DAT565/DIT407 Assignment 6

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This paper is addressing the assignment 6 study queries within the *Introduction to Data Science & AI* course, DIT407 at the University of Gothenburg and DAT565 at Chalmers. The main source of information for this project is derived from the lectures and Skiena [1]. Assignment 6 is about neural networks.

Problem 1: The dataset

The dataset comprises 60,000 training images and 10,000 test images, each measuring 28x28 pixels and in grayscale. Every image is associated with a digit label indicating its value. Figure 1 displays a random selection of images from the dataset.

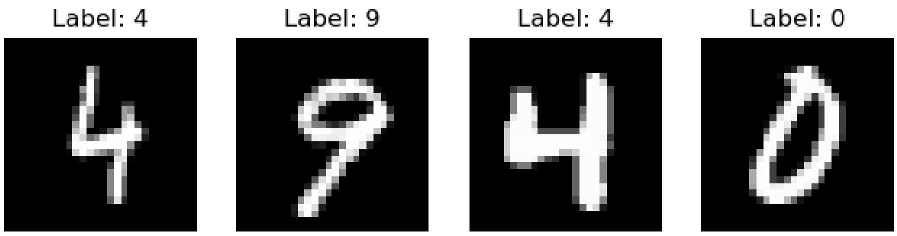

Figure 1: MNIST images

Problem 2: Single hidden layer

The neural network featuring a single hidden layer encompasses 784 input nodes (28x28), 300 hidden nodes, and 10 output nodes. The ReLU function serves as the activation function for the hidden layer, complemented by batch normalization. For the output layer, a logarithmic softmax function is utilized.

Tables 1 and Figure 2 illustrate the metrics for the single hidden layer model. The training loss pertains to the loss observed during training, while the test loss represents the loss incurred during testing. Test accuracy denotes the accuracy achieved on the test dataset.

Epoch	Training Loss	Test Loss	Test Accuracy
1	0.2200	0.1065	0.9695
2	0.1057	0.0921	0.9725
3	0.0768	0.0728	0.9765
4	0.0613	0.0666	0.9793
5	0.0497	0.0643	0.9791
6	0.0421	0.0639	0.9798
7	0.0355	0.0628	0.9811
8	0.0309	0.0569	0.9823
9	0.0279	0.0616	0.9796
10	0.0225	0.0590	0.9816

Table 1: Metrics for single hidden layer

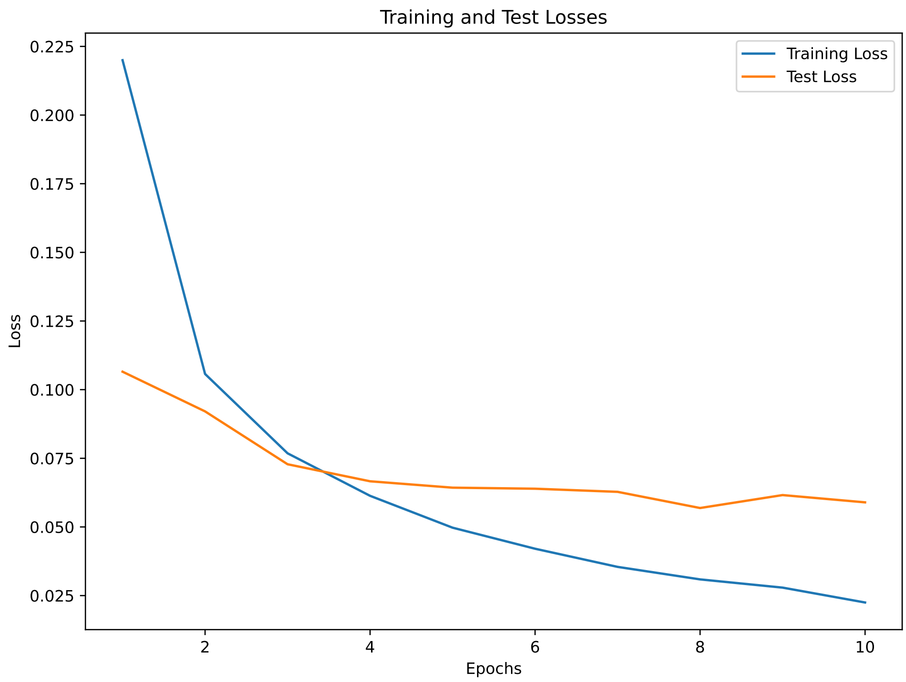

Figure 2: Single hidden layer

Problem 3: Two hidden layers

The neural network with two hidden layers comprises 784 input nodes (28x28), 500 nodes in the first hidden layer, 300 nodes in the second hidden layer, and 10 output nodes. It shares the same layer architecture as the single hidden layer model. During training, the optimizer is configured with a weight decay of 0.0001.

