```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
from torchvision import datasets, transforms
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
import seaborn as sns
import numpy as np


# Define the MLP model with ReLU activation
class Pytorch_MLP(nn.Module):
    def __init__(self, input_size, hidden_size_1, hidden_size_2, hidden_size_3, num
        super(Pytorch_MLP, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size_1)
        self.relu = nn.ReLU()
        self.fc2 = nn.Linear(hidden_size_1, hidden_size_2)
        self.fc3 = nn.Linear(hidden_size_2, hidden_size_3)
        self.fc4 = nn.Linear(hidden_size_3, num_classes)

    def forward(self, x):
        out = self.fc1(x)
        out = self.relu(out)
        out = self.fc2(out)
        out = self.relu(out)
        out = self.fc3(out)
        out = self.relu(out)
        out = self.fc4(out)
        return out

# Parameters
input_size = 784
hidden1_layer = 500
hidden2_layer = 250
hidden3_layer = 100
num_classes = 10
num_epochs = 15
batch_size = 64
learning_rate = 0.01


# MNIST Dataset (images and labels)
train_data = datasets.MNIST(root='data', train=True, transform=transforms.ToTenso
test_data = datasets.MNIST(root='data', train=False, transform=transforms.ToTenso
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Failed to download (trying next):
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```
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-idx3-ul
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-idx3-ul
100%|██████████| 9912422/9912422 [00:00<00:00, 11170513.05it/s]
Extracting data/MNIST/raw/train-images-idx3-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-idx1-ul
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-idx1-ul
100%|██████████| 28881/28881 [00:00<00:00, 2023447.26it/s]Extracting data/MNIS

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz

Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-idx3-uby
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-idx3-uby
100%|██████████| 1648877/1648877 [00:00<00:00, 3740029.98it/s]
Extracting data/MNIST/raw/t10k-images-idx3-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

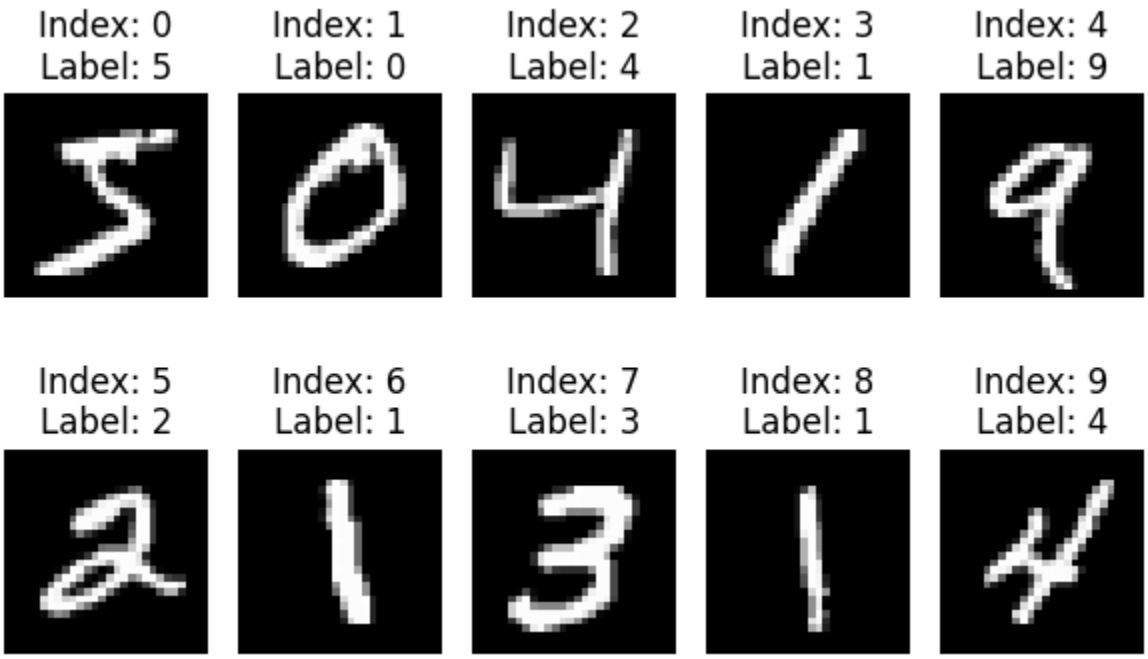
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-idx1-uby
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-idx1-uby
100%|██████████| 4542/4542 [00:00<00:00, 3202307.74it/s]
Extracting data/MNIST/raw/t10k-labels-idx1-ubyte.gz to data/MNIST/raw
```

```
# Data loaders
train_loader = DataLoader(dataset=train_data, batch_size=batch_size, shuffle=True
test_loader = DataLoader(dataset=test_data, batch_size=batch_size, shuffle=False)
```

```
