Convolutional Neural Networks

## 1. Build CNN

For this assignment, the objective is to train a convolutional neural network (CNN) on the CiFAR-10 dataset. For my model architecture, I drew sizing inspiration from *heysachin*'s github repository [1], who tackled the same problem and achieved an accuracy of 70%.

The model utilizes three convolutional layers of sizes 16, 32, and 64. All of them utilize a kernel size of 3x3, a stride of 1, and 1 pixel of padding on the outside of the image. These layers feed into the rectified linear unit activation function (ReLU), which was chosen for its computational efficiency and historic performance.

After each convolution and activation, a max pooling operation of size 2x2 reduces the resolution of the image by a factor of 2. The output of the last convolutional layer is flattened, creating an layer with 64 * 4 * 4 = 1024 nodes. 25% of these 1024 nodes are randomly set to 0 through the dropout operation before being passed into a 500 node fully connected (FC) layer.

The 500 node FC layer passes through a ReLU function, then another 0.25% dropout operation before being connected to 10 output nodes for classification. Finally, the categorical cross entropy function is then used to determine the loss, before the optimizer kicks in.

| **Model Architecture** |
|---|
| Conv2d(in_channels=3, out_channels=16, kernel_size=3, stride=1, padding=1) |
| relu() |
| MaxPool2d(2, 2) |
| Conv2d(in_channels=16, out_channels=32, kernel_size=3, stride=1, padding=1) |
| relu() |
| MaxPool2d(2, 2) |
| Conv2d(in_channels=32, out_channels=64, kernel_size=3, stride=1, padding=1) |
| relu() |
| MaxPool2d(2, 2) |
| FLATTEN |
| Dropout(0.25) |
| Linear(64 * 4 * 4, 500) |
| relu() |
| Dropout(0.25) |

| Linear(500, 10) |
|---|

My hyperparameter selection slightly varies from the original setup in the assigned file. In my case, I increased the epochs from 5 to 100 and added an early stopping mechanism that stops the training after 10 epochs of no validation loss improvement. The learning rate was left at 0.01, however, both stochastic gradient descent and Adam optimizers were tested. Batch sizes of 16, 20, and 32 were experimented with, but it was found that 20 worked best for this model.

| Hyper Parameter | Value |
|---|---|
| Max Epochs | 100 |
| Early Stopping Patience | 10 |
| Batch Size | 20 |
| Learning Rate | 0.01 |
| Optimizer | SGD, Adam |

After trying all of the combinations, it was found the SGD optimizer was far better than the Adam optimizer. The best run ran for 34 epochs before early stopping was triggered, and achieved a validation loss of 0.69.

**Adam Optimizer Training Run**

```
Epoch: 4        Training Loss: 1.871627         Validation Loss: 1.800180
Epoch: 5        Training Loss: 1.865913         Validation Loss: 1.795681
Epoch: 6        Training Loss: 1.876183         Validation Loss: 1.891529
Epoch: 7        Training Loss: 1.869876         Validation Loss: 1.899572
Epoch: 8        Training Loss: 1.867193         Validation Loss: 2.009897
Epoch: 9        Training Loss: 1.887755         Validation Loss: 1.819636
Epoch: 10       Training Loss: 1.861460         Validation Loss: 1.785274
Validation loss decreased (1.788048 --> 1.785274).  Saving model ...
Epoch: 11       Training Loss: 1.865620         Validation Loss: 1.814370
Epoch: 12       Training Loss: 1.879742         Validation Loss: 1.830232
Epoch: 13       Training Loss: 1.874567         Validation Loss: 1.785262
Validation loss decreased (1.785274 --> 1.785262).  Saving model ...
Epoch: 14       Training Loss: 1.875062         Validation Loss: 1.780718
Validation loss decreased (1.785262 --> 1.780718).  Saving model ...
Epoch: 15       Training Loss: 1.873958         Validation Loss: 1.764497
Validation loss decreased (1.780718 --> 1.764497).  Saving model ...
Epoch: 16       Training Loss: 1.884847         Validation Loss: 1.812043
Epoch: 17       Training Loss: 1.893591         Validation Loss: 1.811983
Epoch: 18       Training Loss: 2.092671         Validation Loss: 2.038455
Epoch: 19       Training Loss: 2.046187         Validation Loss: 2.028712
Epoch: 20       Training Loss: 2.066684         Validation Loss: 2.018159
Epoch: 21       Training Loss: 2.036461         Validation Loss: 1.984657
Epoch: 22       Training Loss: 2.024290         Validation Loss: 1.958010
Epoch: 23       Training Loss: 2.057869         Validation Loss: 2.086961
Epoch: 24       Training Loss: 2.035258         Validation Loss: 1.958435
Epoch: 25       Training Loss: 2.015310         Validation Loss: 1.989358
```

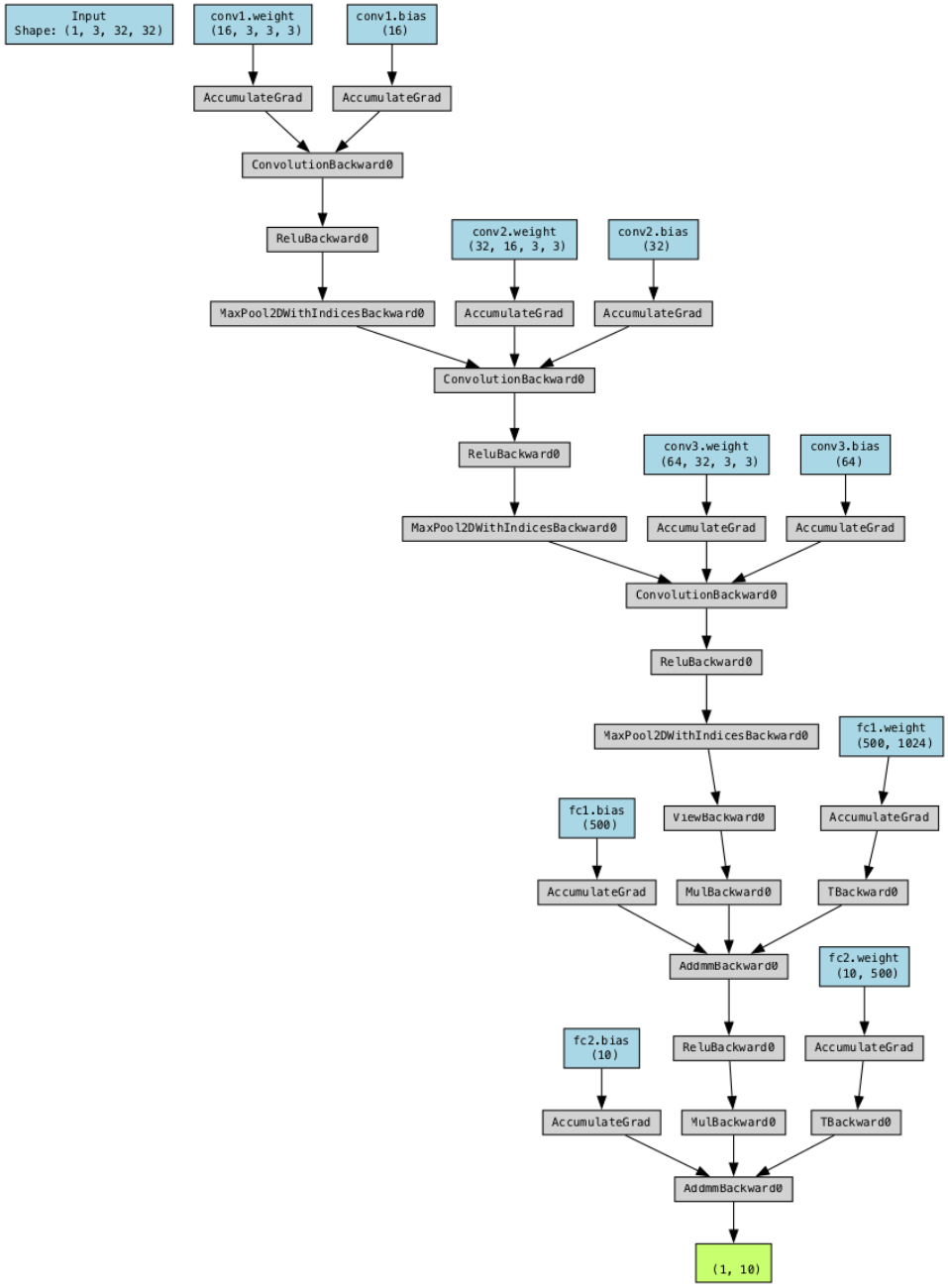
**SGD Training Run (Best Run)**

```
Validation loss decreased (0.799887 --> 0.781168).  Saving model ...
Epoch: 14       Training Loss: 0.751940         Validation Loss: 0.769140
Validation loss decreased (0.781168 --> 0.769140).  Saving model ...
Epoch: 15       Training Loss: 0.714594         Validation Loss: 0.751552
Validation loss decreased (0.769140 --> 0.751552).  Saving model ...
Epoch: 16       Training Loss: 0.686935         Validation Loss: 0.744286
Validation loss decreased (0.751552 --> 0.744286).  Saving model ...
Epoch: 17       Training Loss: 0.656549         Validation Loss: 0.742664
Validation loss decreased (0.744286 --> 0.742664).  Saving model ...
Epoch: 18       Training Loss: 0.633287         Validation Loss: 0.714291
Validation loss decreased (0.742664 --> 0.714291).  Saving model ...
Epoch: 19       Training Loss: 0.606360         Validation Loss: 0.710618
Validation loss decreased (0.714291 --> 0.710618).  Saving model ...
Epoch: 20       Training Loss: 0.581759         Validation Loss: 0.694608
Validation loss decreased (0.710618 --> 0.694608).  Saving model ...
Epoch: 21       Training Loss: 0.560011         Validation Loss: 0.700198
Epoch: 22       Training Loss: 0.530882         Validation Loss: 0.699327
Epoch: 23       Training Loss: 0.510691         Validation Loss: 0.728201
Epoch: 24       Training Loss: 0.493436         Validation Loss: 0.691854
Validation loss decreased (0.694608 --> 0.691854).  Saving model ...
Epoch: 25       Training Loss: 0.464579         Validation Loss: 0.709685
Epoch: 26       Training Loss: 0.455230         Validation Loss: 0.704332
Epoch: 27       Training Loss: 0.428798         Validation Loss: 0.701736
Epoch: 28       Training Loss: 0.414719         Validation Loss: 0.696596
Epoch: 29       Training Loss: 0.396459         Validation Loss: 0.714299
Epoch: 30       Training Loss: 0.383098         Validation Loss: 0.720496
Epoch: 31       Training Loss: 0.364282         Validation Loss: 0.702077
Epoch: 32       Training Loss: 0.350195         Validation Loss: 0.730433
Epoch: 33       Training Loss: 0.329403         Validation Loss: 0.727997
Epoch: 34       Training Loss: 0.320108         Validation Loss: 0.747220
```

| Adam Optimizer Test | SGD Optimizer Test (Best Results) |
|---|---|
| Test Loss: 1.745755<br><br>Test Accuracy of airplane: 20% (205/1000)<br>Test Accuracy of automobile: 50% (504/1000)<br>Test Accuracy of bird: 10% (101/1000)<br>Test Accuracy of cat: 7% (79/1000)<br>Test Accuracy of deer: 24% (241/1000)<br>Test Accuracy of dog: 38% (384/1000)<br>Test Accuracy of frog: 57% (579/1000)<br>Test Accuracy of horse: 31% (319/1000)<br>Test Accuracy of ship: 57% (571/1000)<br>Test Accuracy of truck: 46% (469/1000)<br><br>Test Accuracy (Overall): 34% (3452/10000) | Test Loss: 0.706488<br><br>Test Accuracy of airplane: 79% (792/1000)<br>Test Accuracy of automobile: 89% (896/1000)<br>Test Accuracy of bird: 65% (657/1000)<br>Test Accuracy of cat: 52% (527/1000)<br>Test Accuracy of deer: 66% (666/1000)<br>Test Accuracy of dog: 70% (706/1000)<br>Test Accuracy of frog: 83% (839/1000)<br>Test Accuracy of horse: 82% (821/1000)<br>Test Accuracy of ship: 85% (857/1000)<br>Test Accuracy of truck: 79% (799/1000)<br><br>Test Accuracy (Overall): 75% (7560/10000) |

**Visual Test Results**


## Model Architecture Compute Graph




## Model Architecture Code

```
# define the CNN architecture
class Net(nn.Module):
    def __init__(self):
```

```
        super(Net, self).__init__()

        # TOTO: Build multiple convolutional layers (sees 32x32x3 image tensor in the
first hidden layer)
        self.image_width = 32
        self.image_height = 32

        # for example, conv1, conv2 and conv3
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=16, kernel_size=3,
stride=1, padding=1)
        self.conv2 = nn.Conv2d(in_channels=16, out_channels=32, kernel_size=3,
stride=1, padding=1)
        self.conv3 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3,
stride=1, padding=1)

        # max pooling layer
        self.pool = nn.MaxPool2d(2, 2)

        # TODO: Build some linear layers (fully connected)
        # for example, fc1 and fc2
        self.fc1 = nn.Linear(64 * 4 * 4, 500)
        self.fc2 = nn.Linear(500, 10)

        # TODO: dropout layer (p=0.25, you can adjust)
        # example self.dropout = nn.Dropout(0.25)
        self.dropout = nn.Dropout(0.25)

    def forward(self, x):
        # add sequence of convolutional and max pooling layers
        # assume we have 2 convolutional layers defined agove
        # and we do a maxpooling after each conv layer
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = self.pool(F.relu(self.conv3(x)))

        # TODO: flatten x at this point to get it ready to feed into the fully
connected layer(s)
        # Can use this but need to figure out the actual value for a, b and c
        x = x.view(-1, 4 * 4 * 64)

        # optional add dropout layer
```

```
        x = self.dropout(x)

        # add 1st hidden layer, with relu activation function
        x = F.relu(self.fc1(x))

        # optional add dropout layer
        x = self.dropout(x)

        # add 2nd hidden layer, with relu activation function
        x = self.fc2(x)

        return x
```

**Modified Training Code**

```
import torch.optim as optim

# create a complete CNN
model = Net()
print(model)

# move tensors to GPU if CUDA is available
if train_on_gpu:
    model.cuda()

# specify loss function (categorical cross-entropy)
criterion = nn.CrossEntropyLoss()

# specify optimizer
#optimizer = optim.SGD(model.parameters(), lr=0.01)

# TODO, compare with optimizer ADAM
optimizer = optim.Adam(model.parameters(), lr=0.01)

# number of epochs to train the model, you decide the number
n_epochs = 60
patience = 10
patience_count = 0
```

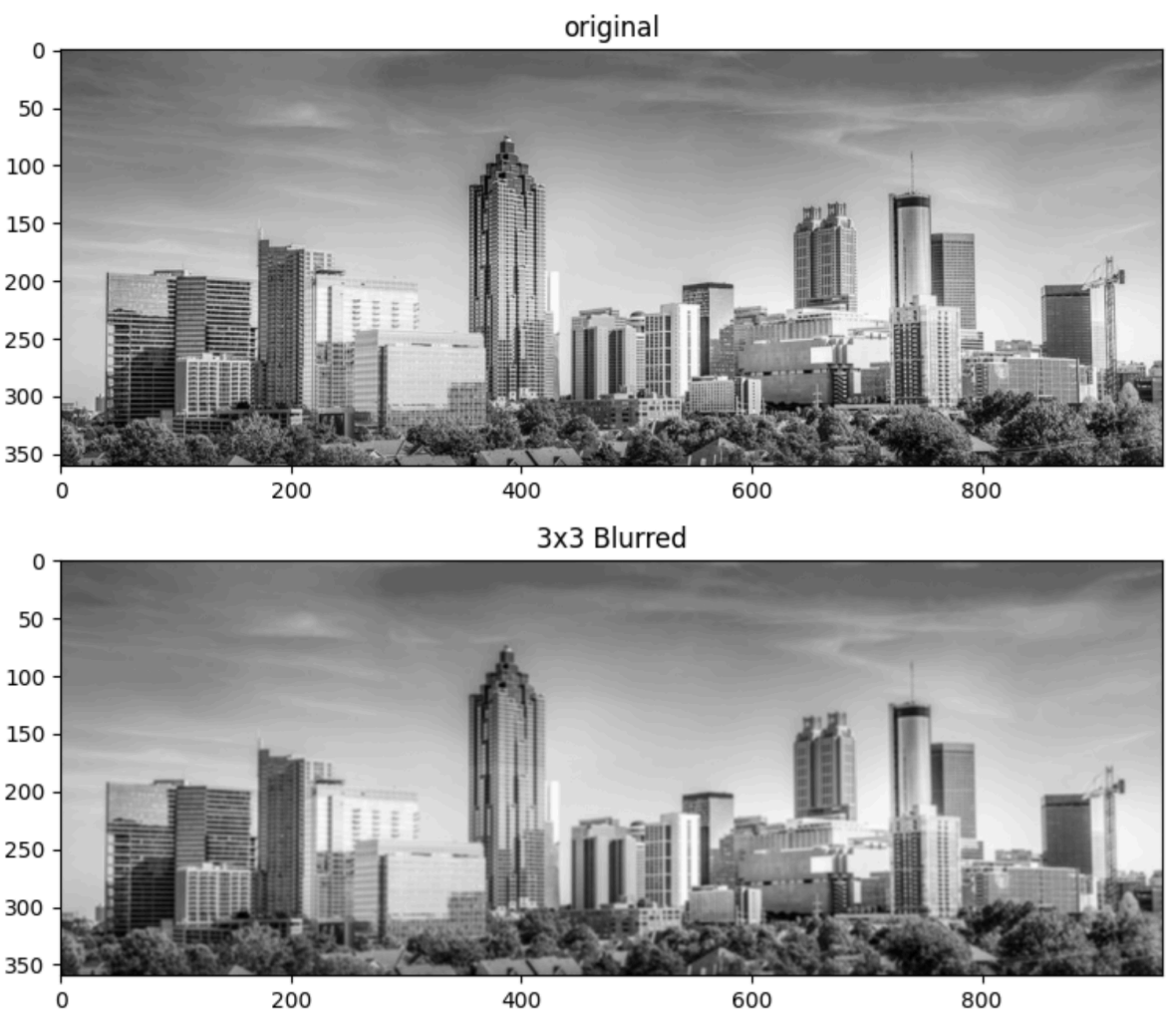
```
valid_loss_min = np.inf # track change in validation loss

for epoch in range(1, n_epochs+1):

   # keep track of training and validation loss
   train_loss = 0.0
   valid_loss = 0.0

   ###################
   # train the model #
   ###################
   model.train()
   for batch_idx, (data, target) in enumerate(train_loader):
       # move tensors to GPU if CUDA is available
       if train_on_gpu:
           data, target = data.cuda(), target.cuda()
       # clear the gradients of all optimized variables
       optimizer.zero_grad()
       # forward pass: compute predicted outputs by passing inputs to the model
       output = model(data)
       # calculate the batch loss
       loss = criterion(output, target)
       # backward pass: compute gradient of the loss with respect to model
parameters
       loss.backward()
       # perform a single optimization step (parameter update)
       optimizer.step()
       # update training loss
       train_loss += loss.item()*data.size(0)

   ######################
   # validate the model #
   ######################
   model.eval()
   for batch_idx, (data, target) in enumerate(valid_loader):
       # move tensors to GPU if CUDA is available
       if train_on_gpu:
           data, target = data.cuda(), target.cuda()
       # forward pass: compute predicted outputs by passing inputs to the model
       output = model(data)
       # calculate the batch loss
```

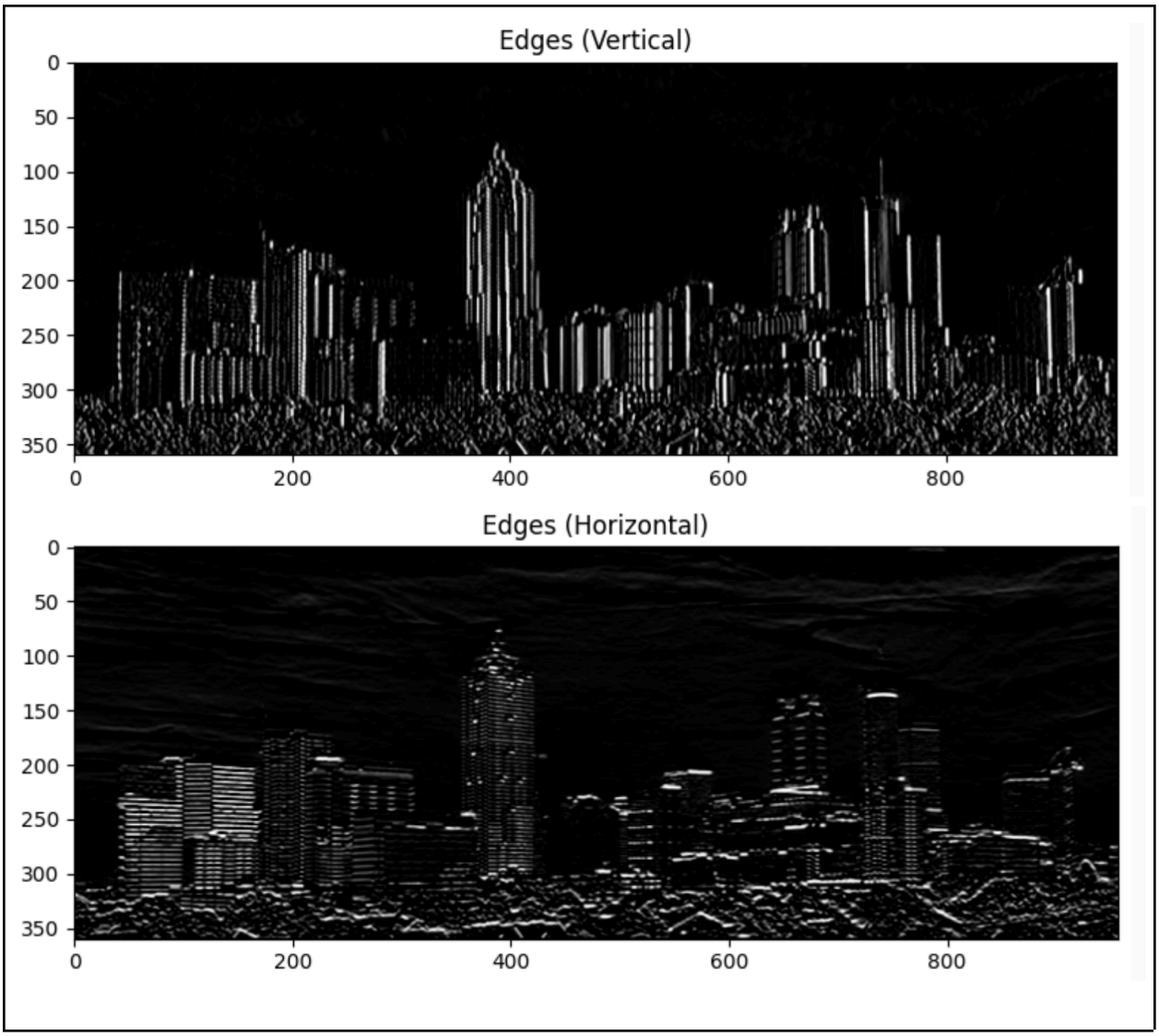
```
        loss = criterion(output, target)
        # update average validation loss
        valid_loss += loss.item()*data.size(0)

    # calculate average losses
    train_loss = train_loss/len(train_loader.sampler)
    valid_loss = valid_loss/len(valid_loader.sampler)

    # print training/validation statistics
    print('Epoch: {} \tTraining Loss: {:.6f} \tValidation Loss: {:.6f}'.format(
        epoch, train_loss, valid_loss))

    # save model if validation loss has decreased
    if valid_loss <= valid_loss_min:
        print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model
...'.format(
        valid_loss_min,
        valid_loss))
        torch.save(model.state_dict(), 'model_trained.pt')
        valid_loss_min = valid_loss
        patience_count = 0
    else:
        patience_count += 1
        if patience_count >= patience:
            break
```

