EN3160 Assignment 3 on Neural Networks

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[1]:
```
import torch
import torch .nn as nn
import torch .optim as optim
import torchvision
import torchvision .transforms as transforms
import matplotlib . pyplot as plt
```

[2]:
```
# 1. Dataloading

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

batch_size = 50

trainset = torchvision . datasets .CIFAR10(root=r'D:\semi 5\IP&CV\Assignment␣
↪3\data', train=True, download=True, transform=transform)

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

testset = torchvision . datasets .CIFAR10(root=r'D:\semi 5\IP&CV\Assignment␣
↪3\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')
```

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```

[3]:
```
# 2. Define Network Parameters
Din = 3 * 32 * 32 # Input size (flattened CIFAR=10 image size)
K = 10 # Output size (number of classes in CIFAR=10)
std = 1e-5

# Initialize weights and biases
w = torch.randn(Din, K) * std # One layer: directly map input to output
b = torch.zeros(K)

# Hyperparameters
iterations = 20
lr = 2e-6 # Learning rate
lr_decay = 0.9 # Learning rate decay
reg = 0 # Regularization
loss_history = []
```

[4]:
```
# 3. Training Loop
for t in range(iterations ):
    running_loss = 0.0
    for i , data in enumerate(trainloader , 0):
        # Get inputs and labels
        inputs , labels = data
        Ntr = inputs.shape[0] # Batch size
        x_train = inputs.view(Ntr, -1) # Flatten input to (Ntr, Din)
        y_train_onehot = nn.functional.one_hot(labels , K). float () # Convert␣
↪labels to one=hot encoding

        # Forward pass
        y_pred = x_train.mm(w) + b # Output layer activation

        # Loss calculation (Mean Squared Error with regularization)
        loss = (1 / Ntr) * torch.sum((y_pred - y_train_onehot) ** 2) + reg *␣
↪torch.sum(w**2)
        loss_history.append(loss.item())
        running_loss += loss.item()

        # Backpropagation
        dy_pred = (2.0 / Ntr) * (y_pred - y_train_onehot)
        dw = x_train.t().mm(dy_pred) + reg * w
        db = dy_pred.sum(dim=0)

        # Parameter update
        w -= lr * dw
        b -= lr * db

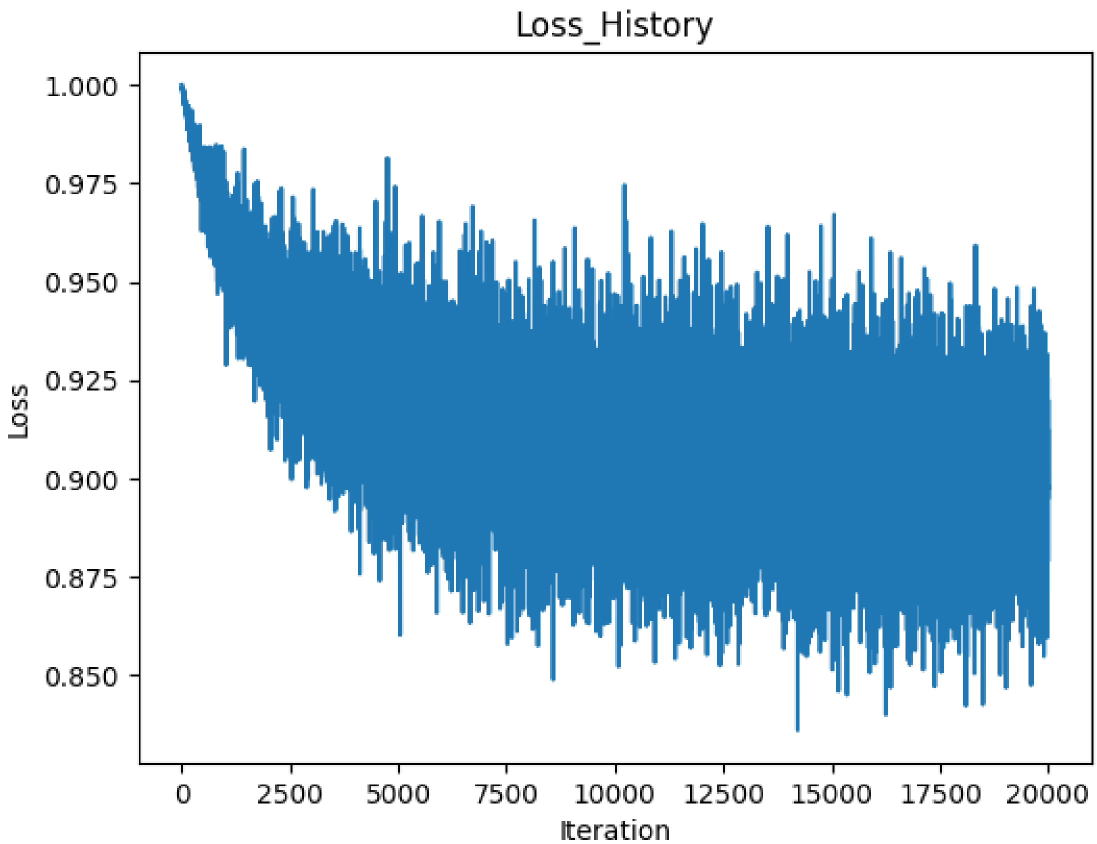
    # Print loss for every epoch
    if t % 1 == 0:
```

```
        print(f"Epoch {t +1}/{ iterations}, Loss:{ running_loss/len (␣
↪trainloader )} " )

    # Learning rate decay
    lr *= lr_decay
```

```
Epoch 1/20, Loss:0.9769474459886551
Epoch 2/20, Loss:0.9498618963956833
Epoch 3/20, Loss:0.9361145228743554
Epoch 4/20, Loss:0.9275588639378548
Epoch 5/20, Loss:0.921618634045124
Epoch 6/20, Loss:0.9172142955064774
Epoch 7/20, Loss:0.9138009185791016
Epoch 8/20, Loss:0.9110727261900902
Epoch 9/20, Loss:0.9088412716984748
Epoch 10/20, Loss:0.9069875936508178
Epoch 11/20, Loss:0.9054266312718391
Epoch 12/20, Loss:0.9040986114740371
Epoch 13/20, Loss:0.9029594156742096
Epoch 14/20, Loss:0.9019756987094879
Epoch 15/20, Loss:0.9011212394833564
Epoch 16/20, Loss:0.9003760864138604
Epoch 17/20, Loss:0.8997233058214188
Epoch 18/20, Loss:0.8991496341824532
Epoch 19/20, Loss:0.8986439597010613
Epoch 20/20, Loss:0.8981972292661667
```