# Visualizing the data
fig, axes = plt.subplots(2, 5, figsize=(6, 4))  # 2 rows, 5 columns

for i in range(10):          # Loop through the first 10 images
  ax = axes[i // 5, i % 5]  # Determine the position of the subplot (row, column)

  ax.imshow(train_data.data[i], cmap='gray') # Display each image in grayscale
  ax.set_title(f"Index: {i}\nLabel: {train_data.targets[i].item()}")
  ax.axis('off')
plt.tight_layout() # Adjust layout to prevent overlap of titles
plt.show()
```




```
# Initialize the model, loss function, and optimizer
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model = Pytorch_MLP(input_size, hidden1_layer, hidden2_layer, hidden3_layer, num_
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=learning_rate)
```

```
# For plotting
train_losses = []
test_losses = []

# Training loop
for epoch in range(num_epochs):
    model.train()
    running_loss = 0.0
    for batch_idx, (images, labels) in enumerate(train_loader):
        # Reshape images to (batch_size, input_size)
        images = images.view(-1, 28*28).to(device).float()  # Ensure images are f
        labels = labels.to(device)  # Keep labels as class indices

        outputs = model(images) # Forward pass
        loss = criterion(outputs, labels)

        optimizer.zero_grad() # Backward pass and optimize
        loss.backward()
        optimizer.step()

        running_loss += loss.item()
```

```
    if (batch_idx + 1) % 100 == 0:
        print(f'Epoch [{epoch + 1}/{num_epochs}], Step [{batch_idx + 1}/{len(

avg_train_loss = running_loss / len(train_loader)
train_losses.append(avg_train_loss)
print(f'Epoch [{epoch + 1}/{num_epochs}], Average Training Loss: {avg_train_l

# Calculate test loss
model.eval()
test_loss = 0.0
with torch.no_grad():
    for images, labels in test_loader:
        images = images.view(-1, 28*28).to(device).float()  # Ensure images a
        labels = labels.to(device)  # Keep labels as class indices
        outputs = model(images)
        loss = criterion(outputs, labels)
        test_loss += loss.item()

avg_test_loss = test_loss / len(test_loader)
test_losses.append(avg_test_loss)
print(f'Epoch [{epoch + 1}/{num_epochs}], Average Test Loss: {avg_test_loss:.
```

```
Epoch [1/15], Step [100/938], Loss: 0.0877
Epoch [1/15], Step [200/938], Loss: 0.1450
Epoch [1/15], Step [300/938], Loss: 0.3208
Epoch [1/15], Step [400/938], Loss: 0.1866
Epoch [1/15], Step [500/938], Loss: 0.0731
Epoch [1/15], Step [600/938], Loss: 0.1485
Epoch [1/15], Step [700/938], Loss: 0.3273
Epoch [1/15], Step [800/938], Loss: 0.0994
Epoch [1/15], Step [900/938], Loss: 0.3205
Epoch [1/15], Average Training Loss: 0.2757
Epoch [1/15], Average Test Loss: 0.1828
