ID: 862334529

```
HW-3
```

In []: import numpy as np

np.random.seed(123)

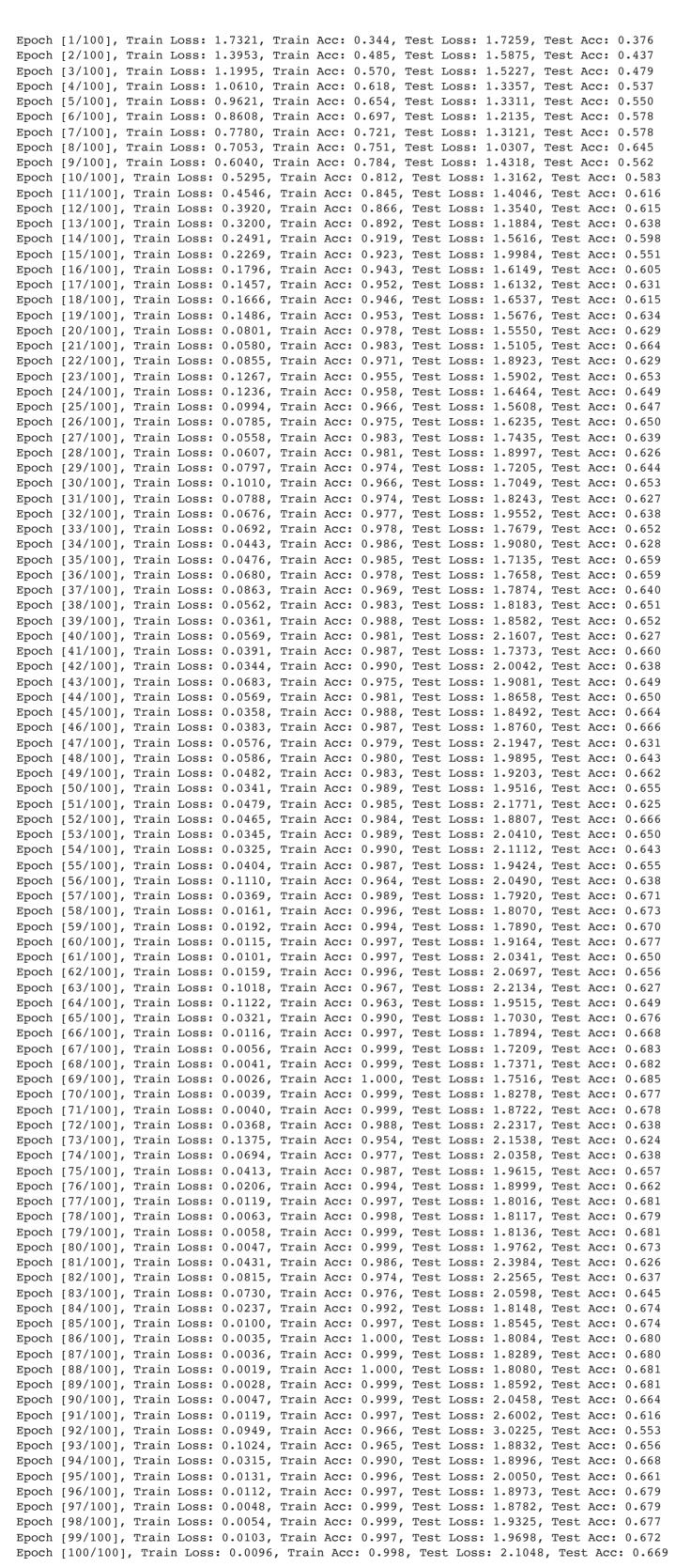
```
import pickle
        import matplotlib.pyplot as plt
        import torch
        import torchvision.models as models
        import torch.nn as nn
        import torch.optim as optim
        from torch.utils.data import DataLoader, TensorDataset, Dataset
        torch.manual_seed(42)
        from torchsummary import summary
In [ ]: def unpickle(file):
            with open(file, 'rb') as fo:
                dict = pickle.load(fo, encoding='bytes')
            return dict
        def preprocess_data(data):
            data = data.astype('float32') / 255.0
            data = data.reshape((-1, 3, 32, 32)) # pytorch dimension = (B, C, H, W)
            mean = np.mean(data, axis=(0, 1, 2))
            std = np.std(data, axis=(0, 1, 2))
            data = (data - mean) / std
            return data
In [ ]: def run_model(model, train_loader, test_loader, ITR=100, data_aug = 'None', alpha=0.2):
            criterion = nn.CrossEntropyLoss()
            optimizer = optim.Adam(model.parameters(), lr=0.001)
            num_epochs = ITR
            train_loss_values = []
            train_acc_values = []
            test loss values = []
            test_acc_values = []
            for epoch in range(num_epochs):
                model.train()
                train loss = 0
                correct = 0
                total = 0
                for images, labels in train_loader:
                    if data_aug == 'cutout':
                        images = apply_cutout_minibatch(images.detach().clone(), 16)
                    if data_aug == 'mixup':
                        images, labels = apply mixup_minibatch(images.detach().clone(), labels.detach().clone(), alpha)
                    if data_aug == 'standard':
                        images = apply_standard_minibatch(images.detach().clone(), 4)
                    if data aug == 'all':
                        images = apply_standard_minibatch(images.detach().clone(), 4)
                        images = apply_cutout_minibatch(images.detach().clone(), 16)
                        images, labels = apply_mixup_minibatch(images.detach().clone(), labels.detach().clone(), 0.2)
                    optimizer.zero_grad()
                    outputs = model(images)
                    loss = criterion(outputs, labels)
                    loss.backward()
                    optimizer.step()
                    train_loss += loss.item()
                    _, predicted = torch.max(outputs.data, 1)
                    total += labels.size(0)
                    correct += (predicted == labels).sum().item()
                train loss /= len(train loader)
                train_accuracy = correct / total
                train_loss_values.append(train_loss)
                train_acc_values.append(train_accuracy)
                model.eval()
                test loss = 0
                correct = 0
                total = 0
                with torch.no_grad():
                    for images, labels in test_loader:
                        outputs = model(images)
                        loss = criterion(outputs, labels)
                        test_loss += loss.item()
                        _, predicted = torch.max(outputs.data, 1)
                        total += labels.size(0)
                        correct += (predicted == labels).sum().item()
                test_loss /= len(test_loader)
                test_accuracy = correct / total
                test_loss_values.append(test_loss)
                test_acc_values.append(test_accuracy)
                print(f"Epoch [{epoch+1}/{num_epochs}], Train Loss: {train_loss:.4f}, Train Acc: {train_accuracy:.3f}, Test Loss: {test_loss:.4f}, Test Acc: {test_accuracy:.3f}")
            history = {}
            history['train_acc'] = train_acc_values
            history['train_loss'] = train_loss_values
            history['test acc'] = test acc values
            history['test_loss'] = test_loss_values
            return history
In [ ]: def plot_history(history, figsize=(12,5), title = 'Training History'):
            num_epochs = len(history['train_loss'])
            plt.figure(figsize=figsize)
            a = plt.subplot(1, 2, 1)
            a.plot(range(1, num epochs+1), history['train loss'], label='Train Loss')
            a.plot(range(1, num_epochs+1), history['test_loss'], label='Test Loss')
            a.set_xlabel('Epoch')
            a.set ylabel('Loss')
            a.set_title('Training and Test Loss')
            a.legend()
            b = plt.subplot(1, 2, 2)
            b.plot(range(1, num_epochs+1), history['train_acc'], label='Train Acc')
            b.plot(range(1, num_epochs+1), history['test_acc'], label='Test Acc')
            b.set_xlabel('Epoch')
            b.set_ylabel('Accuracy')
            b.set title('Training and Test Accuracy')
            b.legend()
            plt.tight_layout()
            plt.show()
            print(f"Final Test Accuracy is {history['test_acc'][-1]}")
```

```
In [ ]: #model = torch.hub.load('pytorch/vision:v0.10.0', 'resnet18', pretrained=False)
        from resnet20 import ResNet, BasicBlock
        model = ResNet(BasicBlock, [3, 3, 3], num_classes=10)
In []: summary(model, (3, 32, 32))
               Layer (type)
                                          Output Shape
        ______
                    Conv2d-1
                                      [-1, 16, 32, 32]
               BatchNorm2d-2
                                      [-1, 16, 32, 32]
                                                                    32
                                      [-1, 16, 32, 32]
                                                                 2,304
                    Conv2d-3
               {\tt BatchNorm2d-4}
                                      [-1, 16, 32, 32]
                                                                    32
                                                                 2,304
                    Conv2d-5
                                      [-1, 16, 32, 32]
               BatchNorm2d-6
                                      [-1, 16, 32, 32]
                                                                    32
               BasicBlock-7
                                      [-1, 16, 32, 32]
                                                                     0
                    Conv2d-8
                                      [-1, 16, 32, 32]
                                                                 2,304
                                      [-1, 16, 32, 32]
               BatchNorm2d-9
                                                                    32
                                      [-1, 16, 32, 32]
                   Conv2d-10
                                                                 2,304
              BatchNorm2d-11
                                      [-1, 16, 32, 32]
                                                                    32
               BasicBlock-12
                                      [-1, 16, 32, 32]
                   Conv2d-13
                                      [-1, 16, 32, 32]
                                                                 2,304
              BatchNorm2d-14
                                      [-1, 16, 32, 32]
                   Conv2d-15
                                      [-1, 16, 32, 32]
                                                                 2,304
              BatchNorm2d-16
                                      [-1, 16, 32, 32]
                                                                    32
               BasicBlock-17
                                      [-1, 16, 32, 32]
                                                                     0
                   Conv2d-18
                                      [-1, 32, 16, 16]
                                                                 4,608
              BatchNorm2d-19
                                      [-1, 32, 16, 16]
                                                                    64
