

DLMiniProjectNotebook

March 30, 2024

```
[1]: # Importing necessary libraries

import torch
import torch.nn as nn
import torch.optim as optim
import torchvision
import torchvision.transforms as transforms
from torch.utils.data import DataLoader
from torchvision.datasets import CIFAR10
from torchsummary import summary
import numpy as np
import matplotlib.pyplot as plt
```

1 Device Information

```
[2]: # Setting up the device

# device = "mps" if torch.backends.mps.is_available() else "cpu" # Metal
↳ Performance Shaders Apple's M1/M2/M3 Chips
device = torch.device("cuda" if torch.cuda.is_available() else "cpu") # If CUDA
↳ supported GPU available
# device = "cpu" # CPU of the device

print(f"Using device: {device}")
```

Using device: cuda

2 Data Augmentation Transformations

```
[3]: # Define data augmentation transformations
transform_train = transforms.Compose([
    transforms.RandomCrop(32, padding=4),
    transforms.RandomHorizontalFlip(),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.
↳ 1),
    transforms.RandomRotation(degrees=15),
    transforms.RandomAffine(degrees=0, translate=(0.1, 0.1)),
```

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        transforms.ToTensor(),
        transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
    ])

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

```

3 CIFAR-10 Dataset

```

[4]: # Load CIFAR-10 dataset
trainset = CIFAR10(root='./data', train=True, download=True,
    ↳transform=transform_train)
trainloader = DataLoader(trainset, batch_size=128, shuffle=True, num_workers=2)

testset = CIFAR10(root='./data', train=False, download=True,
    ↳transform=transform_test)
testloader = DataLoader(testset, batch_size=100, shuffle=False, num_workers=2)

```

Downloading <https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz> to
./data/cifar-10-python.tar.gz

100%| | 170498071/170498071 [00:01<00:00, 93403037.40it/s]

Extracting ./data/cifar-10-python.tar.gz to ./data
Files already downloaded and verified

4 Model Architecture

Residual Block, Modified ResNet Architecture

```

[5]: # Define residual block
class BasicBlock(nn.Module):
    expansion = 1

    def __init__(self, in_planes, planes, stride=1):
        super(BasicBlock, self).__init__()
        self.conv1 = nn.Conv2d(in_planes, planes, kernel_size=3, stride=stride,
    ↳padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(planes)
        self.conv2 = nn.Conv2d(planes, planes, kernel_size=3, stride=1,
    ↳padding=1, bias=False)
        self.bn2 = nn.BatchNorm2d(planes)

        self.shortcut = nn.Sequential()
        if stride != 1 or in_planes != self.expansion*planes:

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        self.shortcut = nn.Sequential(
            nn.Conv2d(in_planes, self.expansion*planes, kernel_size=1,
↳ stride=stride, bias=False),
            nn.BatchNorm2d(self.expansion*planes)
        )

    def forward(self, x):
        out = self.conv1(x)
        out = self.bn1(out)
        out = torch.relu(out)
        out = self.conv2(out)
        out = self.bn2(out)
        out += self.shortcut(x)
        out = torch.relu(out)
        return out

```

```

[6]: # Modified ResNet model
class ModifiedResNet(nn.Module):
    def __init__(self, block, num_blocks, num_classes=10):
        super(ModifiedResNet, self).__init__()
        self.in_planes = 32 # Reduced number of initial channels

        self.conv1 = nn.Conv2d(3, 32, kernel_size=3, stride=1, padding=1,
↳ bias=False) # Reduced initial channels
        self.bn1 = nn.BatchNorm2d(32)
        self.layer1 = self._make_layer(block, 32, num_blocks[0], stride=1)
        self.layer2 = self._make_layer(block, 64, num_blocks[1], stride=2) #
↳ Reduced channels
        self.layer3 = self._make_layer(block, 128, num_blocks[2], stride=2) #
↳ Reduced channels
        self.layer4 = self._make_layer(block, 256, num_blocks[3], stride=2) #
↳ Reduced channels
        self.linear = nn.Linear(256*block.expansion, num_classes)

    def _make_layer(self, block, planes, num_blocks, stride):
        strides = [stride] + [1]*(num_blocks-1)
        layers = []
        for stride in strides:
            layers.append(block(self.in_planes, planes, stride))
            self.in_planes = planes * block.expansion
        return nn.Sequential(*layers)

    def forward(self, x):
        out = self.conv1(x)
        out = self.bn1(out)
        out = torch.relu(out)
        out = self.layer1(out)

