Total:  2219
60% traing 20% test and val
```





## 2. Model Building and Sanity Checking [15 pt]

### Part (a) Convolutional Network - 5 pt

Build a convolutional neural network model that takes the (224x224 RGB) image as input, and predicts the gesture letter. Your model should be a subclass of nn.Module. Explain your choice of neural network architecture: how many layers did you choose? What types of layers did you use? Were they fully-connected or convolutional? What about other decisions like pooling layers, activation functions, number of channels / hidden units?

```
#Convolutional Neural Network Architecture

'''
#Convolutional Neural Network Architecture
class CNN(nn.Module):
    def __init__(self):
        super(CNN, self).__init__()
        self.name = "dynamic"
        self.conv1 = nn.Conv2d(3, 5, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(5, 10, 5)
        self.fc1 = None
        self.fc2 = nn.Linear(32, 9)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        if self.fc1 is None:
            self.fc1 = nn.Linear(x.view(x.size(0), -1).size(1), 32)
        x = x.view(x.size(0), -1)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x

    print('Convolutional Neural Network Architecture Done')
'''

class CNN(nn.Module):
    def __init__(self):
        super(CNN, self).__init__()
        self.name = "CNN"
        self.conv1 = nn.Conv2d(3, 5, 5,stride=3,padding=0)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(5, 10, 5,stride=2,padding=0)
        self.pool2 = nn.MaxPool2d(stride=3, kernel_size=2) #this speed up real good improve the tut c
        self.fc1 = nn.Linear(6* 6 * 10, 32)
        self.fc2 = nn.Linear(32, 9)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool2(F.relu(self.conv2(x)))
        x = x.view(-1, 6 * 6 * 10)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x


    print('Convolutional Neural Network Architecture Done')
```

```
Convolutional Neural Network Architecture Done
```

chose a CNN architecture because it is good when working with images. I used two convolutional layers, two pooling layers, and two fully connected layers. I chose to use two convolutional layers to let the model extract abstract features; I used the pooling layers to reduce the dimension of the feature map, causing the model to train faster. The two fully connected layers at the end are used for classification. In addition, the ReLU activation function lets the model learn non-linearity.

### Part (b) Training Code - 5 pt

## Part (b) Training Code - 5 pt

Write code that trains your neural network given some training data. Your training code should make it easy to tweak the usual hyperparameters, like batch size, learning rate, and the model object itself. Make sure that you are checkpointing your models from time to time (the frequency is up to you). Explain your choice of loss function and optimizer.

base on lab2 code example at first but changed to be able to GPU and combined plot and evoluate into one thing removed a lot of code

```
# Training
def get_model_name(name, batch_size, learning_rate, epoch):
    """ Generate a name for the model consisting of all the hyperparameter values

    Args:
        config: Configuration object containing the hyperparameters
    Returns:
        path: A string with the hyperparameter name and value concatenated
    """
    path = "model_{0}_bs{1}_lr{2}_epoch{3}".format(name,
                                                   batch_size,
                                                   learning_rate,
                                                   epoch)
    return path


def train(model, train_loader,val_loader, batch_size=64, num_epochs=1, learning_rate = 0.01):
    torch.manual_seed(1234)
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=learning_rate, momentum=0.9)

    iters, epoch_itr, losses, val_loss, train_acc, val_acc = [], [], [], [], [], []

    # training
    n = 0 # the number of iterations


     #new things
    progress_total = num_epochs * len(train_loader)
    pbar = tqdm(desc = 'while loop', total = progress_total)
    pbar.update(1)

    start_time = time.time()
    for epoch in range(num_epochs):
        for imgs, labels in iter(train_loader):

            #############################################
            #To Enable GPU Usage
            if use_cuda and torch.cuda.is_available():
              imgs = imgs.cuda()
              labels = labels.cuda()
            #############################################


            out = model(imgs)             # forward pass
            loss = criterion(out, labels) # compute the total loss
            loss.backward()               # backward pass (compute parameter updates)
            optimizer.step()              # make the updates for each parameter
            optimizer.zero_grad()         # a clean up step for PyTorch

            # save
            iters.append(n)
            losses.append(float(loss)/batch_size)

            # get_accuracy
            pred = out.max(1,keepdim = True)[1]
            correct = pred.eq(labels.view_as(pred)).sum().item()
            total = imgs.shape[0]
            t_acc = correct/ total
            train_acc.append(t_acc) # compute training accuracy
            n += 1
            pbar.update(1)

        val_l = 0
        correct = 0
        total = 0

        #do to val
        for valimgs, vallabels in val_loader:


            #############################################
            #To Enable GPU Usage
```

```
        if use_cuda and torch.cuda.is_available():
          valimgs = valimgs.cuda()
          vallabels = vallabels.cuda()
        #############################################

        output = model(valimgs)
        pred = output.max(1, keepdim=True)[1]
        val_l += criterion(output, vallabels).item()  # compute the total loss
        optimizer.zero_grad()
        correct += pred.eq(vallabels.view_as(pred)).sum().item()
        total += valimgs.shape[0]

    v_acc, v_loss = correct / total, float(val_l)/total

    val_acc.append(v_acc)  # compute validation accuracy
    val_loss.append(v_loss)
    epoch_itr.append(n)

    model_path = get_model_name(model.name, batch_size, learning_rate, epoch)
    torch.save(model.state_dict(), model_path)

end_time = time.time()
elapsed_time = end_time - start_time
print("Total time elapsed: {:.2f} seconds\n".format(elapsed_time))

# plotting
plt.title("Training Curve")
plt.plot(iters, losses, label="Train")
plt.plot(epoch_itr, val_loss, label="Validation")
plt.xlabel("Iterations")
plt.ylabel("Loss")
plt.show()

plt.title("Training Curve")
plt.plot(iters, train_acc, label="Train")
plt.plot(epoch_itr, val_acc, label="Validation")
plt.xlabel("Iterations")
plt.ylabel("Training Accuracy")
plt.legend(loc='best')
plt.show()

print("Final Training Accuracy: {}".format(train_acc[-1]))
print("Final Validation Accuracy: {}".format(val_acc[-1]))
```

CrossEntropy Loss is chosen because it is used for multi-class classification tasks.

SGD with Momentum is selected as the optimizer because it is effective and suited for large-scale learning tasks, especially when combined with momentum, which helps improve efficiency and stability.

## Part (c) “Overfit” to a Small Dataset - 5 pt

One way to sanity check our neural network model and training code is to check whether the model is capable of “overfitting” or “memorizing” a small dataset. A properly constructed CNN with correct training code should be able to memorize the answers to a small number of images quickly.

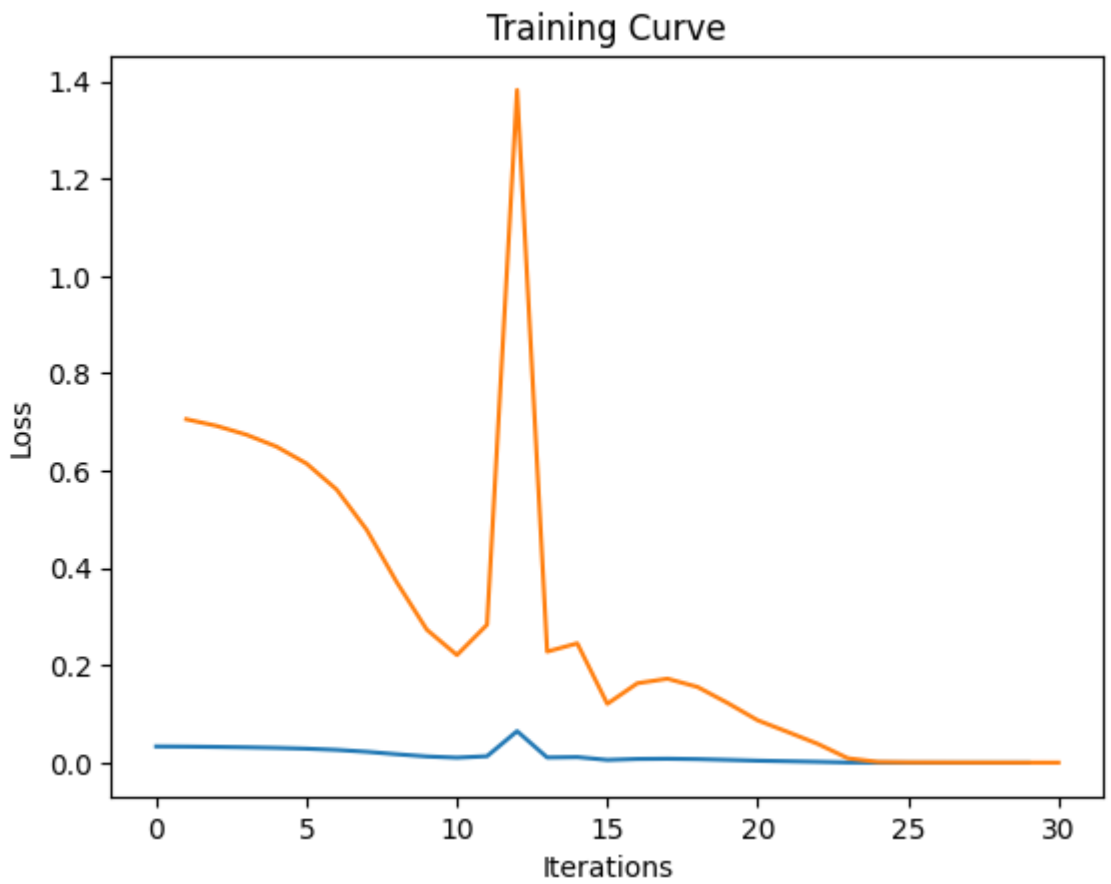
Construct a small dataset (e.g. just the images that you have collected). Then show that your model and training code is capable of memorizing the labels of this small data set.

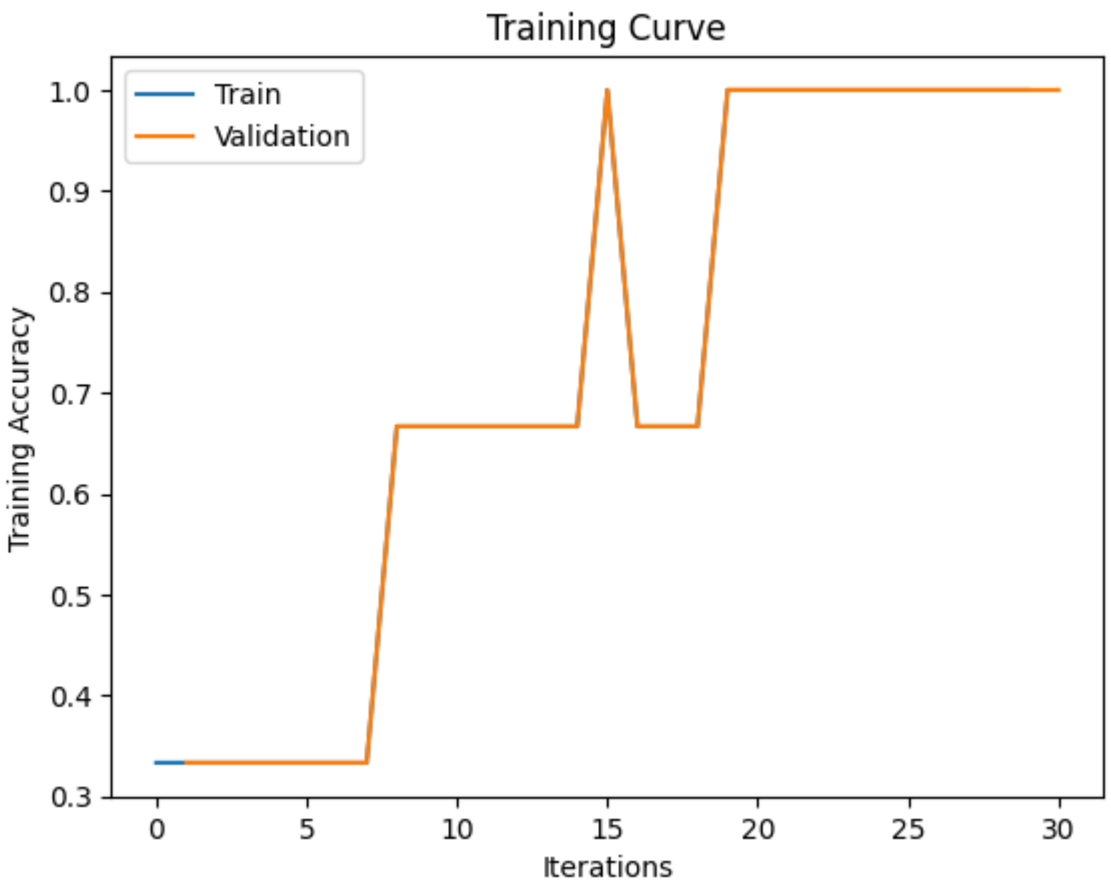
With a large batch size (e.g. the entire small dataset) and learning rate that is not too high, You should be able to obtain a 100% training accuracy on that small dataset relatively quickly (within 200 iterations).

```
small_path = "/content/gdrive/MyDrive/here/small" #3A,3H, 2G

# The output of torchvision datasets are PILImage images of range [0, 1].
# We transform them to Tensors of normalized range [-1, 1].
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
data_folder = ImageFolder(small_path , transform=transform)


class_num = get_class_num(small_path) # where bug located
train_loader, val_loader, test_loader = get_data_loader(data_folder, class_num, 8) #3+3+2 = 8

#from tut_3a
use_cuda = True
model = CNN()
```

```
if use_cuda and torch.cuda.is_available():
  model.cuda()
  print('CUDA is available!  Training on GPU ...\n')
else:
  print('CUDA is not available.  Training on CPU ...\n')


train(model, train_loader, train_loader, batch_size=64, num_epochs=30, learning_rate = 0.05)
```

```
A   3
H   3
G   2
Total:  8
60% traing 20% test and val
CUDA is available!  Training on GPU ...

while loop:                              32/? [27:05<00:00,   5.53it/s]
Total time elapsed: 5.94 seconds
```




```
Final Training Accuracy: 1.0
Final Validation Accuracy: 1.0
```

It is clearly shown that after about 20ish interations (not epoch) we reaches a 100% accuracy on the small dataset. This shows that our model has memorized the training data. Hence, it shows that my model and training code is capable of memorizing the labels of this small data set.

## 3. Hyperparameter Search [15 pt]

### Part (a) - 3 pt

List 3 hyperparameters that you think are most worth tuning. Choose at least one hyperparameter related to the model architecture.

base on lab2, my choices are:

larning rate

batch size

number of hidden nerons

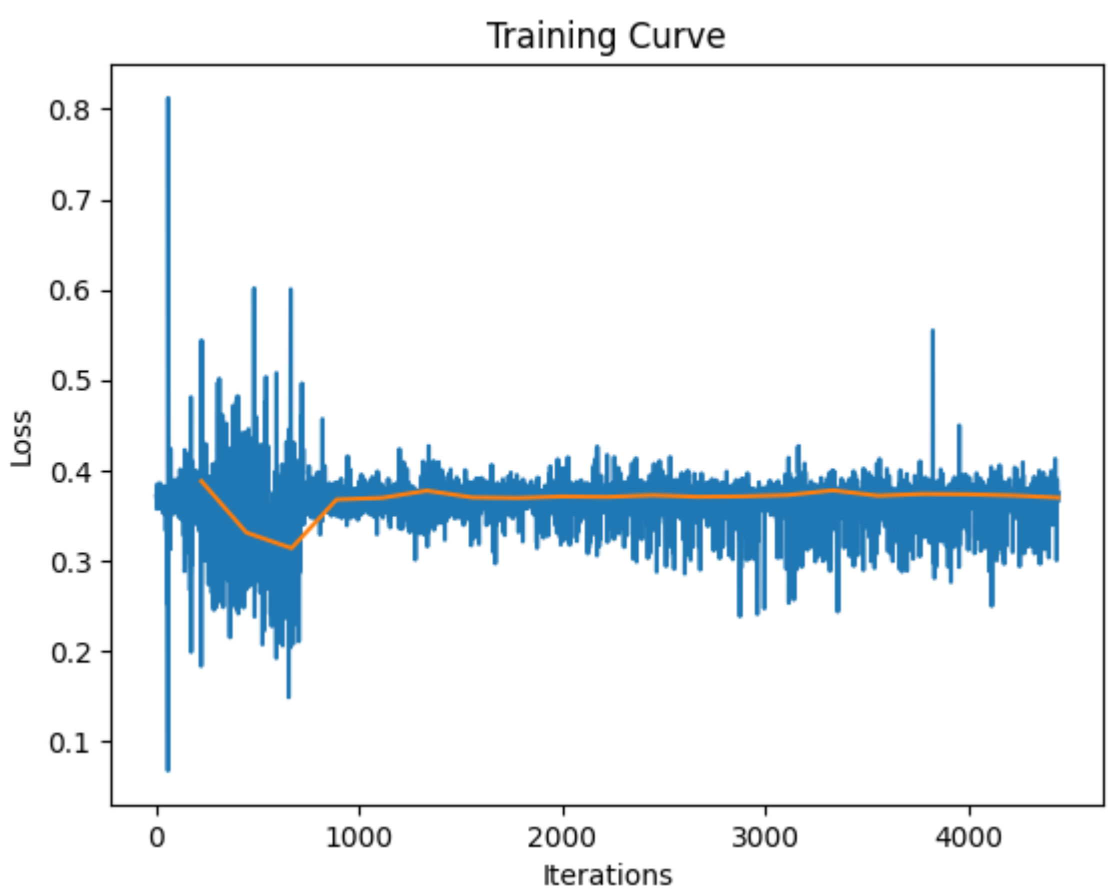
## Part (b) - 5 pt

Tune the hyperparameters you listed in Part (a), trying as many values as you need to until you feel satisfied that you are getting a good model. Plot the training curve of at least 4 different hyperparameter settings.

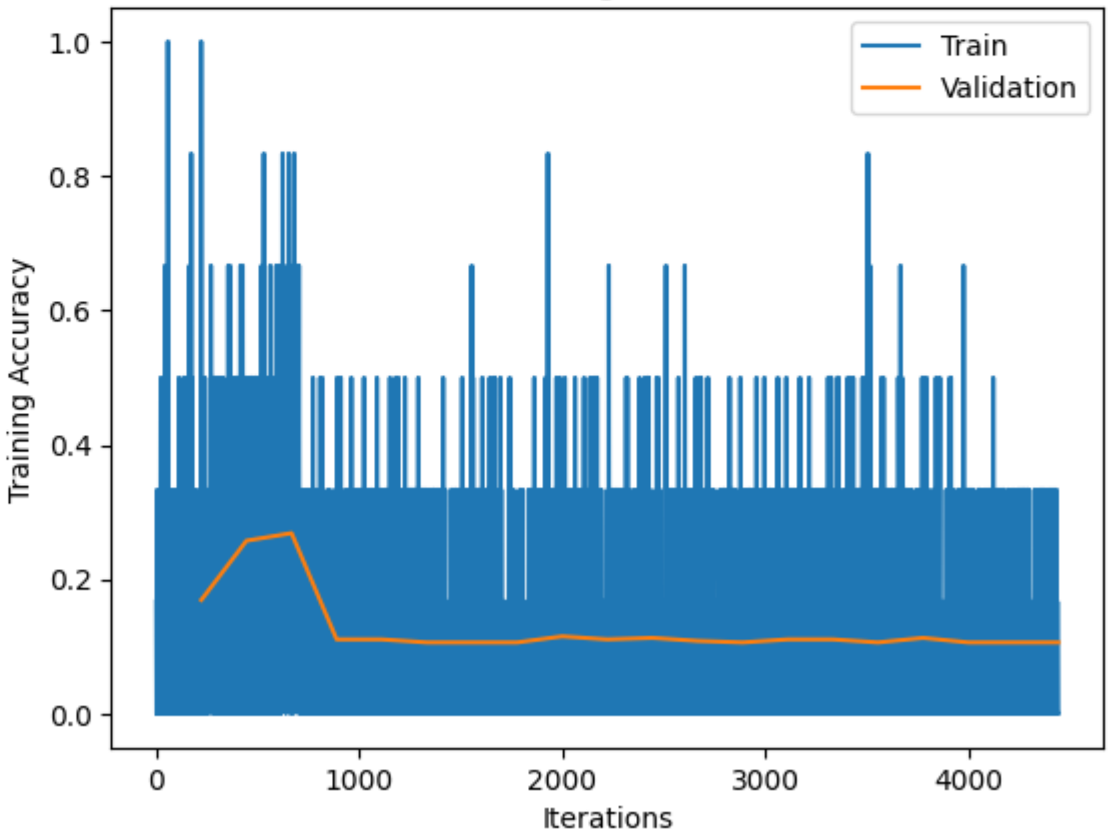
let's start with a small batch size and high learning rate (should not be super good)

```
data_path = "/content/gdrive/MyDrive/here/Lab3_Gestures_Summer"

transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
data_folder = ImageFolder(data_path , transform=transform)


class_num = get_class_num(data_path) # where bug located
train_loader, val_loader, test_loader = get_data_loader(data_folder, class_num, 6)

#from tut_3a
use_cuda = True
model = CNN()

if use_cuda and torch.cuda.is_available():
  model.cuda()
  print('CUDA is available!  Training on GPU ...\n')
else:
  print('CUDA is not available.  Training on CPU ...\n')


train(model, train_loader, val_loader, batch_size=6, num_epochs=20, learning_rate = 0.05)
```

```
F   236
B   247
C   245
D   247
E   247
G   250
I   249
H   244
A   254
Total:  2219
60% traing 20% test and val
CUDA is available!  Training on GPU ...

while loop:                                   4442/? [12:10<00:00, 32.78it/s]
Total time elapsed: 720.75 seconds
```



Training Curve




```
Final Training Accuracy: 0.0
Final Validation Accuracy: 0.10609480812641084
```

change learning rate

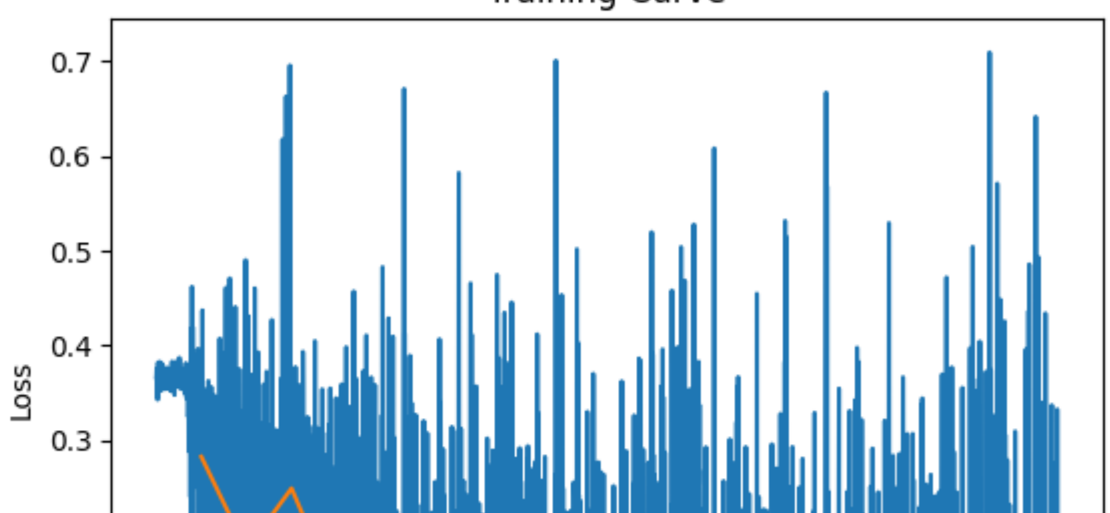
```
data_path = "/content/gdrive/MyDrive/here/Lab3_Gestures_Summer"

transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
data_folder = ImageFolder(data_path , transform=transform)


class_num = get_class_num(data_path) # where bug located

#from tut_3a
use_cuda = True
model = CNN()

if use_cuda and torch.cuda.is_available():
  model.cuda()
  print('CUDA is available!  Training on GPU ...\n')
else:
  print('CUDA is not available.  Training on CPU ...\n')
train_loader, val_loader, test_loader = get_data_loader(data_folder, class_num, 6)


train(model, train_loader, val_loader, batch_size=6, num_epochs=20, learning_rate = 0.01)
```

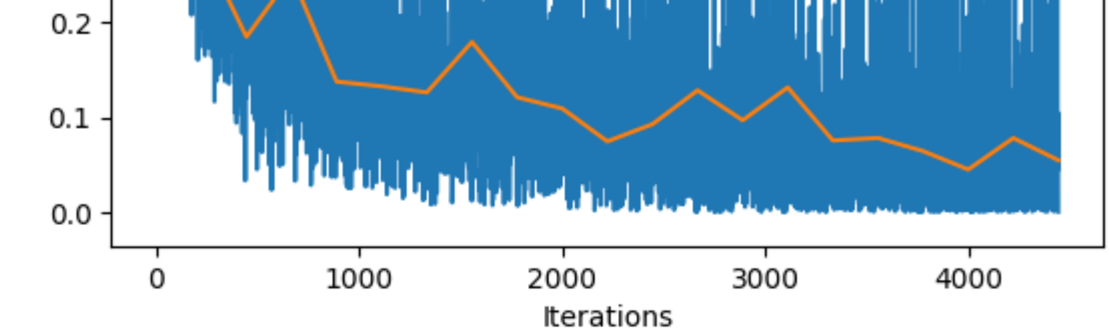
```
B   247
E   247
D   247
C   245
H   244
F   236
A   254
G   250
I   249
Total:  2219
CUDA is available!  Training on GPU ...

60% traing 20% test and val
```

while loop: 4442/? [12:23<00:00, 27.26it/s]

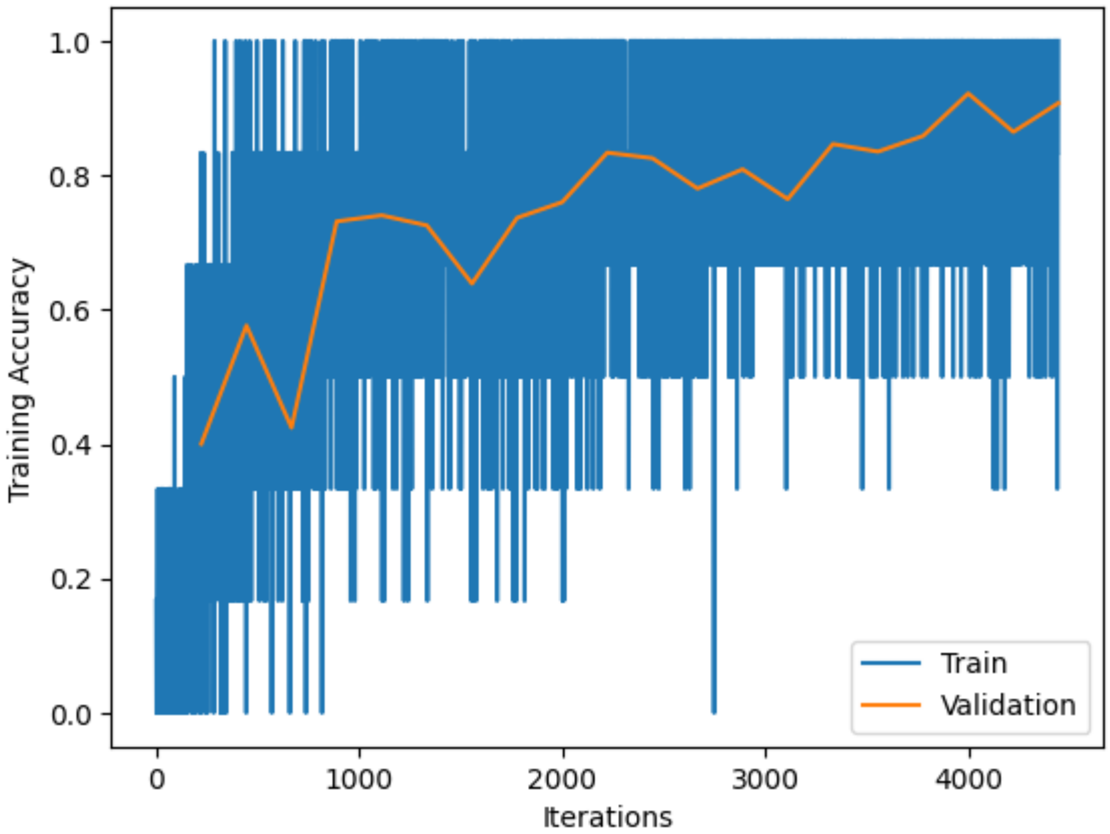
```
Total time elapsed: 294.56 seconds
```

Training Curve






Training Curve




```
Final Training Accuracy: 1.0
Final Validation Accuracy: 0.90744920993228
```

ok, it seems to be better

increase batch size

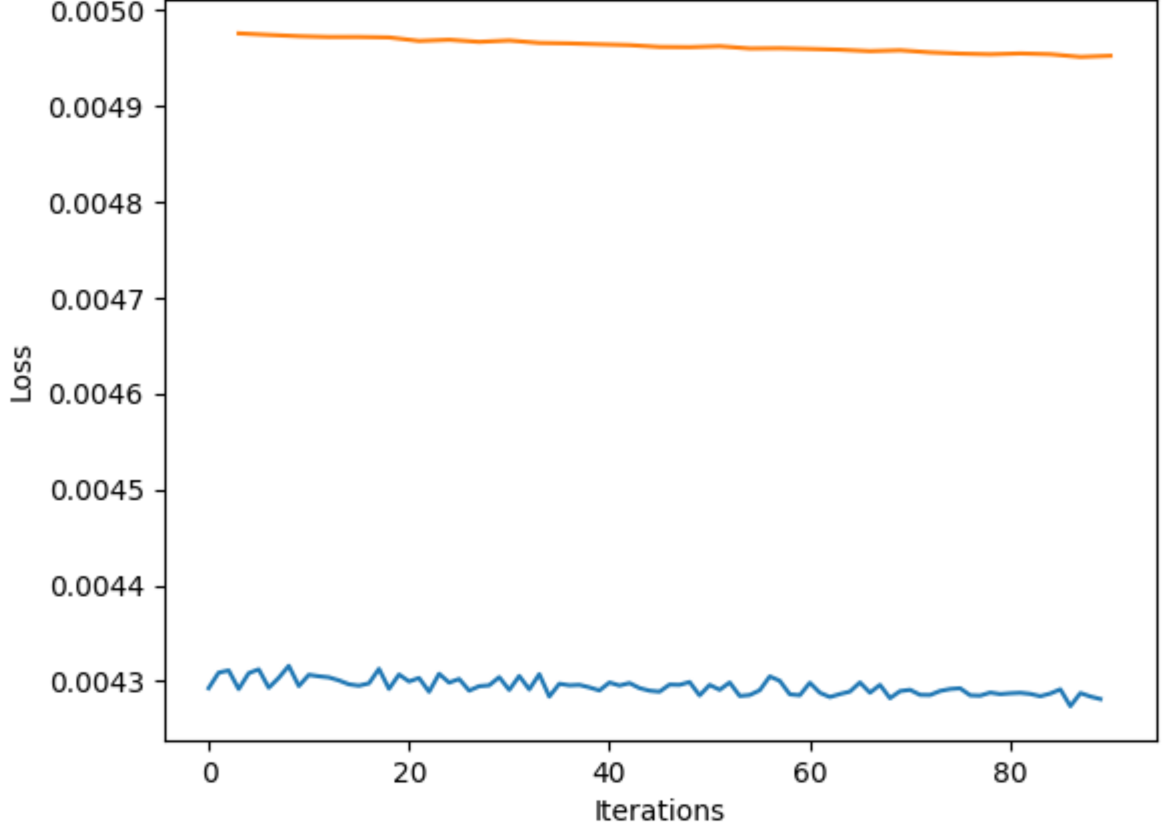
```
data_path = "/content/gdrive/MyDrive/here/Lab3_Gestures_Summer"

transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
data_folder = ImageFolder(data_path , transform=transform)


class_num = get_class_num(data_path) # where bug located

#from tut_3a
use_cuda = True
model = CNN()

if use_cuda and torch.cuda.is_available():
  model.cuda()
  print('CUDA is available!  Training on GPU ...\n')
else:
  print('CUDA is not available.  Training on CPU ...\n')
train_loader, val_loader, test_loader = get_data_loader(data_folder, class_num, 512)


train(model, train_loader, val_loader, batch_size=512, num_epochs=30, learning_rate = 0.01)
```

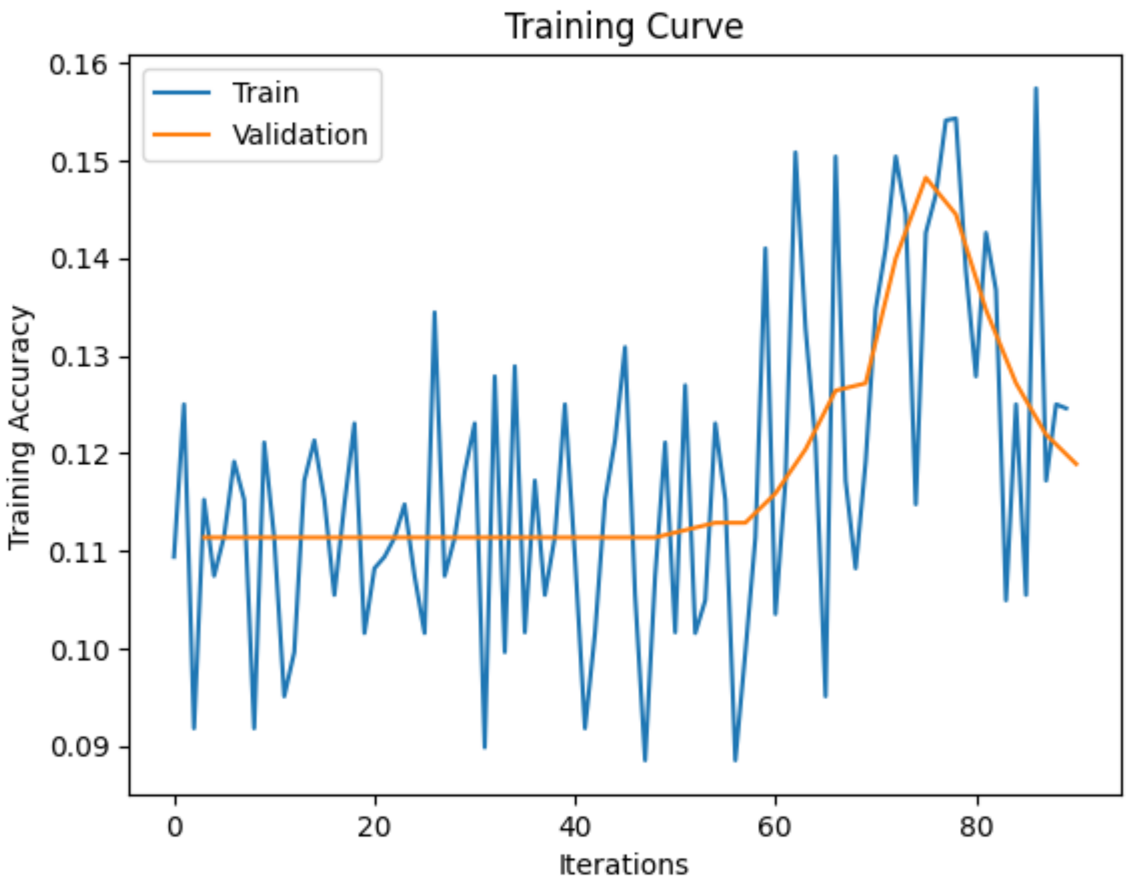
```
B   247
E   247
D   247
C   245
H   244
F   236
A   254
G   250
I   249
Total:  2219
CUDA is available!  Training on GPU ...

60% traing 20% test and val
```

while loop:                                  92/? [34:50<00:00,   3.61s/it]

```
Total time elapsed: 421.75 seconds
```

Training Curve




```
Final Training Accuracy: 0.12459016393442623
Final Validation Accuracy: 0.11888638073739653
```

Maybe not this big of a batch size

change number of CNN model

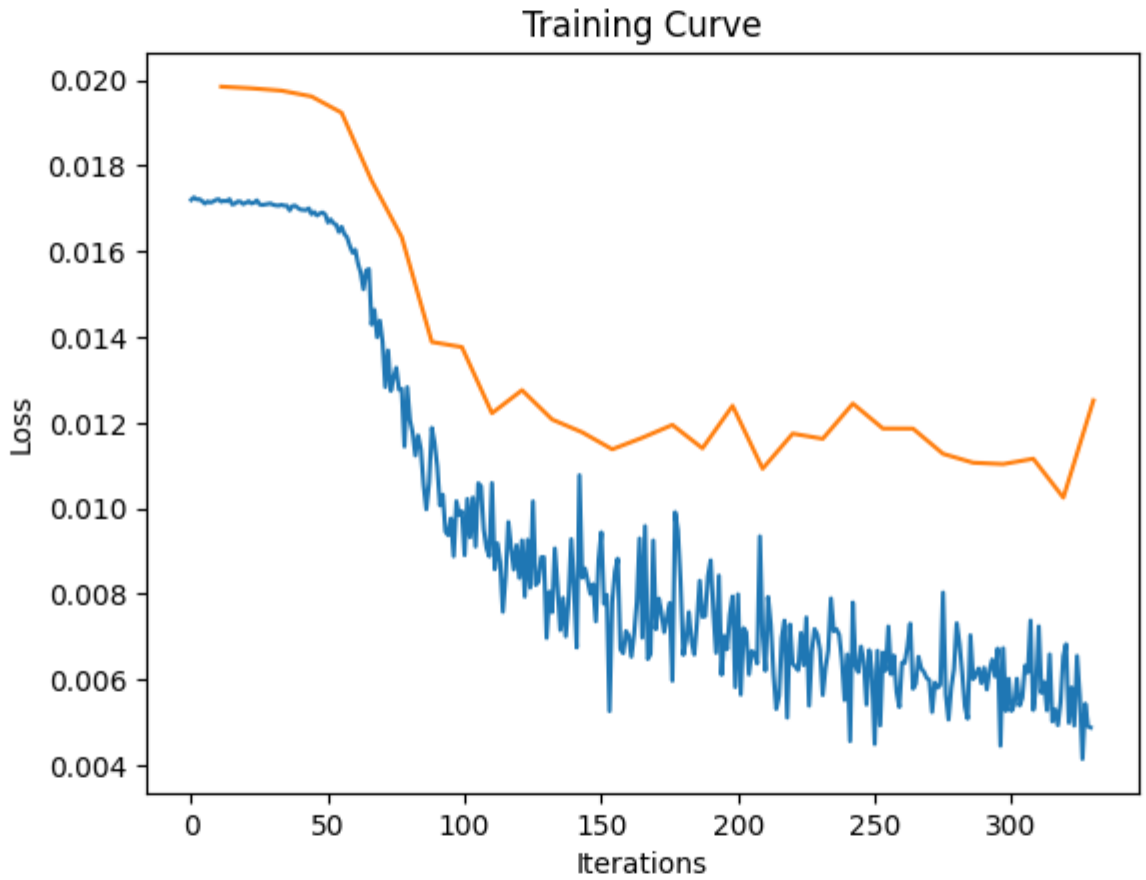
```
class new(nn.Module):
    def __init__(self):
        super(new, self).__init__()
        self.name = "new"
        self.conv1 = nn.Conv2d(3, 8, 5,stride=3,padding=0) #added 3
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(8, 10, 5,stride=2,padding=0)
        self.pool2 = nn.MaxPool2d(stride=3, kernel_size=2)
        self.fc1 = nn.Linear(6* 6 * 10, 32)
        self.fc2 = nn.Linear(32, 9)

        self.dropout = nn.Dropout(0.2)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool2(F.relu(self.conv2(x)))
        x = x.view(-1, 6 * 6 * 10)
        x = F.relu(self.fc1(x))
        x = self.dropout(x)
        x = self.fc2(x)
        return x


data_path = "/content/gdrive/MyDrive/here/Lab3_Gestures_Summer"

transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
```

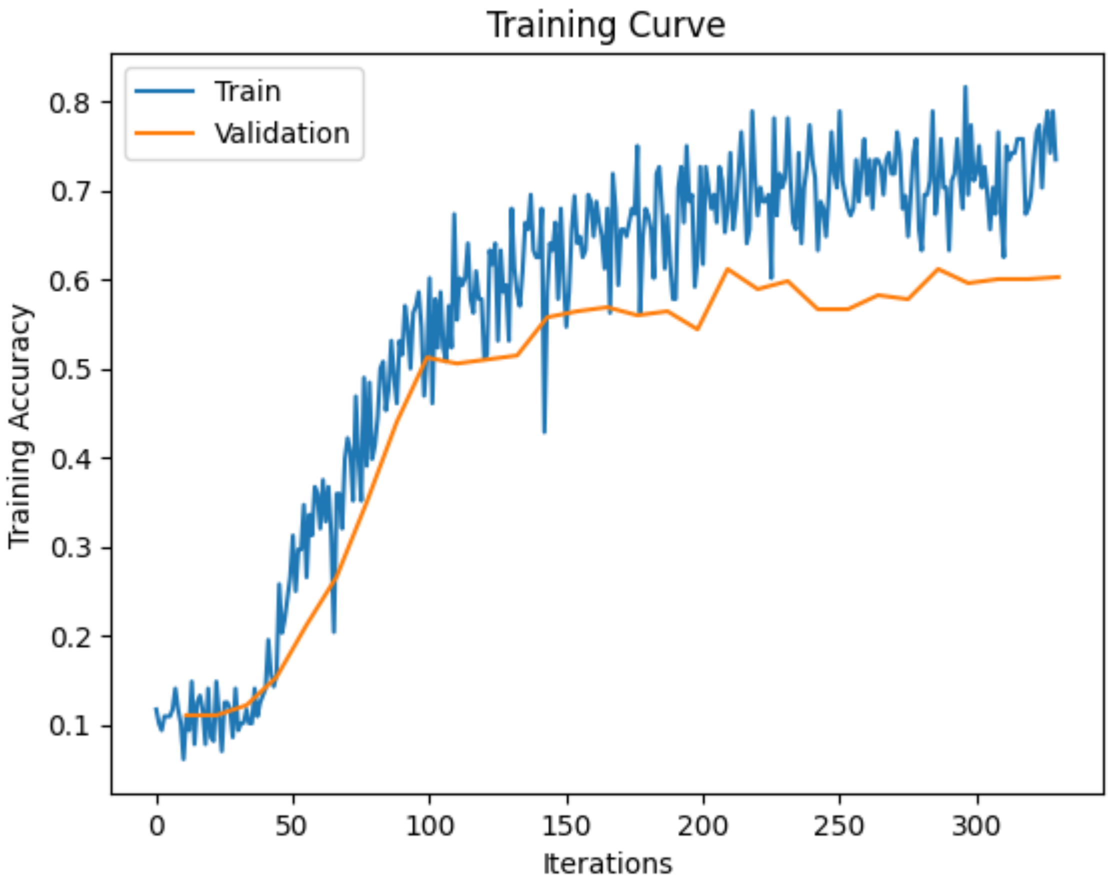
```
data_folder = ImageFolder(data_path , transform=transform)


class_num = get_class_num(data_path) # where bug located

#from tut_3a
use_cuda = True
model = new()

if use_cuda and torch.cuda.is_available():
  model.cuda()
  print('CUDA is available!  Training on GPU ...\n')
else:
  print('CUDA is not available.  Training on CPU ...\n')
train_loader, val_loader, test_loader = get_data_loader(data_folder, class_num, 128)


train(model, train_loader, val_loader, batch_size=128, num_epochs=30, learning_rate = 0.01)
```

```
B   247
E   247
D   247
C   245
H   244
F   236
A   254
G   250
I   249
Total:  2219
CUDA is available!  Training on GPU ...

60% traing 20% test and val
```

while loop:    332/? [16:30<00:00,   1.98it/s]

```
Total time elapsed: 436.96 seconds
```




```
Final Training Accuracy: 0.7346938775510204
Final Validation Accuracy: 0.6027088036117382
```

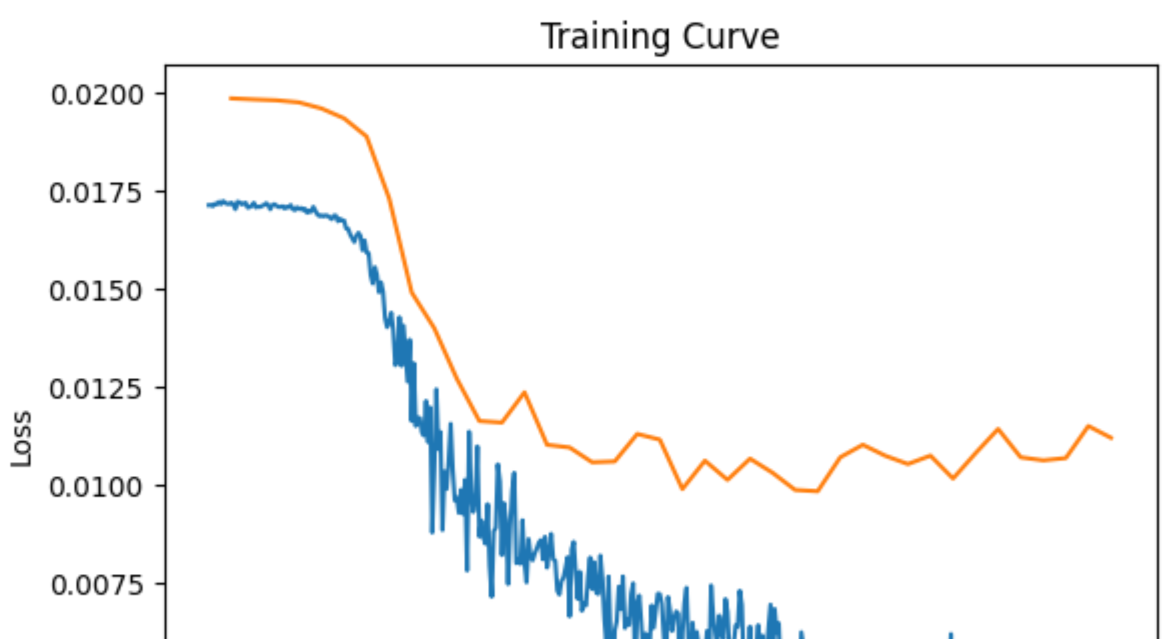
looks like more is good

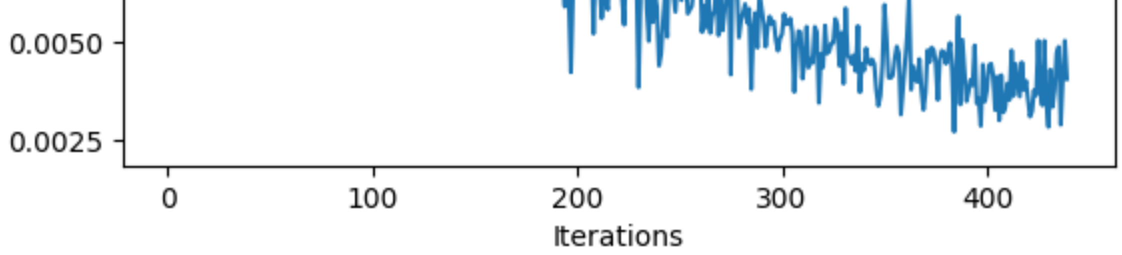
```
class new(nn.Module):
    def __init__(self):
        super(new, self).__init__()
        self.name = "new"
        self.conv1 = nn.Conv2d(3, 10, 5,stride=3,padding=0) #maybe10 this time
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(10, 10, 5,stride=2,padding=0)
        self.pool2 = nn.MaxPool2d(stride=3, kernel_size=2)
        self.fc1 = nn.Linear(6* 6 * 10, 32)
        self.fc2 = nn.Linear(32, 9)

        self.dropout = nn.Dropout(0.2)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool2(F.relu(self.conv2(x)))
        x = x.view(-1, 6 * 6 * 10)
        x = F.relu(self.fc1(x))
        x = self.dropout(x)
        x = self.fc2(x)
        return x


data_path = "/content/gdrive/MyDrive/here/Lab3_Gestures_Summer"

transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
data_folder = ImageFolder(data_path , transform=transform)


class_num = get_class_num(data_path) # where bug located

#from tut_3a
use_cuda = True
model = new()

if use_cuda and torch.cuda.is_available():
  model.cuda()
  print('CUDA is available!  Training on GPU ...\n')
else:
  print('CUDA is not available.  Training on CPU ...\n')
train_loader, val_loader, test_loader = get_data_loader(data_folder, class_num, 128)


train(model, train_loader, val_loader, batch_size=128, num_epochs=40, learning_rate = 0.01)
```

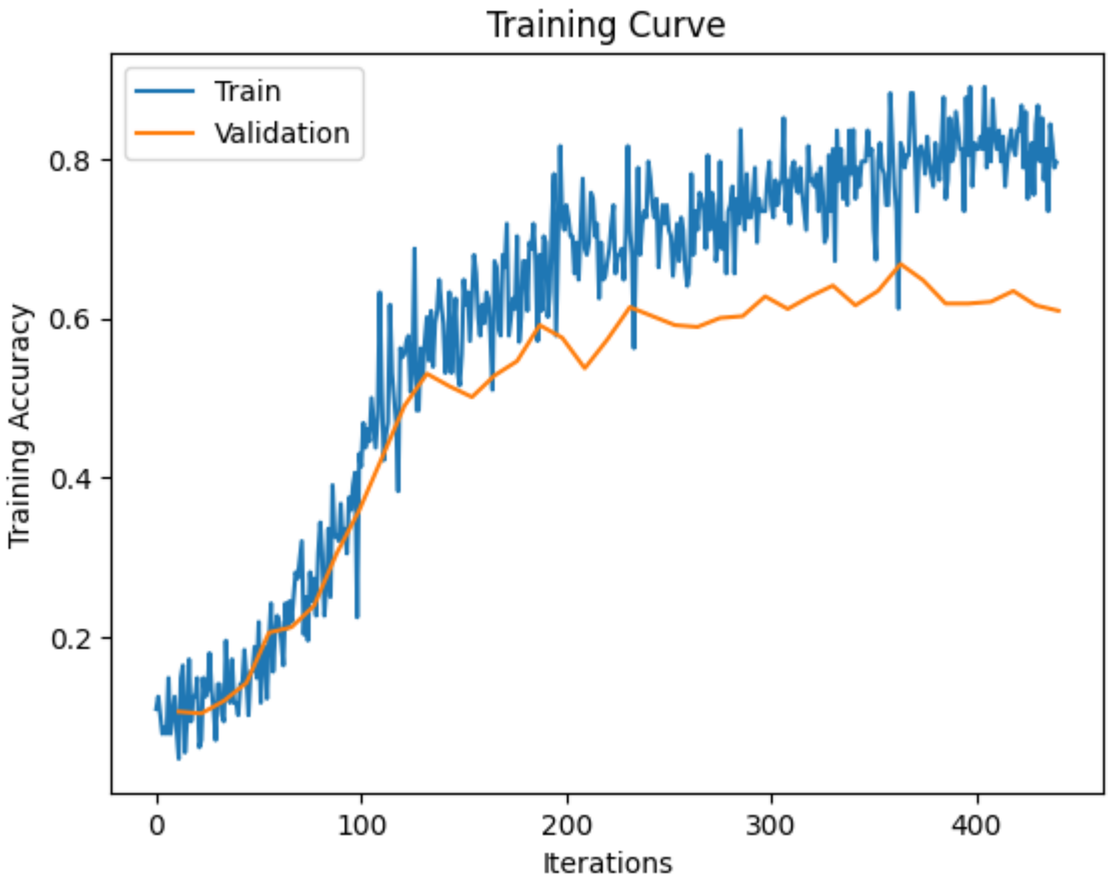
```
F   236
B   247
C   245
D   247
E   247
G   250
I   249
H   244
A   254
Total:  2219
CUDA is not available.  Training on CPU ...

60% traing 20% test and val
```

while loop: 441/? [14:17<00:00, 1.53it/s]

```
Total time elapsed: 859.81 seconds
```



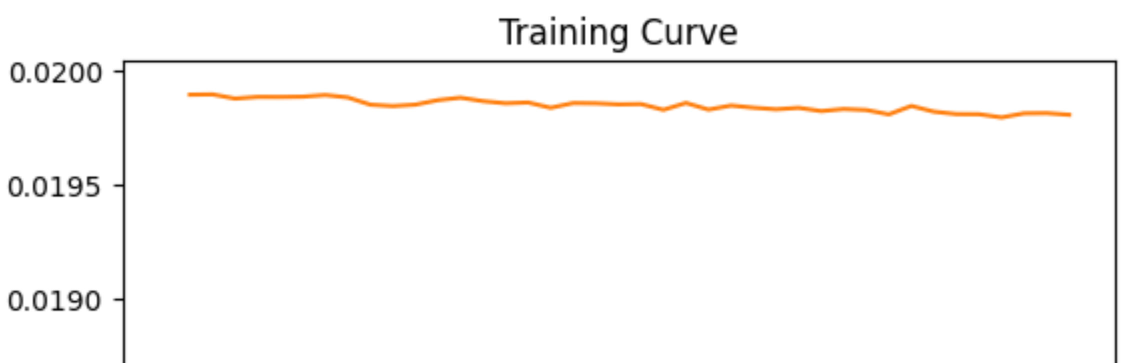


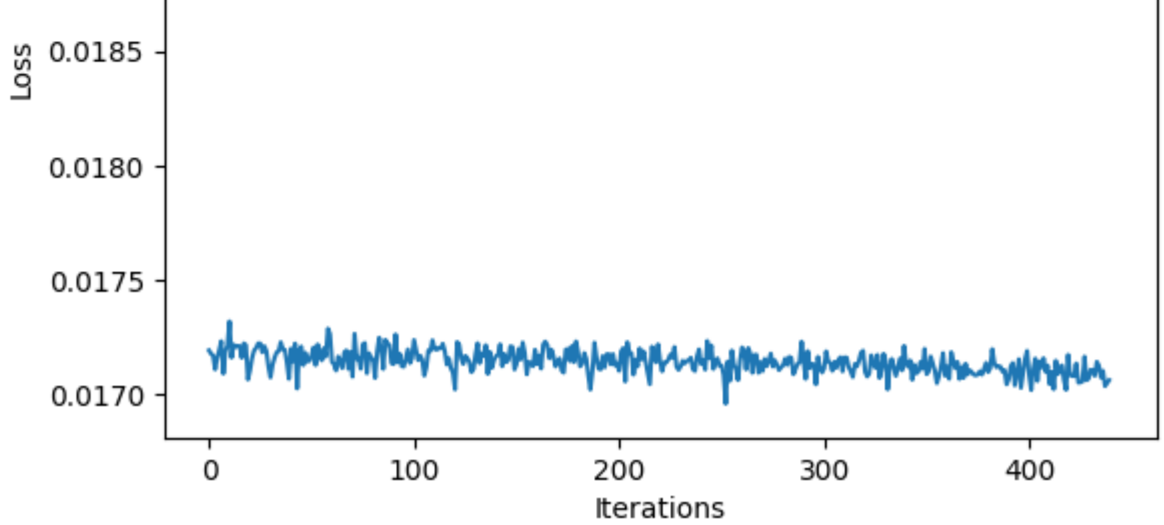



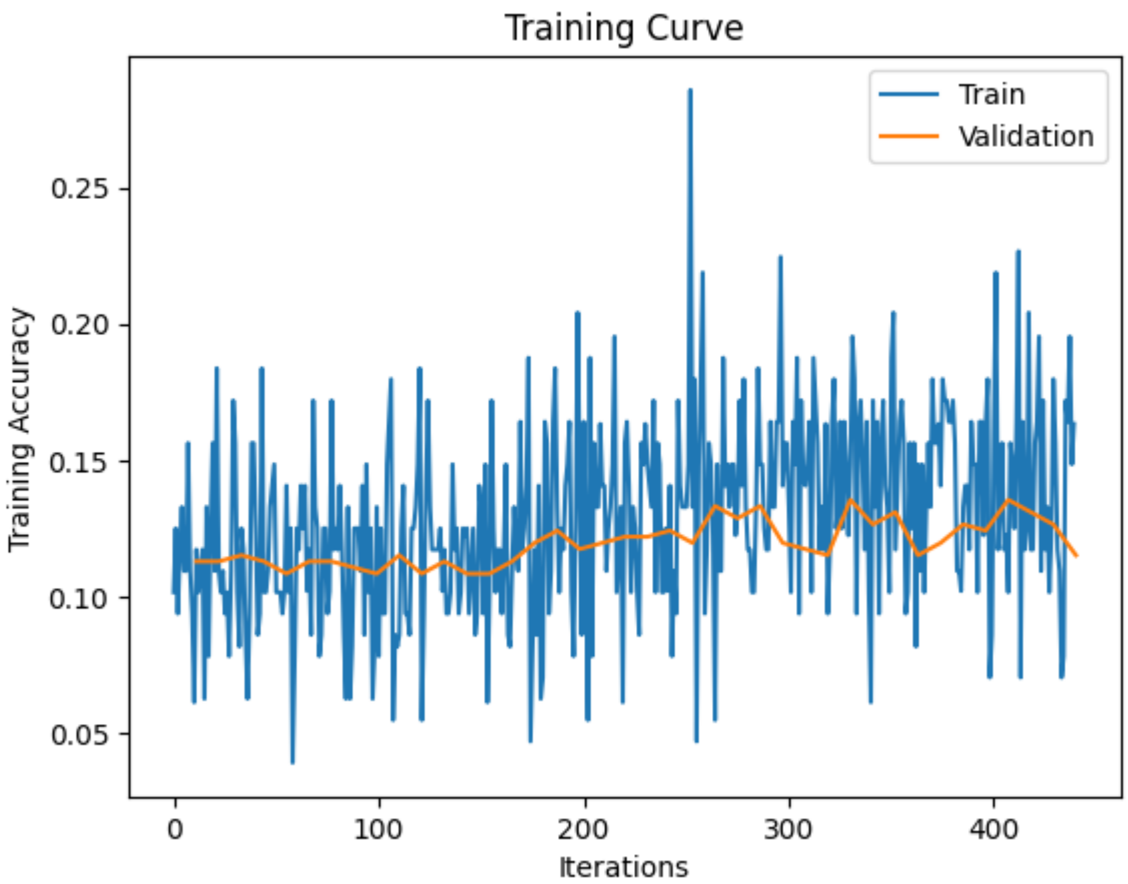

```
Final Training Accuracy: 0.7959183673469388
Final Validation Accuracy: 0.6094808126410836
```

```
data_path = "/content/gdrive/MyDrive/here/Lab3_Gestures_Summer"

transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
data_folder = ImageFolder(data_path , transform=transform)


class_num = get_class_num(data_path) # where bug located

#from tut_3a
use_cuda = True
model = new()

if use_cuda and torch.cuda.is_available():
  model.cuda()
  print('CUDA is available!  Training on GPU ...\n')
else:
  print('CUDA is not available.  Training on CPU ...\n')
train_loader, val_loader, test_loader = get_data_loader(data_folder, class_num, 128)


train(model, train_loader, val_loader, batch_size=128, num_epochs=40, learning_rate = 0.001)
```

```
F   236
B   247
C   245
D   247
E   247
G   250
I   249
H   244
A   254
Total:  2219
CUDA is available!  Training on GPU ...

60% traing 20% test and val
while loop:                                        442/? [06:03<00:00,   1.89it/s]
Total time elapsed: 365.88 seconds
```






```
Final Training Accuracy: 0.16326530612244897
Final Validation Accuracy: 0.11512415349887133
```

## Part (c) - 3 pt

Choose the best model out of all the ones that you have trained. Justify your choice.

The best model is NewNet with batch_size=128, num_epochs=40, learning_rate = 0.01.

Final Training Accuracy: 0.7959183673469388 Final Validation Accuracy: 0.6094808126410836

even though it is not super good but it is the best one out of my tests.

I think maybe adding more nerons can still increase the val accuracy so I think I am on the right track. And base on the curve both val and train is learning.

## Part (d) - 4 pt

Report the test accuracy of your best model. You should only do this step once and prior to this step you should have only used the training and validation data.

```
data_folder = ImageFolder(data_path, transform=transform)
class_num = get_class_num(data_path)
train_loader, val_loader, test_loader = get_data_loader(data_folder, class_num, batch_size=128)
net = new()
net.load_state_dict(torch.load('model_new_bs128_lr0.01_epoch39'))
```

```
F   236
B   247
C   245
D   247
E   247
G   250
I   249
H   244
A   254
Total:  2219
60% traing 20% test and val
<ipython-input-10-d0fe359061a6>:5: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default v
  net.load_state_dict(torch.load('model_new_bs128_lr0.01_epoch39'))
<All keys matched successfully>
```

```
totalr = 0
right = 0
for img, label in test_loader:
    output = net(img)
    pred = output.max(1, keepdim=True)[1]
    right += pred.eq(label.view_as(pred)).sum().item()
    totalr += img.shape[0]

result = right / totalr
print("The test accuracy is {}%".format(result*100))
```

```
    The test accuracy is 58.836689038031324%
```

## 4. Transfer Learning [15 pt]

For many image classification tasks, it is generally not a good idea to train a very large deep neural network model from scratch due to the enormous compute requirements and lack of sufficient amounts of training data.

One of the better options is to try using an existing model that performs a similar task to the one you need to solve. This method of utilizing a pre-trained network for other similar tasks is broadly termed **Transfer Learning**. In this assignment, we will use Transfer Learning to extract features from the hand gesture images. Then, train a smaller network to use these features as input and classify the hand gestures.

As you have learned from the CNN lecture, convolution layers extract various features from the images which get utilized by the fully connected layers for correct classification. AlexNet architecture played a pivotal role in establishing Deep Neural Nets as a go-to tool for image classification problems and we will use an ImageNet pre-trained AlexNet model to extract features in this assignment.

### Part (a) - 5 pt

Here is the code to load the AlexNet network, with pretrained weights. When you first run the code, PyTorch will download the pretrained weights from the internet.

```
import torchvision.models
alexnet = torchvision.models.alexnet(pretrained=True)
```

```
    /usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecat
      warnings.warn(
    /usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or
      warnings.warn(msg)
    Downloading: "https://download.pytorch.org/models/alexnet-owt-7be5be79.pth" to /root/.cache/torch/hub/checkpoints/alexnet-owt
    100%|██████████| 233M/233M [00:05<00:00, 48.1MB/s]
```

The alexnet model is split up into two components: *alexnet.features* and *alexnet.classifier*. The first neural network component, *alexnet.features*, is used to compute convolutional features, which are taken as input in *alexnet.classifier*.

The neural network alexnet.features expects an image tensor of shape Nx3x224x224 as input and it will output a tensor of shape Nx256x6x6 . (N = batch size).

Compute the AlexNet features for each of your training, validation, and test data. Here is an example code snippet showing how you can compute the AlexNet features for some images (your actual code might be different):

```
# img = ... a PyTorch tensor with shape [N,3,224,224] containing hand images ...
#features = alexnet.features(img)
```

**Save the computed features**. You will be using these features as input to your neural network in Part (b), and you do not want to re-compute the features every time. Instead, run *alexnet.features* once for each image, and save the result.

```
data_path = "/content/gdrive/MyDrive/here/Lab3_Gestures_Summer"

transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
data_folder = ImageFolder(data_path , transform=transform)


data_folder = ImageFolder(data_path, transform=transform)  #can I do that prob no
class_num = get_class_num(data_path)
train_loader, val_loader, test_loader = get_data_loader(data_folder, class_num, batch_size=128)


alex_feature = [[],[],[]]
loader_list = [train_loader, val_loader, test_loader]
for loader in range(len(loader_list)):
    for imgs, labels in loader_list[loader]:
        # alnc_feature[loader]
```

```
    # alnc_feature[loader]
    feature = alexnet.features(imgs)
    alex_feature[loader].append([torch.from_numpy(feature.detach().numpy()),labels])


F   236
B   247
C   245
D   247
E   247
G   250
I   249
H   244
A   254
Total:  2219
60% traing 20% test and val
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
<ipython-input-6-5c1538daf667> in <cell line: 16>()
     15 loader_list = [train_loader, val_loader, test_loader]
     16 for loader in range(len(loader_list)):
---> 17     for imgs, labels in loader_list[loader]:
     18         # alnc_feature[loader]
     19         feature = alexnet.features(imgs)

8 frames
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py in __next__(self)
    628                 # TODO(https://github.com/pytorch/pytorch/issues/76750)
    629                 self._reset()  # type: ignore[call-arg]
--> 630             data = self._next_data()
    631             self._num_yielded += 1
    632             if self._dataset_kind == _DatasetKind.Iterable and \

/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py in _next_data(self)
   1325
   1326             assert not self._shutdown and self._tasks_outstanding > 0
-> 1327             idx, data = self._get_data()
   1328             self._tasks_outstanding -= 1
   1329             if self._dataset_kind == _DatasetKind.Iterable:

/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py in _get_data(self)
   1291         else:
   1292             while True:
-> 1293                 success, data = self._try_get_data()
   1294                 if success:
   1295                     return data

/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py in _try_get_data(self, timeout)
   1129         #   (bool: whether successfully get data, any: data if successful else None)
   1130         try:
-> 1131             data = self._data_queue.get(timeout=timeout)
   1132             return (True, data)
   1133         except Exception as e:

/usr/lib/python3.10/multiprocessing/queues.py in get(self, block, timeout)
    111                 if block:
    112                     timeout = deadline - time.monotonic()
--> 113                     if not self._poll(timeout):
    114                         raise Empty
    115                 elif not self._poll():

/usr/lib/python3.10/multiprocessing/connection.py in poll(self, timeout)
    255         self._check_closed()
    256         self._check_readable()
--> 257         return self._poll(timeout)
    258
    259     def __enter__(self):

/usr/lib/python3.10/multiprocessing/connection.py in _poll(self, timeout)
    422
    423     def _poll(self, timeout):
--> 424         r = wait([self], timeout)
    425         return bool(r)
    426

/usr/lib/python3.10/multiprocessing/connection.py in wait(object_list, timeout)
    929
    930             while True:
--> 931                 ready = selector.select(timeout)
    932                 if ready:
    933                     return [key.fileobj for (key, events) in ready]

/usr/lib/python3.10/selectors.py in select(self, timeout)
    414         ready = []
    415         try:
--> 416             fd_event_list = self._selector.poll(timeout)
    417         except InterruptedError:
    418             return ready

KeyboardInterrupt:
```

accidently pressed run here again succesful before, stopped manually, should not have returned error here. the following is just based on the previous run.

## Part (b) - 3 pt

Build a convolutional neural network model that takes as input these AlexNet features, and makes a prediction. Your model should be a subclass of nn.Module.

Explain your choice of neural network architecture: how many layers did you choose? What types of layers did you use: fully-connected or convolutional? What about other decisions like pooling layers, activation functions, number of channels / hidden units in each layer?

Here is an example of how your model may be called:

```
from math import floor
torch.manual_seed(543243)

class AlexNet(nn.Module):
  def __init__(self):
        super(AlexNet, self).__init__()
        self.name = "AlexNet"
        self.fc1 = nn.Linear(6* 6 * 256, 128)
        self.fc2 = nn.Linear(128, 9)
  def forward(self, x):
      x = x.view(-1, 6* 6 * 256)
      x = F.relu(self.fc1(x))
      x = self.fc2(x)
      return x
```

I used 2 fully connected layers and 0 convolution and pooling layer because we are using pretrained weights from AlexNet so there is no need for a really deep network and reduce the layer will help with my run time (it takes too long). I choose 128 as the output for conv1 because it feels like a good fit.

## Part (c) - 5 pt

Train your new network, including any hyperparameter tuning. Plot and submit the training curve of your best model only.

Note: Depending on how you are caching (saving) your AlexNet features, PyTorch might still be tracking updates to the **AlexNet weights**, which we are not tuning. One workaround is to convert your AlexNet feature tensor into a numpy array, and then back into a PyTorch tensor.

training takes only one thing now no need for val and train as two inputs

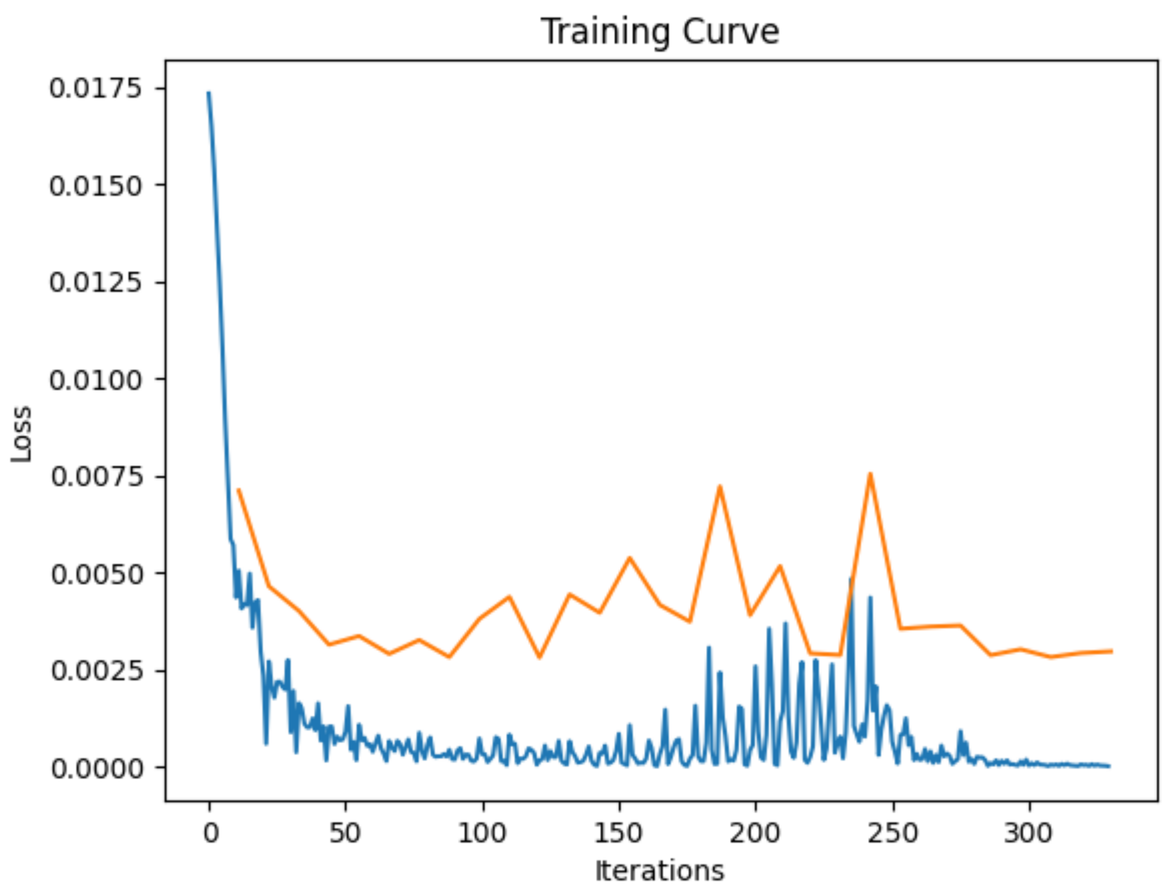
code aobve train and just change to one input state

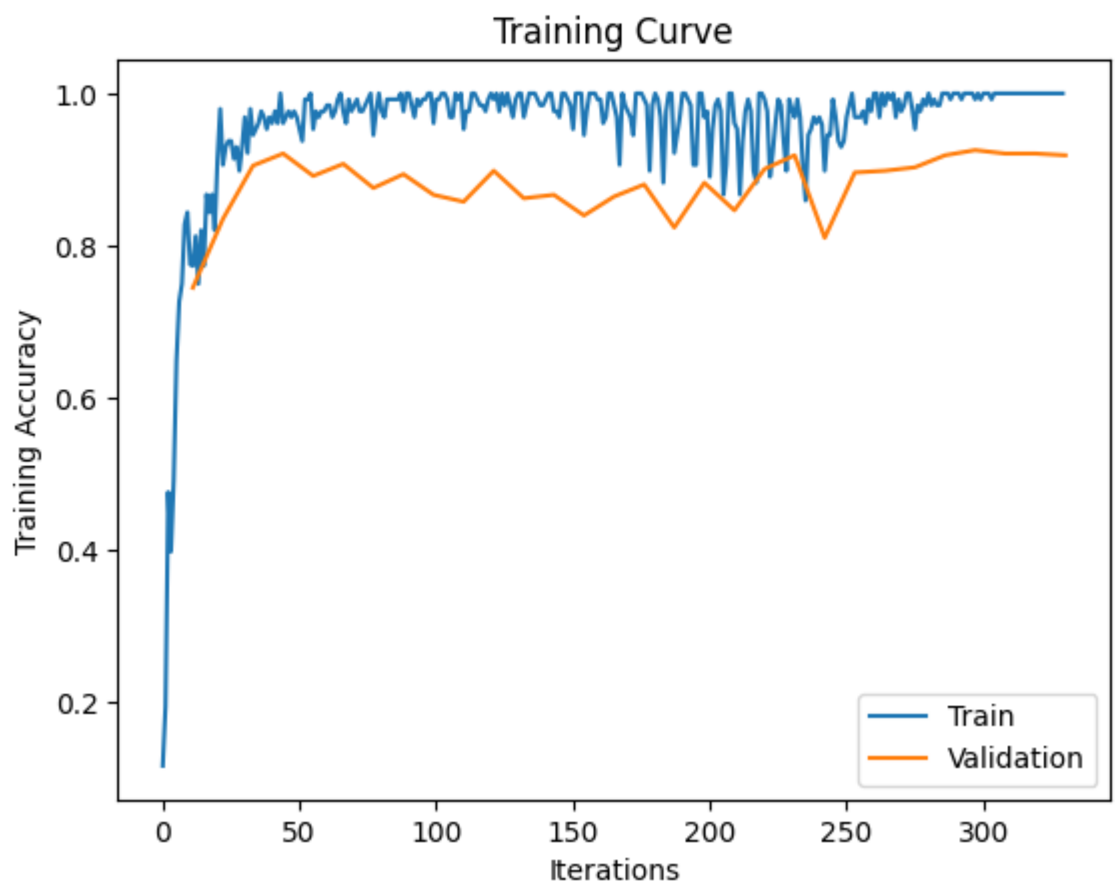
```
def train_new(model, alnc_feature, batch_size=64, num_epochs=1, learning_rate = 0.01):
    torch.manual_seed(1000)
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=learning_rate, momentum=0.9)

    iters, epoch_itr, losses, val_loss, train_acc, val_acc = [], [], [], [], [], []

    # training
    n = 0 # the number of iterations
    #new
    progress_total = num_epochs * len(alnc_feature[0])
    pbar = tqdm(desc = 'while loop', total = progress_total)
    start_time = time.time()
    for epoch in range(num_epochs):
        # feature_iter = iter(alnc_feature[0])
        # val_feature_iter = iter(alnc_feature[1])
        for imgs, labels in iter(alnc_feature[0]):

            ##############################################
            #To Enable GPU Usage
            if use_cuda and torch.cuda.is_available():
                # feature_iter = feature_iter.cuda()
                imgs = imgs.cuda()
                labels = labels.cuda()
            ##############################################


            out = model(imgs)             # forward pass
            loss = criterion(out, labels) # compute the total loss
```

```
            loss.backward()               # backward pass (compute parameter updates)
            optimizer.step()              # make the updates for each parameter
            optimizer.zero_grad()         # a clean up step for PyTorch

            # save the current training information
            iters.append(n)
            losses.append(float(loss)/batch_size)

            # get_accuracy
            pred = out.max(1,keepdim = True)[1]
            correct = pred.eq(labels.view_as(pred)).sum().item()
            total = imgs.shape[0]
            t_acc = correct/ total
            # print(t_acc)
            train_acc.append(t_acc) # compute training accuracy

            n += 1
            pbar.update(1)

        val_l = 0
        correct = 0
        total = 0
        for valimgs, vallabels in alnc_feature[1]:


            #############################################
            #To Enable GPU Usage
            if use_cuda and torch.cuda.is_available():
                # val_feature_iter = val_feature_iter.cuda()
                valimgs = valimgs.cuda()
                vallabels = vallabels.cuda()
            #############################################

            output = model(valimgs)
            pred = output.max(1, keepdim=True)[1]
            val_l += criterion(output, vallabels).item()
            optimizer.zero_grad()
            correct += pred.eq(vallabels.view_as(pred)).sum().item()
            total += valimgs.shape[0]

        v_acc, v_loss = correct / total, float(val_l)/total
        val_acc.append(v_acc)  # compute validation accuracy
        val_loss.append(v_loss)
        epoch_itr.append(n)

        model_path = get_model_name(model.name, batch_size, learning_rate, epoch)
        torch.save(model.state_dict(), model_path)

    end_time = time.time()
    elapsed_time = end_time - start_time
    print("Total time elapsed: {:.2f} seconds\n".format(elapsed_time))

    # plotting
    plt.title("Training Curve")
    plt.plot(iters, losses, label="Train")
    plt.plot(epoch_itr, val_loss, label="Validation")
    plt.xlabel("Iterations")
    plt.ylabel("Loss")
    plt.show()

    plt.title("Training Curve")
    plt.plot(iters, train_acc, label="Train")
    plt.plot(epoch_itr, val_acc, label="Validation")
    plt.xlabel("Iterations")
    plt.ylabel("Training Accuracy")
    plt.legend(loc='best')
    plt.show()

    print("Final Training Accuracy: {}".format(train_acc[-1]))
    print("Final Validation Accuracy: {}".format(val_acc[-1]))



data_path = "/content/gdrive/MyDrive/here/Lab3_Gestures_Summer"

transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
data_folder = ImageFolder(data_path , transform=transform)


class_num = get_class_num(data_path) # where bug located

#from tut_3a
```

```
use_cuda = True
model = AlexNet()

if use_cuda and torch.cuda.is_available():
  model.cuda()
  print('CUDA is available!  Training on GPU ...\n')
else:
  print('CUDA is not available.  Training on CPU ...\n')
train_loader, val_loader, test_loader = get_data_loader(data_folder, class_num, 128)


train_new(model, alex_feature, batch_size=128, num_epochs=30, learning_rate = 0.01)
```

```
F   236
B   247
C   245
D   247
E   247
G   250
I   249
H   244
A   254
Total:  2219
CUDA is available!  Training on GPU ...

60% traing 20% test and val
while loop: 100%                                   330/330 [00:13<00:00, 204.98it/s]
Total time elapsed: 1.70 seconds
```




```
Final Training Accuracy: 1.0
Final Validation Accuracy: 0.9187358916478555
```

Final Training Accuracy: 1.0 Final Validation Accuracy: 0.92

Part (d) - 2 pt

Part (d) - 2 pt

Report the test accuracy of your best model. How does the test accuracy compare to Part 3(d) without transfer learning?

```
data_folder = ImageFolder(data_path, transform=transform)
class_num = get_class_num(data_path)
train_loader, val_loader, test_loader = get_data_loader(data_folder, class_num, batch_size=128)
net = AlexNet()
net.load_state_dict(torch.load('model_AlexNet_bs128_lr0.01_epoch29'))

right = 0
totalr = 0
for img, label in alex_feature[2]:
    output = net(img)
    predic = output.max(1, keepdim=True)[1]
    right += predic.eq(label.view_as(predic)).sum().item()
    totalr += len(img)

test_acc = right / totalr
print("The test accuracy of the best model is {}%".format(test_acc*100))
```

```
F   236
B   247
C   245
D   247
E   247
G   250
I   249
H   244
A   254
Total:  2219
60% traing 20% test and val
The test accuracy for the best model is 82.10290827740492%
<ipython-input-54-2fa9cfe437bf>:5: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default v
  net.load_state_dict(torch.load('model_AlexNet_bs128_lr0.01_epoch29'))
```

The test accuracy for the "best" model is 82.10

```
from ipywidgets import Widget
Widget.close_all()
```

```
!jupyter nbconvert --to html /content/aalab3.ipynb
```

```
[NbConvertApp] Converting notebook /content/aalab3.ipynb to html
[NbConvertApp] ERROR | Notebook JSON is invalid: Additional properties are not allowed ('metadata' was unexpected)

Failed validating 'additionalProperties' in stream:

On instance['cells'][51]['outputs'][0]:
{'metadata': {'tags': None},
 'name': 'stdout',
 'output_type': 'stream',
 'text': 'F   236\n'
         'B   247\n'
         'C   245\n'
         'D   247\n'
         'E   247\n'
         'G   250\n'
         'I   249\n'
         'H   244\n'
         '...'}
Traceback (most recent call last):
  File "/usr/local/bin/jupyter-nbconvert", line 8, in <module>
    sys.exit(main())
  File "/usr/local/lib/python3.10/dist-packages/jupyter_core/application.py", line 283, in launch_instance
    super().launch_instance(argv=argv, **kwargs)
  File "/usr/local/lib/python3.10/dist-packages/traitlets/config/application.py", line 992, in launch_instance
    app.start()
  File "/usr/local/lib/python3.10/dist-packages/nbconvert/nbconvertapp.py", line 423, in start
    self.convert_notebooks()
  File "/usr/local/lib/python3.10/dist-packages/nbconvert/nbconvertapp.py", line 597, in convert_notebooks
    self.convert_single_notebook(notebook_filename)
  File "/usr/local/lib/python3.10/dist-packages/nbconvert/nbconvertapp.py", line 560, in convert_single_notebook
    output, resources = self.export_single_notebook(
  File "/usr/local/lib/python3.10/dist-packages/nbconvert/nbconvertapp.py", line 488, in export_single_notebook
    output, resources = self.exporter.from_filename(
  File "/usr/local/lib/python3.10/dist-packages/nbconvert/exporters/exporter.py", line 189, in from_filename
    return self.from_file(f, resources=resources, **kw)
  File "/usr/local/lib/python3.10/dist-packages/nbconvert/exporters/exporter.py", line 206, in from_file
    return self.from_notebook_node(
  File "/usr/local/lib/python3.10/dist-packages/nbconvert/exporters/html.py", line 223, in from_notebook_node
    return super().from_notebook_node(nb, resources, **kw)
```

```
  File "/usr/local/lib/python3.10/dist-packages/nbconvert/exporters/templateexporter.py", line 413, in from_notebook_node
    output = self.template.render(nb=nb_copy, resources=resources)
  File "/usr/local/lib/python3.10/dist-packages/jinja2/environment.py", line 1304, in render
    self.environment.handle_exception()
  File "/usr/local/lib/python3.10/dist-packages/jinja2/environment.py", line 939, in handle_exception
    raise rewrite_traceback_stack(source=source)
  File "/usr/local/share/jupyter/nbconvert/templates/lab/index.html.j2", line 3, in top-level template code
    {% from 'jupyter_widgets.html.j2' import jupyter_widgets %}
  File "/usr/local/share/jupyter/nbconvert/templates/lab/base.html.j2", line 2, in top-level template code
    {% from 'celltags.j2' import celltags %}
  File "/usr/local/share/jupyter/nbconvert/templates/base/display_priority.j2", line 1, in top-level template code
    {%- extends 'base/null.j2' -%}
  File "/usr/local/share/jupyter/nbconvert/templates/base/null.j2", line 26, in top-level template code
    {%- block body -%}
  File "/usr/local/share/jupyter/nbconvert/templates/base/null.j2", line 29, in block 'body'
    {%- block body_loop -%}
  File "/usr/local/share/jupyter/nbconvert/templates/base/null.j2", line 31, in block 'body_loop'
    {%- block any_cell scoped -%}
  File "/usr/local/share/jupyter/nbconvert/templates/base/null.j2", line 34, in block 'any_cell'
```