Header

4a. Data Augmentation

So far, we've selected a model architecture that vastly improves the model's performance, as it is designed to recognize important features in the images. The validation accuracy is still lagging behind the training accuracy, which is a sign of overfitting: the model is getting confused by things it has not seen before when it tests against the validation dataset.

In order to teach our model to be more robust when looking at new data, we're going to programmatically increase the size and variance in our dataset. This is known as *data augmentation*, a useful technique for many deep learning applications.

The increase in size gives the model more images to learn from while training. The increase in variance helps the model ignore unimportant features and select only the features that are truly important in classification, allowing it to generalize better.

4a.1 Objectives

- Augment the ASL dataset
- Use the augmented data to train an improved model
- Save the well-trained model to disk for use in deployment

In [1]:
```
import torch.nn as nn
import pandas as pd
import torch
from torch.optim import Adam

#Dataset: Is a  base class for all PyTorch datasets. Used to define how your data is accessed and returned.
#DataLoader: Handles batching, shuffling, and parallel loading with multiple workers.
#Commonly used in training loops for loading data in mini-batches.
from torch.utils.data import Dataset, DataLoader

#The need for transforms in PyTorch (especially with torchvision.transforms) arises when working with image or
```

```
#visual data (like photographs, medical scans, signal plots, etc.). Transforms are used to preprocess, augment, and
#prepare data so that models can learn more effectively.
import torchvision.transforms.v2 as transforms
import torchvision.transforms.functional as F

import matplotlib.pyplot as plt

import utils

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
torch.cuda.is_available()
```

Out[1]: True

4a.2 Preparing the Data

As we're in a new notebook, we will load and process our data again. To do this, execute the following cell:

In [2]:
```
IMG_HEIGHT = 28
IMG_WIDTH = 28
IMG_CHS = 1
N_CLASSES = 24

train_df = pd.read_csv("data/asl_data/sign_mnist_train.csv")
valid_df = pd.read_csv("data/asl_data/sign_mnist_valid.csv")

class MyDataset(Dataset):
    def __init__(self, base_df):
        x_df = base_df.copy()
        y_df = x_df.pop('label')
        x_df = x_df.values / 255  # Normalize values from 0 to 1
        x_df = x_df.reshape(-1, IMG_CHS, IMG_WIDTH, IMG_HEIGHT)
        self.xs = torch.tensor(x_df).float().to(device)
        self.ys = torch.tensor(y_df).to(device)

    def __getitem__(self, idx):
        x = self.xs[idx]
        y = self.ys[idx]
        return x, y
```

```
    def __len__(self):
        return len(self.xs)

n = 32
train_data = MyDataset(train_df)
train_loader = DataLoader(train_data, batch_size=n, shuffle=True)
train_N = len(train_loader.dataset)

valid_data = MyDataset(valid_df)
valid_loader = DataLoader(valid_data, batch_size=n)
valid_N = len(valid_loader.dataset)
```

4a.3 Model Creation

We will also need to create our model again. As we learned in the last lesson, convolutional neural networks use a repeated sequence of layers. Let's take advantage of this pattern to make our own custom module. We can then use this module like a layer in our Sequential model.

To do this, we will extend the Module class. Then we will define two methods:

- `__init__` : defines any properties we want our module to have, including our neural network layers. We will effectively be using a model within a model.
- `forward` : defines how we want the module to process any incoming data from the previous layer it is connected to. Since we are using a `Sequential` model, we can pass the input data into it like we are making a prediction.

In [3]:
```
class MyConvBlock(nn.Module):
    def __init__(self, in_ch, out_ch, dropout_p):
        kernel_size = 3
        super().__init__()

        self.model = nn.Sequential(
            nn.Conv2d(in_ch, out_ch, kernel_size, stride=1, padding=1),
            nn.BatchNorm2d(out_ch),
            nn.ReLU(),
            nn.Dropout(dropout_p),
            nn.MaxPool2d(2, stride=2)
        )
```

```
    def forward(self, x):
        return self.model(x)
```

Now that we've define our custom module, let's see it in action. The below model ia archecturially the same as in the previous lesson. Can you see the connection?