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        out = self.layer2(out)
        out = self.layer3(out)
        out = self.layer4(out)
        out = nn.functional.avg_pool2d(out, 4)
        out = out.view(out.size(0), -1)
        out = self.linear(out)
        return out

```

```

[7]: # Define ResNet
def ResNet():
    return ModifiedResNet(BasicBlock, [2,2,2,2])

```

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[8]: # Function to count the number of trainable parameters in the model
def count_parameters(model):
    return sum(p.numel() for p in model.parameters() if p.requires_grad)

```

```

[9]: # Define training function with evaluation and plotting
def train_model(model, criterion, optimizer, scheduler, num_epochs=10):
    train_losses = []
    test_losses = []
    train_accs = []
    test_accs = []

    model.to(device) # Move model to the same device as data

    for epoch in range(num_epochs):
        model.train()
        running_loss = 0.0
        correct = 0
        total = 0
        for i, data in enumerate(trainloader, 0):
            inputs, labels = data[0].to(device), data[1].to(device)
            optimizer.zero_grad()

            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            running_loss += loss.item()
            _, predicted = outputs.max(1)
            total += labels.size(0)
            correct += predicted.eq(labels).sum().item()

        train_loss = running_loss / len(trainloader)
        train_acc = correct / total
        train_losses.append(train_loss)

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train_accs.append(train_acc)

model.eval()
correct = 0
total = 0
test_loss = 0.0
with torch.no_grad():
    for data in testloader:
        inputs, labels = data[0].to(device), data[1].to(device)
        outputs = model(inputs)
        loss = criterion(outputs, labels)
        test_loss += loss.item()
        _, predicted = outputs.max(1)
        total += labels.size(0)
        correct += predicted.eq(labels).sum().item()

test_loss /= len(testloader)
test_acc = correct / total
test_losses.append(test_loss)
test_accs.append(test_acc)

print(f'Epoch [{epoch+1}/{num_epochs}], Train Loss: {train_loss:.4f},  

↪Train Acc: {train_acc:.4f}, Test Loss: {test_loss:.4f}, Test Acc: {test_acc:.  

↪4f}')

scheduler.step(test_loss) # Update learning rate scheduler based on  

↪test loss

# Plotting loss curves
plt.figure(figsize=(10, 5))
plt.plot(train_losses, label='Train Loss')
plt.plot(test_losses, label='Test Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training and Testing Loss Curves')
plt.legend()
plt.show()

# Plotting accuracy curves
plt.figure(figsize=(10, 5))
plt.plot(train_accs, label='Train Accuracy')
plt.plot(test_accs, label='Test Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Training and Testing Accuracy Curves')
plt.legend()
plt.show()

```

```

# Final evaluation
print('Final Test Accuracy: {:.4f}'.format(test_acc))

```

```

[10]: # Instantiate ResNet model
model = ResNet()
model.to(device) # Move model to the same device as data

```

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[10]: ModifiedResNet(
  (conv1): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
    bias=False)
  (bn1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
    track_running_stats=True)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
        bias=False)
      (bn1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
        track_running_stats=True)
      (conv2): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
        bias=False)
      (bn2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
        track_running_stats=True)
      (shortcut): Sequential()
    )
    (1): BasicBlock(
      (conv1): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
        bias=False)
      (bn1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
        track_running_stats=True)
      (conv2): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
        bias=False)
      (bn2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
        track_running_stats=True)
      (shortcut): Sequential()
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1),
        bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
        track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
        bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
        track_running_stats=True)
      (shortcut): Sequential(

```

```

        (0): Conv2d(32, 64, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
)
(1): BasicBlock(
    (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
bias=False)
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
bias=False)
    (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (shortcut): Sequential()
)
)
(layer3): Sequential(
    (0): BasicBlock(
        (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (shortcut): Sequential(
            (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
            (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        )
    )
    (1): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (shortcut): Sequential()
    )
)
(layer4): Sequential(
    (0): BasicBlock(

```

```

        (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (shortcut): Sequential(
          (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        )
      )
    (1): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (shortcut): Sequential()
    )
  )
  (linear): Linear(in_features=256, out_features=10, bias=True)
)

```

5 Model Summary

Total trainable parameters: 2,797,610