Epoch [2/15], Step [100/938], Loss: 0.1551
Epoch [2/15], Step [200/938], Loss: 0.1546
Epoch [2/15], Step [300/938], Loss: 0.0784
Epoch [2/15], Step [400/938], Loss: 0.2538
Epoch [2/15], Step [500/938], Loss: 0.1351
Epoch [2/15], Step [600/938], Loss: 0.2934
Epoch [2/15], Step [700/938], Loss: 0.1648
Epoch [2/15], Step [800/938], Loss: 0.1890
Epoch [2/15], Step [900/938], Loss: 0.1435
Epoch [2/15], Average Training Loss: 0.1668
Epoch [2/15], Average Test Loss: 0.1822
Epoch [3/15], Step [100/938], Loss: 0.2333
Epoch [3/15], Step [200/938], Loss: 0.1188
Epoch [3/15], Step [300/938], Loss: 0.2275
Epoch [3/15], Step [400/938], Loss: 0.0657
Epoch [3/15], Step [500/938], Loss: 0.0869
Epoch [3/15], Step [600/938], Loss: 0.1753
Epoch [3/15], Step [700/938], Loss: 0.0721
Epoch [3/15], Step [800/938], Loss: 0.0803
Epoch [3/15], Step [900/938], Loss: 0.1338
```

```
Epoch [3/15], Step [900/938], Loss: 0.1328
Epoch [3/15], Average Training Loss: 0.1452
Epoch [3/15], Average Test Loss: 0.1706
Epoch [4/15], Step [100/938], Loss: 0.2435
Epoch [4/15], Step [200/938], Loss: 0.0380
Epoch [4/15], Step [300/938], Loss: 0.1155
Epoch [4/15], Step [400/938], Loss: 0.0534
Epoch [4/15], Step [500/938], Loss: 0.0309
Epoch [4/15], Step [600/938], Loss: 0.1221
Epoch [4/15], Step [700/938], Loss: 0.1110
Epoch [4/15], Step [800/938], Loss: 0.2638
Epoch [4/15], Step [900/938], Loss: 0.0733
Epoch [4/15], Average Training Loss: 0.1329
Epoch [4/15], Average Test Loss: 0.1633
Epoch [5/15], Step [100/938], Loss: 0.1904
Epoch [5/15], Step [200/938], Loss: 0.0773
Epoch [5/15], Step [300/938], Loss: 0.0693
Epoch [5/15], Step [400/938], Loss: 0.0409
Epoch [5/15], Step [500/938], Loss: 0.0114
Epoch [5/15], Step [600/938], Loss: 0.0844
Epoch [5/15], Step [700/938], Loss: 0.0132
Epoch [5/15], Step [800/938], Loss: 0.1053
Epoch [5/15], Step [900/938], Loss: 0.1556
Epoch [5/15], Average Training Loss: 0.1253
Epoch [5/15], Average Test Loss: 0.1339
Epoch [6/15], Step [100/938], Loss: 0.2201
Epoch [6/15], Step [200/938], Loss: 0.4536
Epoch [6/15], Step [300/938], Loss: 0.1432
```

```
# Plot training and test loss
plt.figure(figsize=(12, 6))
plt.plot(train_losses, label='Training Loss')
plt.plot(test_losses, label='Test Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training and Test Loss')
plt.legend()
plt.show()

# Testing loop
model.eval()
with torch.no_grad():
    correct = 0
    total = 0
    all_labels = []
    all_preds = []
    for images, labels in test_loader:
        images = images.view(-1, 28*28).to(device).float()  # Ensure images are f
        labels = labels.to(device)  # Keep labels as class indices
        outputs = model(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
```