In [4]:
```
flattened_img_size = 75 * 3 * 3

# Input 1 x 28 x 28
base_model = nn.Sequential(
    MyConvBlock(IMG_CHS, 25, 0), # 25 x 14 x 14
    MyConvBlock(25, 50, 0.2), # 50 x 7 x 7
    MyConvBlock(50, 75, 0),  # 75 x 3 x 3
    # Flatten to Dense Layers
    nn.Flatten(),
    nn.Linear(flattened_img_size, 512),
    nn.Dropout(.3),
    nn.ReLU(),
    nn.Linear(512, N_CLASSES)
)
```

When we print the model, not only will it now show the use of our custom module, it will also show the layers within our custom module:

In [5]:
```
loss_function = nn.CrossEntropyLoss()
optimizer = Adam(base_model.parameters())

model = torch.compile(base_model.to(device))
model
```

Out[5]:
```
OptimizedModule(
  (_orig_mod): Sequential(
    (0): MyConvBlock(
      (model): Sequential(
        (0): Conv2d(1, 25, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
        (1): BatchNorm2d(25, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (2): ReLU()
        (3): Dropout(p=0, inplace=False)
        (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
      )
    )
    (1): MyConvBlock(
      (model): Sequential(
        (0): Conv2d(25, 50, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
        (1): BatchNorm2d(50, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (2): ReLU()
        (3): Dropout(p=0.2, inplace=False)
        (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
      )
    )
    (2): MyConvBlock(
      (model): Sequential(
        (0): Conv2d(50, 75, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
        (1): BatchNorm2d(75, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (2): ReLU()
        (3): Dropout(p=0, inplace=False)
        (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
      )
    )
    (3): Flatten(start_dim=1, end_dim=-1)
    (4): Linear(in_features=675, out_features=512, bias=True)
    (5): Dropout(p=0.3, inplace=False)
    (6): ReLU()
    (7): Linear(in_features=512, out_features=24, bias=True)
  )
)
```

Custom modules are flexible, and we can define any other methods or properties we wish to have. This makes them powerful when data scientists are trying to solve complex problems.

4a.4 Data Augmentation

Before defining our training loop, it's time to set up our data augmentation.

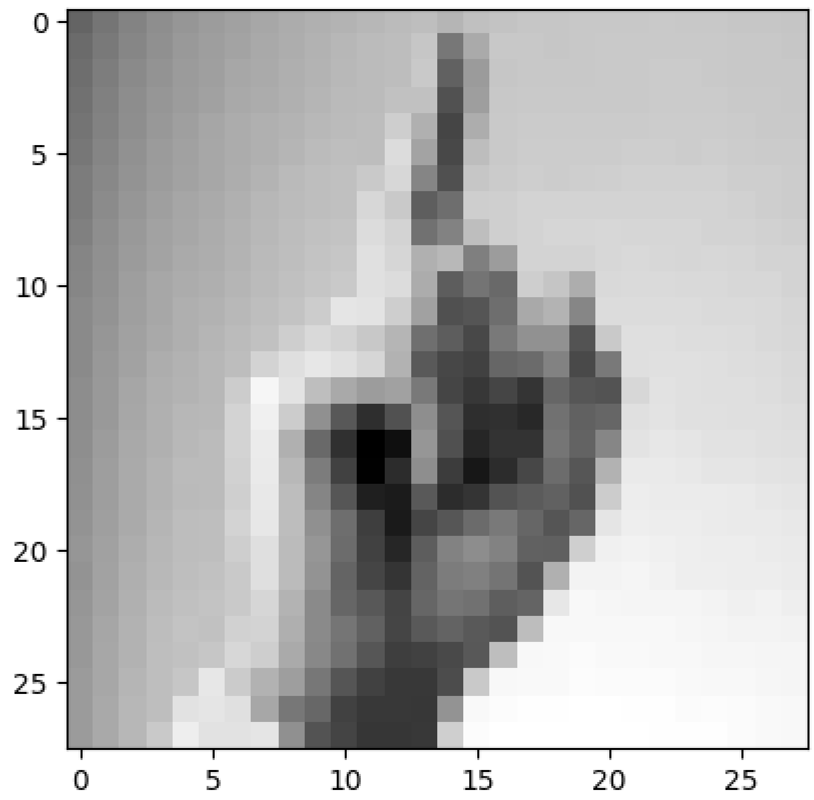
We've seen TorchVision's Transforms before, but in this lesson, we will further explore its data augmentation tools. First, let's get a sample image to test with:

