

3ab4btwxm

March 12, 2024

```
[158]: import os
import torch
import torchvision
import torchvision.transforms as transforms
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import torch.nn.init as init

import matplotlib.pyplot as plt
import numpy as np
from typing import OrderedDict
```

Defining class

```
[159]: class VGG11_CIFR10(nn.Module):
    def __init__(self, num_channels = 3, num_classes = 10):
        super(VGG11_CIFR10, self).__init__();
        self.num_channels = num_channels;
        self.num_classes = num_classes;
        # Convolution and Pooling
        self.convolution_layers = nn.Sequential(OrderedDict([
            ('conv1', nn.
↳Conv2d(in_channels=num_channels, out_channels=64, kernel_size=3, padding=1)),
            ('relu1', nn.
↳ReLU(inplace=True)),
            ('Maxpool1', nn.
↳MaxPool2d(kernel_size=2, stride=2)), # Reducing the resulting image to half
            ('conv2', nn.
↳Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)),
            ('relu2', nn.
↳ReLU(inplace=True)),
            ('Maxpool2', nn.
↳MaxPool2d(kernel_size=2, stride=2)), # Reducing the resulting image to half
```

```

('conv3a', nn.
↳Conv2d(in_channels=128, out_channels=256, kernel_size=3, padding=1)),
('relu3a', nn.
↳ReLU(inplace=True)),
('conv3b', nn.
↳Conv2d(in_channels=256, out_channels=256, kernel_size=3, padding=1)),
('relu3b', nn.
↳ReLU(inplace=True)),
('Maxpool3', nn.
↳MaxPool2d(kernel_size=2, stride=2)), # Reducing the resulting image to half

('conv4a', nn.
↳Conv2d(in_channels=256, out_channels=512, kernel_size=3, padding=1)),
('relu4a', nn.
↳ReLU(inplace=True)),
('conv4b', nn.
↳Conv2d(in_channels=512, out_channels=512, kernel_size=3, padding=1)),
('relu4b', nn.
↳ReLU(inplace=True)),
('Maxpool4', nn.
↳MaxPool2d(kernel_size=2, stride=2)), # Reducing the resulting image to half

('conv5a', nn.
↳Conv2d(in_channels=512, out_channels=512, kernel_size=3, padding=1)),
('relu5a', nn.
↳ReLU(inplace=True)),
('conv5b', nn.
↳Conv2d(in_channels=512, out_channels=512, kernel_size=3, padding=1)),
('relu5b', nn.
↳ReLU(inplace=True)),
# Here the dimension of
↳the features will be 512 * 2 * 2
('Maxpool5', nn.
↳MaxPool2d(kernel_size=2, stride=2)), # Reducing the resulting image to half
# after Maxpool5 the
↳dimension of the image becomes 512 * 1 * 1

]))

# Fully connected Layers
self.fc = nn.Sequential(OrderedDict([
('fc1', nn.Linear(in_features=512*1*1,
↳out_features=4096)),
('relu1', nn.ReLU(inplace=True)),
('Dropout1', nn.Dropout(0.5)),

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        ('fc2', nn.Linear(in_features=4096,
        ↪out_features=4096)),

        ('relu2', nn.ReLU(inplace=True)),
        ('Dropout2', nn.Dropout(0.5)),

        ('fc3', nn.Linear(in_features=4096,
        ↪out_features=1000)),

        ('relu3', nn.ReLU(inplace=True)),
        ('Dropout3', nn.Dropout(0.5)),

        ('fc_out', nn.Linear(in_features=1000,
        ↪out_features=10))

    ]))

# forward Prop
def forward(self, x):
    x = self.convolution_layers(x)
    # flatten the data
    x = torch.flatten(x, 1)
    # Pass thorough Fully connected layers
    x = self.fc(x)
    return x

```

```

[160]: # Query for GPU
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(device)
print(torch.cuda.device_count())
print(torch.cuda.get_device_name(0))

```

```

cuda
1
Tesla P100-PCIE-16GB

```

```

[161]: epochs = 60 # ideal = 59
batch_size = 256
learning_rate = 0.01
momentum = 0.9 # changed from 0.9 to 0.09
wt_decay = 0.0005