[5]:
```
# 4. Plotting the Loss History
plt.plot(loss_history)
plt.title("Loss_History")
plt.xlabel("Iteration")
plt.ylabel("Loss")
plt.show()
```



[6]:
```
# 5. Calculate Accuracy on Training Set
correct_train = 0
total_train = 0
with torch .no_grad ():
    for data in trainloader :
        inputs, labels = data
        Ntr = inputs.shape[0]
        x_train = inputs.view(Ntr, -1)
        y_train_onehot = nn.functional.one_hot(labels, K).float()

        # Forward pass
        y_train_pred = x_train.mm(w) + b
        predicted_train = torch.argmax(y_train_pred ,dim=1)
        total_train += labels.size(0)
        correct_train += (predicted_train == labels).sum().item()

train_acc = 100 * correct_train / total_train
print(f"Training accuracy :{ train_acc :.2f}%")
```

```
Training accuracy :32.21%
```

[7]:
```python
# 6. Calculate Accuracy on Test Set
correct_test = 0
total_test = 0

with torch .no_grad ():
    for data in testloader :
        inputs , labels = data
        Nte = inputs.shape[0]
        x_test = inputs.view(Nte, -1)
        y_test_onehot = nn. functional .one_hot(labels , K). float ()

        # Forward pass
        y_test_pred = x_test .mm(w) + b
        predicted_test = torch .argmax(y_test_pred , dim=1)
        total_test += labels . size (0)
        correct_test += (predicted_test == labels ).sum(). item()

test_acc = 100 * correct_test / total_test
print(f"Test accuracy : {test_acc : .2f}%")
```

```
Test accuracy :  32.41%
```

1. Listing 1 shows the code for a single dense layer network with manually computed forward path and backpropagations. Do the following changes

(a) Add a middle layer with 100 nodes and a sigmoid activation.
(b) Use cross-entropy loss
(c) Run the network for 10 epochs nad report the taining and test accuracies.