```
[11]: # Print model summary
print(summary(model, (3, 32, 32)))
```

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 32, 32, 32]	864
BatchNorm2d-2	[-1, 32, 32, 32]	64
Conv2d-3	[-1, 32, 32, 32]	9,216
BatchNorm2d-4	[-1, 32, 32, 32]	64
Conv2d-5	[-1, 32, 32, 32]	9,216
BatchNorm2d-6	[-1, 32, 32, 32]	64
BasicBlock-7	[-1, 32, 32, 32]	0
Conv2d-8	[-1, 32, 32, 32]	9,216

BatchNorm2d-9	[-1, 32, 32, 32]	64
Conv2d-10	[-1, 32, 32, 32]	9,216
BatchNorm2d-11	[-1, 32, 32, 32]	64
BasicBlock-12	[-1, 32, 32, 32]	0
Conv2d-13	[-1, 64, 16, 16]	18,432
BatchNorm2d-14	[-1, 64, 16, 16]	128
Conv2d-15	[-1, 64, 16, 16]	36,864
BatchNorm2d-16	[-1, 64, 16, 16]	128
Conv2d-17	[-1, 64, 16, 16]	2,048
BatchNorm2d-18	[-1, 64, 16, 16]	128
BasicBlock-19	[-1, 64, 16, 16]	0
Conv2d-20	[-1, 64, 16, 16]	36,864
BatchNorm2d-21	[-1, 64, 16, 16]	128
Conv2d-22	[-1, 64, 16, 16]	36,864
BatchNorm2d-23	[-1, 64, 16, 16]	128
BasicBlock-24	[-1, 64, 16, 16]	0
Conv2d-25	[-1, 128, 8, 8]	73,728
BatchNorm2d-26	[-1, 128, 8, 8]	256
Conv2d-27	[-1, 128, 8, 8]	147,456
BatchNorm2d-28	[-1, 128, 8, 8]	256
Conv2d-29	[-1, 128, 8, 8]	8,192
BatchNorm2d-30	[-1, 128, 8, 8]	256
BasicBlock-31	[-1, 128, 8, 8]	0
Conv2d-32	[-1, 128, 8, 8]	147,456
BatchNorm2d-33	[-1, 128, 8, 8]	256
Conv2d-34	[-1, 128, 8, 8]	147,456
BatchNorm2d-35	[-1, 128, 8, 8]	256
BasicBlock-36	[-1, 128, 8, 8]	0
Conv2d-37	[-1, 256, 4, 4]	294,912
BatchNorm2d-38	[-1, 256, 4, 4]	512
Conv2d-39	[-1, 256, 4, 4]	589,824
BatchNorm2d-40	[-1, 256, 4, 4]	512
Conv2d-41	[-1, 256, 4, 4]	32,768
BatchNorm2d-42	[-1, 256, 4, 4]	512
BasicBlock-43	[-1, 256, 4, 4]	0
Conv2d-44	[-1, 256, 4, 4]	589,824
BatchNorm2d-45	[-1, 256, 4, 4]	512
Conv2d-46	[-1, 256, 4, 4]	589,824
BatchNorm2d-47	[-1, 256, 4, 4]	512
BasicBlock-48	[-1, 256, 4, 4]	0
Linear-49	[-1, 10]	2,570

=====

Total params: 2,797,610

Trainable params: 2,797,610

Non-trainable params: 0

Input size (MB): 0.01

Forward/backward pass size (MB): 5.63

Params size (MB): 10.67
Estimated Total Size (MB): 16.31

None

6 Training, Testing, Loss & Accuracy Curves, and Saving the Model

Loss Fuction: Cross Entropy Loss Optimizer: Adam, lr = 0.001, weight decay = 1e-4 Scheduler: ReduceLROnPlateau

The training loop is executed for 40 epochs, displaying the training and testing loss and accuracy at each epoch. Both training and testing accuracies steadily increase over the epochs, indicating effective training. The loss and accuracy curves are plotted, showing the training and testing loss decreasing while the accuracy increases, which is a positive sign of model learning.

Model saved as “modified_resnet_cifar10_model_40_epochs.pth”