                   Conv2d-20
                                      [-1, 32, 16, 16]
                                                                 9,216
              BatchNorm2d-21
                                      [-1, 32, 16, 16]
                                                                    64
                   Conv2d-22
                                                                   512
                                      [-1, 32, 16, 16]
              BatchNorm2d-23
                                      [-1, 32, 16, 16]
                                                                    64
              BasicBlock-24
                                      [-1, 32, 16, 16]
                                                                     0
                                      [-1, 32, 16, 16]
                   Conv2d-25
                                                                 9,216
              BatchNorm2d-26
                                      [-1, 32, 16, 16]
                                                                    64
                   Conv2d-27
                                      [-1, 32, 16, 16]
                                                                 9,216
              BatchNorm2d-28
                                      [-1, 32, 16, 16]
               BasicBlock-29
                                      [-1, 32, 16, 16]
                                      [-1, 32, 16, 16]
                   Conv2d-30
                                                                 9,216
              BatchNorm2d-31
                                      [-1, 32, 16, 16]
                                                                    64
                                      [-1, 32, 16, 16]
                   Conv2d-32
                                                                 9,216
              BatchNorm2d-33
                                      [-1, 32, 16, 16]
                                                                    64
               BasicBlock-34
                                      [-1, 32, 16, 16]
                                                                     0
                   Conv2d-35
                                                                18,432
                                        [-1, 64, 8, 8]
              BatchNorm2d-36
                                        [-1, 64, 8, 8]
                                                                   128
                                                                36,864
                   Conv2d-37
                                        [-1, 64, 8, 8]
              BatchNorm2d-38
                                                                   128
                                        [-1, 64, 8, 8]
                   Conv2d-39
                                                                 2,048
                                        [-1, 64, 8, 8]
              BatchNorm2d-40
                                        [-1, 64, 8, 8]
                                                                   128
               BasicBlock-41
                                        [-1, 64, 8, 8]
                                                                     0
                   Conv2d-42
                                        [-1, 64, 8, 8]
                                                                36,864
              BatchNorm2d-43
                                        [-1, 64, 8, 8]
                                                                   128
                   Conv2d-44
                                        [-1, 64, 8, 8]
                                                                36,864
              BatchNorm2d-45
                                                                   128
                                        [-1, 64, 8, 8]
               BasicBlock-46
                                        [-1, 64, 8, 8]
                                                                     0
                   Conv2d-47
                                        [-1, 64, 8, 8]
                                                                36,864
              BatchNorm2d-48
                                        [-1, 64, 8, 8]
                                                                   128
                   Conv2d-49
                                                                36,864
                                        [-1, 64, 8, 8]
                                        [-1, 64, 8, 8]
              BatchNorm2d-50
                                                                   128
               BasicBlock-51
                                                                     0
                                        [-1, 64, 8, 8]
                  Linear-52
                                                                   650
                                              [-1, 10]
        Total params: 272,474
        Trainable params: 272,474
        Non-trainable params: 0
        Input size (MB): 0.01
        Forward/backward pass size (MB): 3.72
        Params size (MB): 1.04
        Estimated Total Size (MB): 4.77
In [ ]: def get_data(n=1000):
            data_path = 'cifar-10-batches-py/'
            train_data = np.empty((50000, 3072), dtype=np.uint8)
            train_labels = np.empty((50000,), dtype=np.int64)
            for i in range(1, 6):
                train_batch = unpickle(data_path + 'data_batch_' + str(i))
                train data[(i - 1) * 10000: i * 10000, :] = train batch[b'data']
                train labels[(i - 1) * 10000: i * 10000] = train batch[b'labels']
            test_batch = unpickle(data_path + 'test_batch')
            test data = test batch[b'data']
            test_labels = np.array(test_batch[b'labels'])
            # Sample n examples uniformly at random for each class from the training set
            classes = np.unique(train_labels)
            sampled train data = []
            sampled_train_labels = []
            for class_label in classes:
                indices = np.where(train_labels == class_label)[0]
                np.random.shuffle(indices)
                sampled indices = indices[:n]
                sampled_train data.extend(train data[sampled indices])
                sampled_train_labels.extend(train_labels[sampled_indices])
            indices = np.array(range(len(sampled_train_data)))
            np.random.shuffle(indices)
            sampled train data = np.array(sampled train data)[indices]
            sampled_train_labels = np.array(sampled_train_labels)[indices]
            # normalize features (zero mean and unit variance)
            sampled_train_data = preprocess_data(sampled_train_data)
            test data = preprocess data(test data)
            return sampled_train_data, test_data, sampled_train_labels, test_labels
In []: sampled train data, test data, sampled train labels, test labels = get data()
        print("Sampled Train Data Shape:", sampled_train_data.shape)
        print("Sampled Train Labels Shape:", sampled_train_labels.shape)
        print("Test Data Shape:", test_data.shape)
        print("Test Labels Shape:", test_labels.shape)
        train_dataset = TensorDataset(torch.from_numpy(sampled_train_data), torch.from_numpy(sampled_train_labels))
        test_dataset = TensorDataset(torch.from_numpy(test_data), torch.from_numpy(test_labels))
        batch size = 64
        train loader = DataLoader(train dataset, batch size=batch size, shuffle=True)
        test loader = DataLoader(test dataset, batch size=batch size, shuffle=False)
        Sampled Train Data Shape: (10000, 3, 32, 32)
        Sampled Train Labels Shape: (10000,)
        Test Data Shape: (10000, 3, 32, 32)
        Test Labels Shape: (10000,)
In [ ]: plt.imshow(sampled train data[3].transpose( 1, 2, 0))
        Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```

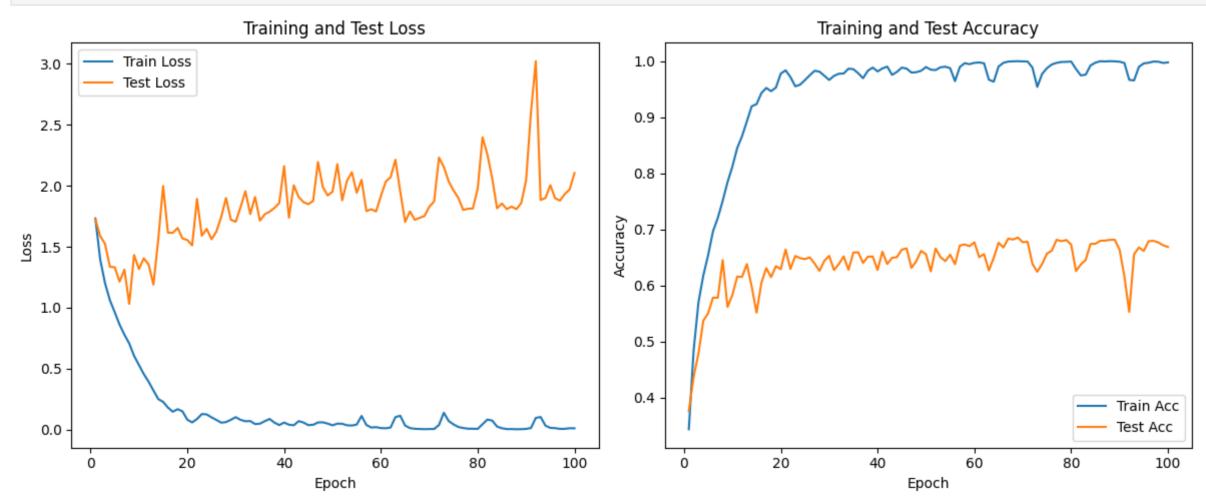
Tn []:

1. (3 pts) Train your Resnet model without augmentation and report the results.