```

```

[162]: transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))]) # Normalize the
    ↪input data to mean = 0.5 and SD = 0.5

trainset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                         download=True, transform=transform)

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trainloader = torch.utils.data.DataLoader(trainset, batch_size=batch_size,
                                           shuffle=True, num_workers=2)

testset = torchvision.datasets.CIFAR10(root='./data', train=False,
                                       download=True, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=batch_size,
                                          shuffle=False, num_workers=2)

classes = ('plane', 'car', 'bird', 'cat',
           'deer', 'dog', 'frog', 'horse', 'ship', 'truck')

```

Files already downloaded and verified  
Files already downloaded and verified

```

[163]: cnn_model = VGG11_CIFR10().to(device=device)

# Using Xavier initialization weights and Biases for convolutional layers
def weights_init(m):
    if isinstance(m, nn.Conv2d) or isinstance(m, nn.Linear):
        init.xavier_uniform_(m.weight.data)
        if m.bias is not None:
            m.bias.data.zero_()

cnn_model.apply(weights_init) # Enable this to initialize the weights

# for param in cnn_model.parameters():
#     print("Total number of parameters : ",param.numel())
#     print("Type : ", type(param), "\tSize : ", param.size())

```

```

[163]: VGG11_CIFR10(
    (convolution_layers): Sequential(
      (conv1): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (relu1): ReLU(inplace=True)
      (Maxpool1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
      (conv2): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (relu2): ReLU(inplace=True)
      (Maxpool2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
      (conv3a): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
      (relu3a): ReLU(inplace=True)
      (conv3b): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
      (relu3b): ReLU(inplace=True)
      (Maxpool3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)

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    (conv4a): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (relu4a): ReLU(inplace=True)
    (conv4b): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (relu4b): ReLU(inplace=True)
    (Maxpool4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (conv5a): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (relu5a): ReLU(inplace=True)
    (conv5b): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (relu5b): ReLU(inplace=True)
    (Maxpool5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    )
    (fc): Sequential(
      (fc1): Linear(in_features=512, out_features=4096, bias=True)
      (relu1): ReLU(inplace=True)
      (Dropout1): Dropout(p=0.5, inplace=False)
      (fc2): Linear(in_features=4096, out_features=4096, bias=True)
      (relu2): ReLU(inplace=True)
      (Dropout2): Dropout(p=0.5, inplace=False)
      (fc3): Linear(in_features=4096, out_features=1000, bias=True)
      (relu3): ReLU(inplace=True)
      (Dropout3): Dropout(p=0.5, inplace=False)
      (fc_out): Linear(in_features=1000, out_features=10, bias=True)
    )
  )
)

```

```

[164]: # loss function
criterion = nn.CrossEntropyLoss()

# the optimizer
optimizer = optim.SGD(cnn_model.parameters(), lr=learning_rate,
    ↪momentum=momentum, weight_decay=wt_decay, nesterov=True ) # ,
    ↪weight_decay=wt_decay

# These parameters are taken from the section 3.1
    ↪of the paper https://arxiv.org/pdf/1409.1556.pdf on VGGNet

```

```

[165]: training_error = [] # To record Training error through the training process
interm_accuracy = [] # To record the intermediate accuracy values for plotting
count = 0
total = 0
correct = 0

```

```

for epoch in range(epochs):
    #set the model in training mode
    cnn_model.train()
    running_loss = 0.0
    interm_total = 0.0
    interm_correct = 0.0

    for i, data in enumerate(trainloader):
        count = count + 1
        inputs, labels = data
        inputs = inputs.to(device) # To perform on the available GPU
        labels = labels.to(device)

        # reset the grads to Zero
        optimizer.zero_grad()

        # forward pass
        outputs = cnn_model(inputs)

        # calculate loss
        loss = criterion(outputs, labels)

        # Back prop
        loss.backward()

        # Gradient update
        optimizer.step()

        running_loss += loss.item()

        predicted_probability, predicted = torch.max(outputs.data, 1) # each input
        ↪image will have 10 probablities for classification,
                                                                    # from that
        ↪we need to pick the maximum probability class as our predicted class
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

        interm_total += labels.size(0)
        interm_correct += (predicted == labels).sum().item()

    avg_training_loss = running_loss / len(trainloader);
    print(f'[Epoch : {epoch + 1} , Average Training loss: {avg_training_loss:.
    ↪6f}'] # running_loss / 2000:.3f
    training_error.append(avg_training_loss)
    interm_accuracy.append((100 * correct)//total)
    running_loss = 0.0

```

```

# Plot the computed stats
fig=plt.figure(figsize=(20, 5))

fig.add_subplot(1,2,1)
plt.plot(training_error, label='Training Loss', color='g')
plt.xlabel('Epoch')
plt.ylabel('Training loss')

fig.add_subplot(1,2,2)
plt.plot(interm_accuracy, label='Training Accuracy', color='r')
plt.xlabel('Epoch')
plt.ylabel('Training Accuracy')
plt.legend()

plt.tight_layout()
plt.show()

print("\nTraining Finished with accuracy : ", ((100 * correct)//total) )

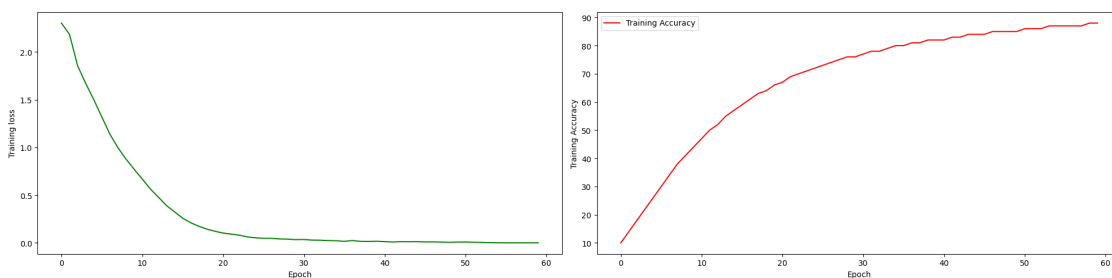
```

```

[Epoch : 1 , Average Training loss: 2.301448
[Epoch : 2 , Average Training loss: 2.181915
[Epoch : 3 , Average Training loss: 1.854509
[Epoch : 4 , Average Training loss: 1.670209
[Epoch : 5 , Average Training loss: 1.500375
[Epoch : 6 , Average Training loss: 1.318303
[Epoch : 7 , Average Training loss: 1.137592
[Epoch : 8 , Average Training loss: 0.995211
[Epoch : 9 , Average Training loss: 0.876587
[Epoch : 10 , Average Training loss: 0.770136
[Epoch : 11 , Average Training loss: 0.669411
[Epoch : 12 , Average Training loss: 0.564914
[Epoch : 13 , Average Training loss: 0.478613
[Epoch : 14 , Average Training loss: 0.391190
[Epoch : 15 , Average Training loss: 0.324903
[Epoch : 16 , Average Training loss: 0.259039
[Epoch : 17 , Average Training loss: 0.211094
[Epoch : 18 , Average Training loss: 0.174194
[Epoch : 19 , Average Training loss: 0.144322
[Epoch : 20 , Average Training loss: 0.122001
[Epoch : 21 , Average Training loss: 0.103295
[Epoch : 22 , Average Training loss: 0.091960
[Epoch : 23 , Average Training loss: 0.081046
[Epoch : 24 , Average Training loss: 0.062890
[Epoch : 25 , Average Training loss: 0.053578
[Epoch : 26 , Average Training loss: 0.048001
[Epoch : 27 , Average Training loss: 0.047832
[Epoch : 28 , Average Training loss: 0.041291