```
[12]: # Define loss function, optimizer, and learning rate scheduler
criterion = nn.CrossEntropyLoss()
# optimizer = optim.SGD(model.parameters(), lr=0.1, momentum=0.9,
    ↪weight_decay=5e-4)
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-4)
# scheduler = optim.lr_scheduler.MultiStepLR(optimizer, milestones=[150, 250],
    ↪gamma=0.1)
scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='min',
    ↪factor=0.1, patience=5, verbose=True)
```

```
/usr/local/lib/python3.10/dist-packages/torch/optim/lr_scheduler.py:28:
UserWarning: The verbose parameter is deprecated. Please use get_last_lr() to
access the learning rate.
  warnings.warn("The verbose parameter is deprecated. Please use get_last_lr() "
```

```
[13]: # Training the model
train_model(model, criterion, optimizer, scheduler, num_epochs=40)

# Save the trained model
torch.save(model.state_dict(), 'modified_resnet_cifar10_model_40_epochs.pth')
print('Model saved successfully!')

def evaluate_model(model, dataloader):
    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for data in dataloader:
            inputs, labels = data[0].to(device), data[1].to(device)
            outputs = model(inputs)
```

```

        _, predicted = torch.max(outputs, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
    accuracy = correct / total
    print(f'Accuracy on the dataset: {100 * accuracy:.2f}%',)

# Evaluate the model on the test dataset
evaluate_model(model, testloader)

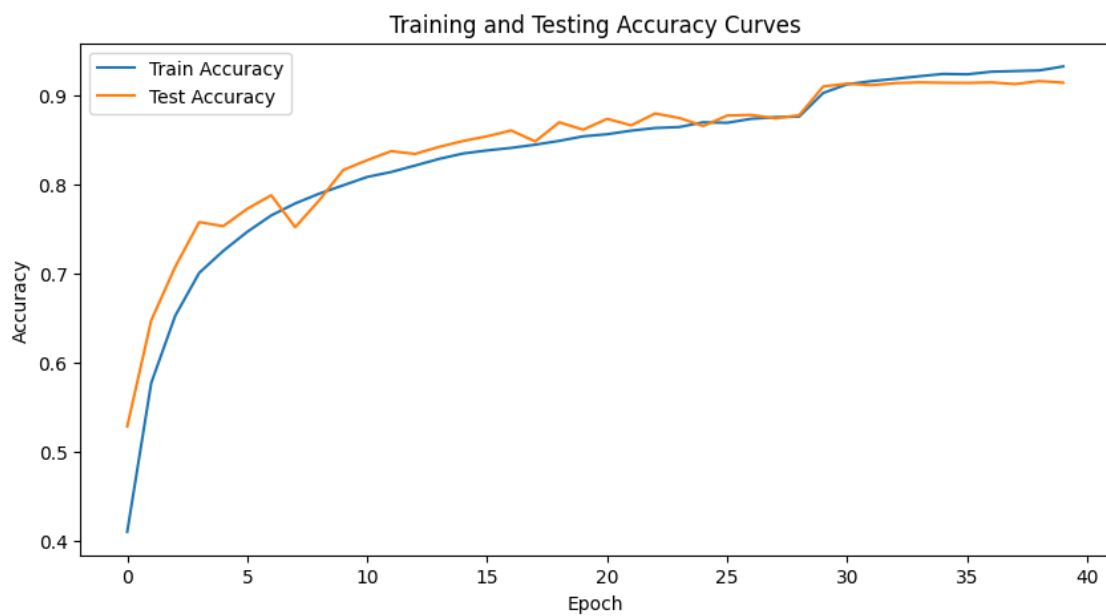
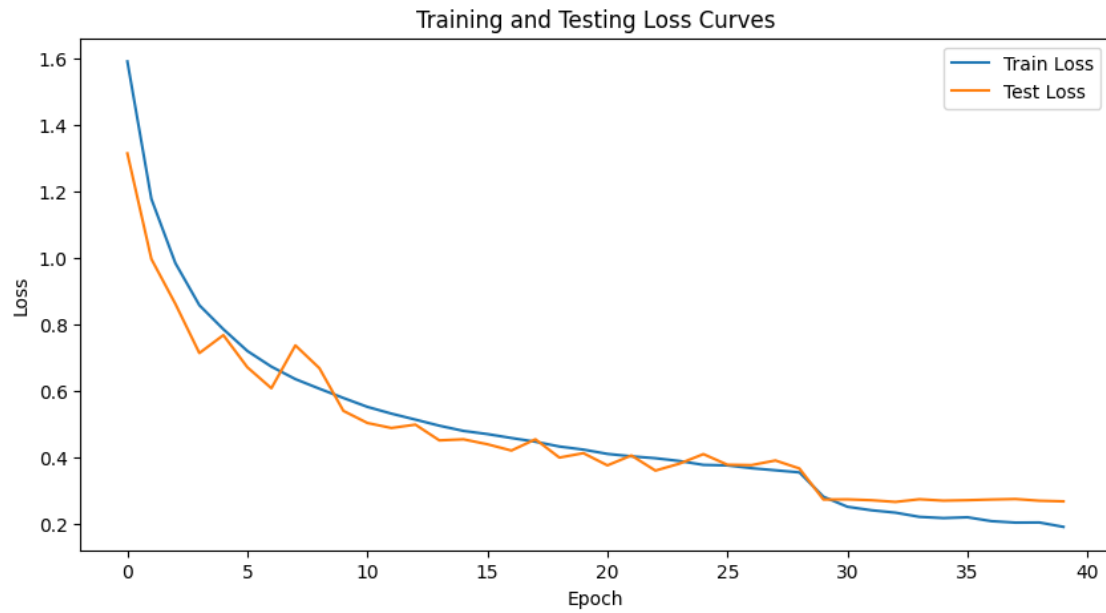
```

```

Epoch [1/40], Train Loss: 1.5893, Train Acc: 0.4095, Test Loss: 1.3130, Test
Acc: 0.5280
Epoch [2/40], Train Loss: 1.1762, Train Acc: 0.5769, Test Loss: 0.9956, Test
Acc: 0.6473
Epoch [3/40], Train Loss: 0.9832, Train Acc: 0.6525, Test Loss: 0.8607, Test
Acc: 0.7076
Epoch [4/40], Train Loss: 0.8567, Train Acc: 0.7008, Test Loss: 0.7129, Test
Acc: 0.7579
Epoch [5/40], Train Loss: 0.7845, Train Acc: 0.7255, Test Loss: 0.7668, Test
Acc: 0.7534
Epoch [6/40], Train Loss: 0.7191, Train Acc: 0.7470, Test Loss: 0.6701, Test
Acc: 0.7728
Epoch [7/40], Train Loss: 0.6721, Train Acc: 0.7654, Test Loss: 0.6071, Test
Acc: 0.7881
Epoch [8/40], Train Loss: 0.6346, Train Acc: 0.7789, Test Loss: 0.7360, Test
Acc: 0.7523
Epoch [9/40], Train Loss: 0.6058, Train Acc: 0.7899, Test Loss: 0.6675, Test
Acc: 0.7824
Epoch [10/40], Train Loss: 0.5779, Train Acc: 0.7993, Test Loss: 0.5392, Test
Acc: 0.8165
Epoch [11/40], Train Loss: 0.5511, Train Acc: 0.8087, Test Loss: 0.5028, Test
Acc: 0.8276
Epoch [12/40], Train Loss: 0.5309, Train Acc: 0.8143, Test Loss: 0.4877, Test
Acc: 0.8377
Epoch [13/40], Train Loss: 0.5129, Train Acc: 0.8216, Test Loss: 0.4978, Test
Acc: 0.8347
Epoch [14/40], Train Loss: 0.4946, Train Acc: 0.8291, Test Loss: 0.4505, Test
Acc: 0.8426
Epoch [15/40], Train Loss: 0.4789, Train Acc: 0.8351, Test Loss: 0.4537, Test
Acc: 0.8492
Epoch [16/40], Train Loss: 0.4694, Train Acc: 0.8386, Test Loss: 0.4388, Test
Acc: 0.8545
Epoch [17/40], Train Loss: 0.4576, Train Acc: 0.8414, Test Loss: 0.4199, Test
Acc: 0.8610
Epoch [18/40], Train Loss: 0.4464, Train Acc: 0.8451, Test Loss: 0.4537, Test
Acc: 0.8487
Epoch [19/40], Train Loss: 0.4320, Train Acc: 0.8493, Test Loss: 0.3988, Test
Acc: 0.8702
Epoch [20/40], Train Loss: 0.4227, Train Acc: 0.8544, Test Loss: 0.4120, Test

```

Acc: 0.8619
Epoch [21/40], Train Loss: 0.4098, Train Acc: 0.8568, Test Loss: 0.3753, Test Acc: 0.8741
Epoch [22/40], Train Loss: 0.4025, Train Acc: 0.8608, Test Loss: 0.4051, Test Acc: 0.8668
Epoch [23/40], Train Loss: 0.3968, Train Acc: 0.8638, Test Loss: 0.3596, Test Acc: 0.8801
Epoch [24/40], Train Loss: 0.3885, Train Acc: 0.8649, Test Loss: 0.3805, Test Acc: 0.8751
Epoch [25/40], Train Loss: 0.3769, Train Acc: 0.8702, Test Loss: 0.4092, Test Acc: 0.8661
Epoch [26/40], Train Loss: 0.3752, Train Acc: 0.8697, Test Loss: 0.3773, Test Acc: 0.8778
Epoch [27/40], Train Loss: 0.3669, Train Acc: 0.8742, Test Loss: 0.3761, Test Acc: 0.8785
Epoch [28/40], Train Loss: 0.3606, Train Acc: 0.8759, Test Loss: 0.3900, Test Acc: 0.8746
Epoch [29/40], Train Loss: 0.3542, Train Acc: 0.8767, Test Loss: 0.3660, Test Acc: 0.8782
Epoch [30/40], Train Loss: 0.2812, Train Acc: 0.9032, Test Loss: 0.2726, Test Acc: 0.9105
Epoch [31/40], Train Loss: 0.2509, Train Acc: 0.9130, Test Loss: 0.2732, Test Acc: 0.9137
Epoch [32/40], Train Loss: 0.2404, Train Acc: 0.9165, Test Loss: 0.2706, Test Acc: 0.9120
Epoch [33/40], Train Loss: 0.2333, Train Acc: 0.9192, Test Loss: 0.2655, Test Acc: 0.9143
Epoch [34/40], Train Loss: 0.2206, Train Acc: 0.9220, Test Loss: 0.2735, Test Acc: 0.9151
Epoch [35/40], Train Loss: 0.2169, Train Acc: 0.9246, Test Loss: 0.2693, Test Acc: 0.9147
Epoch [36/40], Train Loss: 0.2194, Train Acc: 0.9242, Test Loss: 0.2707, Test Acc: 0.9145
Epoch [37/40], Train Loss: 0.2077, Train Acc: 0.9271, Test Loss: 0.2727, Test Acc: 0.9151
Epoch [38/40], Train Loss: 0.2034, Train Acc: 0.9279, Test Loss: 0.2742, Test Acc: 0.9132
Epoch [39/40], Train Loss: 0.2037, Train Acc: 0.9286, Test Loss: 0.2691, Test Acc: 0.9166
Epoch [40/40], Train Loss: 0.1905, Train Acc: 0.9330, Test Loss: 0.2672, Test Acc: 0.9148



Final Test Accuracy: 0.9148
Model saved successfully!
Accuracy on the dataset: 91.48%

7 Performance of the Model

The model achieves a final test accuracy of 91.48%, demonstrating its effectiveness in classifying the CIFAR-10 dataset.

```
[14]: # Instantiate and load the model
      '''
      model = ResNet()
      model.to(device) # Move model to the same device as data
      model.load_state_dict(torch.load('modified_resnet_cifar10_model_40_epochs.pth'))

      criterion = nn.CrossEntropyLoss()
      optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-4)
      scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='min',
        ↪ factor=0.1, patience=5, verbose=True)

      # Training the model for additional 5 epochs
      train_model(model, criterion, optimizer, scheduler, num_epochs=5)
      '''
```

```
[14]: "\nmodel = ResNet18()\nmodel.to(device) # Move model to the same device as data\n\nmodel.load_state_dict(torch.load('modified_resnet_cifar10_model_40_epochs.pth'))\n\ncriterion = nn.CrossEntropyLoss()\noptimizer =\noptim.Adam(model.parameters(), lr=0.001, weight_decay=1e-4)\nscheduler =\noptim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='min', factor=0.1,\npatience=5, verbose=True)\n\n# Training the model for additional 5\nepochs\ntrain_model(model, criterion, optimizer, scheduler, num_epochs=5)\n"
```