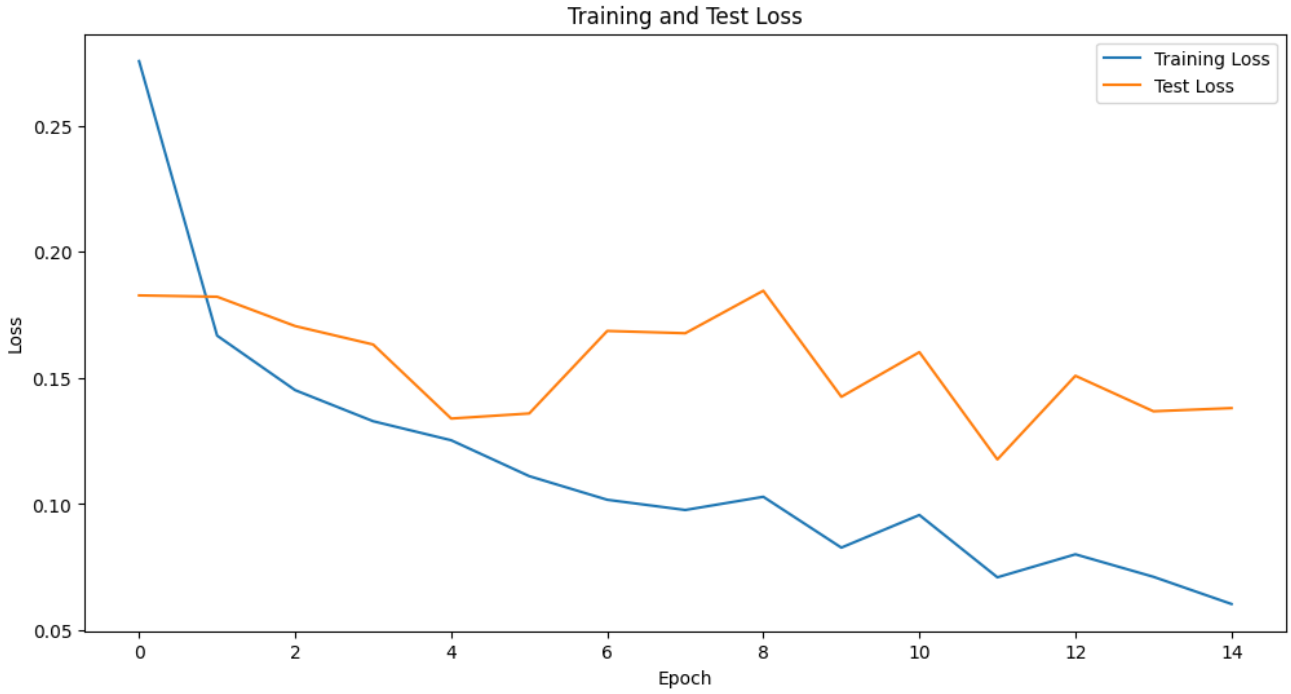
```
        all_labels.extend(labels.cpu().numpy())
        all_preds.extend(predicted.cpu().numpy())

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

# Confusion Matrix
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=range(10), yti
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

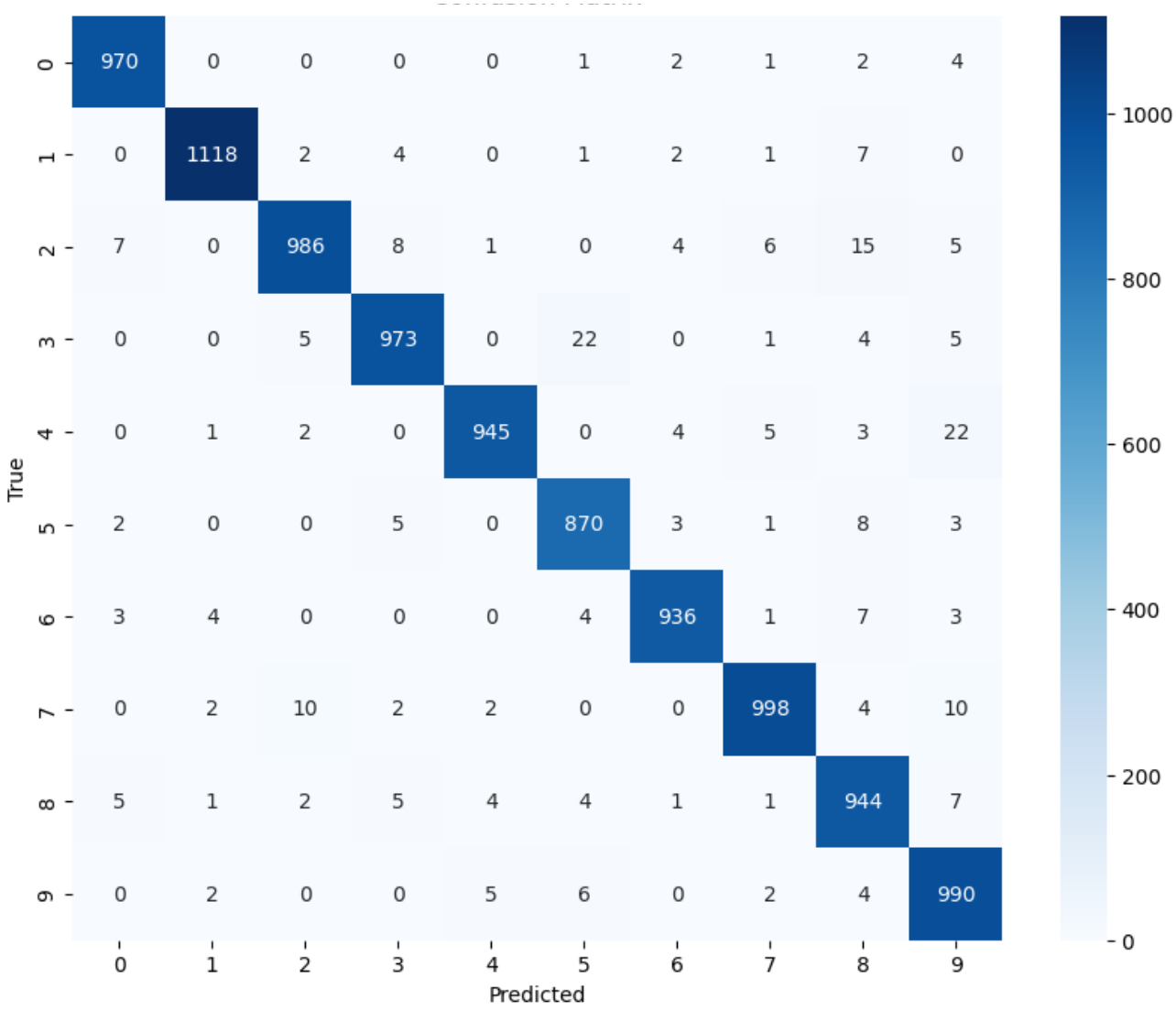
# Training Accuracy
correct_train = 0
total_train = 0
with torch.no_grad():
    for images, labels in train_loader:
        images = images.view(-1, 28*28).to(device).float()  # Ensure images a
        labels = labels.to(device)  # Keep labels as class indices
        outputs = model(images)
        _, predicted = torch.max(outputs.data, 1)
        total_train += labels.size(0)
        correct_train += (predicted == labels).sum().item()

train_accuracy = 100 * correct_train / total_train
print(f'Training Accuracy: {train_accuracy:.2f}%')
```




```
Test Accuracy: 97.30%
```