In [6]:
```
row_0 = train_df.head(1)
y_0 = row_0.pop('label')
x_0 = row_0.values / 255
x_0 = x_0.reshape(IMG_CHS, IMG_WIDTH, IMG_HEIGHT)
x_0 = torch.tensor(x_0)
x_0.shape
```

Out[6]:
```
torch.Size([1, 28, 28])
```

In [7]:
```
image = F.to_pil_image(x_0)
plt.imshow(image, cmap='gray')
```

Out[7]:
```
<matplotlib.image.AxesImage at 0x7f0e35da9120>
```



4a.4.1 RandomResizeCrop

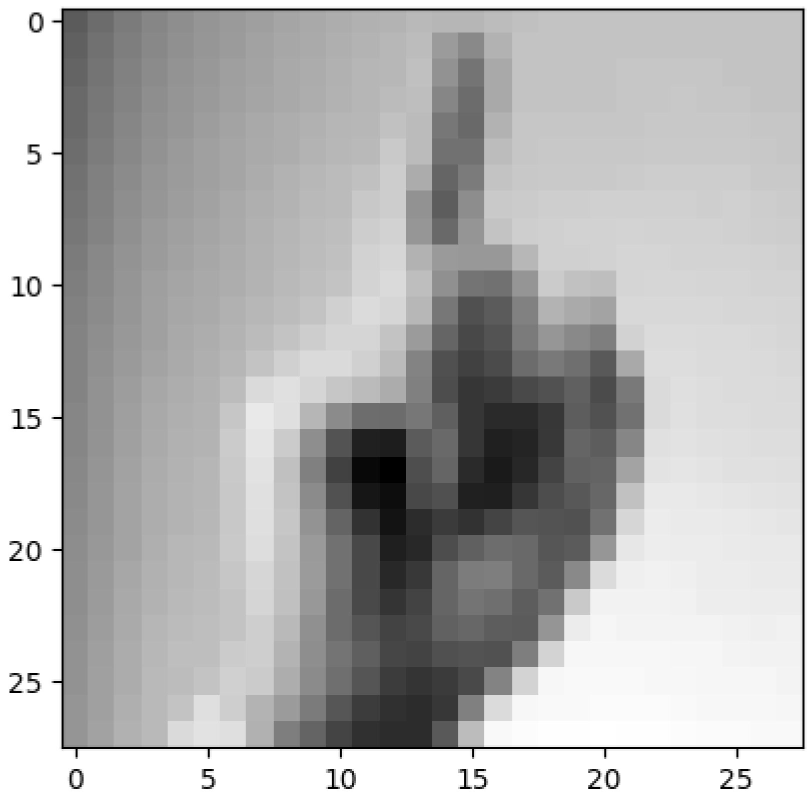
This transform will randomly resize the input image based on `scale`, and then crop) it to a size we specify. In this case, we will crop it to the original image dimensions. To do this, TorchVision needs to know the aspect ratio) of the image it is scaling. Since our height is the same as our width, our aspect `ratio` is 1:1.

In [13]:
```
trans = transforms.Compose([
    transforms.RandomResizedCrop((IMG_WIDTH, IMG_HEIGHT), scale=(.7, 1), ratio=(1, 1)),
])
```

Try running the below cell a few times. It should be different each time.

In [14]:
```
new_x_0 = trans(x_0)
image = F.to_pil_image(new_x_0)
plt.imshow(image, cmap='gray')
```

Out[14]: <matplotlib.image.AxesImage at 0x7f0e282979a0>



In [15]:
```
new_x_0.shape
```

Out[15]: torch.Size([1, 28, 28])

4a.4.2 RandomHorizontalFlip

We can also randomly flip our images Horizontally or Vertically. However, for these images, we will only flip them horizontally.

Take a moment to think about why we would want to flip images horizontally, but not vertically. When you have an idea, reveal the text below.