Tables 2 and Figure 3 showcase the metrics for the two hidden layers model.

Epoch	Training Loss	Test Loss	Test Accuracy
1	0.1935	0.0757	0.9759
2	0.0892	0.0623	0.9795
3	0.0633	0.0592	0.9803
4	0.0477	0.0558	0.9823
5	0.0390	0.0574	0.9817
6	0.0319	0.0553	0.9830
7	0.0262	0.0526	0.9826
8	0.0226	0.0561	0.9815
9	0.0199	0.0549	0.9833
10	0.0175	0.0530	0.9845
11	0.0176	0.0549	0.9835
12	0.0136	0.0515	0.9846
13	0.0120	0.0499	0.9853
14	0.0111	0.0526	0.9846
15	0.0122	0.0550	0.9827
16	0.0103	0.0484	0.9851
17	0.0097	0.0526	0.9839
18	0.0082	0.0496	0.9854
19	0.0086	0.0507	0.9853
20	0.0073	0.0482	0.9859
21	0.0091	0.0498	0.9853
22	0.0083	0.0522	0.9839
23	0.0095	0.0496	0.9849
24	0.0086	0.0507	0.9840
25	0.0080	0.0567	0.9838
26	0.0065	0.0485	0.9851
27	0.0069	0.0510	0.9843
28	0.0073	0.0520	0.9840
29	0.0069	0.0535	0.9837
30	0.0056	0.0482	0.9856
31	0.0061	0.0513	0.9851
32	0.0068	0.0498	0.9847
33	0.0047	0.0517	0.9848
34	0.0058	0.0497	0.9856
35	0.0072	0.0508	0.9849
36	0.0075	0.0501	0.9842
37	0.0061	0.0477	0.9855
38	0.0063	0.0489	0.9854
39	0.0052	0.0486	0.9848
40	0.0058	0.0490	0.9856

Table 2: Metrics for two hidden layers

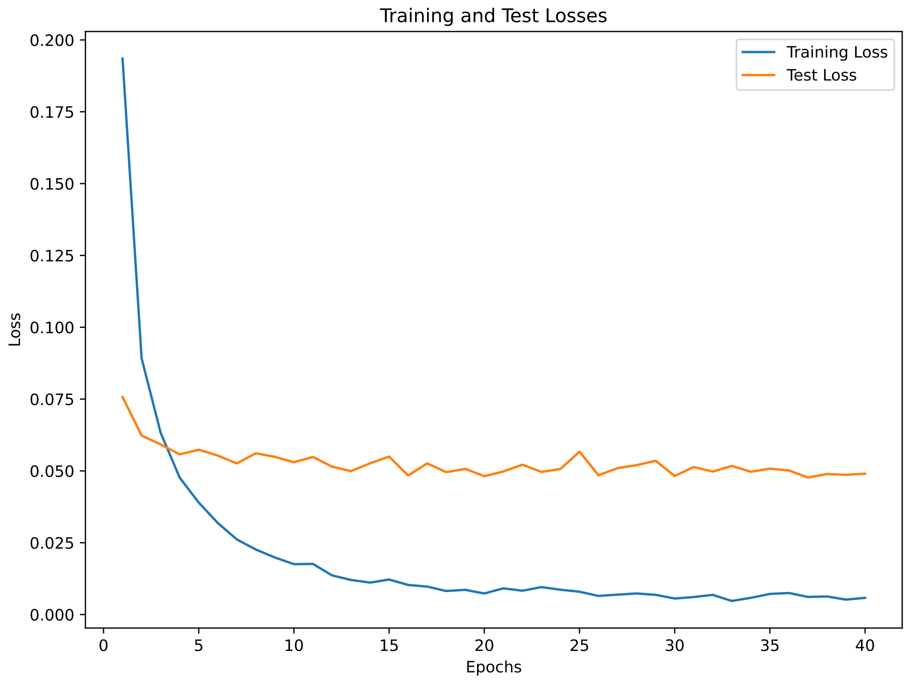

Figure 3: Two hidden layers

Problem 4: Convolutional neural network

The CNN model consists of two convolutional layers, each followed by a max-pooling layer, and two fully connected layers. The output layer utilizes logarithmic softmax activation. The first convolutional layer has 16 output channels, and the second has 32 output channels. The fully connected layers have 128 and 10 neurons, respectively. Performance metrics for the CNN model are detailed in Tables 3 and Figure 4