In []: history1 = run_model(model, train_loader, test_loader)



In []: plot_history(history1)



2. (4 pts) Implement mixup and report the results for $\alpha = 0.2$ and $\alpha = 0.4$

```
In [ ]: def mixup(img1, img2, lb1, lb2, alpha_value):
            lam = np.random.beta(alpha_value, alpha_value)
            mixed_image = lam * img1 + (1 - lam) * img2
            mixed_label = lam * lb1 + (1 - lam) * lb2
            mixed_image = np.array(mixed_image)
            mixed_label = np.array(mixed_label)
            return mixed_image, mixed_label
In [ ]: def apply_mixup_minibatch(minibatch_images, minibatch_labels, mask_size):
            for i in range(minibatch_images.shape[0]):
                idx = np.random.randint(minibatch_images.shape[0])
                img1 = minibatch_images[i]
                img2 = minibatch_images[idx]
                lb1 = minibatch_labels[i]
                lb2 = minibatch_labels[idx]
                new_im, new_lb = mixup(img1, img2, lb1, lb2, mask_size)
                minibatch_images[i] = torch.from_numpy(new_im).float()
                minibatch_labels[i] = torch.from_numpy(new_lb).float()
            return minibatch_images, minibatch_labels
In [ ]: sampled_train_data, test_data, sampled_train_labels, test_labels = get_data()
In [ ]: i=3
        plt.figure(figsize=(12,5))
        plt.subplot(121)
        plt.imshow(sampled_train_data[i].transpose( 1, 2, 0))
        plt.subplot(122)
        im, lb = mixup(sampled_train_data[i].copy(), sampled_train_data[i*2].copy(), sampled_train_labels[i].copy(), sampled_train_labels[i*2].copy(), 0.2)
        plt.imshow(im.transpose( 1, 2, 0))
        plt.show()
        Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
        Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
          5
        10
                                                                         10
        15
                                                                         15
        20
                                                                         20
                                                                         25
        25
```

15

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In []: history2 = run_model(model, train_loader, test_loader, data_aug='mixup', alpha=0.2)

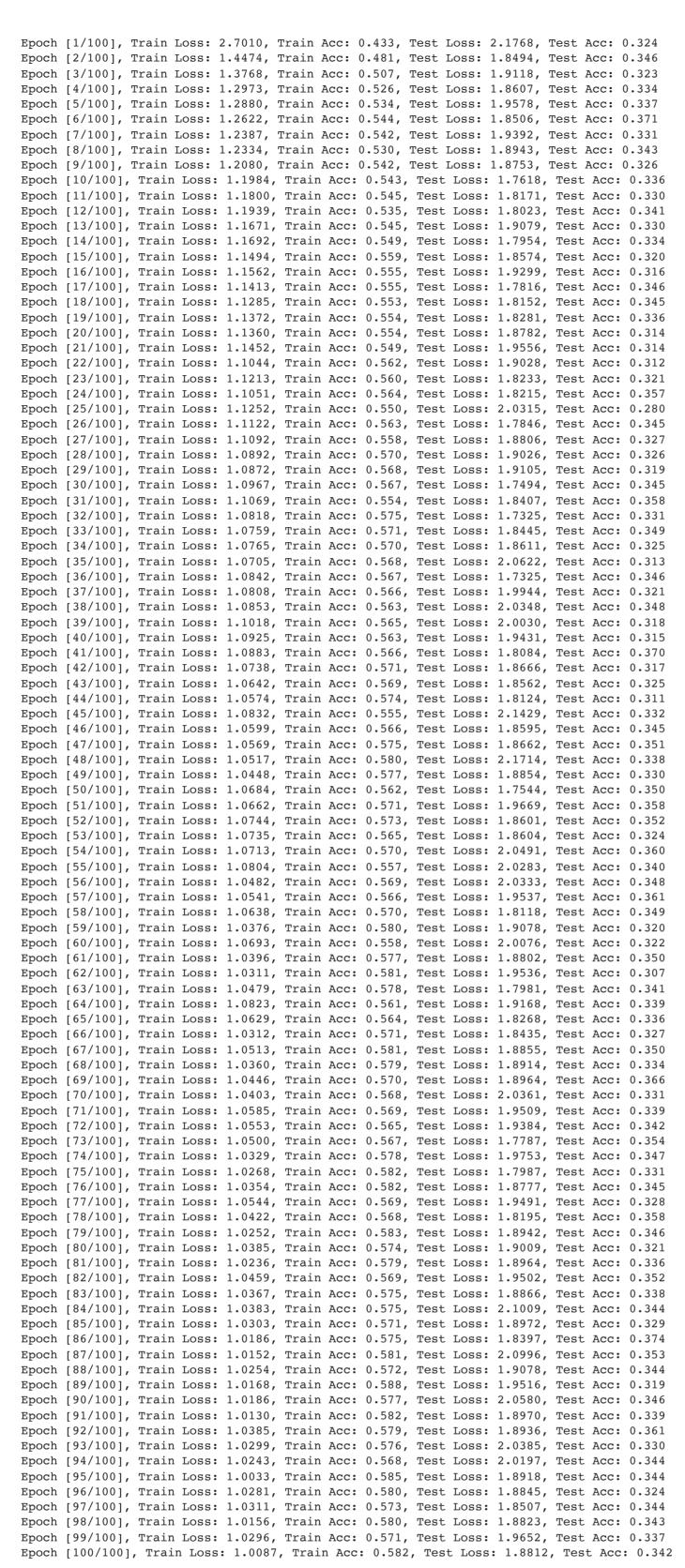
25

30

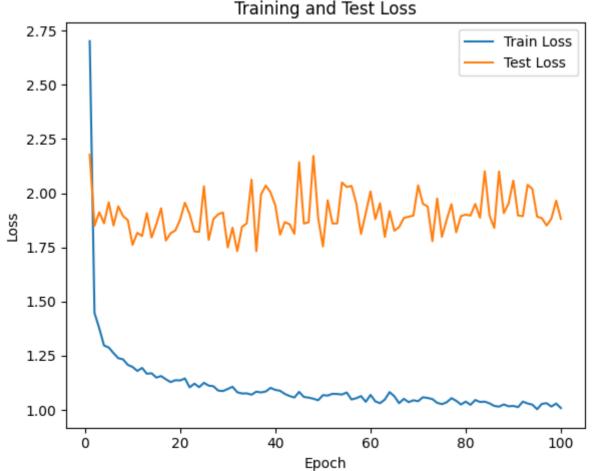
20

10

15



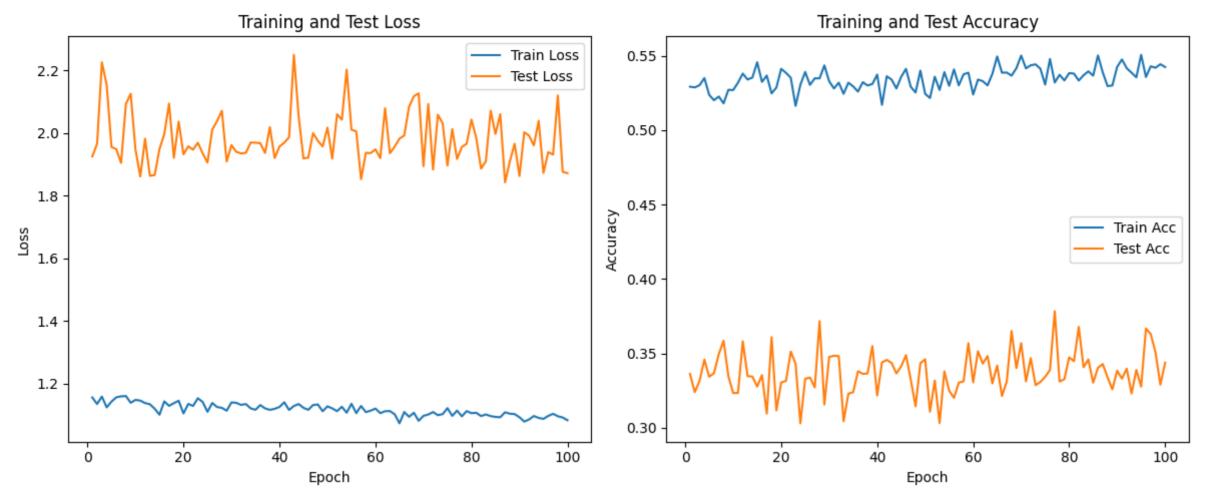
In []: plot_history(history2)





```
In [ ]: history22 = run_model(model, train_loader, test_loader, data_aug='mixup', alpha=0.4)
        Epoch [1/100], Train Loss: 1.1550, Train Acc: 0.529, Test Loss: 1.9249, Test Acc: 0.336
        Epoch [2/100], Train Loss: 1.1342, Train Acc: 0.529, Test Loss: 1.9654, Test Acc: 0.324
        Epoch [3/100], Train Loss: 1.1579, Train Acc: 0.530, Test Loss: 2.2257, Test Acc: 0.332
        Epoch [4/100], Train Loss: 1.1234, Train Acc: 0.535, Test Loss: 2.1534, Test Acc: 0.346
        Epoch [5/100], Train Loss: 1.1418, Train Acc: 0.524, Test Loss: 1.9551, Test Acc: 0.334
        Epoch [6/100], Train Loss: 1.1555, Train Acc: 0.520, Test Loss: 1.9481, Test Acc: 0.337
        Epoch [7/100], Train Loss: 1.1586, Train Acc: 0.523, Test Loss: 1.9041, Test Acc: 0.350
        Epoch [8/100], Train Loss: 1.1597, Train Acc: 0.518, Test Loss: 2.0926, Test Acc: 0.359
        Epoch [9/100], Train Loss: 1.1380, Train Acc: 0.527, Test Loss: 2.1252, Test Acc: 0.335
        Epoch [10/100], Train Loss: 1.1472, Train Acc: 0.527, Test Loss: 1.9465, Test Acc: 0.323
        Epoch [11/100], Train Loss: 1.1450, Train Acc: 0.532, Test Loss: 1.8610, Test Acc: 0.324
        Epoch [12/100], Train Loss: 1.1370, Train Acc: 0.538, Test Loss: 1.9813, Test Acc: 0.358
        Epoch [13/100], Train Loss: 1.1334, Train Acc: 0.534, Test Loss: 1.8632, Test Acc: 0.335
        Epoch [14/100], Train Loss: 1.1190, Train Acc: 0.535, Test Loss: 1.8654, Test Acc: 0.335
        Epoch [15/100], Train Loss: 1.0999, Train Acc: 0.546, Test Loss: 1.9484, Test Acc: 0.328
        Epoch [16/100], Train Loss: 1.1425, Train Acc: 0.532, Test Loss: 1.9963, Test Acc: 0.336