```

[Epoch : 29 , Average Training loss: 0.039359  
[Epoch : 30 , Average Training loss: 0.034428  
[Epoch : 31 , Average Training loss: 0.035521  
[Epoch : 32 , Average Training loss: 0.029276  
[Epoch : 33 , Average Training loss: 0.028225  
[Epoch : 34 , Average Training loss: 0.024312  
[Epoch : 35 , Average Training loss: 0.022319  
[Epoch : 36 , Average Training loss: 0.016360  
[Epoch : 37 , Average Training loss: 0.024411  
[Epoch : 38 , Average Training loss: 0.016330  
[Epoch : 39 , Average Training loss: 0.015206  
[Epoch : 40 , Average Training loss: 0.017430  
[Epoch : 41 , Average Training loss: 0.013321  
[Epoch : 42 , Average Training loss: 0.009372  
[Epoch : 43 , Average Training loss: 0.013115  
[Epoch : 44 , Average Training loss: 0.012020  
[Epoch : 45 , Average Training loss: 0.013103  
[Epoch : 46 , Average Training loss: 0.010126  
[Epoch : 47 , Average Training loss: 0.010536  
[Epoch : 48 , Average Training loss: 0.008786  
[Epoch : 49 , Average Training loss: 0.006090  
[Epoch : 50 , Average Training loss: 0.008611  
[Epoch : 51 , Average Training loss: 0.009399  
[Epoch : 52 , Average Training loss: 0.006452  
[Epoch : 53 , Average Training loss: 0.004940  
[Epoch : 54 , Average Training loss: 0.002023  
[Epoch : 55 , Average Training loss: 0.001689  
[Epoch : 56 , Average Training loss: 0.000613  
[Epoch : 57 , Average Training loss: 0.000619  
[Epoch : 58 , Average Training loss: 0.000606  
[Epoch : 59 , Average Training loss: 0.000639  
[Epoch : 60 , Average Training loss: 0.000781



Training Finished with accuracy : 88



```

[171]: correct = 0
total = 0
count = 0
validation_error = []
prediction_accuracy = []
validation_running_loss = 0.0
cnn_model.eval()

# since we're not training, we don't need to calculate the gradients for our
    ↪ outputs
with torch.no_grad():
    for i, data in enumerate(testloader):
        count+=1
        images, labels = data

        images = images.to(device) # To perform on the available GPU if
    ↪ present else on cpu
        labels = labels.to(device)

        # calculate outputs by running images through the network
        outputs = cnn_model(images) # forward pass

        loss = criterion(outputs, labels)
        validation_running_loss += loss.item()

        predicted_probability, predicted = torch.max(outputs.data, 1) # each
    ↪ input image will have 10 probabilities for classification,
                                                                    # from
    ↪ that we need to pick the maximum probability class as our predicted class

        total += labels.size(0)
        # print((predicted == labels))
        correct += (predicted == labels).sum().item()
        # print(total , " , ", correct)
        if ((i+1) % 10) == 0:
            # print("inside loop")
            avg_validating_loss = validation_running_loss / 10;
            print(f'[Step : {i + 1:5d}] , Average Validation loss:
    ↪ {avg_validating_loss}') # running_loss / 2000:.3f
            validation_error.append(avg_validating_loss)
            validation_running_loss = 0.0

# Plot the stats recorded in the above steps
plt.figure(figsize=(12, 5))
plt.plot(validation_error, label='Validation Loss', color = 'g')
plt.xlabel(f'Mini batch step(Batch_size = {batch_size})')
plt.ylabel('Validation loss')

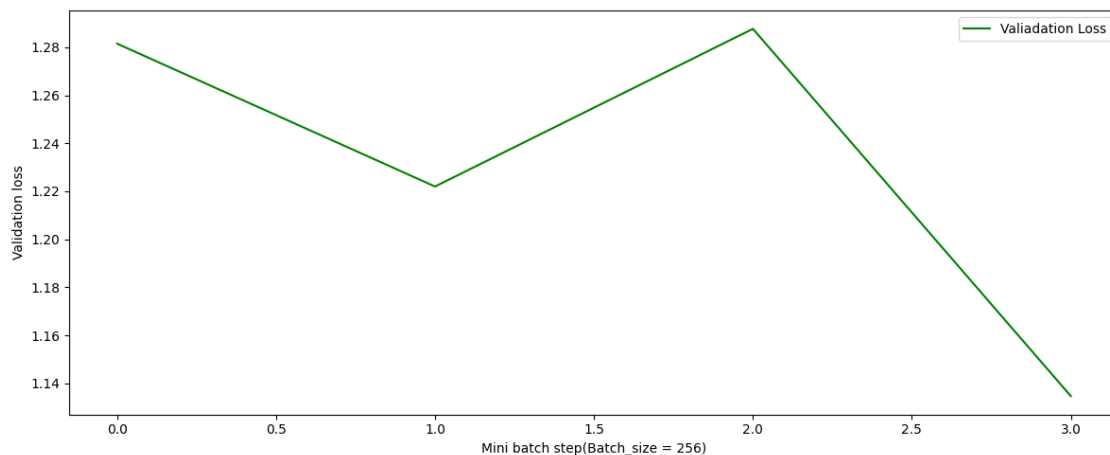
```

```
plt.legend()

plt.tight_layout()
plt.show()

print(f'\n Accuracy of the network on the 10000 test images: {100 * correct // total} %')
```

```
[Step :    10] , Average Validation loss: 1.281476366519928
[Step :    20] , Average Validation loss: 1.2219786763191223
[Step :    30] , Average Validation loss: 1.2876520037651062
[Step :    40] , Average Validation loss: 1.1347105026245117
```