## 2. Image Filtering

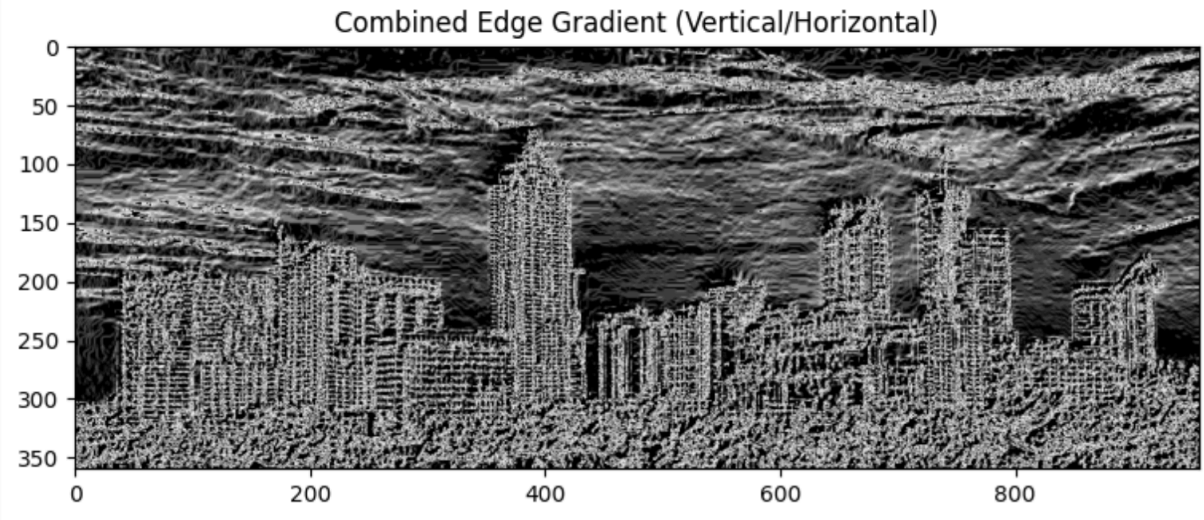
For this assignment, we are to combine blurring with the sobel operator to perform basic edge detection on the provided images. The blurring operation used is a 3x3 matrix of 1s. Larger matrices of 5x5 and 7x7 were experimented with, but washed out too many details from the image, so were discarded. The sobel operation was implemented using the OpenCV filter2d function along with the standard vertical and horizontal matrices. Finally, the magnitude of both horizontal and vertical images is taken at each picture to create the complete edge gradient of the image. This operation was conducted using numpy.square and numpy.sqrt functions on the vertical and horizontal sobel filtered images.

**Blurring and Vertical/Horizontal Sobel Filtering Output**




Edges (Vertical)
0
50
100
150
200
250
300
350
0
200
400
600
800
Edges (Horizontal)
0
50
100
150
200
250
300
350
0
200
400
600
800

**Resulting Edge Gradient from Combining Vertical and Horizontal Filters**




**Blurring and Vertical/Horizontal Sobel Filtering Code**

```
plt.clf()

# Define kernels
S3x3 = np.ones(shape=(3,3), dtype=np.float32)

# Sobel kernels for edge detection
Kx = np.array([[-1, 0, 1],
               [-2, 0, 2],
               [-1, 0, 1]])

Ky = np.array([[-1, -2, -1],
               [ 0,  0,  0],
               [ 1,  2,  1]])

fig = plt.figure(figsize=(48, 20))
fig.add_subplot(5,1,1)
plt.imshow(gray, cmap='gray')
plt.title('original')

# Blur image using a 3x3 average
blurred_image = cv2.filter2D(gray, -1, S3x3/9.0)
fig.add_subplot(5,1,2)
```

```
plt.imshow(blurred_image, cmap='gray')
plt.title('3x3 Blurred')

# Detect edges using Sobel operator (vertical edges)
edges_x = cv2.filter2D(blurred_image, -1, Kx)
fig.add_subplot(5,1,3)
plt.imshow(edges_x, cmap='gray')
plt.title('Edges (Vertical)')

# Detect edges using Sobel operator (horizontal edges)
edges_y = cv2.filter2D(blurred_image, -1, Ky)
fig.add_subplot(5,1,4)
plt.imshow(edges_y, cmap='gray')
plt.title('Edges (Horizontal)')

combined = np.sqrt(np.square(edges_x) +  np.square(edges_y))
fig.add_subplot(5,1,5)
plt.imshow(combined, cmap='gray')
plt.title('Combined Edge Gradient (Vertical/Horizontal)')

plt.show()
```

**References**

[1] *heysachine*, Convolutional-Neural-Network-CIFAR-10-PyTorch, Github, 2018, https://github.com/heysachin/Convolutional-Neural-Network-CIFAR-10-PyTorch/blob/master/cifar10_cnn.ipynb.