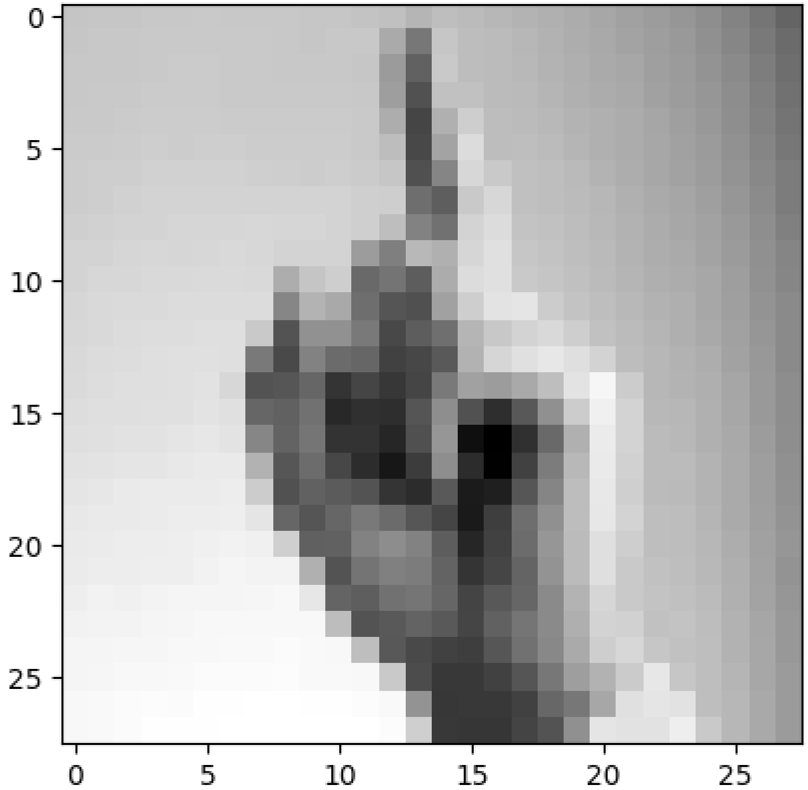
`# SOLUTION` Fun fact: American Sign Language can be done with either the left or right hand being dominant. However, it is unlikely to see sign language from upside down. This kind of domain-specific reasoning can help make good decisions for your own deep learning applications.

In [16]:
```
trans = transforms.Compose([
    transforms.RandomHorizontalFlip()
])
```

Try running the below cell a few times. Does the image flip about half the time?

In [17]:
```
new_x_0 = trans(x_0)
image = F.to_pil_image(new_x_0)
plt.imshow(image, cmap='gray')
```

Out[17]:
```
<matplotlib.image.AxesImage at 0x7f0e28138fa0>
```



4a.4.3 RandomRotation

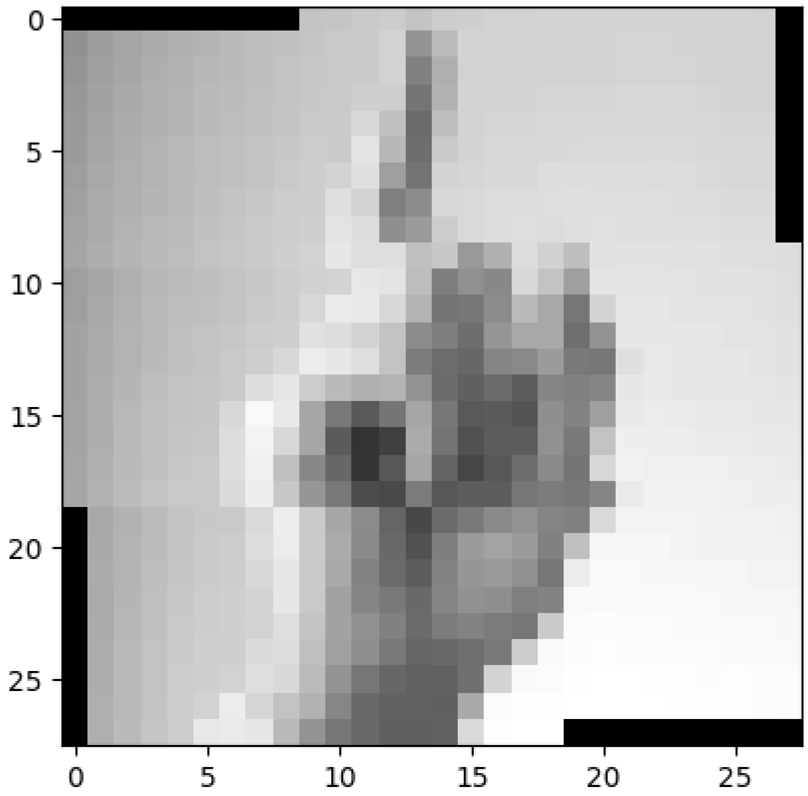
We can also randomly rotate the image to add more variability. Just like with with other augmentation techniques, it's easy to accidentally go too far. With ASL, if we rotate too much, our `D` s might look like `G` s and visa versa. Because of this, let's limit it to `30` degrees.