        Epoch [17/100], Train Loss: 1.1282, Train Acc: 0.537, Test Loss: 2.0937, Test Acc: 0.310
        Epoch [18/100], Train Loss: 1.1368, Train Acc: 0.525, Test Loss: 1.9206, Test Acc: 0.361
        Epoch [19/100], Train Loss: 1.1445, Train Acc: 0.529, Test Loss: 2.0363, Test Acc: 0.312
        Epoch [20/100], Train Loss: 1.1040, Train Acc: 0.541, Test Loss: 1.9315, Test Acc: 0.331
        Epoch [21/100], Train Loss: 1.1344, Train Acc: 0.539, Test Loss: 1.9575, Test Acc: 0.332
        Epoch [22/100], Train Loss: 1.1279, Train Acc: 0.535, Test Loss: 1.9466, Test Acc: 0.351
        Epoch [23/100], Train Loss: 1.1526, Train Acc: 0.516, Test Loss: 1.9687, Test Acc: 0.343
        Epoch [24/100], Train Loss: 1.1405, Train Acc: 0.531, Test Loss: 1.9349, Test Acc: 0.303
        Epoch [25/100], Train Loss: 1.1092, Train Acc: 0.539, Test Loss: 1.9053, Test Acc: 0.333
        Epoch [26/100], Train Loss: 1.1374, Train Acc: 0.530, Test Loss: 2.0112, Test Acc: 0.334
        Epoch [27/100], Train Loss: 1.1245, Train Acc: 0.535, Test Loss: 2.0377, Test Acc: 0.327
        Epoch [28/100], Train Loss: 1.1218, Train Acc: 0.535, Test Loss: 2.0708, Test Acc: 0.372
        Epoch [29/100], Train Loss: 1.1128, Train Acc: 0.544, Test Loss: 1.9087, Test Acc: 0.316
        Epoch [30/100], Train Loss: 1.1393, Train Acc: 0.533, Test Loss: 1.9612, Test Acc: 0.348
        Epoch [31/100], Train Loss: 1.1378, Train Acc: 0.528, Test Loss: 1.9398, Test Acc: 0.348
        Epoch [32/100], Train Loss: 1.1312, Train Acc: 0.532, Test Loss: 1.9345, Test Acc: 0.348
        Epoch [33/100], Train Loss: 1.1340, Train Acc: 0.524, Test Loss: 1.9365, Test Acc: 0.304
        Epoch [34/100], Train Loss: 1.1202, Train Acc: 0.532, Test Loss: 1.9694, Test Acc: 0.323
        Epoch [35/100], Train Loss: 1.1157, Train Acc: 0.529, Test Loss: 1.9689, Test Acc: 0.324
        Epoch [36/100], Train Loss: 1.1307, Train Acc: 0.526, Test Loss: 1.9674, Test Acc: 0.338
        Epoch [37/100], Train Loss: 1.1200, Train Acc: 0.532, Test Loss: 1.9360, Test Acc: 0.336
        Epoch [38/100], Train Loss: 1.1155, Train Acc: 0.530, Test Loss: 2.0185, Test Acc: 0.337
        Epoch [39/100], Train Loss: 1.1188, Train Acc: 0.531, Test Loss: 1.9199, Test Acc: 0.355
        Epoch [40/100], Train Loss: 1.1246, Train Acc: 0.537, Test Loss: 1.9565, Test Acc: 0.322
        Epoch [41/100], Train Loss: 1.1397, Train Acc: 0.517, Test Loss: 1.9689, Test Acc: 0.344
        Epoch [42/100], Train Loss: 1.1151, Train Acc: 0.536, Test Loss: 1.9863, Test Acc: 0.346
        Epoch [43/100], Train Loss: 1.1278, Train Acc: 0.534, Test Loss: 2.2495, Test Acc: 0.344
        Epoch [44/100], Train Loss: 1.1339, Train Acc: 0.528, Test Loss: 2.0526, Test Acc: 0.337
        Epoch [45/100], Train Loss: 1.1219, Train Acc: 0.536, Test Loss: 1.9185, Test Acc: 0.341
        Epoch [46/100], Train Loss: 1.1156, Train Acc: 0.541, Test Loss: 1.9213, Test Acc: 0.349
        Epoch [47/100], Train Loss: 1.1309, Train Acc: 0.529, Test Loss: 1.9995, Test Acc: 0.332
        Epoch [48/100], Train Loss: 1.1326, Train Acc: 0.525, Test Loss: 1.9746, Test Acc: 0.315
        Epoch [49/100], Train Loss: 1.1109, Train Acc: 0.540, Test Loss: 1.9568, Test Acc: 0.344
        Epoch [50/100], Train Loss: 1.1267, Train Acc: 0.524, Test Loss: 2.0171, Test Acc: 0.346
        Epoch [51/100], Train Loss: 1.1201, Train Acc: 0.522, Test Loss: 1.9178, Test Acc: 0.311
        Epoch [52/100], Train Loss: 1.1113, Train Acc: 0.536, Test Loss: 2.0598, Test Acc: 0.332
        Epoch [53/100], Train Loss: 1.1254, Train Acc: 0.527, Test Loss: 2.0422, Test Acc: 0.303
        Epoch [54/100], Train Loss: 1.1063, Train Acc: 0.539, Test Loss: 2.2022, Test Acc: 0.338
        Epoch [55/100], Train Loss: 1.1348, Train Acc: 0.530, Test Loss: 2.0103, Test Acc: 0.325
        Epoch [56/100], Train Loss: 1.1051, Train Acc: 0.541, Test Loss: 2.0050, Test Acc: 0.320
        Epoch [57/100], Train Loss: 1.1278, Train Acc: 0.530, Test Loss: 1.8523, Test Acc: 0.330
        Epoch [58/100], Train Loss: 1.1082, Train Acc: 0.538, Test Loss: 1.9363, Test Acc: 0.331