[ ]:
```python
# Model definition
class NeuralNetwork(nn.Module):
    def __init__(self):
        super(NeuralNetwork, self).__init__()
        self.fc1 = nn.Linear(3 * 32 * 32, 100)  # Input to hidden layer with␣
 ↪100 nodes
        self.sigmoid = nn.Sigmoid()             # Sigmoid activation
        self.fc2 = nn.Linear(100, 10)          # 100 Hidden layer nodes to␣
 ↪output layer

    def forward(self, x):
        x = self.fc1(x)
        x = self.sigmoid(x)
        x = self.fc2(x)
        return x
```

[ ]:
```python
model = NeuralNetwork()
criterion = nn.CrossEntropyLoss()
```

```
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)  # learning␣
↪rate = 0.01, momentum = 0.9

# Dataloading and transformations
transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize((0.
↪5, 0.5, 0.5), (0.5, 0.5, 0.5))])
batch_size = 50

trainset = torchvision.datasets.CIFAR10(root=r'D:\semi 5\IP&CV\Assignment␣
↪3\data', train=True, download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=batch_size,␣
↪shuffle=True, num_workers=2)

testset = torchvision.datasets.CIFAR10(root=r'D:\semi 5\IP&CV\Assignment␣
↪3\data', train=False, download=True, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=batch_size,␣
↪shuffle=False, num_workers=2)
```

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[ ]:
```
# Training loop
epochs = 10
for epoch in range(epochs):
    running_loss = 0.0
    for i, data in enumerate(trainloader):
        inputs, labels = data
        inputs = inputs.view(inputs.shape[0], -1)
        optimizer.zero_grad()
        outputs = model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()

    print(f'Epoch {epoch + 1}, Loss: {running_loss / len(trainloader)}')
```

```
Epoch 1, Loss: 1.8407409086227418
Epoch 2, Loss: 1.691075718641281
Epoch 3, Loss: 1.6235661569833755
Epoch 4, Loss: 1.573109028339386
Epoch 5, Loss: 1.5269226109981537
Epoch 6, Loss: 1.486977286696434
Epoch 7, Loss: 1.446461871623993
Epoch 8, Loss: 1.412262617468834
Epoch 9, Loss: 1.379416198015213
Epoch 10, Loss: 1.348554687321186
```

[11]:
```python
# Test accuracy calculation
correct = 0
total = 0
with torch.no_grad():
    for data in testloader:
        images, labels = data
        images = images.view(images.size(0), -1)
        outputs = model(images)
        _, predicted = torch.max(outputs, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

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

```
Accuracy of the network on the 10000 test images: 47.92%
```

2. Create a LeNet-5 network for MNIST using Pytorch. Report the training and test accuracies after 10 epochs.

[ ]:
```python
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision
import torchvision.transforms as transforms
```

[ ]:
```python
class LeNet5(nn.Module):
    def __init__(self):
        super(LeNet5, self).__init__()
        self.conv1 = nn.Conv2d(1, 6, 5)  # 1 input channel (grayscale), 6␣
 ↪output channels, 5x5 kernel size
        self.pool = nn.AvgPool2d(2, 2)   # Average pooling with 2x2 kernel size␣
 ↪and stride 2
        self.conv2 = nn.Conv2d(6, 16, 5) # 6 input channels, 16 output␣
 ↪channels, 5x5 kernel size
        self.fc1 = nn.Linear(16 * 4 * 4, 120)  # 16 channels, 4x4 image size␣
 ↪after pooling, 120 output features
        self.fc2 = nn.Linear(120, 84) # 120 input features, 84 output features
        self.fc3 = nn.Linear(84, 10)  # 84 input features, 10 output features/
 ↪classes for MNIST

    def forward(self, x):
        x = self.pool(torch.tanh(self.conv1(x)))
        x = self.pool(torch.tanh(self.conv2(x)))
        x = x.view(-1, 16 * 4 * 4)  # Flatten the 16x4x4 tensor into a 1D tensor
        x = torch.tanh(self.fc1(x))
        x = torch.tanh(self.fc2(x))
        x = self.fc3(x)
```

```
        return x
```

[ ]:
```
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

trainset = torchvision.datasets.MNIST(root=r'D:\semi 5\IP&CV\Assignment␣
↪3\data', train=True, download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=64, shuffle=True)

testset = torchvision.datasets.MNIST(root=r'D:\semi 5\IP&CV\Assignment 3\data',␣
↪train=False, download=True, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=64, shuffle=False)
```

[ ]:
```
model = LeNet5()
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)

for epoch in range(10):
    running_loss = 0.0
    correct = 0
    total = 0
    for inputs, labels in trainloader:
        optimizer.zero_grad()
        outputs = model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()