Accuracy of the network on the 10000 test images: 79 %

```
[172]: #save the model for inference
PATH = './cifar10_vgg_net.pth'
torch.save(cnn_model.state_dict(), PATH)

[173]: # Compare the results of the Ground Truth vs Prediction
saved_model = VGG11_CIFR10().to(device)
# Load the CNN Model
saved_model.load_state_dict(torch.load(PATH))
```

[173]: <All keys matched successfully>

```
[180]: from itertools import count
#since data shuffling has been turned on earlier, now we will load the data
#using pickle to verify the images class wise
def unpickle(file):
```

```

import pickle
with open(file, 'rb') as fo:
    dict = pickle.load(fo, encoding='latin1')
return dict

file = r'./data/cifar-10-batches-py/test_batch'
meta_file = r'./data/cifar-10-batches-py/batches.meta'
meta_data = unpickle(meta_file)
ground_truth = unpickle(file)

# take the images data from batch data
images = ground_truth['data']
# reshape and transpose the images
# print("images type : ", type(images), "shape : ", images.shape)
images = images.reshape(len(images),3,32,32).transpose(0,2,3,1)
# take labels of the images
labels = ground_truth['labels']
# label names of the images
label_names = meta_data['label_names']

print(type(label_names),label_names)

rows, columns = 10, 5
# print(type(images), images.shape)
tmp_dict = dict()
# pick 5 images from each class from test_batch
for i, label in enumerate(labels):
    if len(tmp_dict.setdefault(label, [])) < 5:
        tmp_dict[label].append(i)

imageId = np.array(list(tmp_dict.values())).flatten()

# print('Generated Image ID : ', imageId, '\nShape : ', imageId.shape)

# take images for above random image ids
images = images[imageId]
# take labels for these images only
labels = [labels[i] for i in imageId]

images_torch = torch.from_numpy(images.astype(np.float32)).to(device)
images_torch = images_torch.permute(0, 3, 1, 2)

# print("images: ", type(images_torch), " , ", images_torch.shape)
trained_outputs = saved_model(images_torch)
print(type(trained_outputs), trained_outputs.shape)
predicted_probability, predicted = torch.max(trained_outputs, 1)