        Epoch [59/100], Train Loss: 1.1129, Train Acc: 0.539, Test Loss: 1.9356, Test Acc: 0.357
        Epoch [60/100], Train Loss: 1.1195, Train Acc: 0.524, Test Loss: 1.9477, Test Acc: 0.331
        Epoch [61/100], Train Loss: 1.1050, Train Acc: 0.534, Test Loss: 1.9196, Test Acc: 0.351
        Epoch [62/100], Train Loss: 1.1110, Train Acc: 0.533, Test Loss: 2.0789, Test Acc: 0.343
        Epoch [63/100], Train Loss: 1.1117, Train Acc: 0.530, Test Loss: 1.9352, Test Acc: 0.348
        Epoch [64/100], Train Loss: 1.1014, Train Acc: 0.538, Test Loss: 1.9561, Test Acc: 0.330
        Epoch [65/100], Train Loss: 1.0725, Train Acc: 0.550, Test Loss: 1.9818, Test Acc: 0.342
        Epoch [66/100], Train Loss: 1.1085, Train Acc: 0.539, Test Loss: 1.9920, Test Acc: 0.321
        Epoch [67/100], Train Loss: 1.0932, Train Acc: 0.539, Test Loss: 2.0839, Test Acc: 0.331
        Epoch [68/100], Train Loss: 1.1062, Train Acc: 0.537, Test Loss: 2.1172, Test Acc: 0.365
        Epoch [69/100], Train Loss: 1.0804, Train Acc: 0.542, Test Loss: 2.1266, Test Acc: 0.340
        Epoch [70/100], Train Loss: 1.0963, Train Acc: 0.550, Test Loss: 1.8935, Test Acc: 0.357
        Epoch [71/100], Train Loss: 1.1006, Train Acc: 0.542, Test Loss: 2.0922, Test Acc: 0.331
        Epoch [72/100], Train Loss: 1.1084, Train Acc: 0.544, Test Loss: 1.8831, Test Acc: 0.347
        Epoch [73/100], Train Loss: 1.0984, Train Acc: 0.544, Test Loss: 2.0584, Test Acc: 0.329
        Epoch [74/100], Train Loss: 1.1019, Train Acc: 0.541, Test Loss: 2.0306, Test Acc: 0.331
        Epoch [75/100], Train Loss: 1.1209, Train Acc: 0.531, Test Loss: 1.8958, Test Acc: 0.334
        Epoch [76/100], Train Loss: 1.0963, Train Acc: 0.548, Test Loss: 2.0124, Test Acc: 0.339
        Epoch [77/100], Train Loss: 1.1131, Train Acc: 0.532, Test Loss: 1.9168, Test Acc: 0.378
        Epoch [78/100], Train Loss: 1.0948, Train Acc: 0.537, Test Loss: 1.9553, Test Acc: 0.331
        Epoch [79/100], Train Loss: 1.1114, Train Acc: 0.533, Test Loss: 1.9654, Test Acc: 0.333
        Epoch [80/100], Train Loss: 1.1048, Train Acc: 0.538, Test Loss: 2.0426, Test Acc: 0.347
        Epoch [81/100], Train Loss: 1.1061, Train Acc: 0.538, Test Loss: 1.9839, Test Acc: 0.345
        Epoch [82/100], Train Loss: 1.0957, Train Acc: 0.533, Test Loss: 1.8859, Test Acc: 0.368
        Epoch [83/100], Train Loss: 1.1008, Train Acc: 0.537, Test Loss: 1.9098, Test Acc: 0.341
        Epoch [84/100], Train Loss: 1.0954, Train Acc: 0.540, Test Loss: 2.0712, Test Acc: 0.346
        Epoch [85/100], Train Loss: 1.0929, Train Acc: 0.537, Test Loss: 1.9967, Test Acc: 0.330
        Epoch [86/100], Train Loss: 1.0919, Train Acc: 0.550, Test Loss: 2.0599, Test Acc: 0.340
        Epoch [87/100], Train Loss: 1.1077, Train Acc: 0.539, Test Loss: 1.8422, Test Acc: 0.343
        Epoch [88/100], Train Loss: 1.1031, Train Acc: 0.530, Test Loss: 1.9093, Test Acc: 0.334
        Epoch [89/100], Train Loss: 1.1019, Train Acc: 0.530, Test Loss: 1.9656, Test Acc: 0.326
        Epoch [90/100], Train Loss: 1.0919, Train Acc: 0.543, Test Loss: 1.8622, Test Acc: 0.338
        Epoch [91/100], Train Loss: 1.0779, Train Acc: 0.548, Test Loss: 2.0023, Test Acc: 0.333
        Epoch [92/100], Train Loss: 1.0846, Train Acc: 0.542, Test Loss: 1.9913, Test Acc: 0.340
        Epoch [93/100], Train Loss: 1.0958, Train Acc: 0.539, Test Loss: 1.9602, Test Acc: 0.323
        Epoch [94/100], Train Loss: 1.0896, Train Acc: 0.536, Test Loss: 2.0386, Test Acc: 0.339
        Epoch [95/100], Train Loss: 1.0866, Train Acc: 0.551, Test Loss: 1.8724, Test Acc: 0.328
        Epoch [96/100], Train Loss: 1.0961, Train Acc: 0.536, Test Loss: 1.9388, Test Acc: 0.367
        Epoch [97/100], Train Loss: 1.1028, Train Acc: 0.543, Test Loss: 1.9308, Test Acc: 0.363
        Epoch [98/100], Train Loss: 1.0950, Train Acc: 0.542, Test Loss: 2.1197, Test Acc: 0.351
        Epoch [99/100], Train Loss: 1.0910, Train Acc: 0.544, Test Loss: 1.8762, Test Acc: 0.329
```

Epoch [100/100], Train Loss: 1.0824, Train Acc: 0.542, Test Loss: 1.8714, Test Acc: 0.344



Final Test Accuracy is 0.3438

3. (4 pts) Cutout augmentation (K = 16)

```
In [ ]: def cutout(image, mask_size):
            if np.random.rand() < 0.5:</pre>
                return image
            channels, height, width = image.shape
            center_y = np.random.randint(0, height)
            center_x = np.random.randint(0, width)
            half_size = mask_size // 2
            top = max(0, center_y - half_size)
            bottom = min(height, center_y + half_size)
            left = max(0, center_x - half_size)
            right = min(width, center_x + half_size)
            image[:, top:bottom, left:right] = 0
            return image
In [ ]: def apply_cutout_minibatch(minibatch_images, mask_size):
            for i in range(minibatch_images.shape[0]):
                minibatch_images[i] = cutout(minibatch_images[i], mask_size)
            return minibatch_images
In [ ]: sampled_train_data, test_data, sampled_train_labels, test_labels = get_data()
In [ ]: i=3
        plt.figure(figsize=(12,5))
        plt.subplot(121)
        plt.imshow(sampled_train_data[i].transpose( 1, 2, 0))
        plt.subplot(122)
        plt.imshow(cutout(sampled_train_data[i].copy(), 16).transpose( 1, 2, 0))
        plt.show()
        Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
        Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
         10
                                                                          10
        15
                                                                          15
        20
                                                                         20
        25
                                                                         25
```

10

5

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25

30

In []: history3 = run_model(model, train_loader, test_loader, data_aug='cutout')

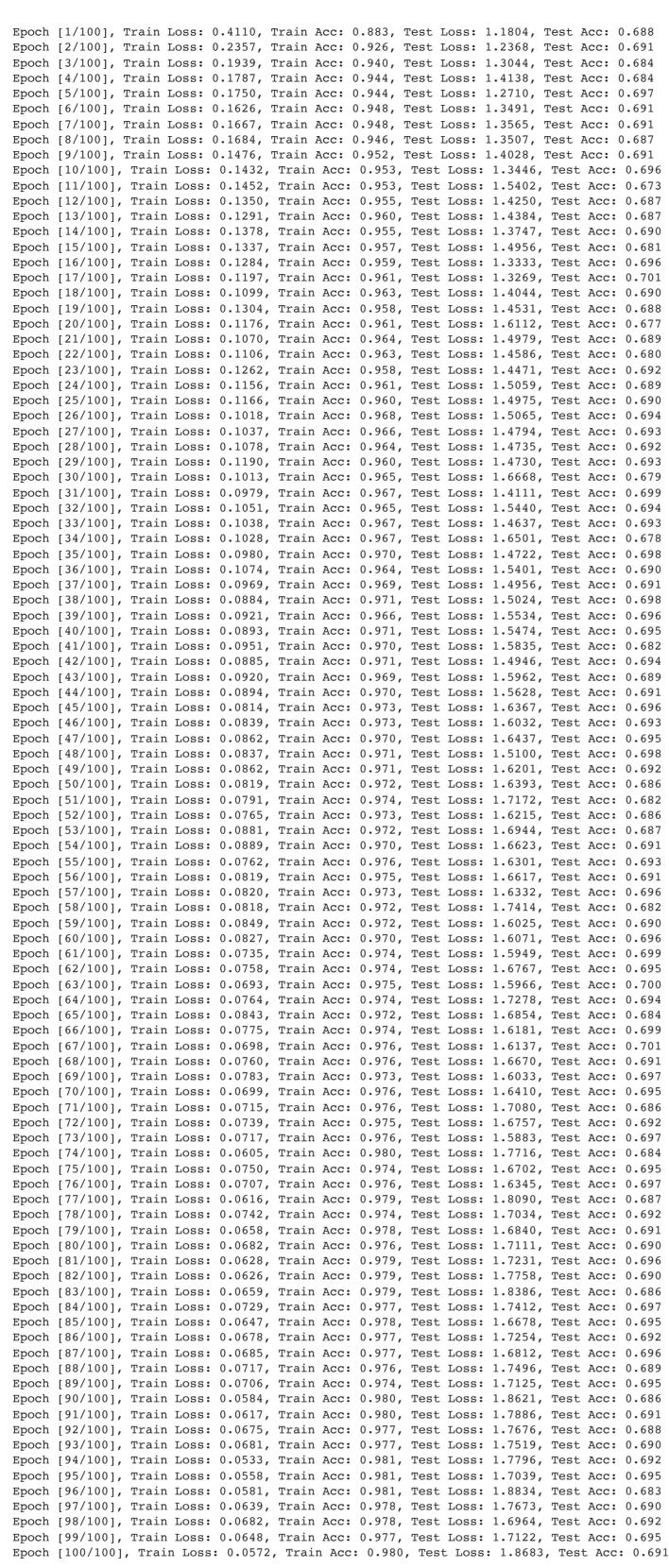
20

25

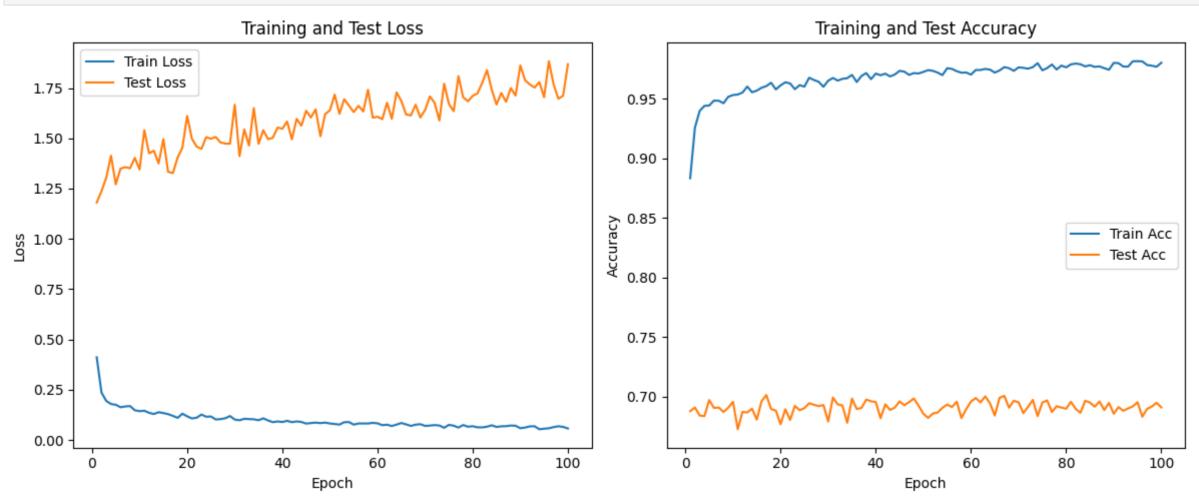
30

15

10



In []: plot_history(history3)



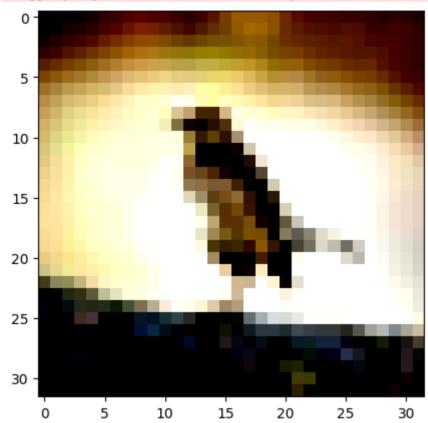
4. (4 pts) Standard augmentation

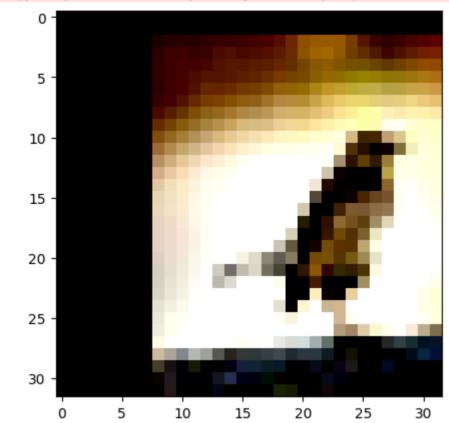
```
In [ ]: def standard(image, K):
            k1 = np.random.randint(-K, K+1)
            k2 = np.random.randint(-K, K+1)
            shifted_image = np.zeros_like(image)
            if k1 >= 0 and k2 >= 0:
                shifted_image[:, :image.shape[1]-k1, :image.shape[2]-k2] = image[:, k1:, k2:]
            elif k1 >= 0 and k2 < 0:
                shifted_image[:, :image.shape[1]-k1, -k2:] = image[:, k1:, :image.shape[2]+k2]
            elif k1 < 0 and k2 >= 0:
                shifted_image[:, -k1:, :image.shape[2]-k2] = image[:, :image.shape[1]+k1, k2:]
            else:
                shifted_image[:, -k1:, -k2:] = image[:, :image.shape[1]+k1, :image.shape[2]+k2]
            if np.random.rand() < 0.5:</pre>
                flipped_image = np.flip(shifted_image, axis=2)
            else:
                flipped_image = shifted_image
            return flipped_image
```

```
In [ ]: sampled_train_data, test_data, sampled_train_labels, test_labels = get_data()
```

```
In [ ]: i=0
        plt.figure(figsize=(12,5))
        plt.subplot(121)
        plt.imshow(sampled_train_data[i].transpose( 1, 2, 0))
        plt.subplot(122)
        plt.imshow(standard(sampled_train_data[i].copy(), 10).transpose( 1, 2, 0))
        plt.show()
```

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers). Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



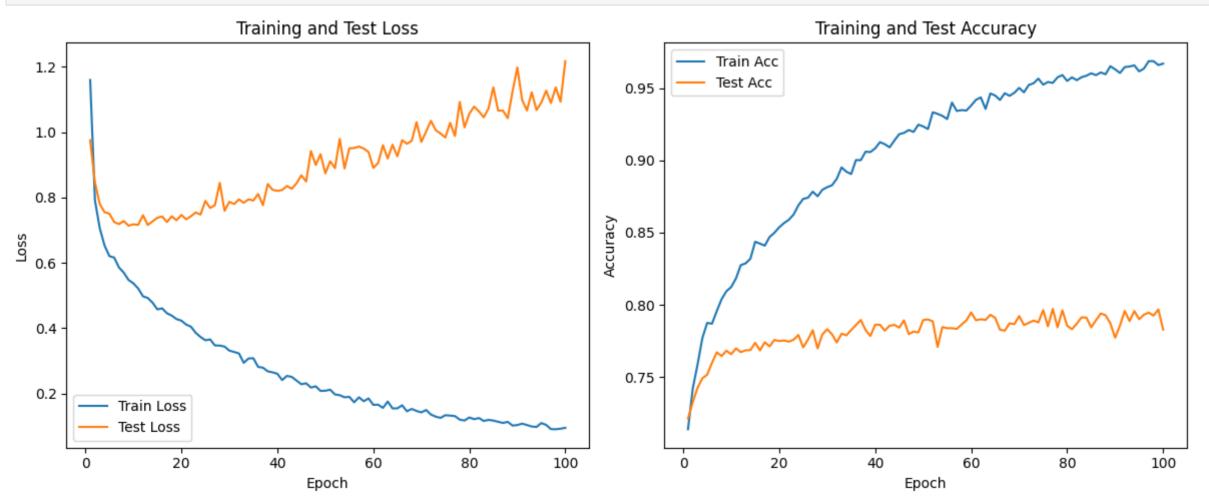


```
In [ ]: def apply_standard_minibatch(minibatch_images, K):
            for i in range(minibatch_images.shape[0]):
                std_img = standard(minibatch_images[i], K)
                minibatch_images[i] = torch.from_numpy(std_img.copy()).float()
            return minibatch_images
```

In []: history4 = run_model(model, train_loader, test_loader, data_aug='standard')



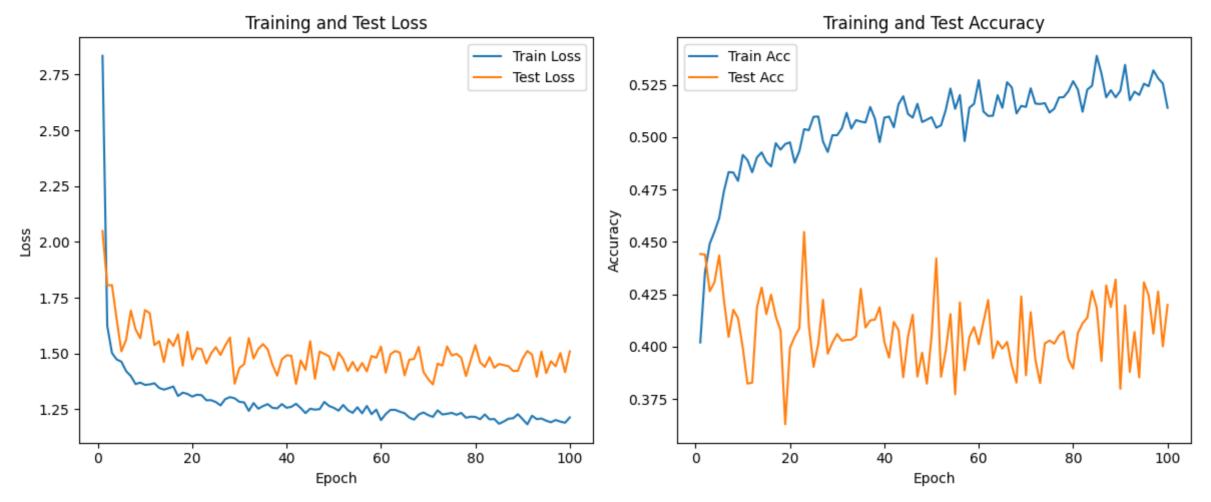
In []: plot_history(history4)



In []:

5. (3 pts) Combine all augmentations together.