In [18]:
```
trans = transforms.Compose([
    transforms.RandomRotation(10)
])
```

When we run the cell block below, some black pixels may appear. The corners or our image disappear when we rotate, and for almost every pixel we lose, we gain an empty pixel.

In [19]:
```
new_x_0 = trans(x_0)
image = F.to_pil_image(new_x_0)
plt.imshow(image, cmap='gray')
```

Out[19]: <matplotlib.image.AxesImage at 0x7f0e281a5660>



4a.4.3 ColorJitter

The `ColorJitter` transform has 4 arguments:

- brightness
- contrast)
- saturation

- hue

The latter 2 apply to color images, so we will only use the first 2 for now.

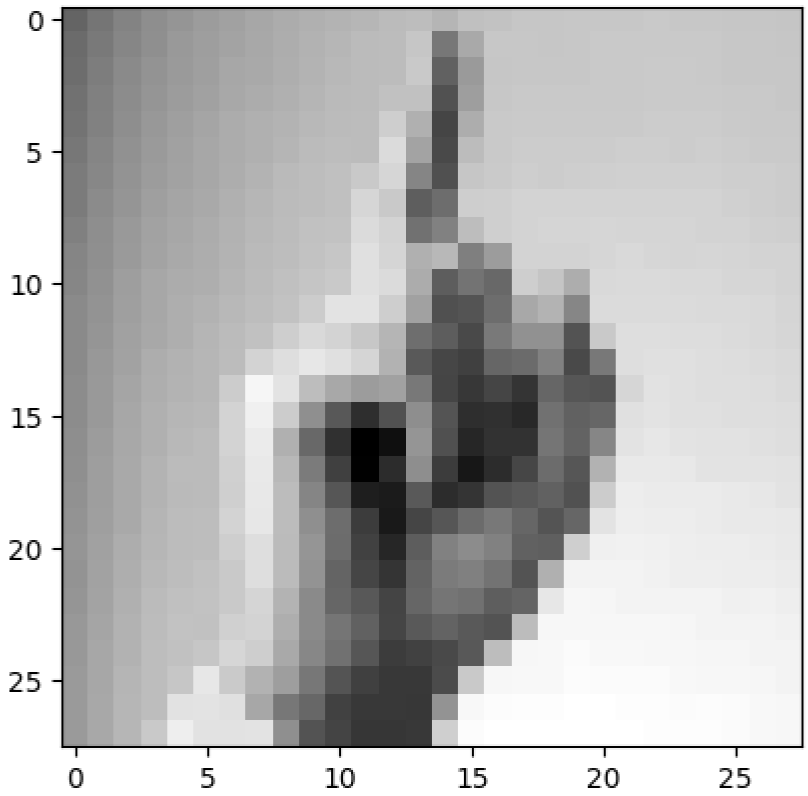
In [20]:
```
brightness = .2  # Change to be from 0 to 1
contrast = .5  # Change to be from 0 to 1

trans = transforms.Compose([
    transforms.ColorJitter(brightness=brightness, contrast=contrast)
])
```

Try running the below a few times, but also try changing either `brightness` or `contrast` to `1`. Get any intersting results?