        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

    train_accuracy = 100 * correct / total
    print(f'Epoch {epoch + 1}, Loss: {running_loss / len(trainloader):.4f},␣
↪Training Accuracy: {train_accuracy:.2f}%')

correct = 0
total = 0
with torch.no_grad():
    for inputs, labels in testloader:
        outputs = model(inputs)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
```

```
test_accuracy = 100 * correct / total
print(f'Test Accuracy: {test_accuracy:.2f}%')
```

```
Epoch 1, Loss: 1.5365, Training Accuracy: 55.22%
Epoch 2, Loss: 0.5226, Training Accuracy: 86.18%
Epoch 3, Loss: 0.3634, Training Accuracy: 89.91%
Epoch 4, Loss: 0.2954, Training Accuracy: 91.56%
Epoch 5, Loss: 0.2481, Training Accuracy: 92.93%
Epoch 6, Loss: 0.2115, Training Accuracy: 93.94%
Epoch 7, Loss: 0.1829, Training Accuracy: 94.75%
Epoch 8, Loss: 0.1607, Training Accuracy: 95.37%
Epoch 9, Loss: 0.1431, Training Accuracy: 95.85%
Epoch 10, Loss: 0.1289, Training Accuracy: 96.26%
Test Accuracy: 96.65%
```

3. Based on the PyTorch tutorial on transfer learning get the pre-trained ResNet18 network trained on ImageNet15. classify hymenoptera dataset by

(a) fine tuning, and
(b) using the network as a feature extracter.

[31]:
```
import torch
import torchvision
import torchvision.transforms as transforms
from torchvision import datasets, models, transforms
import os
from torch import nn, optim
from torch.optim import lr_scheduler
import time
import copy
```

[33]:
```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f'Using device: {device}')

model_conv = models.resnet18(pretrained=True)

data_transforms = {
    'train': transforms.Compose([
        transforms.RandomResizedCrop(224),
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
    'val': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
```

```
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
}

data_dir = r'D:\semi 5\IP&CV\Assignment 3\data\hymenoptera_data'
image_datasets = {x: datasets.ImageFolder(os.path.join(data_dir, x),␣
 ↪data_transforms[x]) for x in ['train', 'val']}
dataloaders = {x: torch.utils.data.DataLoader(image_datasets[x], batch_size=4,␣
 ↪shuffle=True, num_workers=4) for x in ['train', 'val']}
dataset_sizes = {x: len(image_datasets[x]) for x in ['train', 'val']}
class_names = image_datasets['train'].classes
```

```
Using device: cpu
```

[ ]:
```
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()

    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    for epoch in range(num_epochs):
        print(f'Epoch {epoch}/{num_epochs - 1}')
        print('-' * 10)

        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()  # Set model to training mode
            else:
                model.eval()   # Set model to evaluate mode

            running_loss = 0.0
            running_corrects = 0

            for inputs, labels in dataloaders[phase]:
                inputs = inputs.to(device)
                labels = labels.to(device)

                optimizer.zero_grad()

                with torch.set_grad_enabled(phase == 'train'): # Set gradient␣
 ↪calculation only for training phase
                    outputs = model(inputs)
                    _, preds = torch.max(outputs, 1)
                    loss = criterion(outputs, labels)

                    if phase == 'train': # Only perform backward and␣
 ↪optimization during training phase
```

```
                        loss.backward()
                        optimizer.step()

                    running_loss += loss.item() * inputs.size(0)
                    running_corrects += torch.sum(preds == labels.data)
                if phase == 'train':
                    scheduler.step()

                epoch_loss = running_loss / dataset_sizes[phase]
                epoch_acc = running_corrects.double() / dataset_sizes[phase]

                print(f'{phase}- Loss: {epoch_loss:.4f} Accuracy: {epoch_acc:.4f}')

                if phase == 'val' and epoch_acc > best_acc: # Save the best model
                    best_acc = epoch_acc
                    best_model_wts = copy.deepcopy(model.state_dict())

            print()

        time_elapsed = time.time() - since
        print(f'Training complete in {time_elapsed // 60:.0f}m {time_elapsed % 60:.
    ↪0f}s')
        print(f'Best val Accuracy: {best_acc:.4f}')

        model.load_state_dict(best_model_wts)
        return model
```

(a) Fine tuning

[35]:
```
model_ft = models.resnet18(pretrained=True)
num_ftrs = model_ft.fc.in_features
model_ft.fc = nn.Linear(num_ftrs, 2)

model_ft = model_ft.to(device)
criterion = nn.CrossEntropyLoss()

optimizer_ft = optim.SGD(model_ft.parameters(), lr=0.001, momentum=0.9)

exp_lr_scheduler = lr_scheduler.StepLR(optimizer_ft, step_size=7, gamma=0.1)

model_ft = train_model(model_ft, criterion, optimizer_ft, exp_lr_scheduler,␣
 ↪num_epochs=25)
```