Epoch	Training Loss	Test Loss	Test Accuracy
1	0.1771	0.0477	0.9839
2	0.0459	0.0328	0.9896
3	0.0324	0.0306	0.9888
4	0.0239	0.0334	0.9906
5	0.0188	0.0275	0.9913
6	0.0150	0.0276	0.9911
7	0.0117	0.0275	0.9915
8	0.0100	0.0277	0.9910
9	0.0074	0.0253	0.9914
10	0.0055	0.0303	0.9909
11	0.0050	0.0270	0.9921
12	0.0044	0.0316	0.9917
13	0.0027	0.0297	0.9918
14	0.0037	0.0278	0.9913
15	0.0021	0.0263	0.9922
16	0.0016	0.0268	0.9918
17	0.0009	0.0262	0.9918
18	0.0009	0.0246	0.9920
19	0.0007	0.0256	0.9923
20	0.0005	0.0263	0.9922
21	0.0006	0.0254	0.9925
22	0.0005	0.0245	0.9926
23	0.0005	0.0251	0.9919
24	0.0005	0.0244	0.9928
25	0.0006	0.0248	0.9921
26	0.0006	0.0259	0.9921
27	0.0020	0.0257	0.9924
28	0.0027	0.0268	0.9918
29	0.0032	0.0371	0.9891
30	0.0032	0.0275	0.9913
31	0.0046	0.0283	0.9920
32	0.0022	0.0298	0.9913
33	0.0016	0.0273	0.9922
34	0.0007	0.0318	0.9906
35	0.0006	0.0257	0.9925
36	0.0004	0.0256	0.9928
37	0.0004	0.0258	0.9924
38	0.0004	0.0252	0.9925
39	0.0004	0.0247	0.9922
40	0.0005	0.0249	0.9930

Table 3: Metrics for Convolutional neural network

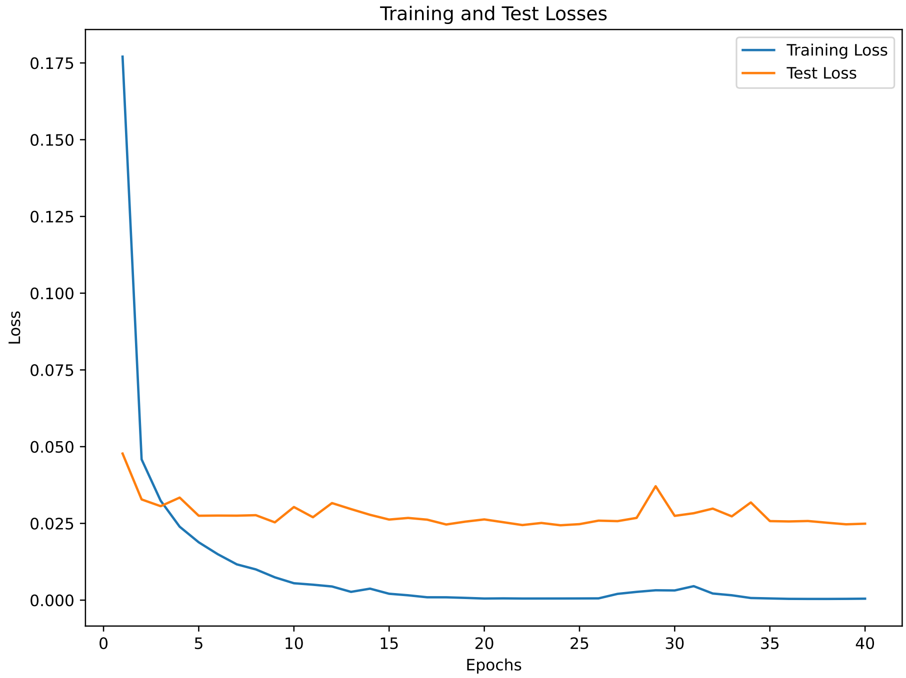

Figure 4: Convolutional neural network

References

[1] Steven S Skiena. *The Data Science Design Manual*. Retrieved 2024-01-20. 2024. URL: https://ebookcentral.proquest.com/lib/gu/detail.action?docID=6312797.

Appendix: Source Code

```python
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from torchvision import datasets
from torch.utils.data import DataLoader


class NeuralNet(nn.Module):
    def __init__(self, input_size, hidden_sizes, output_size):
        super(NeuralNet, self).__init__()
        layer_sizes = [input_size] + hidden_sizes + [output_size]

        layers = []
        for i in range(len(layer_sizes) - 1):
            layers.append(nn.Linear(layer_sizes[i], layer_sizes[i+1]))
            if i < len(layer_sizes) - 2:  # Add ReLU and batch normalization except for the last layer
                layers.append(nn.BatchNorm1d(layer_sizes[i+1]))
                layers.append(nn.ReLU())
            else:
                layers.append(nn.LogSoftmax(dim=1)) #layers.append(nn.Softmax(dim=1))


        self.model = nn.Sequential(*layers)

    def forward(self, x):
        x = x.view(-1, 28 * 28)
        x = self.model(x)
        return x

class CNN(nn.Module):
    def __init__(self):
        super(CNN, self).__init__()
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=16, kernel_size=3, stride=1, padding=1)
        self.conv2 = nn.Conv2d(in_channels=16, out_channels=32, kernel_size=3, stride=1, padding=1)
        self.fc1 = nn.Linear(32 * 7 * 7, 128)
        self.fc2 = nn.Linear(128, 10)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        x = F.max_pool2d(x, kernel_size=2, stride=2)
```

```python
        x = F.relu(self.conv2(x))
        x = F.max_pool2d(x, kernel_size=2, stride=2)
        x = x.view(-1, 32 * 7 * 7)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        x = F.log_softmax(x, dim=1)
        return x

def plot_images(dataloader, classes):

    for images, labels in train_loader:
        print("Image shape:", images.size())
        print("Label shape:", labels.size())

        fig = plt.figure(figsize=(10, 10))
        for i in range(4):
            plt.subplot(5, 5, i + 1)
            plt.imshow(images[i].squeeze(), cmap='gray')
            plt.title(f'Label: {labels[i]}')
            plt.axis('off')
        plt.show()
        fig.savefig('mnist_images.png', bbox_inches='tight')
        break



def train(model, criterion, optimizer, train_loader, test_loader, num_epochs, name):
    train_losses = []
    test_losses = []

    for epoch in range(num_epochs):
        model.train()
        running_loss = 0.0

        for images, labels in train_loader:
            outputs = model(images)
            loss = criterion(outputs, labels)

            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

            running_loss += loss.item()


        epoch_loss = running_loss / len(train_loader)
        train_losses.append(epoch_loss)

        model.eval()
        correct = 0
        total = 0
        test_loss = 0.0
        with torch.no_grad():
            for images, labels in test_loader:
                outputs = model(images)
                _, predicted = torch.max(outputs, 1)
                correct += (predicted == labels).sum().item()
                total += labels.size(0)
                loss = criterion(outputs, labels)
                test_loss += loss.item()
        accuracy = correct / total
```

```python
        test_loss /= len(test_loader)
        test_losses.append(test_loss)

        print(f"Epoch [{epoch+1}/{num_epochs}], Training Loss: {epoch_loss:.4f}, Test Loss: {test_loss:.4f}, Test Accuracy: {accuracy:.4f}")


    fig, ax = plt.subplots(figsize=(8, 6), layout='constrained')
    ax.plot(range(1, num_epochs + 1), train_losses, label='Training Loss')
    ax.plot(range(1, num_epochs + 1), test_losses, label='Test Loss')
    ax.set_xlabel('Epochs')
    ax.set_ylabel('Loss')
    ax.set_title('Training and Test Losses')
    ax.legend()
    plt.show()
    fig.savefig(name + ".pdf", bbox_inches='tight')


# Importing the dataset
batch_size = 32
transform = transforms.Compose([
    transforms.Resize((28, 28)),
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

train_dataset = datasets.MNIST(root='Assignment6/', train=True, download=True, transform=transform)
test_dataset = datasets.MNIST(root='Assignment6/', train=False, download=True, transform=transform)

train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, num_workers=2)
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, num_workers=2)

print("train dataset: ", len(train_dataset))
print("test dataset: ", len(test_dataset))


# Single hidden layer
input_size = 28 * 28
hidden_sizes = [300]
output_size = 10

modelSHL = NeuralNet(input_size, hidden_sizes, output_size)
learning_rate = 0.1
optimizer = optim.SGD(modelSHL.parameters(), lr=learning_rate)
num_epochs = 10
criterion = nn.CrossEntropyLoss()

train(modelSHL, criterion, optimizer, train_loader, test_loader, num_epochs, "single_hidden_layer")


# Two hidden layers
hidden_sizes = [500, 300]
weight_decay = 0.0001
modelTHL = NeuralNet(input_size, hidden_sizes, output_size)
```

```
optimizer = optim.SGD(modelTHL.parameters(), lr=learning_rate, weight_decay=weight_decay)
num_epochs = 40

train(modelTHL, criterion, optimizer, train_loader, test_loader, num_epochs, "two_hidden_layer")


# Convolutional neural network
modelCNN = CNN()
weight_decay = 0.0001
optimizer = optim.SGD(modelCNN.parameters(), lr=learning_rate, weight_decay=weight_decay)
num_epochs = 40

train(modelCNN, criterion, optimizer, train_loader, test_loader, num_epochs, "cnn")
```