In [21]:
```
new_x_0 = trans(x_0)
image = F.to_pil_image(new_x_0)
plt.imshow(image, cmap='gray')
```

Out[21]:
```
<matplotlib.image.AxesImage at 0x7f0e206f2bf0>
```



4a.3.4 Compose

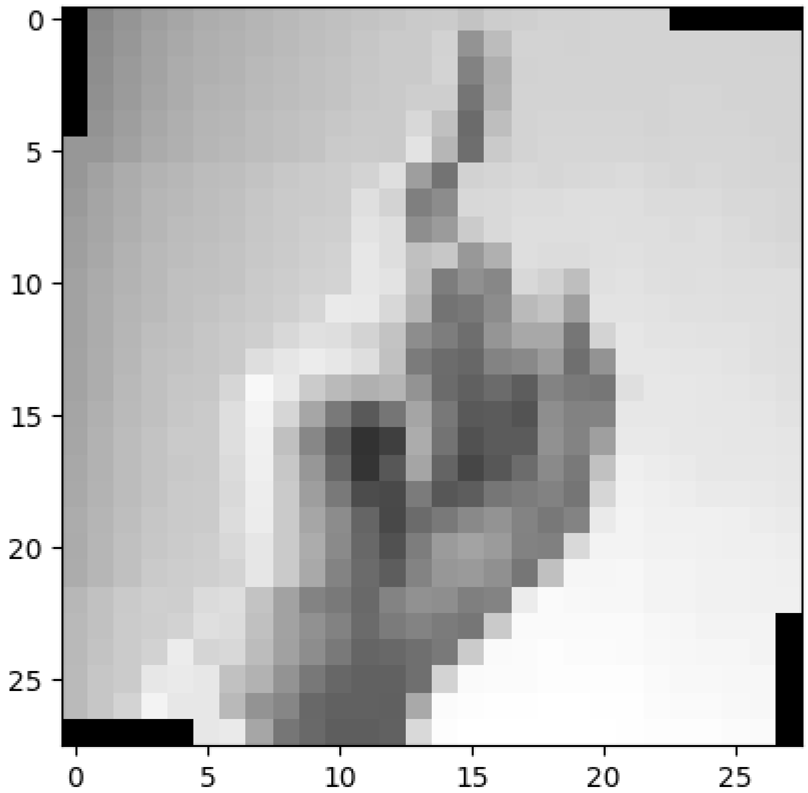
Time to bring it all together. We can create a sequence of these random transformations with `Compose`.

In [22]:
```
random_transforms = transforms.Compose([
    transforms.RandomRotation(5),
    transforms.RandomResizedCrop((IMG_WIDTH, IMG_HEIGHT), scale=(.9, 1), ratio=(1, 1)),
    transforms.RandomHorizontalFlip(),
    transforms.ColorJitter(brightness=.2, contrast=.5)
])
```

Let's test it out. With all the different combinations how many varations are there of this one image? Infinite?

In [23]:
```
new_x_0 = random_transforms(x_0)
image = F.to_pil_image(new_x_0)
plt.imshow(image, cmap='gray')
```

Out[23]: <matplotlib.image.AxesImage at 0x7f0e20760ca0>



4a.4 Training with Augmentation

Our training is mostly the same, but there is one line of change. Before passing our images to our model, we will apply our `random_transforms`. For conveneince, we moved `get_batch_accuracy` to a utils file.

In [24]:
```
def train():
    loss = 0
```

```
    accuracy = 0

    model.train()
    for x, y in train_loader:
        output = model(random_transforms(x))  # Updated
        optimizer.zero_grad()
        batch_loss = loss_function(output, y)
        batch_loss.backward()
        optimizer.step()

        loss += batch_loss.item()
        accuracy += utils.get_batch_accuracy(output, y, train_N)
    print('Train - Loss: {:.4f} Accuracy: {:.4f}'.format(loss, accuracy))
```

On the other hamd, validation remains the same. There are no random transformations.

In [25]:
```
def validate():
    loss = 0
    accuracy = 0

    model.eval()
    with torch.no_grad():
        for x, y in valid_loader:
            output = model(x)

            loss += loss_function(output, y).item()
            accuracy += utils.get_batch_accuracy(output, y, valid_N)
    print('Valid - Loss: {:.4f} Accuracy: {:.4f}'.format(loss, accuracy))
```

Let's put data augmentation to the test.