```
Epoch 0/24
----------
train- Loss: 0.5393 Accuracy: 0.7172
val- Loss: 0.2172 Accuracy: 0.9216
```

```
Epoch 1/24
----------
train- Loss: 0.4260 Accuracy: 0.8402
val- Loss: 0.4550 Accuracy: 0.8170

Epoch 2/24
----------
train- Loss: 0.5254 Accuracy: 0.7787
val- Loss: 0.3230 Accuracy: 0.9020

Epoch 3/24
----------
train- Loss: 0.6947 Accuracy: 0.7664
val- Loss: 0.2025 Accuracy: 0.9216

Epoch 4/24
----------
train- Loss: 0.6024 Accuracy: 0.7623
val- Loss: 0.2493 Accuracy: 0.8954

Epoch 5/24
----------
train- Loss: 0.4619 Accuracy: 0.8156
val- Loss: 0.3072 Accuracy: 0.8954

Epoch 6/24
----------
train- Loss: 0.8062 Accuracy: 0.6967
val- Loss: 0.5599 Accuracy: 0.8235

Epoch 7/24
----------
train- Loss: 0.4273 Accuracy: 0.8115
val- Loss: 0.3046 Accuracy: 0.9150

Epoch 8/24
----------
train- Loss: 0.4436 Accuracy: 0.8074
val- Loss: 0.2835 Accuracy: 0.9085

Epoch 9/24
----------
train- Loss: 0.3257 Accuracy: 0.8484
val- Loss: 0.2748 Accuracy: 0.9216

Epoch 10/24
----------
train- Loss: 0.2825 Accuracy: 0.8852
```

```
val- Loss: 0.2603 Accuracy: 0.9281

Epoch 11/24
----------
train- Loss: 0.2884 Accuracy: 0.8607
val- Loss: 0.2426 Accuracy: 0.9281

Epoch 12/24
----------
train- Loss: 0.2042 Accuracy: 0.9180
val- Loss: 0.2577 Accuracy: 0.9281

Epoch 13/24
----------
train- Loss: 0.2788 Accuracy: 0.8770
val- Loss: 0.2336 Accuracy: 0.9346

Epoch 14/24
----------
train- Loss: 0.2652 Accuracy: 0.8934
val- Loss: 0.2368 Accuracy: 0.9281

Epoch 15/24
----------
train- Loss: 0.2566 Accuracy: 0.9057
val- Loss: 0.2320 Accuracy: 0.9281

Epoch 16/24
----------
train- Loss: 0.3060 Accuracy: 0.8730
val- Loss: 0.2338 Accuracy: 0.9412

Epoch 17/24
----------
train- Loss: 0.3132 Accuracy: 0.8934
val- Loss: 0.2471 Accuracy: 0.9216

Epoch 18/24
----------
train- Loss: 0.2000 Accuracy: 0.9262
val- Loss: 0.2300 Accuracy: 0.9346

Epoch 19/24
----------
train- Loss: 0.2233 Accuracy: 0.9016
val- Loss: 0.2212 Accuracy: 0.9346

Epoch 20/24
```

```
----------
train- Loss: 0.2678 Accuracy: 0.8689
val- Loss: 0.2319 Accuracy: 0.9346

Epoch 21/24
----------
train- Loss: 0.2537 Accuracy: 0.9057
val- Loss: 0.2264 Accuracy: 0.9346

Epoch 22/24
----------
train- Loss: 0.2131 Accuracy: 0.9262
val- Loss: 0.2360 Accuracy: 0.9281

Epoch 23/24
----------
train- Loss: 0.2720 Accuracy: 0.8730
val- Loss: 0.2320 Accuracy: 0.9346

Epoch 24/24
----------
train- Loss: 0.3468 Accuracy: 0.8402
val- Loss: 0.2212 Accuracy: 0.9412