Confusion Matrix




```
Training Accuracy: 98.86%
```

Weight decay for L2 regularization

```
# Parameters
input_size = 784
hidden1_layer = 500
hidden2_layer = 250
hidden3_layer = 100
num_classes = 10
num_epochs = 15
batch_size = 64
learning_rate = 0.01
weight_decay = 0.001  # L2 regularization term


# Initialize the model, loss function, and optimizer
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model = Pytorch_MLP(input_size, hidden1_layer, hidden2_layer, hidden3_layer, num_
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=learning_rate, weight_decay=weight_


# For plotting
train_losses = []
test_losses = []



# Training loop
for epoch in range(num_epochs):
    model.train()
    running_loss = 0.0
    for batch_idx, (images, labels) in enumerate(train_loader):
        # Reshape images to (batch_size, input_size)
        images = images.view(-1, 28*28).to(device).float()  # Ensure images are f
        labels = labels.to(device)  # Keep labels as class indices

        # Forward pass
        outputs = model(images)
        loss = criterion(outputs, labels)

        # Backward pass and optimize
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

        if (batch_idx + 1) % 100 == 0:
            print(f'Epoch [{epoch + 1}/{num_epochs}], Step [{batch_idx + 1}/{len(

    avg_train_loss = running_loss / len(train_loader)
    train_losses.append(avg_train_loss)
    print(f'Epoch [{epoch + 1}/{num_epochs}], Average Training Loss: {avg_train_l

    # Calculate test loss
    model.eval()
    test_loss = 0.0
    with torch.no_grad():
        for images, labels in test_loader:
            images = images.view(-1, 28*28).to(device).float()  # Ensure images a
            labels = labels.to(device)  # Keep labels as class indices
            outputs = model(images)
            loss = criterion(outputs, labels)
            test_loss += loss.item()

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

```
        test_losses.append(avg_test_loss)
        print(f'Epoch [{epoch + 1}/{num_epochs}], Average Test Loss: {avg_test_loss:.

    # Plot training and test loss
    plt.figure(figsize=(12, 6))
    plt.plot(train_losses, label='Training Loss')
    plt.plot(test_losses, label='Test Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.title('Training and Test Loss')
    plt.legend()
    plt.show()

    # Testing loop
    model.eval()
    with torch.no_grad():
        correct = 0
        total = 0
        all_labels = []
        all_preds = []
        for images, labels in test_loader:
            images = images.view(-1, 28*28).to(device).float()  # Ensure images are f
            labels = labels.to(device)  # Keep labels as class indices
            outputs = model(images)
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()
            all_labels.extend(labels.cpu().numpy())
            all_preds.extend(predicted.cpu().numpy())

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

        # Confusion Matrix
        cm = confusion_matrix(all_labels, all_preds)
        plt.figure(figsize=(10, 8))
        sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=range(10), yti
        plt.xlabel('Predicted')
        plt.ylabel('True')
        plt.title('Confusion Matrix')
        plt.show()

        # Training Accuracy
        correct_train = 0
        total_train = 0
        with torch.no_grad():
            for images, labels in train_loader:
                images = images.view(-1, 28*28).to(device).float()  # Ensure images a
                labels = labels.to(device)  # Keep labels as class indices
                outputs = model(images)
                _, predicted = torch.max(outputs.data, 1)
```

```
            total_train += labels.size(0)
            correct_train += (predicted == labels).sum().item()

    train_accuracy = 100 * correct_train / total_train
    print(f'Training Accuracy: {train_accuracy:.2f}%')
```

```
Epoch [1/15], Step [100/938], Loss: 0.4471
Epoch [1/15], Step [200/938], Loss: 0.4636
Epoch [1/15], Step [300/938], Loss: 0.3924
Epoch [1/15], Step [400/938], Loss: 0.5679
Epoch [1/15], Step [500/938], Loss: 0.2690
Epoch [1/15], Step [600/938], Loss: 0.3099
Epoch [1/15], Step [700/938], Loss: 0.1700
Epoch [1/15], Step [800/938], Loss: 0.1897
Epoch [1/15], Step [900/938], Loss: 0.0715
Epoch [1/15], Average Training Loss: 0.3153
Epoch [1/15], Average Test Loss: 0.2124
Epoch [2/15], Step [100/938], Loss: 0.1813
Epoch [2/15], Step [200/938], Loss: 0.1704
Epoch [2/15], Step [300/938], Loss: 0.0687
Epoch [2/15], Step [400/938], Loss: 0.2740
Epoch [2/15], Step [500/938], Loss: 0.4000
Epoch [2/15], Step [600/938], Loss: 0.1669
Epoch [2/15], Step [700/938], Loss: 0.3361
Epoch [2/15], Step [800/938], Loss: 0.2058
Epoch [2/15], Step [900/938], Loss: 0.2210
Epoch [2/15], Average Training Loss: 0.2275
Epoch [2/15], Average Test Loss: 0.2031
Epoch [3/15], Step [100/938], Loss: 0.1150
Epoch [3/15], Step [200/938], Loss: 0.1315
Epoch [3/15], Step [300/938], Loss: 0.3058
Epoch [3/15], Step [400/938], Loss: 0.4612
Epoch [3/15], Step [500/938], Loss: 0.3596
Epoch [3/15], Step [600/938], Loss: 0.1647
Epoch [3/15], Step [700/938], Loss: 0.1193
Epoch [3/15], Step [800/938], Loss: 0.0916
Epoch [3/15], Step [900/938], Loss: 0.2691
Epoch [3/15], Average Training Loss: 0.2130
Epoch [3/15], Average Test Loss: 0.2038
Epoch [4/15], Step [100/938], Loss: 0.1673
Epoch [4/15], Step [200/938], Loss: 0.1708
Epoch [4/15], Step [300/938], Loss: 0.1233
Epoch [4/15], Step [400/938], Loss: 0.3423
Epoch [4/15], Step [500/938], Loss: 0.3483
Epoch [4/15], Step [600/938], Loss: 0.2386
Epoch [4/15], Step [700/938], Loss: 0.0916
Epoch [4/15], Step [800/938], Loss: 0.1166
Epoch [4/15], Step [900/938], Loss: 0.1885
Epoch [4/15], Average Training Loss: 0.2059
Epoch [4/15], Average Test Loss: 0.1789
Epoch [5/15], Step [100/938], Loss: 0.1941
Epoch [5/15], Step [200/938], Loss: 0.2009
```

```
Epoch [5/15], Step [200/938], Loss: 0.2909
Epoch [5/15], Step [300/938], Loss: 0.4484
Epoch [5/15], Step [400/938], Loss: 0.1522
Epoch [5/15], Step [500/938], Loss: 0.3480
Epoch [5/15], Step [600/938], Loss: 0.1398
Epoch [5/15], Step [700/938], Loss: 0.2846
Epoch [5/15], Step [800/938], Loss: 0.1604
Epoch [5/15], Step [900/938], Loss: 0.1965
Epoch [5/15], Average Training Loss: 0.2015
Epoch [5/15], Average Test Loss: 0.1572
Epoch [6/15], Step [100/938], Loss: 0.0758
Epoch [6/15], Step [200/938], Loss: 0.1788
Epoch [6/15], Step [300/938], Loss: 0.0488
Epoch [6/15], Step [400/938], Loss: 0.1959
Epoch [6/15], Step [500/938], Loss: 0.1849
Epoch [6/15], Step [600/938], Loss: 0.2426
Epoch [6/15], Step [700/938], Loss: 0.1535
Epoch [6/15], Step [800/938], Loss: 0.2497
Epoch [6/15], Step [900/938], Loss: 0.0675
Epoch [6/15], Average Training Loss: 0.2017
Epoch [6/15], Average Test Loss: 0.1879
Epoch [7/15], Step [100/938], Loss: 0.2086
Epoch [7/15], Step [200/938], Loss: 0.2914
Epoch [7/15], Step [300/938], Loss: 0.4106
Epoch [7/15], Step [400/938], Loss: 0.1394
Epoch [7/15], Step [500/938], Loss: 0.1785
Epoch [7/15], Step [600/938], Loss: 0.1311
Epoch [7/15], Step [700/938], Loss: 0.3142
Epoch [7/15], Step [800/938], Loss: 0.1611
Epoch [7/15], Step [900/938], Loss: 0.1985
Epoch [7/15], Average Training Loss: 0.1925
Epoch [7/15], Average Test Loss: 0.1746
```