model.eval()

test\_loss = 0.0
with torch.no\_grad():
 for images, labels in test\_loader:

images, labels = images.to(device), labels.to(device)
outputs = model(images)
loss = criterion(outputs, labels)

print(f"Epoch[{epoch+1}/{num\_epochs}, Train Loss:{train\_losses[-1]:.4f}, Test Loss:{test\_losses[-1]:.4f}")

train\_losses, test\_losses = train\_and\_evaluate(model, train\_loader, test\_loader, criterion, optimizer, num\_epochs)

test\_loss += loss.item() \* len(images)
test\_losses.append(test\_loss / len(test\_loader))

```
⊙ ↑ ↓ 占 〒 盲
         Train a VGG on MNIST dataset
          import torch.nn as nn
          import torch.optim as optim
          import torchvision.transforms as transforms
          import matplotlib.pyplot as plt
          from torch.utils.data import DataLoader
[5]: device_name = "cuda" if torch.cuda.is_available() else "cpu"
    device = torch.device(device_name)
    print(f"Device:(device_name)")
[17]: class SmallVGG(nn.Module):
              ass SmallVeG(nn.Noute):

def __init__(self):
    super(SmallVGG, self).__init__()
    self.conv_layers = nn.Sequential(
        nn.Conv2d(1, 8, kernel_size=3, padding=1), nn.ReLU(),
        nn.Conv2d(8, 16, kernel_size=3, padding=1), nn.ReLU(),
        nn.MaxPool2d(kernel_size=2, stride=2), # 14x14
                           nn.Conv2d(16, 32, kernel_size=3, padding=1), nn.ReLU(),
nn.Conv2d(32, 32, kernel_size=3, padding=1), nn.ReLU(),
nn.MaxPool2d(kernel_size=2, stride=2), # 7x7
                            nn.Conv2d(32, 32, kernel_size=3, padding=1), nn.ReLU(),
nn.Conv2d(32, 32, kernel_size=3, padding=1), nn.ReLU(),
                            nn.MaxPool2d(kernel_size=2, stride=2), # 3x3
                     self.fc layers = nn.Sequential(
                           nn.Linear(32*3*3, 256), nn.ReLU(),
nn.Linear(256, 10) # Output Layer: 10 classes
               def forward(self, x):
    x = self.conv_layers(x)
                     x = x.view(x.size(0), -1) # Flatten tensor
x = self.fc_layers(x)
          Prepare Datasets
[18]: # Defined composed transformation on the dataset
          transform = transforms.Compose(|
    transforms.Resize((28,28)),
               transforms.ToTensor()
               transforms.Normalize((0.1307,), (0.3081,))
         ])
         train_dataset = datasets.NWIST(root='./data', train=True, download=True, transform=transform)
test_dataset = datasets.NWIST(root='./data', train=False, download=True, transform=transform)
          train_loader = DataLoader(train_dataset, batch_size=128, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=128, shuffle=False)
          # Initialize Model. Loss Function and Optimizer
          # Intractize Model, Loss Function and Optimizer model = SmallVGG().to(device) criterion = nn.CrossEntropyLoss() optimizer = optim.Adam(model.parameters(), lr=0.001)
          Train and Evaluate
[22]: def train_and_evaluate(model,
                                             train_loader,
                                            test loader.
                                             optimizer,
                                            num epochs=100):
                # Record losses to plot
               train_losses = []
test_losses = []
                for epoch in range(num_epochs):
                       model.train()
running_loss = 0.0
                      for images, labels in tqdm(train loader):
                           images, labels = images.to(device), labels.to(device)
                            optimizer.zero_grad()
                            outputs = model(images)
loss = criterion(outputs, labels)
loss.backward()
                            optimizer.step()
                            running_loss += loss.item() * len(images)
                      train_losses.append(running_loss / len(train_loader))
```

	469 [00:19<00:00, 23.90it/s]
Epoch[1/20, Train Loss:36.2943, Test Loss:9.1432	
	469 [00:19<00:00, 23.68it/s]
Epoch[2/20, Train Loss:8.0915, Test Loss:5.3832	
	469 [00:19<00:00, 23.82it/s]
Epoch[3/20, Train Loss:5.5270, Test Loss:4.2761	
	469 [00:19<00:00, 23.72it/s]
Epoch[4/20, Train Loss:4.3243, Test Loss:4.1856	
100% 469/ Epoch[5/20, Train Loss:3.5566, Test Loss:3.8797	469 [00:19<00:00, 24.61it/s]
100% 469/ Epoch[6/20, Train Loss:3.1175, Test Loss:4.2280	469 [00:18<00:00, 24.98it/s]
· · · · · · · · · · · · · · · · · · ·	450 F00:40:00:00 OF 44i+/-1
Epoch[7/20, Train Loss:2.6472, Test Loss:3.5115	469 [00:18<00:00, 25.44it/s]
· ·	469 [00:19<00:00, 23.46it/s]
Epoch[8/20, Train Loss:2.1011, Test Loss:4.8168	405 [00.15(00.00, 25.4011/5]
	469 [00:19<00:00, 23.50it/s]
Epoch[9/20, Train Loss:1.9912, Test Loss:3.6292	405 [00.15(00.00, 23.5011/5]
	469 [00:19<00:00, 23.62it/s]
Epoch[10/20, Train Loss:1.8905, Test Loss:3.0222	100 [00125100100, 2510224/0]
	469 [00:19<00:00, 23.60it/s]
Epoch[11/20, Train Loss:1.6861, Test Loss:4.8750	[,,
100%	469 [00:19<00:00, 24.07it/s]
Epoch[12/20, Train Loss:1.4032, Test Loss:5.4678	
100%	469 [00:19<00:00, 24.28it/s]
Epoch[13/20, Train Loss:1.6684, Test Loss:3.7368	
100%	469 [00:18<00:00, 24.82it/s]
Epoch[14/20, Train Loss:1.3882, Test Loss:3.5021	
	469 [00:19<00:00, 24.18it/s]
Epoch[15/20, Train Loss:1.1176, Test Loss:3.6386	
	469 [00:19<00:00, 24.05it/s]
Epoch[16/20, Train Loss:1.0991, Test Loss:3.5877	
	469 [00:18<00:00, 24.73it/s]
Epoch[17/20, Train Loss:1.1092, Test Loss:6.3189	
	469 [00:19<00:00, 24.14it/s]
Epoch[18/20, Train Loss:0.9793, Test Loss:3.7140	
	469 [00:19<00:00, 23.87it/s]
Epoch[19/20, Train Loss:0.9093, Test Loss:4.7622	
	469 [00:19<00:00, 24.15it/s]
Epoch[20/20, Train Loss:1.0800, Test Loss:4.2345	

## Plot loss curves

```
[24]: plt.figure(figsize=(5,5))
plt.plot(train_losses, label="Training Loss")
plt.plot(test_losses, label="Testing Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.vitle("Training and Testing Loss Curves")
plt.legend()
plt.show()
```

## Training and Testing Loss Curves Training Loss Training Loss Testing Loss

[]: