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://colab.research.google.com/drive/13_WvGllSbdMF2DAgaFHBEbOH7iEepP6n?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)

In [ ]:
```
import numpy as np
import time
import torch
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
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
```

In [ ]:
```
from google.colab import drive
drive.mount('/content/gdrive')
```

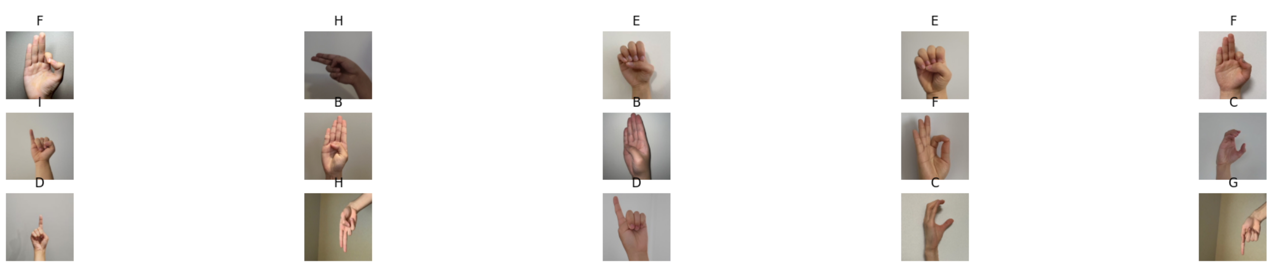
```
Mounted at /content/gdrive
```

In [ ]:
```
#load data
transform = transforms.Compose([transforms.Resize((224, 224)),
              transforms.ToTensor()])
data_path = "/content/gdrive/MyDrive/Colab Notebooks/APS360 LAB/lab3/Lab3_Ge
dataset = torchvision.datasets.ImageFolder(data_path, transform = transform)

data_loader = torch.utils.data.DataLoader(dataset, batch_size=1,
                                          shuffle=True)
train_size = int(0.65 * len(dataset))
val_size = int(0.17 * len(dataset))
test_size = int(0.17 * len(dataset))
overfit_size = len(dataset) - train_size - val_size - test_size

train_dataset, val_dataset, test_dataset, overfit_dataset= torch.utils.data.
    dataset, [train_size, val_size, test_size, overfit_size],
    generator=torch.Generator().manual_seed(42)
)

train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=1,
                                           num_workers=1, shuffle=True)
val_loader = torch.utils.data.DataLoader(val_dataset, batch_size=1,
                                           num_workers=1, shuffle=True)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=1,
                                           num_workers=1, shuffle=True)
overfit_loader = torch.utils.data.DataLoader(overfit_dataset, batch_size=1,
                                           num_workers=1, shuffle=True)
```

In [ ]:
```
print('There are',len(train_loader),
      'training images, which is {:.2f} % of the entire dataset.'.format(len
print('There are',len(val_loader),
      'validation images, which is {:.2f} % of the entire dataset.'.format(l
print('There are',len(test_loader),
      'test images, which is {:.2f} % of the entire dataset.'.format(len(tes

#I used torch.utils.data.DataLoader for loading data,
#and torch.utils.data.random_split for splitting data.
#The splitting strategy are as shown in the code, where
#I put 65% of the dataset for training, 17% for validation,
#17% for testing, and a very small portion for model sanity check.
```

```
There are 1442 training images, which is 64.98 % of the entire dataset.
There are 377 validation images, which is 16.99 % of the entire dataset.
There are 377 test images, which is 16.99 % of the entire dataset.
```

In [ ]:
```
#visualizing sample data
k = 0
classes = ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I']
fig = plt.figure(figsize=(25, 4))

for images, labels in train_loader:
    # since batch_size = 1, there is only 1 image in `images`
    image = images[0]
    label = labels[0]
    # place the colour channel at the end, instead of at the beginning
    img = np.transpose(image, [1, 2, 0])
    # normalize pixel intensity values to [0, 1]
    img = img

    # Display the image
    ax = fig.add_subplot(3, 5, k+1)
    ax.axis('off')
    ax.imshow(img)
    ax.set_title(classes[label])  # Use label index to get the corresponding

    k += 1
    if k >= 15:
        break
```



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?

In [ ]:
```python
class GestRec(nn.Module):
    def __init__(self):
        super(GestRec, self).__init__()
        self.name = "GestRec"
        self.conv1 = nn.Conv2d(3, 5, 5) #in channels, #out channels, #kernal
        self.pool = nn.MaxPool2d(2, 2) #kernal size, stride
        self.conv2 = nn.Conv2d(5, 10, 5)
        self.fc1 = nn.Linear(10 * 53 * 53, 32) #input size, output size
        self.fc2 = nn.Linear(32, 9) #input size, output size

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 10 * 53 * 53)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        x = x.squeeze(1) # Flatten to [batch_size]
        return x

model = GestRec()
```

Answer: I choose an CNNs Model with 2 convolution layers, 2 pooling layers, and 2 fully-connected layers. By using two convolution layers, the model is able to learn and capture both low-level and high-level features of the hand gestures. Pooling helps reduce dimension of the feature map, allowing the model to be trained faster. The 2 fully-connected layers are used for classification in the end. ReLu activation function is utilized in multiple steps in the model so that the model can learn non-linearity.

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.

In [ ]:
```
def get_model_name(name, batch_size, learning_rate, epoch):
    path = "model_{0}_bs{1}_lr{2}_epoch{3}".format(name,
                                                    batch_size,
                                                    learning_rate,
                                                  epoch)
    return path

def get_accuracy(model, batch_size, train=False):
    if train:
        data = train_dataset
    else:
        data = val_dataset

    correct = 0
    total = 0

    for imgs, labels in torch.utils.data.DataLoader(data, batch_size=batch_s

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

        #############################################

        output = model(imgs)

        #select index with maximum prediction score
        pred = output.max(1, keepdim=True)[1]
        correct += pred.eq(labels.view_as(pred)).sum().item()
        total += imgs.shape[0]
    return correct / total
```

In [ ]:
```
def train(model, train_data, batch_size=64, learning_rate =0.001, num_epochs
    torch.manual_seed(1000)
    train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_

    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=learning_rate, momentum=0.9

    iters, losses, train_acc, val_acc = [], [], [], []
```

```
    # training
    start_time = time.time()
    n = 0 # the number of iterations
    for epoch in range(num_epochs):
        for imgs, labels in iter(train_loader):
          # Loop over each batch of images and labels
          #############################################
          # 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 u
          optimizer.step()              # make the updates for each paramete
          optimizer.zero_grad()         # a clean-up step for PyTorch

          # save the current training information
          iters.append(n)
          losses.append(float(loss) / batch_size)             # compute *ave
          n += 1

          # Save the current model (checkpoint) to a file
          model_path = get_model_name(model.name, batch_size, learning_rate,
          torch.save(model.state_dict(), model_path)

        train_acc.append(get_accuracy(model, batch_size, train=True))   # co
        val_acc.append(get_accuracy(model, batch_size, train=False))    #com
        print(("Epoch {}: Train accuracy: {} |" +
                "Validation accuracy: {} ").format(
                    epoch +1,
                    train_acc[epoch],
                    val_acc[epoch]))

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

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

    plt.title("Training Curve")
    plt.plot(range(num_epochs+1), train_acc, label="Train")
    plt.plot(range(num_epochs+1), 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]))
```

Answer:

For loss function, I chose the Cross-Entropy loss function, which is optimal for multi-class classification training. The optimizer I chose is the Stochastic Gradient Descent optimizer because it is suited for large-scale datasets, and it updates on a randomly selected subset of training examples at each iteration. This optimizer is computationally-efficient.

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).

In [ ]:
```
def get_model_name(name, batch_size, learning_rate, epoch):
    path = "model_{0}_bs{1}_lr{2}_epoch{3}".format(name,
                                                    batch_size,
                                                    learning_rate,
                                                   epoch)
    return path

def get_accuracy_overfit(model, batch_size = 23):

    data = overfit_dataset

    correct = 0
    total = 0
    for imgs, labels in torch.utils.data.DataLoader(data, batch_size=batch_s


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

        #############################################


        output = model(imgs)

        #select index with maximum prediction score
        pred = output.max(1, keepdim=True)[1]
        correct += pred.eq(labels.view_as(pred)).sum().item()
        total += imgs.shape[0]
    return correct / total
```

In [ ]:
```
def train_overfit(model, data, batch_size=23, learning_rate =0.001, num_epoc

    torch.manual_seed(1000)
    train_loader = torch.utils.data.DataLoader(data, batch_size=batch_size,
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=learning_rate, momentum = 0

    iters, losses, train_acc = [], [], []

    # training
    start_time = time.time()
    n = 0 # the number of iterations
    for epoch in range(num_epochs):
        for imgs, labels in iter(train_loader):
          # Loop over each batch of images and labels
          #############################################

          # To Enable GPU Usage
          if use_cuda and torch.cuda.is_available():
```

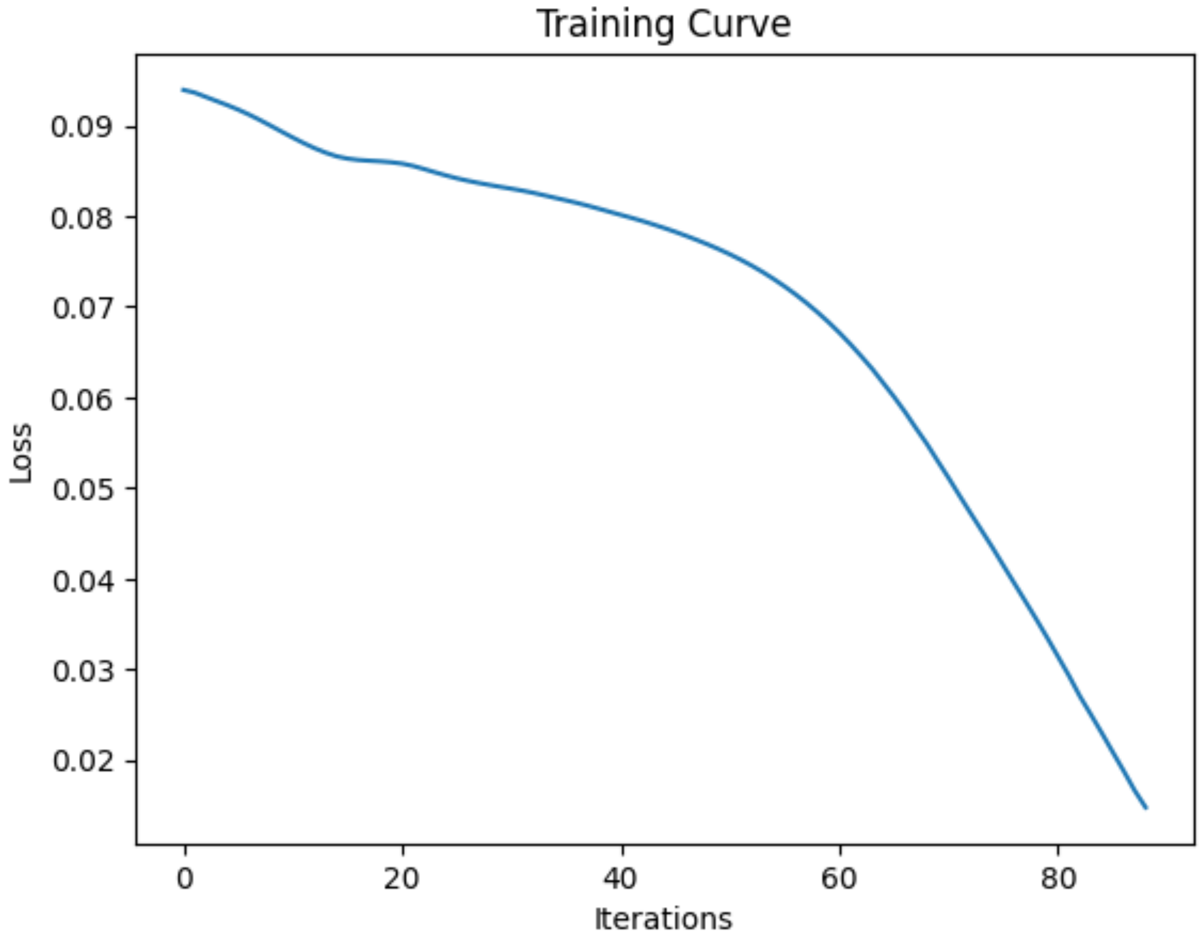
```
            imgs = imgs.cuda()
            labels = labels.cuda()

        ##############################################

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

        # save the current training information
        iters.append(n)
        losses.append(float(loss) / batch_size)            # compute *ave
        train_acc.append(get_accuracy_overfit(model, batch_size))   # comp
        n += 1

        # Save the current model (checkpoint) to a file
        model_path = get_model_name(model.name, batch_size, learning_rate,
        torch.save(model.state_dict(), model_path)

      print(("Epoch {}: Train accuracy: {}").format(
          epoch + 1,
          train_acc[epoch]))

      if(get_accuracy_overfit(model, batch_size) == 1):
          break

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

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

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

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

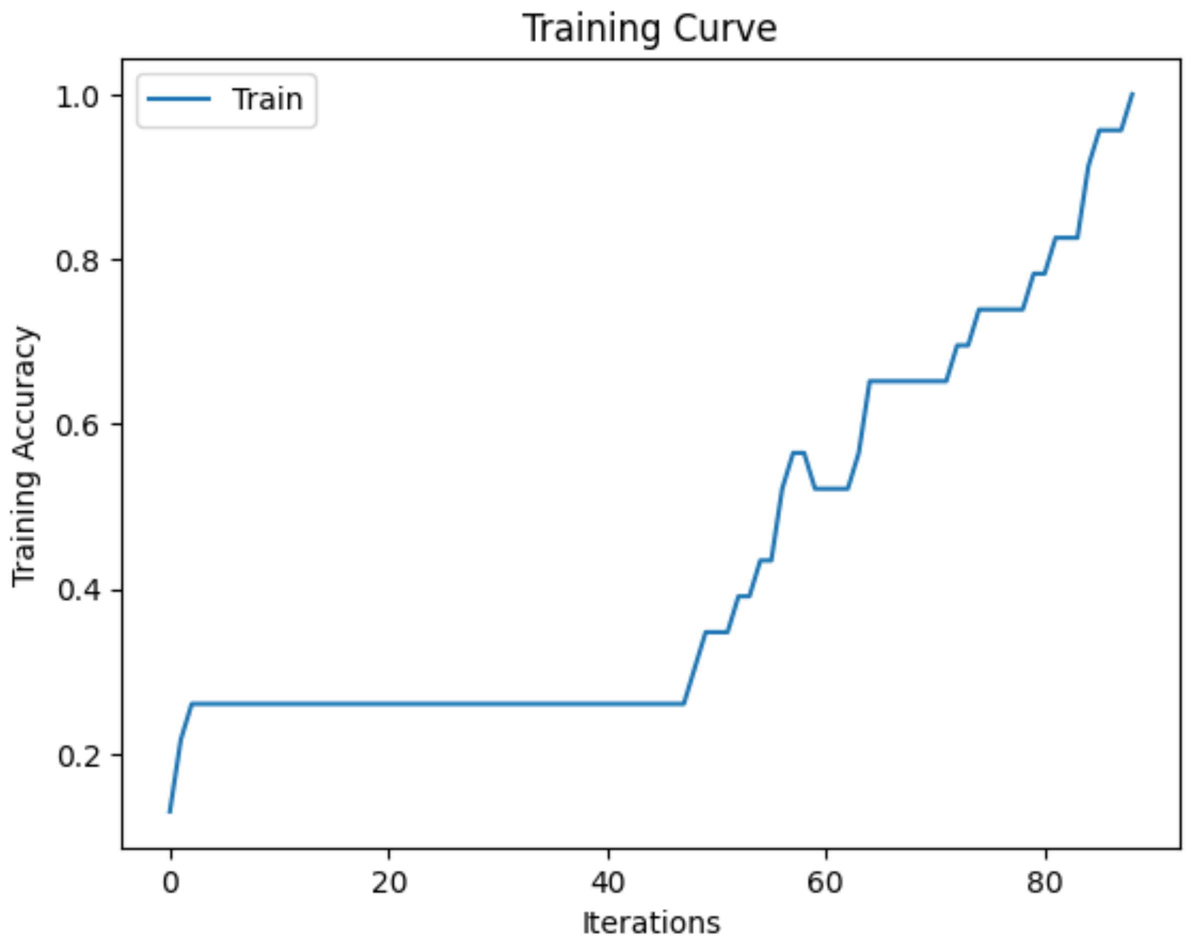
In [ ]:
```
use_cuda = True

model = GestRec()

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

#proper model

train_overfit(model, overfit_dataset,
      batch_size = 23, num_epochs = 120)
```

```
CUDA is available!  Training on GPU ...
Epoch 1: Train accuracy: 0.13043478260869565
Epoch 2: Train accuracy: 0.21739130434782608
Epoch 3: Train accuracy: 0.2608695652173913
Epoch 4: Train accuracy: 0.2608695652173913
Epoch 5: Train accuracy: 0.2608695652173913
Epoch 6: Train accuracy: 0.2608695652173913
Epoch 7: Train accuracy: 0.2608695652173913
Epoch 8: Train accuracy: 0.2608695652173913
Epoch 9: Train accuracy: 0.2608695652173913
Epoch 10: Train accuracy: 0.2608695652173913
Epoch 11: Train accuracy: 0.2608695652173913
Epoch 12: Train accuracy: 0.2608695652173913
Epoch 13: Train accuracy: 0.2608695652173913
Epoch 14: Train accuracy: 0.2608695652173913
Epoch 15: Train accuracy: 0.2608695652173913
Epoch 16: Train accuracy: 0.2608695652173913
Epoch 17: Train accuracy: 0.2608695652173913
Epoch 18: Train accuracy: 0.2608695652173913
Epoch 19: Train accuracy: 0.2608695652173913
Epoch 20: Train accuracy: 0.2608695652173913
Epoch 21: Train accuracy: 0.2608695652173913
Epoch 22: Train accuracy: 0.2608695652173913
Epoch 23: Train accuracy: 0.2608695652173913
Epoch 24: Train accuracy: 0.2608695652173913
Epoch 25: Train accuracy: 0.2608695652173913
Epoch 26: Train accuracy: 0.2608695652173913
Epoch 27: Train accuracy: 0.2608695652173913
Epoch 28: Train accuracy: 0.2608695652173913
Epoch 29: Train accuracy: 0.2608695652173913
Epoch 30: Train accuracy: 0.2608695652173913
Epoch 31: Train accuracy: 0.2608695652173913
Epoch 32: Train accuracy: 0.2608695652173913
Epoch 33: Train accuracy: 0.2608695652173913
Epoch 34: Train accuracy: 0.2608695652173913
Epoch 35: Train accuracy: 0.2608695652173913
Epoch 36: Train accuracy: 0.2608695652173913
Epoch 37: Train accuracy: 0.2608695652173913
```

```
Epoch 38: Train accuracy: 0.2608695652173913
Epoch 39: Train accuracy: 0.2608695652173913
Epoch 40: Train accuracy: 0.2608695652173913
Epoch 41: Train accuracy: 0.2608695652173913
Epoch 42: Train accuracy: 0.2608695652173913
Epoch 43: Train accuracy: 0.2608695652173913
Epoch 44: Train accuracy: 0.2608695652173913
Epoch 45: Train accuracy: 0.2608695652173913
Epoch 46: Train accuracy: 0.2608695652173913
Epoch 47: Train accuracy: 0.2608695652173913
Epoch 48: Train accuracy: 0.2608695652173913
Epoch 49: Train accuracy: 0.30434782608695654
Epoch 50: Train accuracy: 0.34782608695652173
Epoch 51: Train accuracy: 0.34782608695652173
Epoch 52: Train accuracy: 0.34782608695652173
Epoch 53: Train accuracy: 0.391304347826087
Epoch 54: Train accuracy: 0.391304347826087
Epoch 55: Train accuracy: 0.43478260869565216
Epoch 56: Train accuracy: 0.43478260869565216
Epoch 57: Train accuracy: 0.5217391304347826
Epoch 58: Train accuracy: 0.5652173913043478
Epoch 59: Train accuracy: 0.5652173913043478
Epoch 60: Train accuracy: 0.5217391304347826
Epoch 61: Train accuracy: 0.5217391304347826
Epoch 62: Train accuracy: 0.5217391304347826
Epoch 63: Train accuracy: 0.5217391304347826
Epoch 64: Train accuracy: 0.5652173913043478
Epoch 65: Train accuracy: 0.6521739130434783
Epoch 66: Train accuracy: 0.6521739130434783
Epoch 67: Train accuracy: 0.6521739130434783
Epoch 68: Train accuracy: 0.6521739130434783
Epoch 69: Train accuracy: 0.6521739130434783
Epoch 70: Train accuracy: 0.6521739130434783
Epoch 71: Train accuracy: 0.6521739130434783
Epoch 72: Train accuracy: 0.6521739130434783
Epoch 73: Train accuracy: 0.6956521739130435
Epoch 74: Train accuracy: 0.6956521739130435
Epoch 75: Train accuracy: 0.7391304347826086
Epoch 76: Train accuracy: 0.7391304347826086
Epoch 77: Train accuracy: 0.7391304347826086
Epoch 78: Train accuracy: 0.7391304347826086
Epoch 79: Train accuracy: 0.7391304347826086
Epoch 80: Train accuracy: 0.782608695652174
Epoch 81: Train accuracy: 0.782608695652174
Epoch 82: Train accuracy: 0.8260869565217391
Epoch 83: Train accuracy: 0.8260869565217391
Epoch 84: Train accuracy: 0.8260869565217391
Epoch 85: Train accuracy: 0.9130434782608695
Epoch 86: Train accuracy: 0.9565217391304348
Epoch 87: Train accuracy: 0.9565217391304348
Epoch 88: Train accuracy: 0.9565217391304348
Epoch 89: Train accuracy: 1.0
Finish Training
```

```
Total time elapsed: 23.79 seconds
```






```
Final Training Accuracy: 1.0
```

3. Hyperparameter Search [10 pt]

Part (a) - 1 pt

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

In [ ]:
```
#The three hyperparameters that
#I think most worth tuning is:
  #1. Batch_size
  #2. padding/stride
  #3. number of hidden layers/output channels
```

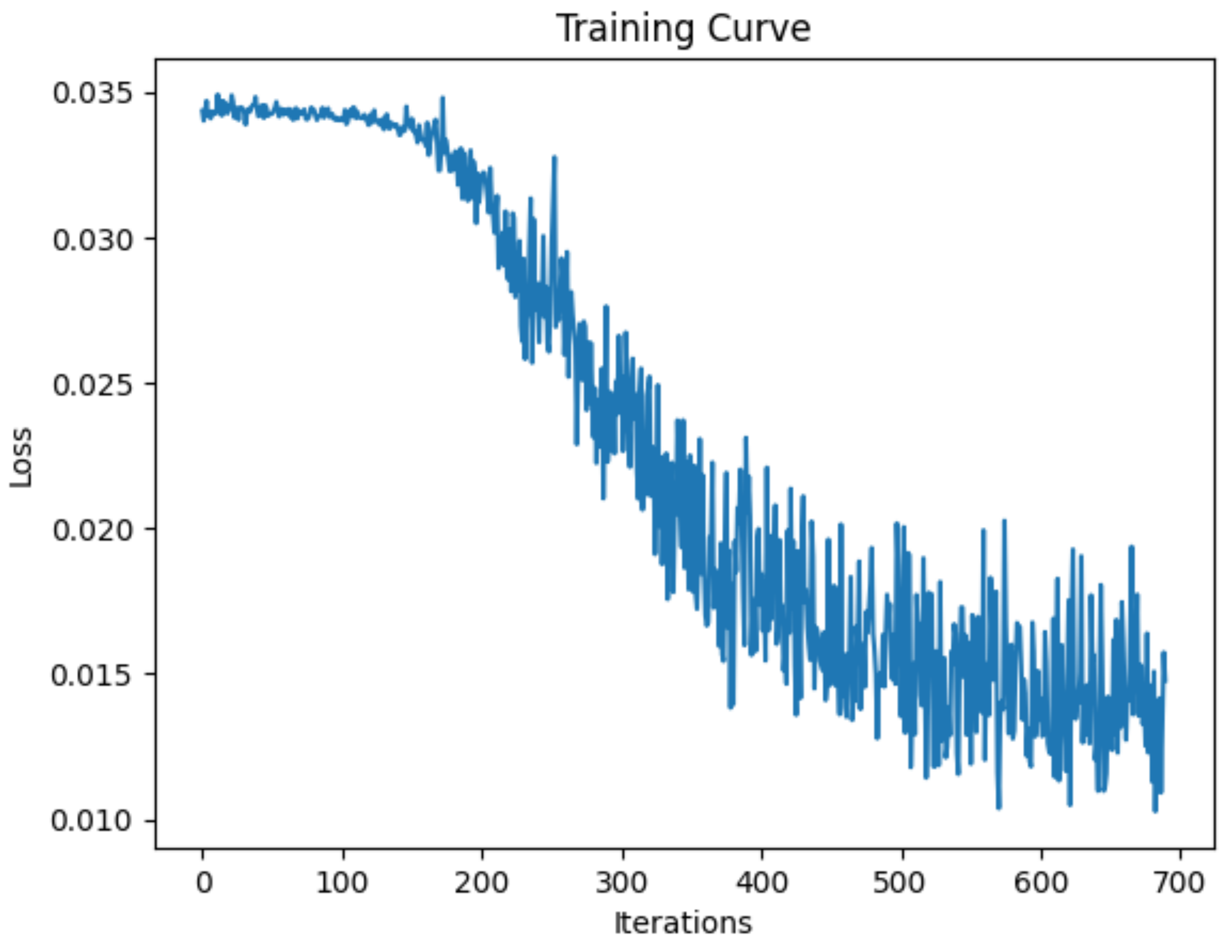
Part (b) - 5 pt

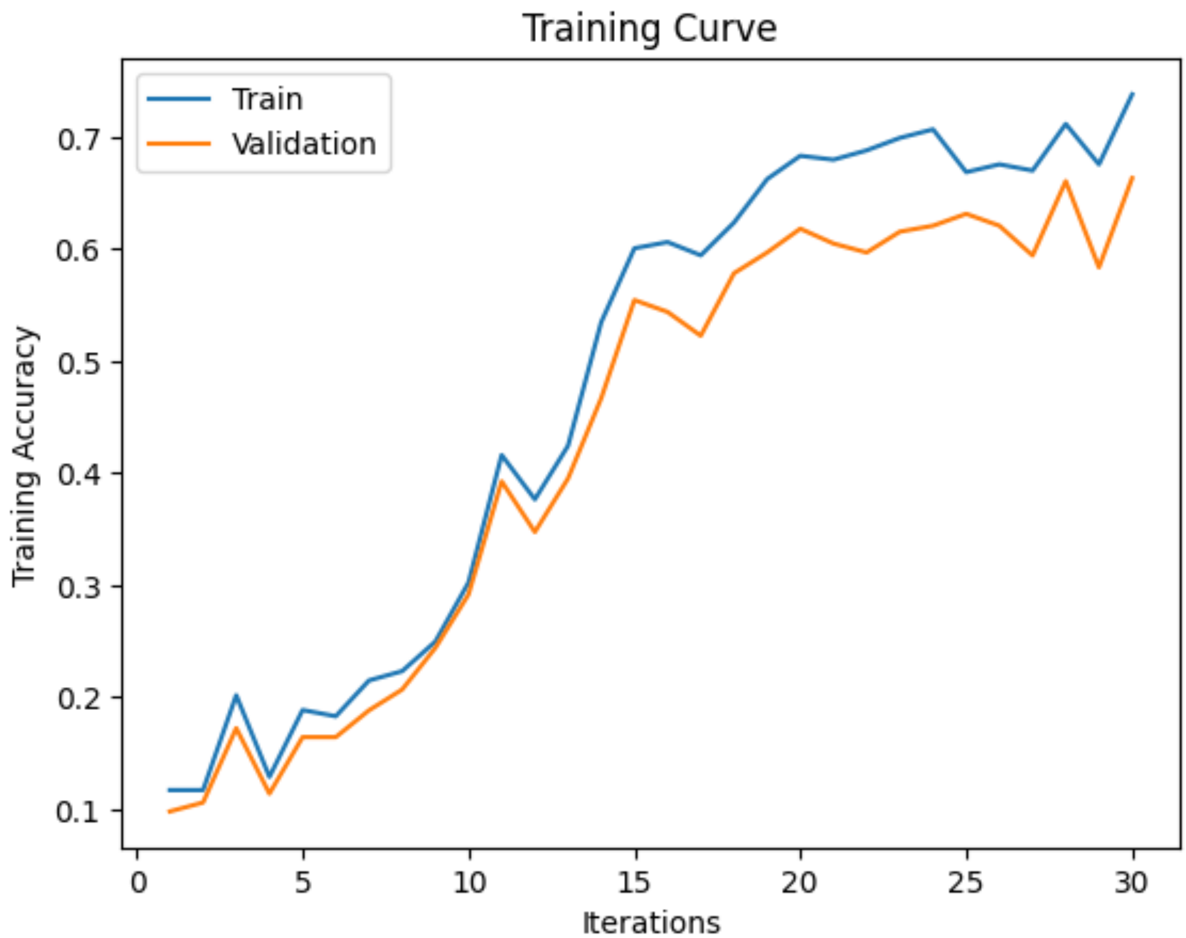
Tune the hyperparameters you listed in Part (a), trying as many values as you need to until you feel satisfied that you are getting a good model. Plot the training curve of at least 4 different hyperparameter settings.

In [ ]:
```
use_cuda = True

model = GestRec()

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

train(model, train_dataset)
```

```
CUDA is available!  Training on GPU ...
Epoch 1: Train accuracy: 0.11719833564493759 |Validation accuracy: 0.0981432
3607427056
Epoch 2: Train accuracy: 0.11719833564493759 |Validation accuracy: 0.1061007
9575596817
Epoch 3: Train accuracy: 0.20180305131761442 |Validation accuracy: 0.1724137
931034483
Epoch 4: Train accuracy: 0.1289875173370319 |Validation accuracy: 0.11405835
543766578
Epoch 5: Train accuracy: 0.18862690707350901 |Validation accuracy: 0.1644562
3342175067
Epoch 6: Train accuracy: 0.18307905686546463 |Validation accuracy: 0.1644562
3342175067
Epoch 7: Train accuracy: 0.21497919556171982 |Validation accuracy: 0.1883289
124668435
Epoch 8: Train accuracy: 0.22330097087378642 |Validation accuracy: 0.2068965
5172413793
Epoch 9: Train accuracy: 0.24965325936199723 |Validation accuracy: 0.2440318
302387268
Epoch 10: Train accuracy: 0.30235783633841884 |Validation accuracy: 0.291777
1883289125
Epoch 11: Train accuracy: 0.4160887656033287 |Validation accuracy: 0.3925729
442970822
Epoch 12: Train accuracy: 0.3765603328710125 |Validation accuracy: 0.3474801
0610079577
Epoch 13: Train accuracy: 0.42441054091539526 |Validation accuracy: 0.395225
4641909814
Epoch 14: Train accuracy: 0.5346740638002774 |Validation accuracy: 0.4668435
0132625996
Epoch 15: Train accuracy: 0.6005547850208044 |Validation accuracy: 0.5543766
578249337
Epoch 16: Train accuracy: 0.6061026352288488 |Validation accuracy: 0.5437665
```

```
782493368
Epoch 17: Train accuracy: 0.5943134535367545 |Validation accuracy: 0.5225464
190981433
Epoch 18: Train accuracy: 0.6234396671289875 |Validation accuracy: 0.5782493
368700266
Epoch 19: Train accuracy: 0.6622746185852982 |Validation accuracy: 0.5968169
76127321
Epoch 20: Train accuracy: 0.6830790568654647 |Validation accuracy: 0.6180371
352785146
Epoch 21: Train accuracy: 0.6796116504854369 |Validation accuracy: 0.6047745
358090185
Epoch 22: Train accuracy: 0.6879334257975035 |Validation accuracy: 0.5968169
76127321
Epoch 23: Train accuracy: 0.6990291262135923 |Validation accuracy: 0.6153846
153846154
Epoch 24: Train accuracy: 0.7066574202496533 |Validation accuracy: 0.6206896
551724138
Epoch 25: Train accuracy: 0.6685159500693482 |Validation accuracy: 0.6312997
347480106
Epoch 26: Train accuracy: 0.6754507628294036 |Validation accuracy: 0.6206896
551724138
Epoch 27: Train accuracy: 0.6699029126213593 |Validation accuracy: 0.5941644
562334217
Epoch 28: Train accuracy: 0.7115117891816921 |Validation accuracy: 0.6604774
535809018
Epoch 29: Train accuracy: 0.6754507628294036 |Validation accuracy: 0.5835543
76657825
Epoch 30: Train accuracy: 0.7378640776699029 |Validation accuracy: 0.6631299
734748011
Finish Training
Total time elapsed: 382.71 seconds
```


Training Curve
Loss
Iterations
0.035
0.030
0.025
0.020
0.015
0.010
0
100
200
300
400
500
600
700



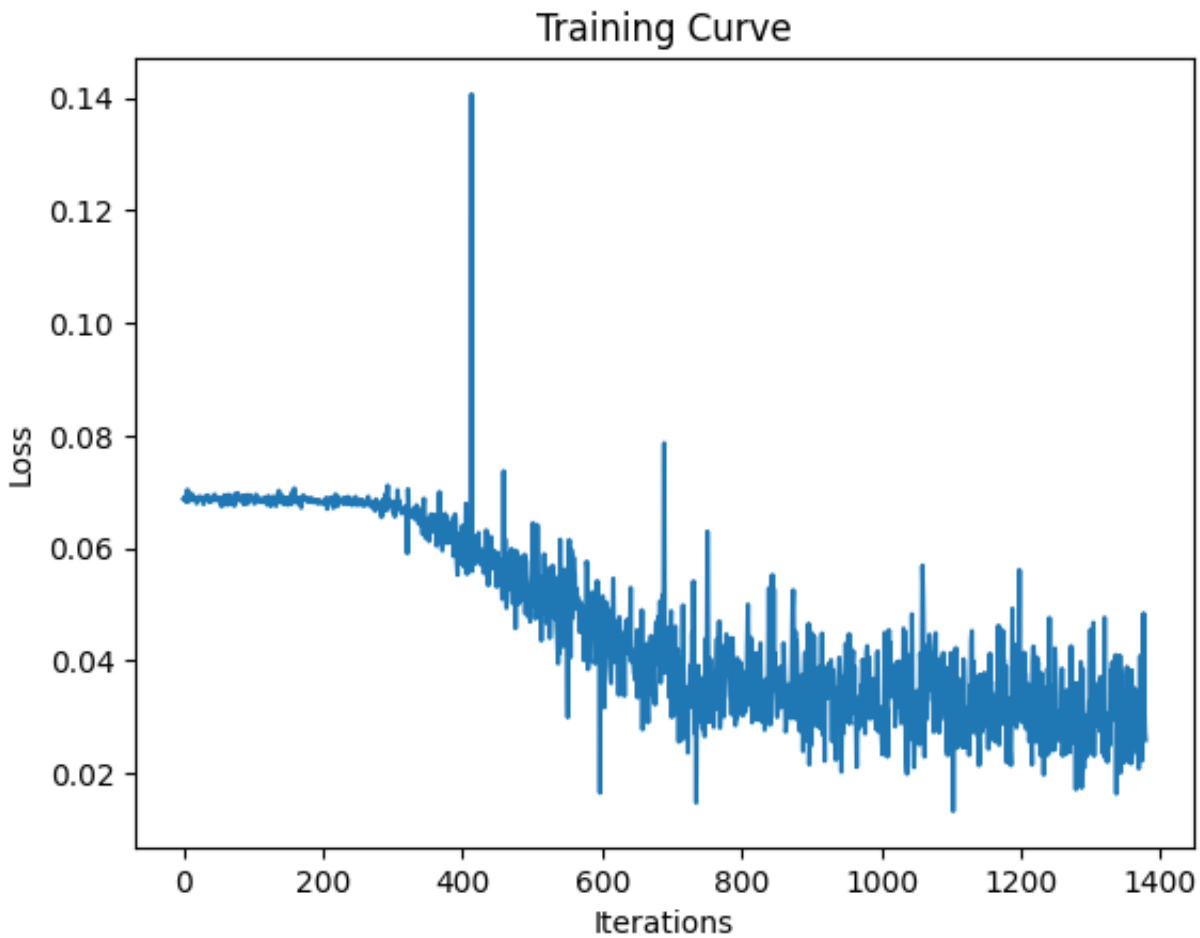

```
Final Training Accuracy: 0.7378640776699029
Final Validation Accuracy: 0.6631299734748011
```

In [ ]:
```
class GestRec_mod1(nn.Module):
    def __init__(self):
        super(GestRec_mod1, self).__init__()
        self.name = "GestRec_mod1"
        self.conv1 = nn.Conv2d(3, 5, 5, padding = 1) #in channels, #out char
        self.pool = nn.MaxPool2d(2, 2) #kernal size, stride
        self.conv2 = nn.Conv2d(5, 10, 5, padding = 1)
        self.fc1 = nn.Linear(10 * 54 * 54, 35) #input size, output size
        self.fc2 = nn.Linear(35, 9) #input size, output size

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 10 * 54 * 54)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        x = x.squeeze(1) # Flatten to [batch_size]
        return x

model_1 = GestRec_mod1()
```

In [ ]:
```
#changing network architechture and batch_size

use_cuda = True

model_1 = GestRec_mod1()

if use_cuda and torch.cuda.is_available():
  model_1.cuda()

  print('CUDA is available!  Training on GPU ...')
else:
  print('CUDA is not available.  Training on CPU ...')

#proper model

train(model_1, train_dataset, batch_size = 32)
```

```
CUDA is available!  Training on GPU ...
Epoch 1: Train accuracy: 0.11858529819694869 |Validation accuracy: 0.1140583
5543766578
Epoch 2: Train accuracy: 0.11858529819694869 |Validation accuracy: 0.1140583
5543766578
Epoch 3: Train accuracy: 0.12274618585298197 |Validation accuracy: 0.1034482
7586206896
Epoch 4: Train accuracy: 0.16574202496532595 |Validation accuracy: 0.1405835
5437665782
Epoch 5: Train accuracy: 0.12413314840499307 |Validation accuracy: 0.1087533
1564986737
Epoch 6: Train accuracy: 0.1650485436893204 |Validation accuracy: 0.13262599
469496023
Epoch 7: Train accuracy: 0.19764216366158113 |Validation accuracy: 0.1697612
7320954906
Epoch 8: Train accuracy: 0.2565880721220527 |Validation accuracy: 0.24403183
02387268
Epoch 9: Train accuracy: 0.24895977808599168 |Validation accuracy: 0.2466843
50132626
Epoch 10: Train accuracy: 0.2538141470180305 |Validation accuracy: 0.2440318
302387268
Epoch 11: Train accuracy: 0.25866851595006934 |Validation accuracy: 0.267904
50928381965
Epoch 12: Train accuracy: 0.3106796116504854 |Validation accuracy: 0.3103448
275862069
Epoch 13: Train accuracy: 0.5069348127600555 |Validation accuracy: 0.4694960
2122015915
Epoch 14: Train accuracy: 0.5852981969486823 |Validation accuracy: 0.5517241
379310345
Epoch 15: Train accuracy: 0.5533980582524272 |Validation accuracy: 0.4827586
206896552
Epoch 16: Train accuracy: 0.6151178918169209 |Validation accuracy: 0.5384615
384615384
Epoch 17: Train accuracy: 0.6095700416088765 |Validation accuracy: 0.5490716
180371353
Epoch 18: Train accuracy: 0.616504854368932 |Validation accuracy: 0.57559681
```

```
69761273
Epoch 19: Train accuracy: 0.5748959778085991 |Validation accuracy: 0.5251989
389920424
Epoch 20: Train accuracy: 0.5533980582524272 |Validation accuracy: 0.5039787
798408488
Epoch 21: Train accuracy: 0.6171983356449375 |Validation accuracy: 0.5543766
578249337
Epoch 22: Train accuracy: 0.6359223300970874 |Validation accuracy: 0.5755968
169761273
Epoch 23: Train accuracy: 0.5783633841886269 |Validation accuracy: 0.5384615
384615384
Epoch 24: Train accuracy: 0.6830790568654647 |Validation accuracy: 0.6047745
358090185
Epoch 25: Train accuracy: 0.5679611650485437 |Validation accuracy: 0.5172413
793103449
Epoch 26: Train accuracy: 0.6054091539528432 |Validation accuracy: 0.5649867
374005305
Epoch 27: Train accuracy: 0.628987517337032 |Validation accuracy: 0.56763925
72944297
Epoch 28: Train accuracy: 0.7059639389736477 |Validation accuracy: 0.6286472
148541115
Epoch 29: Train accuracy: 0.6692094313453537 |Validation accuracy: 0.6100795
75596817
Epoch 30: Train accuracy: 0.5970873786407767 |Validation accuracy: 0.5782493
368700266
Finish Training
Total time elapsed: 374.60 seconds
```


Training Curve
Loss
Iterations
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0
200
400
600
800
1000
1200
1400


```
Final Training Accuracy: 0.5970873786407767
Final Validation Accuracy: 0.5782493368700266
```

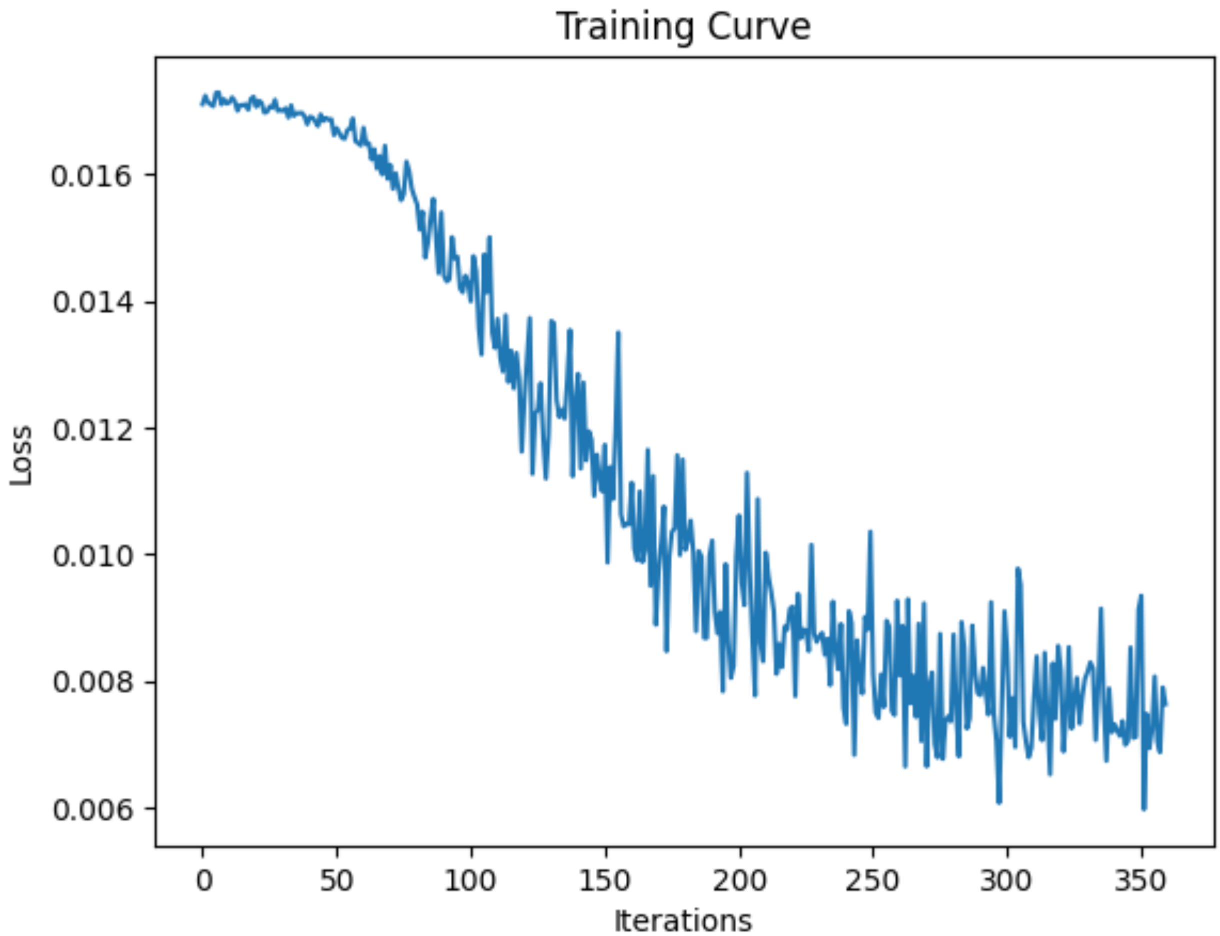
In [ ]:

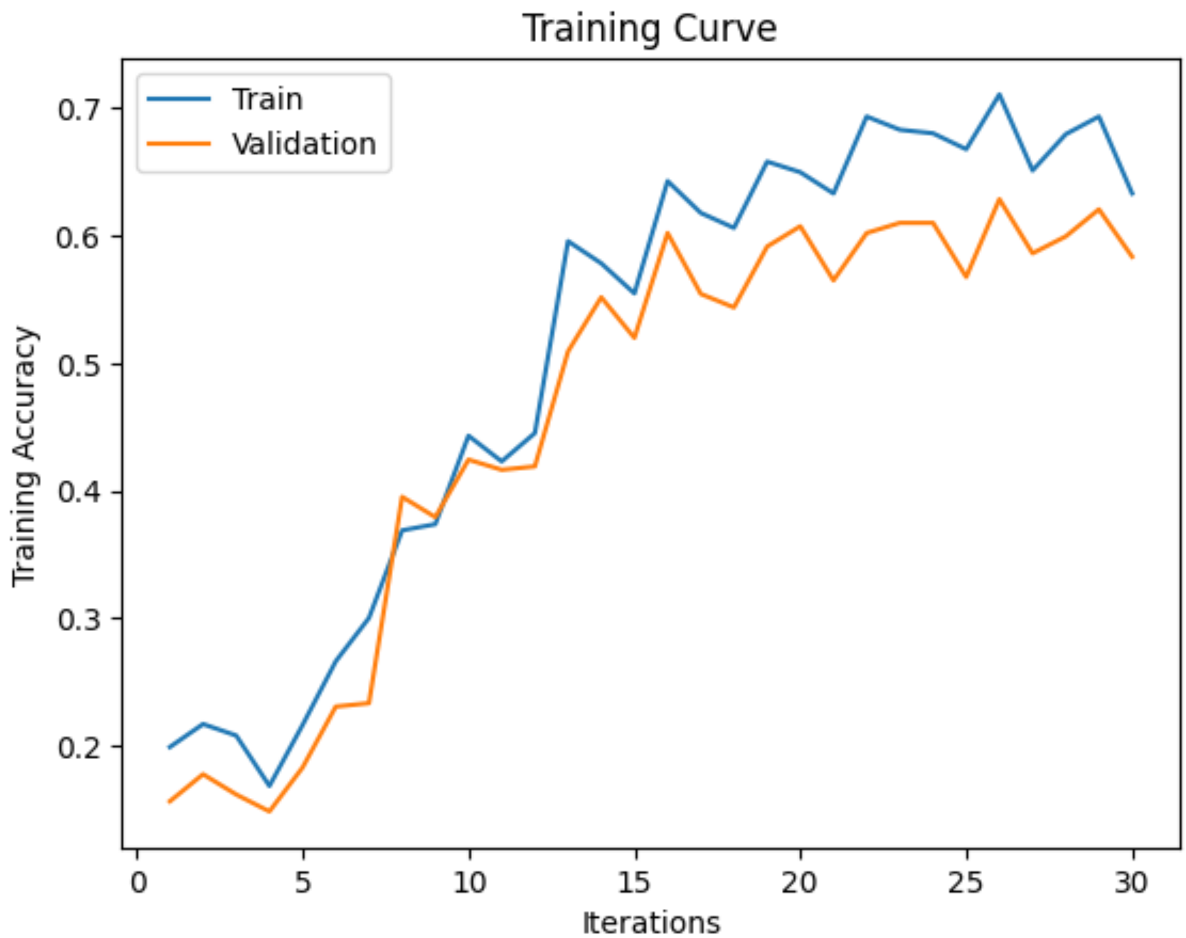
```
##only changing batch_size

use_cuda = True

model_2 = GestRec()

if use_cuda and torch.cuda.is_available():
  model_2.cuda()

  print('CUDA is available!  Training on GPU ...')
else:
  print('CUDA is not available.  Training on CPU ...')

#proper model

train(model_2, train_dataset, batch_size = 128)
```

```
CUDA is available!  Training on GPU ...
Epoch 1: Train accuracy: 0.19902912621359223 |Validation accuracy: 0.1564986
7374005305
Epoch 2: Train accuracy: 0.21705963938973646 |Validation accuracy: 0.1777188
3289124668
```

```
Epoch 3: Train accuracy: 0.20804438280166435 |Validation accuracy: 0.1618037
1352785147
Epoch 4: Train accuracy: 0.16851595006934814 |Validation accuracy: 0.1485411
1405835543
Epoch 5: Train accuracy: 0.21636615811373092 |Validation accuracy: 0.1830238
726790451
Epoch 6: Train accuracy: 0.26629680998613037 |Validation accuracy: 0.2307692
3076923078
Epoch 7: Train accuracy: 0.3002773925104022 |Validation accuracy: 0.23342175
066312998
Epoch 8: Train accuracy: 0.36893203883495146 |Validation accuracy: 0.3952254
641909814
Epoch 9: Train accuracy: 0.3737864077669903 |Validation accuracy: 0.37931034
48275862
Epoch 10: Train accuracy: 0.4431345353675451 |Validation accuracy: 0.4244031
830238727
Epoch 11: Train accuracy: 0.42302357836338417 |Validation accuracy: 0.416445
62334217505
Epoch 12: Train accuracy: 0.44521497919556174 |Validation accuracy: 0.419098
14323607425
Epoch 13: Train accuracy: 0.5957004160887656 |Validation accuracy: 0.5092838
196286472
Epoch 14: Train accuracy: 0.5783633841886269 |Validation accuracy: 0.5517241
379310345
Epoch 15: Train accuracy: 0.5547850208044383 |Validation accuracy: 0.5198938
99204244
Epoch 16: Train accuracy: 0.6428571428571429 |Validation accuracy: 0.6021220
159151194
Epoch 17: Train accuracy: 0.6178918169209431 |Validation accuracy: 0.5543766
578249337
Epoch 18: Train accuracy: 0.6061026352288488 |Validation accuracy: 0.5437665
782493368
Epoch 19: Train accuracy: 0.658113730929265 |Validation accuracy: 0.59151193
63395226
Epoch 20: Train accuracy: 0.6497919556171984 |Validation accuracy: 0.6074270
557029178
Epoch 21: Train accuracy: 0.6331484049930652 |Validation accuracy: 0.5649867
374005305
Epoch 22: Train accuracy: 0.6934812760055479 |Validation accuracy: 0.6021220
159151194
Epoch 23: Train accuracy: 0.6830790568654647 |Validation accuracy: 0.6100795
75596817
Epoch 24: Train accuracy: 0.6803051317614425 |Validation accuracy: 0.6100795
75596817
Epoch 25: Train accuracy: 0.6678224687933426 |Validation accuracy: 0.5676392
572944297
Epoch 26: Train accuracy: 0.7108183079056866 |Validation accuracy: 0.6286472
148541115
Epoch 27: Train accuracy: 0.6511789181692095 |Validation accuracy: 0.5862068
965517241
Epoch 28: Train accuracy: 0.6796116504854369 |Validation accuracy: 0.5994694
960212201
Epoch 29: Train accuracy: 0.6934812760055479 |Validation accuracy: 0.6206896
```

```
551724138
Epoch 30: Train accuracy: 0.6331484049930652 |Validation accuracy: 0.5835543
76657825
Finish Training
Total time elapsed: 396.30 seconds
```






```
Final Training Accuracy: 0.6331484049930652
Final Validation Accuracy: 0.583554376657825
```

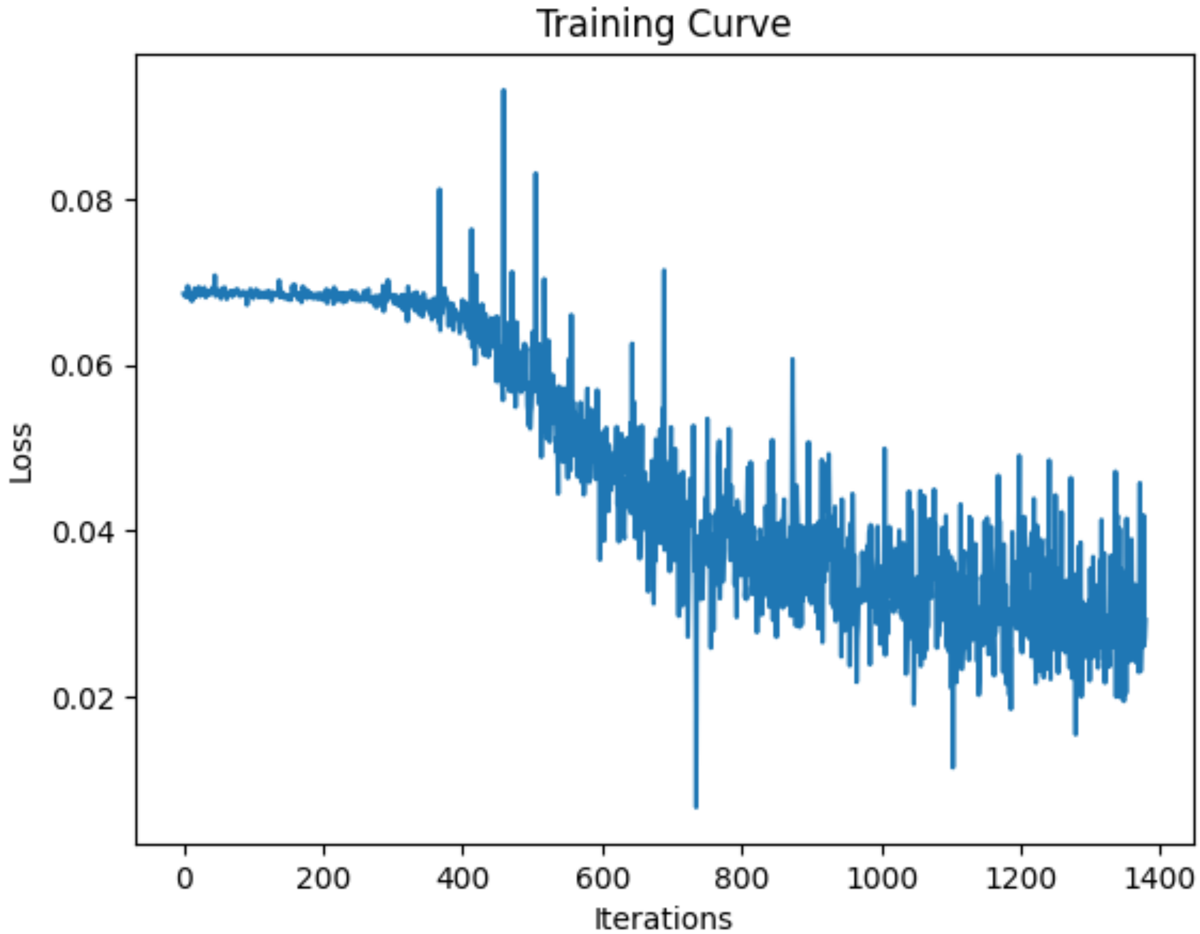
In [ ]:

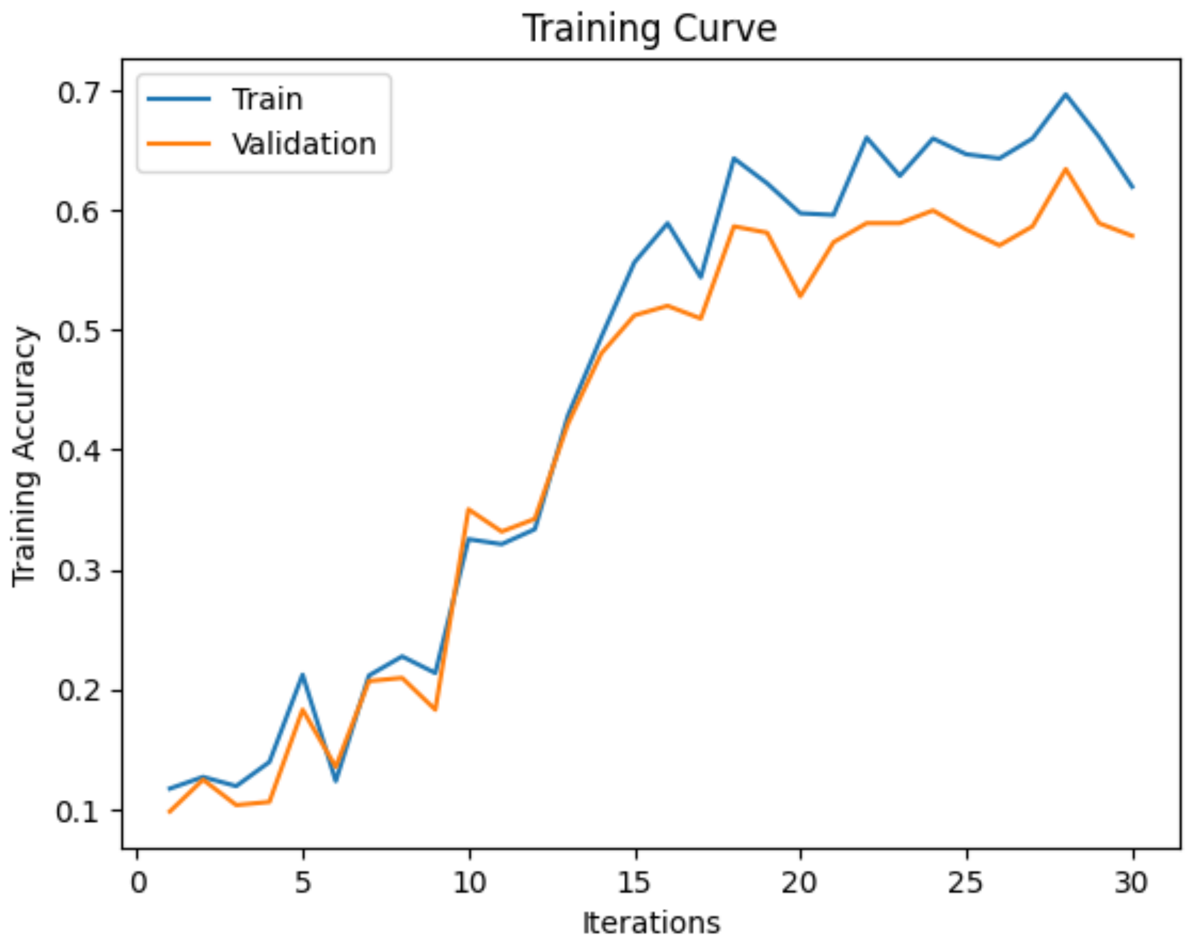
```
class GestRec_mod2(nn.Module):
    def __init__(self):
        super(GestRec_mod2, self).__init__()
        self.name = "GestRec_mod2"
        self.conv1 = nn.Conv2d(3, 10, 5, stride = 2, padding = 1) #in channe
        self.pool = nn.MaxPool2d(2, 2) #kernal size, stride
        self.conv2 = nn.Conv2d(10, 20, 7, stride = 2, padding = 1)
        self.fc1 = nn.Linear(20 * 13 * 13, 50) #input size, output size
        self.fc2 = nn.Linear(50, 9) #input size, output size

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 20 * 13 * 13)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        x = x.squeeze(1) # Flatten to [batch_size]
        return x

model_3 = GestRec_mod2()
```

In [ ]:
```
#changing stride and paading, and hidden layers

use_cuda = True

model_3 = GestRec_mod2()

if use_cuda and torch.cuda.is_available():
  model_3.cuda()

  print('CUDA is available!  Training on GPU ...')
else:
  print('CUDA is not available.  Training on CPU ...')