Training complete in 13m 11s
Best val Accuracy: 0.9412
```

(b) Network as a feature extracter

[36]:
```
model_conv = torchvision.models.resnet18(pretrained=True)
for param in model_conv.parameters():
    param.requires_grad = False

num_ftrs = model_conv.fc.in_features
model_conv.fc = nn.Linear(num_ftrs, 2)

model_conv = model_conv.to(device)
criterion = nn.CrossEntropyLoss()

optimizer_conv = optim.SGD(model_conv.fc.parameters(), lr=0.001, momentum=0.9)

exp_lr_scheduler = lr_scheduler.StepLR(optimizer_conv, step_size=7, gamma=0.1)

model_conv = train_model(model_conv, criterion, optimizer_conv,
 exp_lr_scheduler, num_epochs=25)
```

```
Epoch 0/24
----------
train- Loss: 0.5542 Accuracy: 0.7172
```

```
val- Loss: 0.2496 Accuracy: 0.9085

Epoch 1/24
----------
train- Loss: 0.4786 Accuracy: 0.7541
val- Loss: 0.1975 Accuracy: 0.9216

Epoch 2/24
----------
train- Loss: 0.4831 Accuracy: 0.7910
val- Loss: 0.5865 Accuracy: 0.7778

Epoch 3/24
----------
train- Loss: 0.4871 Accuracy: 0.7664
val- Loss: 0.2344 Accuracy: 0.9150

Epoch 4/24
----------
train- Loss: 0.5491 Accuracy: 0.7541
val- Loss: 0.2346 Accuracy: 0.9216

Epoch 5/24
----------
train- Loss: 0.5867 Accuracy: 0.7541
val- Loss: 0.3169 Accuracy: 0.8889

Epoch 6/24
----------
train- Loss: 0.3908 Accuracy: 0.8197
val- Loss: 0.2522 Accuracy: 0.9085

Epoch 7/24
----------
train- Loss: 0.3870 Accuracy: 0.8238
val- Loss: 0.2197 Accuracy: 0.9216

Epoch 8/24
----------
train- Loss: 0.3586 Accuracy: 0.8443
val- Loss: 0.1810 Accuracy: 0.9412

Epoch 9/24
----------
train- Loss: 0.3468 Accuracy: 0.8197
val- Loss: 0.1811 Accuracy: 0.9477

Epoch 10/24
```

```
----------
train- Loss: 0.3483 Accuracy: 0.8443
val- Loss: 0.1770 Accuracy: 0.9281

Epoch 11/24
----------
train- Loss: 0.3391 Accuracy: 0.8443
val- Loss: 0.1689 Accuracy: 0.9412

Epoch 12/24
----------
train- Loss: 0.3749 Accuracy: 0.8197
val- Loss: 0.1942 Accuracy: 0.9412

Epoch 13/24
----------
train- Loss: 0.3013 Accuracy: 0.8607
val- Loss: 0.1868 Accuracy: 0.9412

Epoch 14/24
----------
train- Loss: 0.2513 Accuracy: 0.8934
val- Loss: 0.1828 Accuracy: 0.9412

Epoch 15/24
----------
train- Loss: 0.2469 Accuracy: 0.9057
val- Loss: 0.1729 Accuracy: 0.9477

Epoch 16/24
----------
train- Loss: 0.2748 Accuracy: 0.9016
val- Loss: 0.2437 Accuracy: 0.9216

Epoch 17/24
----------
train- Loss: 0.2543 Accuracy: 0.9016
val- Loss: 0.1866 Accuracy: 0.9346

Epoch 18/24
----------
train- Loss: 0.3329 Accuracy: 0.8525
val- Loss: 0.1675 Accuracy: 0.9412

Epoch 19/24
----------
train- Loss: 0.3754 Accuracy: 0.8484
val- Loss: 0.1705 Accuracy: 0.9412
```

```
Epoch 20/24
----------
train- Loss: 0.3203 Accuracy: 0.8525
val- Loss: 0.2097 Accuracy: 0.9216

Epoch 21/24
----------
train- Loss: 0.2706 Accuracy: 0.8811
val- Loss: 0.1968 Accuracy: 0.9281

Epoch 22/24
----------
train- Loss: 0.2644 Accuracy: 0.8934
val- Loss: 0.2084 Accuracy: 0.9216

Epoch 23/24
----------
train- Loss: 0.3636 Accuracy: 0.8484
val- Loss: 0.1918 Accuracy: 0.9281

Epoch 24/24
----------
train- Loss: 0.2513 Accuracy: 0.8975
val- Loss: 0.2239 Accuracy: 0.9281

Training complete in 8m 4s
Best val Accuracy: 0.9477
```