```
In [ ]: history5 = run_model(model, train_loader, test_loader, data_aug='all')
        Epoch [1/100], Train Loss: 2.8334, Train Acc: 0.402, Test Loss: 2.0489, Test Acc: 0.444
        Epoch [2/100], Train Loss: 1.6240, Train Acc: 0.436, Test Loss: 1.8058, Test Acc: 0.444
        Epoch [3/100], Train Loss: 1.5026, Train Acc: 0.449, Test Loss: 1.8065, Test Acc: 0.426
        Epoch [4/100], Train Loss: 1.4737, Train Acc: 0.455, Test Loss: 1.6529, Test Acc: 0.431
        Epoch [5/100], Train Loss: 1.4635, Train Acc: 0.461, Test Loss: 1.5099, Test Acc: 0.444
        Epoch [6/100], Train Loss: 1.4214, Train Acc: 0.474, Test Loss: 1.5623, Test Acc: 0.422
        Epoch [7/100], Train Loss: 1.3994, Train Acc: 0.483, Test Loss: 1.6930, Test Acc: 0.405
        Epoch [8/100], Train Loss: 1.3635, Train Acc: 0.483, Test Loss: 1.6082, Test Acc: 0.418
        Epoch [9/100], Train Loss: 1.3701, Train Acc: 0.479, Test Loss: 1.5688, Test Acc: 0.413
        Epoch [10/100], Train Loss: 1.3597, Train Acc: 0.491, Test Loss: 1.6947, Test Acc: 0.400
        Epoch [11/100], Train Loss: 1.3619, Train Acc: 0.489, Test Loss: 1.6811, Test Acc: 0.382
        Epoch [12/100], Train Loss: 1.3670, Train Acc: 0.483, Test Loss: 1.5378, Test Acc: 0.383
        Epoch [13/100], Train Loss: 1.3463, Train Acc: 0.490, Test Loss: 1.5555, Test Acc: 0.419
        Epoch [14/100], Train Loss: 1.3386, Train Acc: 0.493, Test Loss: 1.4626, Test Acc: 0.428
        Epoch [15/100], Train Loss: 1.3450, Train Acc: 0.488, Test Loss: 1.5650, Test Acc: 0.415
        Epoch [16/100], Train Loss: 1.3527, Train Acc: 0.486, Test Loss: 1.5340, Test Acc: 0.425
        Epoch [17/100], Train Loss: 1.3100, Train Acc: 0.497, Test Loss: 1.5863, Test Acc: 0.414
        Epoch [18/100], Train Loss: 1.3252, Train Acc: 0.494, Test Loss: 1.4456, Test Acc: 0.408
        Epoch [19/100], Train Loss: 1.3193, Train Acc: 0.497, Test Loss: 1.5976, Test Acc: 0.363
        Epoch [20/100], Train Loss: 1.3074, Train Acc: 0.497, Test Loss: 1.4739, Test Acc: 0.399
        Epoch [21/100], Train Loss: 1.3158, Train Acc: 0.488, Test Loss: 1.5238, Test Acc: 0.405
        Epoch [22/100], Train Loss: 1.3136, Train Acc: 0.493, Test Loss: 1.5196, Test Acc: 0.409
        Epoch [23/100], Train Loss: 1.2910, Train Acc: 0.504, Test Loss: 1.4560, Test Acc: 0.455
        Epoch [24/100], Train Loss: 1.2914, Train Acc: 0.503, Test Loss: 1.5000, Test Acc: 0.410
        Epoch [25/100], Train Loss: 1.2831, Train Acc: 0.510, Test Loss: 1.5289, Test Acc: 0.390
        Epoch [26/100], Train Loss: 1.2680, Train Acc: 0.510, Test Loss: 1.4938, Test Acc: 0.401
        Epoch [27/100], Train Loss: 1.2961, Train Acc: 0.498, Test Loss: 1.5363, Test Acc: 0.422
        Epoch [28/100], Train Loss: 1.3049, Train Acc: 0.493, Test Loss: 1.5716, Test Acc: 0.397
        Epoch [29/100], Train Loss: 1.2997, Train Acc: 0.501, Test Loss: 1.3649, Test Acc: 0.402
        Epoch [30/100], Train Loss: 1.2839, Train Acc: 0.501, Test Loss: 1.4353, Test Acc: 0.406
        Epoch [31/100], Train Loss: 1.2813, Train Acc: 0.504, Test Loss: 1.4527, Test Acc: 0.403
        Epoch [32/100], Train Loss: 1.2435, Train Acc: 0.512, Test Loss: 1.5694, Test Acc: 0.403
        Epoch [33/100], Train Loss: 1.2785, Train Acc: 0.504, Test Loss: 1.4782, Test Acc: 0.403
        Epoch [34/100], Train Loss: 1.2530, Train Acc: 0.508, Test Loss: 1.5205, Test Acc: 0.405
        Epoch [35/100], Train Loss: 1.2649, Train Acc: 0.507, Test Loss: 1.5425, Test Acc: 0.428
        Epoch [36/100], Train Loss: 1.2736, Train Acc: 0.507, Test Loss: 1.5188, Test Acc: 0.409
        Epoch [37/100], Train Loss: 1.2571, Train Acc: 0.514, Test Loss: 1.4503, Test Acc: 0.412
        Epoch [38/100], Train Loss: 1.2546, Train Acc: 0.509, Test Loss: 1.4011, Test Acc: 0.413
        Epoch [39/100], Train Loss: 1.2737, Train Acc: 0.498, Test Loss: 1.4740, Test Acc: 0.419
        Epoch [40/100], Train Loss: 1.2572, Train Acc: 0.509, Test Loss: 1.4922, Test Acc: 0.402
        Epoch [41/100], Train Loss: 1.2615, Train Acc: 0.510, Test Loss: 1.4904, Test Acc: 0.395
        Epoch [42/100], Train Loss: 1.2751, Train Acc: 0.505, Test Loss: 1.3639, Test Acc: 0.412
        Epoch [43/100], Train Loss: 1.2560, Train Acc: 0.516, Test Loss: 1.4694, Test Acc: 0.408
        Epoch [44/100], Train Loss: 1.2334, Train Acc: 0.519, Test Loss: 1.4272, Test Acc: 0.385
        Epoch [45/100], Train Loss: 1.2530, Train Acc: 0.511, Test Loss: 1.5555, Test Acc: 0.405
        Epoch [46/100], Train Loss: 1.2489, Train Acc: 0.509, Test Loss: 1.3868, Test Acc: 0.415
        Epoch [47/100], Train Loss: 1.2512, Train Acc: 0.516, Test Loss: 1.5092, Test Acc: 0.386
        Epoch [48/100], Train Loss: 1.2835, Train Acc: 0.507, Test Loss: 1.4986, Test Acc: 0.397
        Epoch [49/100], Train Loss: 1.2653, Train Acc: 0.508, Test Loss: 1.4878, Test Acc: 0.382
        Epoch [50/100], Train Loss: 1.2570, Train Acc: 0.509, Test Loss: 1.4265, Test Acc: 0.405
        Epoch [51/100], Train Loss: 1.2445, Train Acc: 0.504, Test Loss: 1.5047, Test Acc: 0.442
        Epoch [52/100], Train Loss: 1.2698, Train Acc: 0.506, Test Loss: 1.4747, Test Acc: 0.386
        Epoch [53/100], Train Loss: 1.2460, Train Acc: 0.513, Test Loss: 1.4218, Test Acc: 0.398
        Epoch [54/100], Train Loss: 1.2347, Train Acc: 0.523, Test Loss: 1.4629, Test Acc: 0.415
        Epoch [55/100], Train Loss: 1.2596, Train Acc: 0.513, Test Loss: 1.4220, Test Acc: 0.377
        Epoch [56/100], Train Loss: 1.2325, Train Acc: 0.520, Test Loss: 1.4578, Test Acc: 0.421
        Epoch [57/100], Train Loss: 1.2656, Train Acc: 0.498, Test Loss: 1.4203, Test Acc: 0.389
        Epoch [58/100], Train Loss: 1.2286, Train Acc: 0.514, Test Loss: 1.4892, Test Acc: 0.405
        Epoch [59/100], Train Loss: 1.2490, Train Acc: 0.516, Test Loss: 1.4813, Test Acc: 0.409
        Epoch [60/100], Train Loss: 1.2019, Train Acc: 0.527, Test Loss: 1.5314, Test Acc: 0.401
        Epoch [61/100], Train Loss: 1.2292, Train Acc: 0.512, Test Loss: 1.4142, Test Acc: 0.412
        Epoch [62/100], Train Loss: 1.2478, Train Acc: 0.510, Test Loss: 1.4970, Test Acc: 0.422
        Epoch [63/100], Train Loss: 1.2481, Train Acc: 0.510, Test Loss: 1.5116, Test Acc: 0.394
        Epoch [64/100], Train Loss: 1.2396, Train Acc: 0.520, Test Loss: 1.5044, Test Acc: 0.403
        Epoch [65/100], Train Loss: 1.2329, Train Acc: 0.514, Test Loss: 1.4024, Test Acc: 0.399
        Epoch [66/100], Train Loss: 1.2136, Train Acc: 0.526, Test Loss: 1.4728, Test Acc: 0.402
        Epoch [67/100], Train Loss: 1.2041, Train Acc: 0.524, Test Loss: 1.4760, Test Acc: 0.391
        Epoch [68/100], Train Loss: 1.2270, Train Acc: 0.511, Test Loss: 1.5300, Test Acc: 0.383
        Epoch [69/100], Train Loss: 1.2364, Train Acc: 0.515, Test Loss: 1.4179, Test Acc: 0.424
        Epoch [70/100], Train Loss: 1.2244, Train Acc: 0.514, Test Loss: 1.3856, Test Acc: 0.386
        Epoch [71/100], Train Loss: 1.2164, Train Acc: 0.523, Test Loss: 1.3617, Test Acc: 0.416
        Epoch [72/100], Train Loss: 1.2459, Train Acc: 0.516, Test Loss: 1.4549, Test Acc: 0.394
        Epoch [73/100], Train Loss: 1.2274, Train Acc: 0.516, Test Loss: 1.4461, Test Acc: 0.383
        Epoch [74/100], Train Loss: 1.2302, Train Acc: 0.516, Test Loss: 1.5319, Test Acc: 0.402
        Epoch [75/100], Train Loss: 1.2345, Train Acc: 0.512, Test Loss: 1.4913, Test Acc: 0.403
        Epoch [76/100], Train Loss: 1.2257, Train Acc: 0.514, Test Loss: 1.4988, Test Acc: 0.401
        Epoch [77/100], Train Loss: 1.2343, Train Acc: 0.519, Test Loss: 1.4813, Test Acc: 0.405
        Epoch [78/100], Train Loss: 1.2127, Train Acc: 0.519, Test Loss: 1.3990, Test Acc: 0.407
        Epoch [79/100], Train Loss: 1.2174, Train Acc: 0.522, Test Loss: 1.4698, Test Acc: 0.394
        Epoch [80/100], Train Loss: 1.2163, Train Acc: 0.527, Test Loss: 1.5381, Test Acc: 0.390
        Epoch [81/100], Train Loss: 1.2060, Train Acc: 0.523, Test Loss: 1.4612, Test Acc: 0.406
        Epoch [82/100], Train Loss: 1.2274, Train Acc: 0.512, Test Loss: 1.4404, Test Acc: 0.411
        Epoch [83/100], Train Loss: 1.2053, Train Acc: 0.523, Test Loss: 1.4838, Test Acc: 0.414
        Epoch [84/100], Train Loss: 1.2072, Train Acc: 0.524, Test Loss: 1.4365, Test Acc: 0.427
        Epoch [85/100], Train Loss: 1.1857, Train Acc: 0.539, Test Loss: 1.4537, Test Acc: 0.418
        Epoch [86/100], Train Loss: 1.1956, Train Acc: 0.530, Test Loss: 1.4485, Test Acc: 0.393
        Epoch [87/100], Train Loss: 1.2081, Train Acc: 0.519, Test Loss: 1.4433, Test Acc: 0.429
        Epoch [88/100], Train Loss: 1.2104, Train Acc: 0.522, Test Loss: 1.4220, Test Acc: 0.419
        Epoch [89/100], Train Loss: 1.2285, Train Acc: 0.519, Test Loss: 1.4225, Test Acc: 0.432
        Epoch [90/100], Train Loss: 1.2065, Train Acc: 0.522, Test Loss: 1.4772, Test Acc: 0.380
        Epoch [91/100], Train Loss: 1.1833, Train Acc: 0.534, Test Loss: 1.5114, Test Acc: 0.420
        Epoch [92/100], Train Loss: 1.2219, Train Acc: 0.518, Test Loss: 1.4954, Test Acc: 0.388
        Epoch [93/100], Train Loss: 1.2063, Train Acc: 0.522, Test Loss: 1.3962, Test Acc: 0.407
        Epoch [94/100], Train Loss: 1.2093, Train Acc: 0.520, Test Loss: 1.5090, Test Acc: 0.385
        Epoch [95/100], Train Loss: 1.1994, Train Acc: 0.525, Test Loss: 1.4123, Test Acc: 0.431
        Epoch [96/100], Train Loss: 1.1925, Train Acc: 0.524, Test Loss: 1.4661, Test Acc: 0.424
        Epoch [97/100], Train Loss: 1.2025, Train Acc: 0.532, Test Loss: 1.4432, Test Acc: 0.406
        Epoch [98/100], Train Loss: 1.1954, Train Acc: 0.528, Test Loss: 1.5025, Test Acc: 0.426
        Epoch [99/100], Train Loss: 1.1902, Train Acc: 0.526, Test Loss: 1.4165, Test Acc: 0.400
        Epoch [100/100], Train Loss: 1.2141, Train Acc: 0.514, Test Loss: 1.5102, Test Acc: 0.420
```

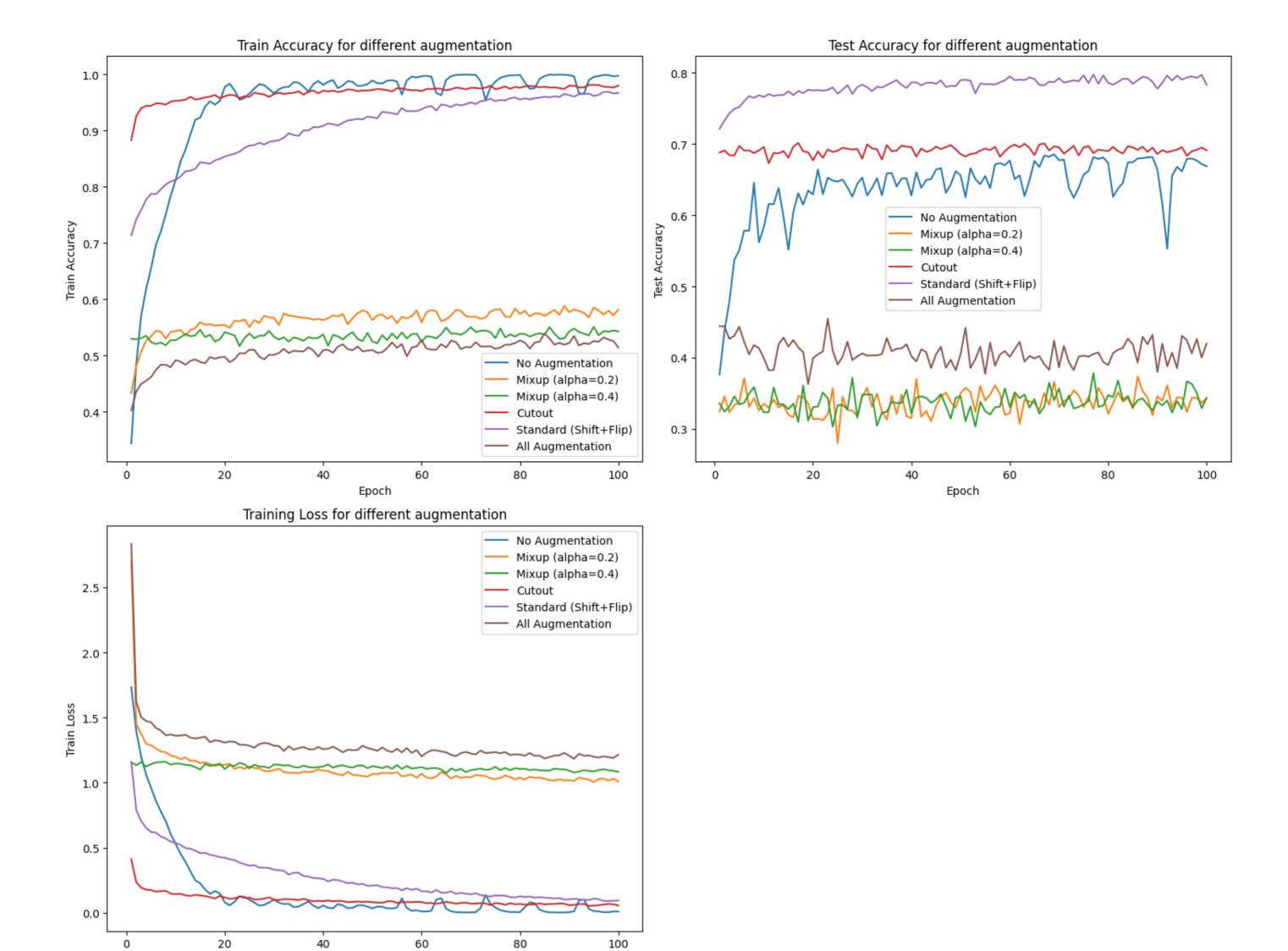


Final Test Accuracy is 0.4199

Does combining improve things further?

-> No. Combining all three augmentation does not improve further. Becasue, we have included augmentation which brings too much randomness to the dataset. For that reason, combining the augementation is not the best way to train model in this case.

```
In [ ]:
In [ ]: plt.figure(figsize=(15,12))
        c = plt.subplot(2, 2, 1)
        c.plot(range(1, 101), history1['train_acc'], label='No Augmentation')
        c.plot(range(1, 101), history2['train_acc'], label='Mixup (alpha=0.2)')
        c.plot(range(1, 101), history22['train_acc'], label='Mixup (alpha=0.4)')
        c.plot(range(1, 101), history3['train_acc'], label='Cutout')
        c.plot(range(1, 101), history4['train_acc'], label='Standard (Shift+Flip)')
        c.plot(range(1, 101), history5['train_acc'], label='All Augmentation')
        c.set_xlabel('Epoch')
        c.set_ylabel('Train Accuracy')
        c.set_title('Train Accuracy for different augmentation')
        c.legend()
        b = plt.subplot(2, 2, 2)
        b.plot(range(1, 101), history1['test_acc'], label='No Augmentation')
        b.plot(range(1, 101), history2['test_acc'], label='Mixup (alpha=0.2)')
        b.plot(range(1, 101), history22['test_acc'], label='Mixup (alpha=0.4)')
        b.plot(range(1, 101), history3['test_acc'], label='Cutout')
        b.plot(range(1, 101), history4['test_acc'], label='Standard (Shift+Flip)')
        b.plot(range(1, 101), history5['test_acc'], label='All Augmentation')
        b.set_xlabel('Epoch')
        b.set_ylabel('Test Accuracy')
        b.set_title('Test Accuracy for different augmentation')
        b.legend()
        a = plt.subplot(2, 2, 3)
        a.plot(range(1, 101), history1['train_loss'], label='No Augmentation')
        a.plot(range(1, 101), history2['train_loss'], label='Mixup (alpha=0.2)')
        a.plot(range(1, 101), history22['train_loss'], label='Mixup (alpha=0.4)')
        a.plot(range(1, 101), history3['train_loss'], label='Cutout')
        a.plot(range(1, 101), history4['train_loss'], label='Standard (Shift+Flip)')
        a.plot(range(1, 101), history5['train_loss'], label='All Augmentation')
        a.set xlabel('Epoch')
        a.set_ylabel('Train Loss')
        a.set title('Training Loss for different augmentation')
        a.legend()
        plt.tight_layout()
        #plt.title(title)
        plt.show()
```



6. (2 pts) Comment on the role of data augmentation.

How does it affect test accuracy, train accuracy and the convergence of optimization? Is test accuracy higher? Does training loss converge faster?

Epoch

Based on the observed plots, it can be concluded that:

- Without augmentation, the model tends to overfit the training data.
- Mixup augmentation leads to lower train and test accuracies. This augmentation introduces excessive randomness, making it difficult for the model to learn meaningful features. However, when comparing different mixup values, alpha = 0.2 performs relatively better than alpha = 0.4. Both values reach a plateau in terms of optimization, indicating that this augmentation technique is not suitable for this dataset.
- Cutout augmentation shows improvements compared to the base case. The difference between train and test accuracies is smaller, indicating reduced overfitting. The training loss initially decreases quickly, and then the performance plateaus.
- Standard augmentation performs the best among the techniques evaluated. It exhibits the least overfitting, with the highest test accuracy. Both train and test accuracies improve over time, and the training loss continuously decreases.
- Augmenting with a combination of techniques, including mixup, does not yield good performance. Mixup introduces excessive randomness, hindering the model's ability to find patterns. Although the accuracies and losses are better than with mixup alone, this technique does not compare favorably to the others.

Overall, the standard augmentation technique performs the best. However, it is worth noting that if the model were trained for additional epochs, it could potentially achieve even better performance.