#proper model

train(model_3, train_dataset, batch_size = 32)
```

```
CUDA is available!  Training on GPU ...
Epoch 1: Train accuracy: 0.11719833564493759 |Validation accuracy: 0.0981432
3607427056
Epoch 2: Train accuracy: 0.12690707350901526 |Validation accuracy: 0.1246684
350132626
Epoch 3: Train accuracy: 0.11927877947295423 |Validation accuracy: 0.1034482
7586206896
Epoch 4: Train accuracy: 0.1393897364771151 |Validation accuracy: 0.10610079
575596817
Epoch 5: Train accuracy: 0.21220527045769763 |Validation accuracy: 0.1830238
726790451
Epoch 6: Train accuracy: 0.12343966712898752 |Validation accuracy: 0.1352785
1458885942
Epoch 7: Train accuracy: 0.21151178918169208 |Validation accuracy: 0.2068965
5172413793
Epoch 8: Train accuracy: 0.2274618585298197 |Validation accuracy: 0.20954907
161803712
Epoch 9: Train accuracy: 0.21359223300970873 |Validation accuracy: 0.1830238
726790451
Epoch 10: Train accuracy: 0.32524271844660196 |Validation accuracy: 0.350132
62599469497
Epoch 11: Train accuracy: 0.3210818307905687 |Validation accuracy: 0.3315649
8673740054
Epoch 12: Train accuracy: 0.33356449375866853 |Validation accuracy: 0.342175
0663129973
Epoch 13: Train accuracy: 0.42857142857142855 |Validation accuracy: 0.421750
6631299735
Epoch 14: Train accuracy: 0.49375866851595007 |Validation accuracy: 0.480106
10079575594
Epoch 15: Train accuracy: 0.5561719833564494 |Validation accuracy: 0.5119363
395225465
Epoch 16: Train accuracy: 0.5887656033287101 |Validation accuracy: 0.5198938
99204244
Epoch 17: Train accuracy: 0.5436893203883495 |Validation accuracy: 0.5092838
196286472
Epoch 18: Train accuracy: 0.6428571428571429 |Validation accuracy: 0.5862068
```

```
965517241
Epoch 19: Train accuracy: 0.6220527045769764 |Validation accuracy: 0.5809018
567639257
Epoch 20: Train accuracy: 0.5970873786407767 |Validation accuracy: 0.5278514
588859416
Epoch 21: Train accuracy: 0.5957004160887656 |Validation accuracy: 0.5729442
970822282
Epoch 22: Train accuracy: 0.6601941747572816 |Validation accuracy: 0.5888594
164456233
Epoch 23: Train accuracy: 0.6282940360610264 |Validation accuracy: 0.5888594
164456233
Epoch 24: Train accuracy: 0.659500693481276 |Validation accuracy: 0.59946949
60212201
Epoch 25: Train accuracy: 0.6463245492371706 |Validation accuracy: 0.5835543
76657825
Epoch 26: Train accuracy: 0.6428571428571429 |Validation accuracy: 0.5702917
771883289
Epoch 27: Train accuracy: 0.659500693481276 |Validation accuracy: 0.58620689
65517241
Epoch 28: Train accuracy: 0.6962552011095701 |Validation accuracy: 0.6339522
546419099
Epoch 29: Train accuracy: 0.6608876560332871 |Validation accuracy: 0.5888594
164456233
Epoch 30: Train accuracy: 0.6192787794729542 |Validation accuracy: 0.5782493
368700266
Finish Training
Total time elapsed: 326.51 seconds
```


Training Curve
0.08
0.06
0.04
0.02
Loss
0
200
400
600
800
1000
1200
1400
Iterations




```
Final Training Accuracy: 0.6192787794729542
Final Validation Accuracy: 0.5782493368700266
```

Part (c) - 2 pt

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

In [ ]:
```
#I chose the original model with no modifications to
#network architechture, batch_size, and other parameters.
#Because it provides the best validation accuracy among
#all four testing hyperparameter sets. Also, it does not
#show any overfitting.
```

Part (d) - 2 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.

In [ ]:
```
def get_test_accuracy(model, data, batch_size):

    data = test_dataset

    correct = 0
    total = 0

    for imgs, labels in torch.utils.data.DataLoader(data, batch_size=batch_s

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

        #############################################

        output = model(imgs)

        #select index with maximum prediction score
        pred = output.max(1, keepdim=True)[1]
        correct += pred.eq(labels.view_as(pred)).sum().item()
        total += imgs.shape[0]
    return correct / total
```

In [ ]:
```
accuracy = get_test_accuracy(model, test_dataset, 64)
print('The test accuracy on the best model is {:.2f} %'.format(accuracy * 10
```

```
The test accuracy on the best model is 63.40 %
```

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.

In [ ]:
```
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 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=AlexNet_Weights.IMAGENET1K_V1`. You can also use `weights=AlexNet_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/alexnet-owt-7be5be79.pth" to /root/.cache/torch/hub/checkpoints/alexnet-owt-7be5be79.pth
100%|██████████| 233M/233M [00:02<00:00, 81.5MB/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):

In [ ]:
```
# img = ... a PyTorch tensor with shape [N,3,224,224] containing hand images
classes = ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I']

#folders
path = '/content/gdrive/MyDrive/Colab Notebooks/APS360 LAB/lab3/Alex_feature

def get_alex_feature(dataset, datatype):
  loader = torch.utils.data.DataLoader(dataset,
                                       batch_size=1,
                                       shuffle=True)
  n = 0
  folder = path + '/' + datatype + '/'

  for imgs, labels in iter(loader):
    features = alexnet.features(imgs)
    features_tensor = torch.from_numpy(features.detach().numpy())
    torch.save(features_tensor.squeeze(0),
              folder + '/' + str(classes[labels]) +'/'
             + str(classes[labels]) +'_'+ str(n)
              + '.tensor')
    n += 1
```

In [ ]:
```
get_alex_feature(train_dataset, 'train')
get_alex_feature(val_dataset, 'val')
get_alex_feature(test_dataset, 'test')
```

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.

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:

In [ ]:
```
# features = ... load precomputed alexnet.features(img) ...
output = model(features)
prob = F.softmax(output)
```

In [ ]:
```
class trans_GestRec(nn.Module):
  def __init__(self):
        super(trans_GestRec, self).__init__()
        self.name = "trans_GestRec"
        self.conv1 = nn.Conv2d(256, 128, 5, padding = 1) #in channels, #out
        self.pool = nn.MaxPool2d(2, 2) #kernal size, stride
        self.fc1 = nn.Linear(128 * 2 * 2, 32) #input size, output size
        self.fc2 = nn.Linear(32, 9) #input size, output size

  def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = x.view(-1, 128 * 2 * 2)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        x = x.squeeze(1) # Flatten to [batch_size]
        return x

transfer_model = trans_GestRec()
```

Answer: I chose an CNN model with 1 convolutional layer, 1 pooling layer, and 2 fully-connected layers. The reason why I reduce the number of convolutional filters is that, the model is already pretrained, so by reducing the filters, the training with take less time but still having high accuracy. The input channels are acquired from the pretrained features, which have 25666 dimensions. The hidden layer, I kept at 32 because it seems to be a good fit for the fully-connected layers. Max pooling is used for reducing feature map dimension. ReLu activation functions are used for model learning extracting non-linearity from training data.

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.

In [ ]:
```
alex_train_folder = "/content/gdrive/MyDrive/Colab Notebooks/APS360 LAB/lab3
alex_val_folder = "/content/gdrive/MyDrive/Colab Notebooks/APS360 LAB/lab3/A
alex_test_folder = "/content/gdrive/MyDrive/Colab Notebooks/APS360 LAB/lab3/
```

In [ ]:
```
alex_train_data = torchvision.datasets.DatasetFolder(alex_train_folder, load
alex_val_data = torchvision.datasets.DatasetFolder(alex_val_folder, loader=t
alex_test_data = torchvision.datasets.DatasetFolder(alex_test_folder, loader
```

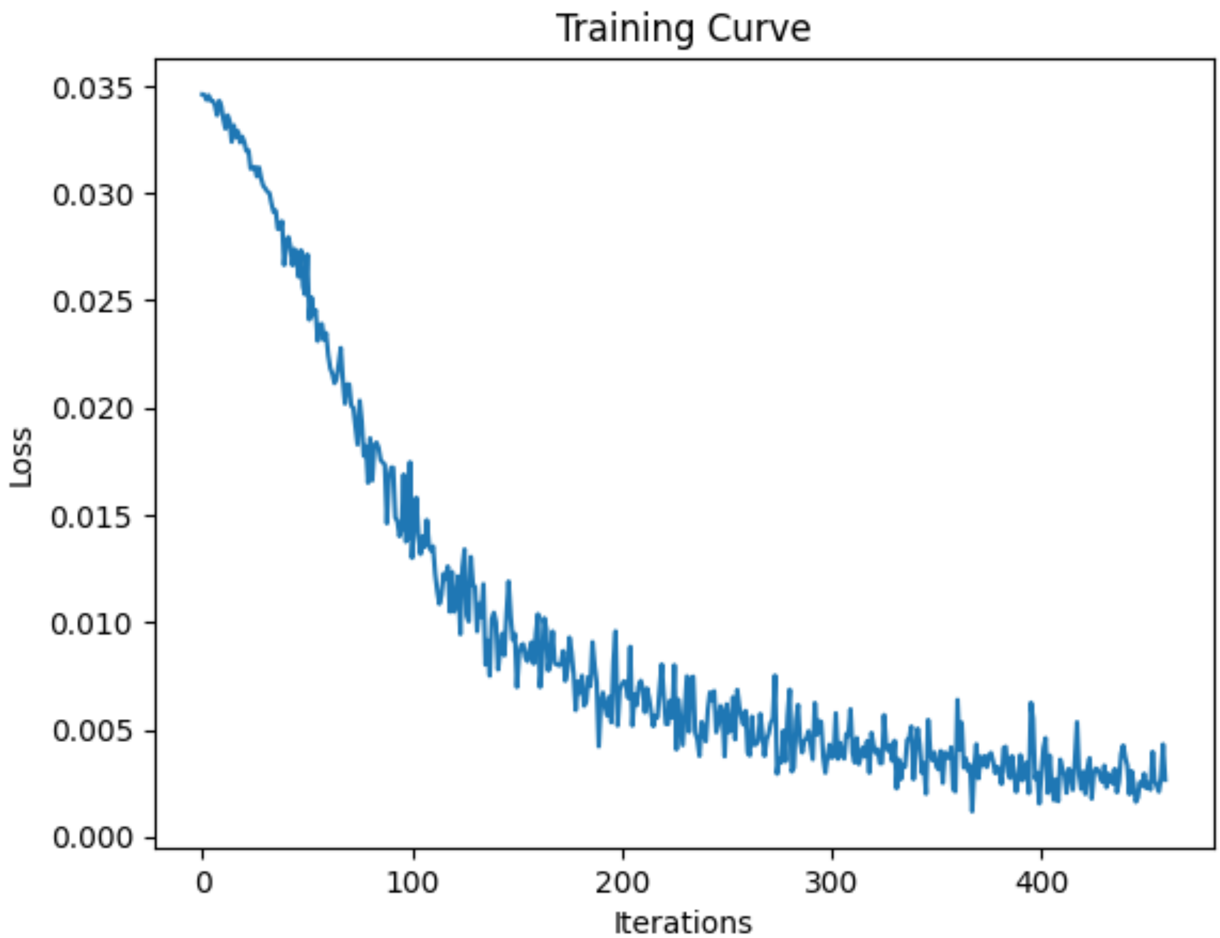
In [ ]:
```
def get_model_name(name, batch_size, learning_rate, epoch):
    path = "model_{0}_bs{1}_lr{2}_epoch{3}".format(name,
                                                    batch_size,
                                                    learning_rate,
                                                   epoch)
    return path

def get_accuracy_trans(model, batch_size, train=False):
    if train:
        data = alex_train_data
    else:
        data = alex_val_data

    correct = 0
    total = 0

    for imgs, labels in torch.utils.data.DataLoader(data, batch_size=batch_s

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

        #############################################

        output = model(imgs)

        #select index with maximum prediction score
        pred = output.max(1, keepdim=True)[1]
        correct += pred.eq(labels.view_as(pred)).sum().item()
        total += imgs.shape[0]
    return correct / total
```

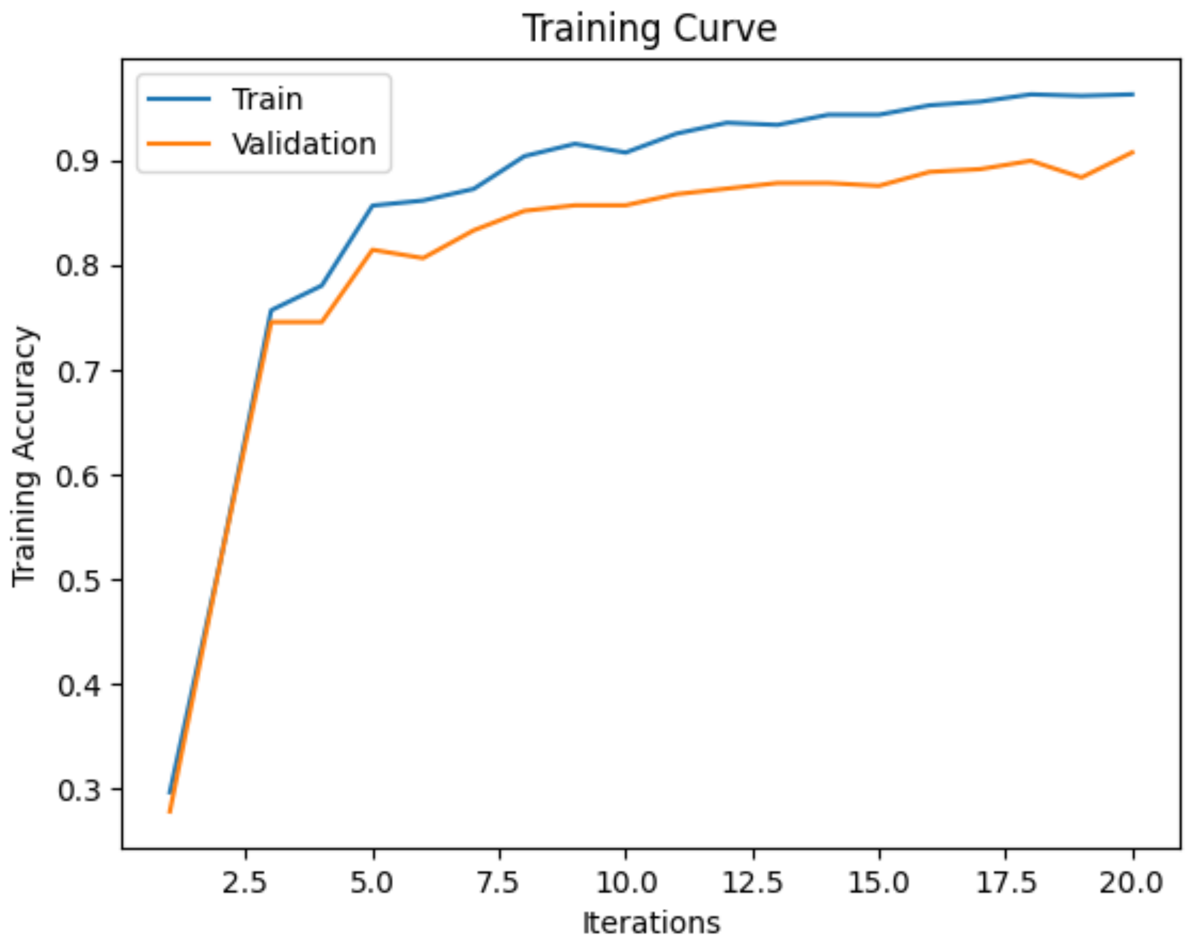
In [ ]:
```
def train(model, train_data, batch_size=64, learning_rate =0.001, num_epochs
    torch.manual_seed(1000)
    train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_

    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=learning_rate, momentum=0.9

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

    # training
    start_time = time.time()
    n = 0 # the number of iterations
    for epoch in range(num_epochs):
        for imgs, labels in iter(train_loader):
          # Loop over each batch of images and labels
          #############################################
          # 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 u
            optimizer.step()              # make the updates for each paramete
            optimizer.zero_grad()         # a clean-up step for PyTorch

            # save the current training information
            iters.append(n)
            losses.append(float(loss) / batch_size)             # compute *ave
            n += 1

            # Save the current model (checkpoint) to a file
            model_path = get_model_name(model.name, batch_size, learning_rate,
            torch.save(model.state_dict(), model_path)

        train_acc.append(get_accuracy_trans(model, batch_size, train=True))
        val_acc.append(get_accuracy_trans(model, batch_size, train=False))
        print(("Epoch {}: Train accuracy: {} |" +
                "Validation accuracy: {} ").format(
            epoch +1,
            train_acc[epoch],
            val_acc[epoch]))

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

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

    plt.title("Training Curve")
    plt.plot(range(1,num_epochs+1), train_acc, label="Train")
    plt.plot(range(1,num_epochs+1), 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]))
```

In [ ]:
```
use_cuda = True

trans_model = trans_GestRec()

if use_cuda and torch.cuda.is_available():
  trans_model.cuda()

  print('CUDA is available!  Training on GPU ...')
else:
  print('CUDA is not available.  Training on CPU ...')

#proper model

train(trans_model, alex_train_data, batch_size = 64, num_epochs = 20)
```

```
CUDA is not available.  Training on CPU ...
Epoch 1: Train accuracy: 0.29680998613037446 |Validation accuracy: 0.2785145
8885941643
Epoch 2: Train accuracy: 0.5180305131761442 |Validation accuracy: 0.51724137
93103449
Epoch 3: Train accuracy: 0.7565880721220527 |Validation accuracy: 0.74535809
01856764
Epoch 4: Train accuracy: 0.7801664355062413 |Validation accuracy: 0.74535809
01856764
Epoch 5: Train accuracy: 0.8564493758668515 |Validation accuracy: 0.81432360
74270557
Epoch 6: Train accuracy: 0.8613037447988904 |Validation accuracy: 0.80636604
77453581
Epoch 7: Train accuracy: 0.8723994452149791 |Validation accuracy: 0.83289124
66843501
Epoch 8: Train accuracy: 0.9036061026352289 |Validation accuracy: 0.85145888
59416445
Epoch 9: Train accuracy: 0.9153952843273232 |Validation accuracy: 0.85676392
57294429
Epoch 10: Train accuracy: 0.9070735090152566 |Validation accuracy: 0.8567639
257294429
Epoch 11: Train accuracy: 0.9251040221914009 |Validation accuracy: 0.8673740
053050398
Epoch 12: Train accuracy: 0.9355062413314841 |Validation accuracy: 0.8726790
450928382
Epoch 13: Train accuracy: 0.9334257975034674 |Validation accuracy: 0.8779840
848806366
Epoch 14: Train accuracy: 0.9431345353675451 |Validation accuracy: 0.8779840
848806366
Epoch 15: Train accuracy: 0.9431345353675451 |Validation accuracy: 0.8753315
649867374
Epoch 16: Train accuracy: 0.9521497919556172 |Validation accuracy: 0.8885941
644562334
Epoch 17: Train accuracy: 0.955617198335645 |Validation accuracy: 0.89124668
43501327
Epoch 18: Train accuracy: 0.9625520110957004 |Validation accuracy: 0.8992042
440318302
Epoch 19: Train accuracy: 0.9611650485436893 |Validation accuracy: 0.8832891
24668435
Epoch 20: Train accuracy: 0.9625520110957004 |Validation accuracy: 0.9071618
037135278
Finish Training
Total time elapsed: 205.52 seconds
```


Training Curve
Loss
Iterations
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
100
200
300
400




```
Final Training Accuracy: 0.9625520110957004
Final Validation Accuracy: 0.9071618037135278
```

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?

In [ ]:
```
def get_test_accuracy_trans(model, dataset, batch_size):

    data = dataset

    correct = 0
    total = 0

    for imgs, labels in torch.utils.data.DataLoader(data, batch_size=batch_s

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

        ##############################################

        output = model(imgs)

        #select index with maximum prediction score
        pred = output.max(1, keepdim=True)[1]
        correct += pred.eq(labels.view_as(pred)).sum().item()
        total += imgs.shape[0]
    return correct / total
```

In [ ]:
```
alex_accuracy = get_test_accuracy_trans(trans_model, alex_test_data, 64)
print('The test accuracy on the transfer learning model is {:.2f} %'.format(
print('While the test accuracy on the best model from part3 is only {:.2f} %

#the test accuracy is much more higher than
#the model accuracy we got from part3 (64.30%) before
#we applied transfer learning.

#Transfer learning helps us reduce model
#training time and increases model accuracy.
#The new model requires less layers, less epochs to train,
#which makes the training process more efficient.
```

```
The test accuracy on the transfer learning model is 91.51 %
```

5. Additional Testing [5 pt]

As a final step in testing we will be revisiting the sample images that you had collected and submitted at the start of this lab. These sample images should be untouched and will be used to demonstrate how well your model works at identifying your hand guestures.

Using the best transfer learning model developed in Part 4. Report the test accuracy on your sample images and how it compares to the test accuracy obtained in Part 4(d)? How well did your model do for the different hand guestures? Provide an explanation for why you think your model performed the way it did?

In [ ]:
```
#I will explain what I would do:

#I will use similar method in part 4a to
#transfer my overfit_dataset to AlexNet features
#Then I will use the code below to get the accuracy
#of the small sample data.

sample_accurracy = get_test_accuracy(trans_model,
                                     overfit_dataset, #this should be
                                                      #AlexNet features
                                     batch_size = 23)

#due to an unexpected accident, the original file that
#I was working on crashed, so I need to retrieve an older
#version of the file and start working from this document.
#However, for this question, I need re-run most of the code
#above from part 4, which was very time consuming, so I decided
#to write down my thoughts in words:
  #I believe that accuracy we get of our transfer learning
  #on this sample set will be high. Because our model is trained
  #using transfer learning method, in which it learned high-level
  #features using the AlexNet baseline model. So upon making
  #prediction on images it has never seen before, it will
  #perform well. Compare to the accuracy we obtained from part4,
  #I believe the accuracy will be similar, since the model
  #has never seen the test dataset before as well.
```