In [26]:
```
epochs = 20

for epoch in range(epochs):
    print('Epoch: {}'.format(epoch))
    train()
    validate()
```

```
Epoch: 0
Train - Loss: 616.5396 Accuracy: 0.7670
Valid - Loss: 48.0441 Accuracy: 0.9318
Epoch: 1
Train - Loss: 110.0408 Accuracy: 0.9601
Valid - Loss: 72.3511 Accuracy: 0.8758
Epoch: 2
Train - Loss: 57.2960 Accuracy: 0.9783
Valid - Loss: 47.4540 Accuracy: 0.9260
Epoch: 3
Train - Loss: 44.0439 Accuracy: 0.9835
Valid - Loss: 55.7494 Accuracy: 0.9120
Epoch: 4
Train - Loss: 35.0739 Accuracy: 0.9867
Valid - Loss: 11.5175 Accuracy: 0.9795
Epoch: 5
Train - Loss: 34.9787 Accuracy: 0.9868
Valid - Loss: 16.2646 Accuracy: 0.9780
Epoch: 6
Train - Loss: 27.4221 Accuracy: 0.9895
Valid - Loss: 10.4014 Accuracy: 0.9767
Epoch: 7
Train - Loss: 25.0239 Accuracy: 0.9899
Valid - Loss: 30.9695 Accuracy: 0.9689
Epoch: 8
Train - Loss: 21.1323 Accuracy: 0.9921
Valid - Loss: 27.4925 Accuracy: 0.9678
Epoch: 9
Train - Loss: 18.7138 Accuracy: 0.9930
Valid - Loss: 43.4133 Accuracy: 0.9499
Epoch: 10
Train - Loss: 16.4422 Accuracy: 0.9941
Valid - Loss: 22.1741 Accuracy: 0.9677
Epoch: 11
Train - Loss: 19.4554 Accuracy: 0.9925
Valid - Loss: 8.9422 Accuracy: 0.9820
Epoch: 12
Train - Loss: 14.7099 Accuracy: 0.9945
Valid - Loss: 12.3284 Accuracy: 0.9776
Epoch: 13
Train - Loss: 16.8019 Accuracy: 0.9936
```

```
Valid - Loss: 13.9909 Accuracy: 0.9757
Epoch: 14
Train - Loss: 14.1544 Accuracy: 0.9947
Valid - Loss: 10.8890 Accuracy: 0.9838
Epoch: 15
Train - Loss: 14.0295 Accuracy: 0.9946
Valid - Loss: 30.0554 Accuracy: 0.9664
Epoch: 16
Train - Loss: 10.8135 Accuracy: 0.9960
Valid - Loss: 10.2812 Accuracy: 0.9842
Epoch: 17
Train - Loss: 16.8174 Accuracy: 0.9934
Valid - Loss: 17.6942 Accuracy: 0.9835
Epoch: 18
Train - Loss: 12.4902 Accuracy: 0.9960
Valid - Loss: 7.4012 Accuracy: 0.9927
Epoch: 19
Train - Loss: 8.6292 Accuracy: 0.9968
Valid - Loss: 107.8251 Accuracy: 0.9115
```

Discussion of Results

You will notice that the validation accuracy is higher, and more consistent. This means that our model is no longer overfitting in the way it was; it generalizes better, making better predictions on new data.

The training accuracy may be lower, and that's ok. Compared to before, the model is being exposed to a much larger variety of data.

Saving the Model

Now that we have a well-trained model, we will want to deploy it to perform inference on new images.

It is common, once we have a trained model that we are happy with to save it to disk. PyTorch has multiple ways to do this, but for now, we will use `torch.save`. We will also need to save the code for our `MyConvBlock` custom module, which we did in utils.py. In the next notebook, we'll load the model and use it to read new sign language pictures.

PyTorch cannot save a compiled model (see this post), so we will instead

In [28]:
```
torch.save(base_model, 'model.pth')
```

Summary

In this section, you used TorchVision to augment a dataset. This resulted in a trained model with less overfitting and excellent validation image results.

Clear the Memory

Before moving on, please execute the following cell to clear up the GPU memory.

In [29]:
```
import IPython
app = IPython.Application.instance()
app.kernel.do_shutdown(True)
```

Out[29]:
```
{'status': 'ok', 'restart': True}
```

Next

Now that you have a well-trained model saved to disk, you will, in the next section, deploy it to make predictions on not-yet-seen images.

Please continue to the next notebook: *Model Predictions*.

Header