```

```

# define figure
fig=plt.figure(figsize=(20, 50))
# visualize these random images
for i, pred_val in enumerate(predicted):
    fig.add_subplot(rows, columns, i+1)
    plt.imshow(images[i])
    plt.xticks([])
    plt.yticks([])
    plt.title("{}"
              .format(f'Ground Truth : {label_names[labels[i]]}\nPredicted label :␣
↪{label_names[pred_val.item()]}'))

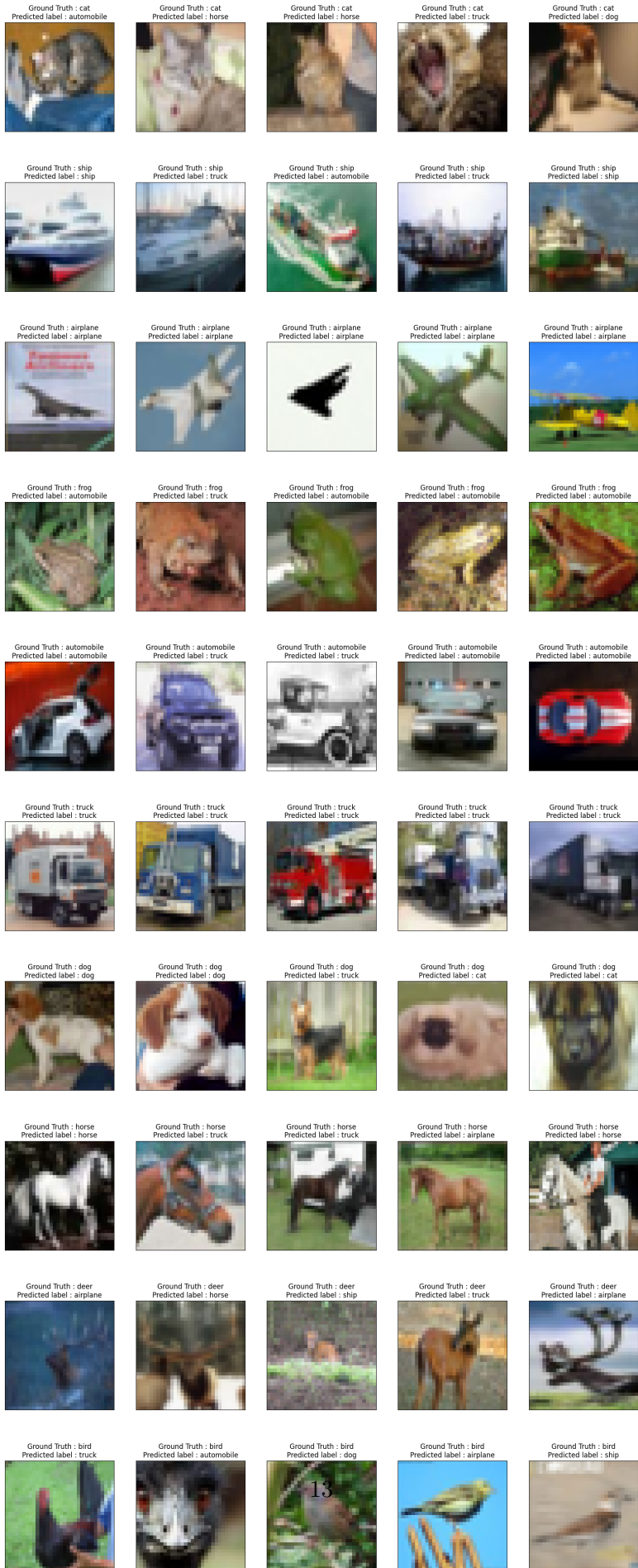
plt.show()
plt.subplots_adjust(hspace=0.5)

```

```

<class 'list'> ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog',
'horse', 'ship', 'truck']
<class 'torch.Tensor'> torch.Size([50, 10])

```



<Figure size 640x480 with 0 Axes>

```
[181]: random_img_path = '/kaggle/input/cnns-dataset/'
labels = ['automobile', 'cat', 'plane', 'deer', 'truck']
predicted_labels = []
images_list = os.listdir(random_img_path)
all_image_data = []

reloaded_model = VGG11_CIFR10().to(device)
reloaded_model.load_state_dict(torch.load('./cifar10_vgg_net.pth'))
reloaded_model.eval()

fig=plt.figure(figsize=(10, 8))

# add images to a np-array
for image in images_list:
    img = plt.imread(random_img_path+image)
    all_image_data.append(img)

concat_images = np.stack(all_image_data, axis = 0)
concat_images = concat_images.transpose(0, 3, 1,2)

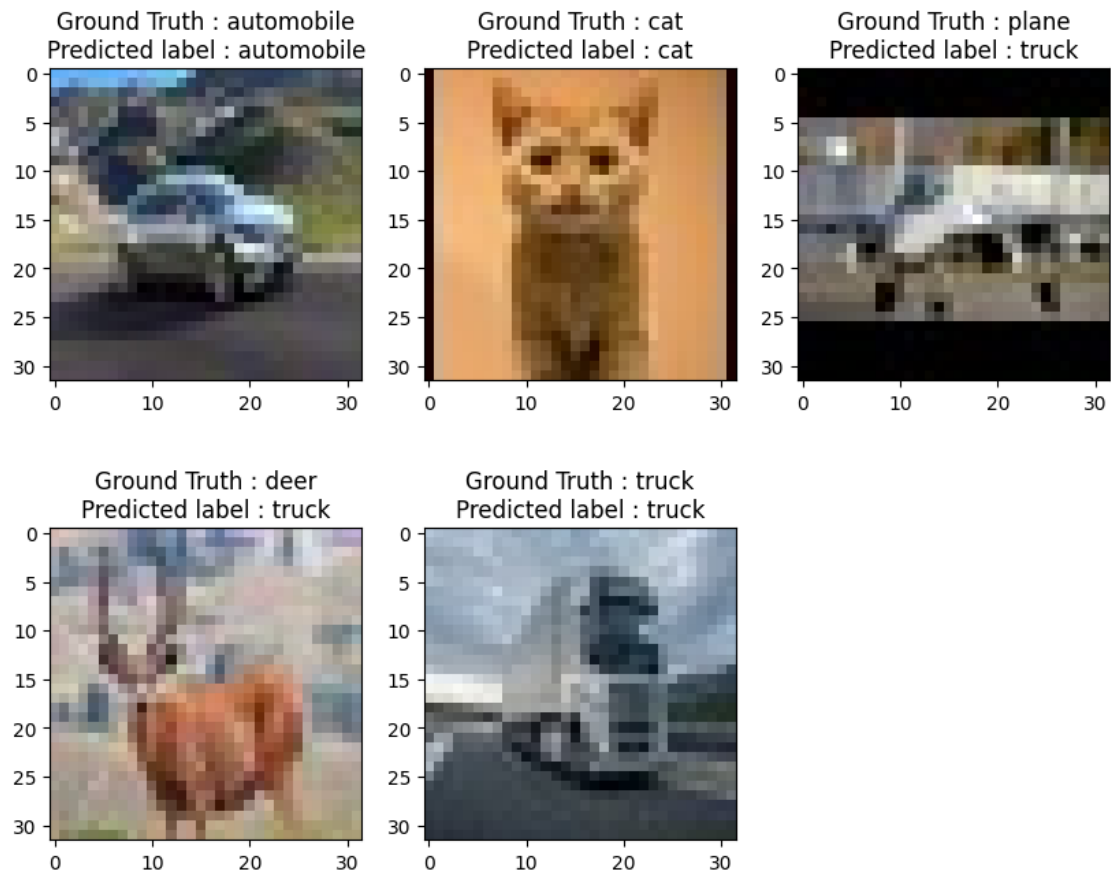
images_torch = torch.from_numpy(concat_images.astype(np.float32)).to(device)
trained_outputs = saved_model(images_torch)
predicted_probability, predicted = torch.max(trained_outputs, 1)
# print(type(predicted),predicted.shape)

for i, image in enumerate(images_list):
    # print(image)
    fig.add_subplot(2,3,i+1)
    img = plt.imread(random_img_path+image)
    plt.imshow(img)

    #perform classification
    img_torch = torch.from_numpy(img.astype(np.float32)).to(device)
    # print(type(img_torch), img_torch.shape)
    img_torch = img_torch.permute(2,0,1)
    # print(type(img_torch), img_torch.shape)
    outs = reloaded_model(images_torch)
    # print(type(outs), outs.shape)
    new_predicted_probability, new_predicted = torch.max(outs, 1)
    # print(type(new_predicted), new_predicted.shape, new_predicted)
    plt.title("{}"
```

```
.format(f'Ground Truth : {labels[i]}\nPredicted label : {label_names[predicted[i]]}'))
```

```
plt.show()
plt.subplots_adjust(hspace=0.5)
```



<Figure size 640x480 with 0 Axes>

[ ]: