model

December 10, 2025

[7]:
```python
# ============================================================
# Final Project: Train neural net on MNIST and evaluate on local digits
# ============================================================

import os
import glob
from io import BytesIO

import numpy as np
import matplotlib.pyplot as plt
from PIL import Image, ImageFilter, ImageEnhance

import torch
from torch import nn
import torch.nn.functional as F
from torchvision import datasets, transforms
from torch.utils.data import Dataset, Subset
from sklearn.metrics import classification_report, confusion_matrix

# ------------------------------------------------------------
# Device
# ------------------------------------------------------------
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("Using device:", device)
```

```
Using device: cpu
```

[8]:
```python
# ============================================================
# 1. Data and augmentation setup
# ============================================================


class RaiseDarkPoint(object):
    def __init__(self, grayRange=(10, 60)):
        self.grayRange = grayRange

    def __call__(self, img):
        arr = np.array(img).astype(np.float32)
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        grayVal = np.random.uniform(*self.grayRange)
        mask = arr < 30
        arr[mask] = arr[mask] + grayVal
        arr = np.clip(arr, 0, 255)
        return Image.fromarray(arr.astype(np.uint8), mode="L")


class LowerWhitePoint(object):
    def __init__(self, factorRange=(0.7, 0.95)):
        self.factorRange = factorRange

    def __call__(self, img):
        arr = np.array(img, dtype=np.float32)
        factor = float(np.random.uniform(self.factorRange[0], self.
 ↪factorRange[1]))
        arr = arr * factor
        arr = np.clip(arr, 0, 255)
        return Image.fromarray(arr.astype(np.uint8), mode="L")


class AddNoise(object):
    def __init__(self, noiseStd=0.05):
        self.noiseStd = noiseStd

    def __call__(self, img):
        arr = np.array(img).astype(np.float32)
        noise = np.random.normal(0, self.noiseStd * 255, arr.shape)
        arr = arr + noise
        arr = np.clip(arr, 0, 255)
        return Image.fromarray(arr.astype(np.uint8), mode="L")


class BubblyDigits(object):
    def __init__(self, blurRange=(0.4, 1.0), contrastRange=(1.1, 1.6)):
        self.blurRange = blurRange
        self.contrastRange = contrastRange

    def __call__(self, img):
        sigma = float(np.random.uniform(self.blurRange[0], self.blurRange[1]))
        img = img.filter(ImageFilter.GaussianBlur(radius=sigma))
        c = float(np.random.uniform(self.contrastRange[0], self.
 ↪contrastRange[1]))
        img = ImageEnhance.Contrast(img).enhance(c)
        return img


class JPEGCompression(object):
```

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    def __init__(self, qualityRange=(40, 80)):
        self.qualityRange = qualityRange

    def __call__(self, img):
        q = int(np.random.randint(self.qualityRange[0], self.qualityRange[1]))
        buf = BytesIO()
        img.save(buf, format="JPEG", quality=q)
        buf.seek(0)
        return Image.open(buf).convert("L")


trainTransform = transforms.Compose(
    [
        transforms.RandomApply(
            [
                transforms.Pad(4, fill=0),
                transforms.RandomCrop(28),
            ],
            p=0.5,
        ),
        transforms.RandomApply(
            [
                transforms.RandomAffine(
                    degrees=(-5, 20),
                    translate=(0.25, 0.25),
                    scale=(0.6, 1.1),
                    fill=0,
                )
            ],
            p=0.5,
        ),
        transforms.RandomApply([AddNoise()], p=0.1),
        transforms.RandomApply([BubblyDigits()], p=0.5),
        transforms.RandomApply([LowerWhitePoint()], p=0.4),
        transforms.RandomApply([RaiseDarkPoint()], p=0.4),
        transforms.RandomApply(
            [transforms.GaussianBlur(kernel_size=3, sigma=(0.1, 1.5))], p=1
        ),
        transforms.RandomApply([JPEGCompression()], p=0.25),
        transforms.ToTensor(),
        transforms.Normalize((0.5,), (0.5,)),
    ]
)

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

```python
def PreprocessSingle(image):
    if image.mode != "RGB":
        image = image.convert("RGB")

    blurred = image.filter(ImageFilter.GaussianBlur(radius=0.75))
    arr = np.array(blurred).astype(np.float32)
    gray = arr.mean(axis=2)

    minVal = gray.min()
    maxVal = gray.max()

    if maxVal - minVal < 1e-6:
        stretched = np.zeros_like(gray)
    else:
        stretched = (gray - minVal) / (maxVal - minVal) * 255.0

    stretched = stretched.astype(np.uint8)
    return Image.fromarray(stretched, mode="L")


# -----------------------------
# MNIST train/val/test split
# -----------------------------
fullTrainAug = datasets.MNIST(
    "~/.pytorch/MNIST_data/", download=True, train=True,␣
 ↪transform=trainTransform
)
fullTrainPlain = datasets.MNIST(
    "~/.pytorch/MNIST_data/", download=True, train=True, transform=transform
)

trainSize = int(0.9 * len(fullTrainAug))
valSize = len(fullTrainAug) - trainSize

indices = torch.randperm(len(fullTrainAug)).tolist()
trainIdx = indices[:trainSize]
valIdx = indices[trainSize:]

trainSet = Subset(fullTrainAug, trainIdx)    # with augmentation
valSet = Subset(fullTrainPlain, valIdx)      # no augmentation

trainLoader = torch.utils.data.DataLoader(trainSet, batch_size=64, shuffle=True)
valLoader = torch.utils.data.DataLoader(valSet, batch_size=64, shuffle=False)

testSet = datasets.MNIST(
```

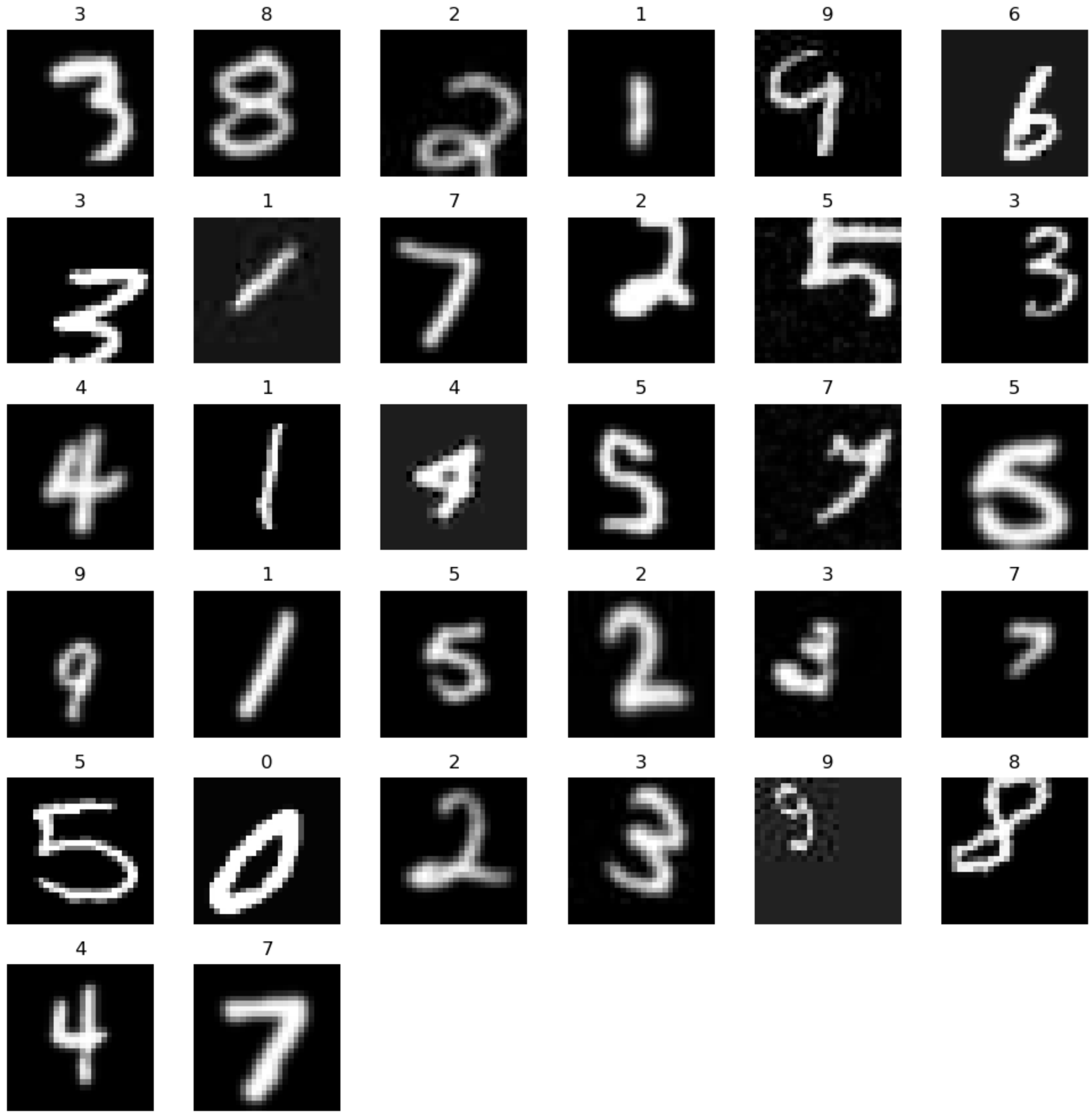
```
    "~/.pytorch/MNIST_data/", download=True, train=False, transform=transform
)
testLoader = torch.utils.data.DataLoader(testSet, batch_size=64, shuffle=False)

print("Trainloader loaded:", len(trainLoader))
print("Valloader loaded:", len(valLoader))

dataIter = iter(trainLoader)
imgs, labels = next(dataIter)
imgsVis = imgs * 0.5 + 0.5

plt.figure(figsize=(10, 10))
for i in range(32):
    plt.subplot(6, 6, i + 1)
    plt.imshow(imgsVis[i].squeeze().cpu(), cmap="gray")
    plt.title(labels[i].item())
    plt.axis("off")
plt.tight_layout()
plt.show(block=False)
plt.pause(0.001)
```

```
Trainloader loaded: 844
Valloader loaded: 94
```



[9]:
```
# ============================================================
# 2. Model definition
# ============================================================


class MNISTMLP(nn.Module):
    def __init__(self):
        super().__init__()
        self.fc1 = nn.Linear(784, 512)
        self.bn1 = nn.BatchNorm1d(512)
        self.fc2 = nn.Linear(512, 256)
        self.bn2 = nn.BatchNorm1d(256)
```

```
        self.fc3 = nn.Linear(256, 128)
        self.bn3 = nn.BatchNorm1d(128)
        self.fc4 = nn.Linear(128, 10)
        self.dropout = nn.Dropout(0.3)

    def forward(self, x):
        x = x.view(x.shape[0], -1)
        x = F.relu(self.bn1(self.fc1(x)))
        x = self.dropout(x)
        x = F.relu(self.bn2(self.fc2(x)))
        x = self.dropout(x)
        x = F.relu(self.bn3(self.fc3(x)))
        x = self.fc4(x)
        return x


model = MNISTMLP().to(device)
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=5e-4, weight_decay=1e-4)

scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(
    optimizer,
    factor=0.5,
    patience=5,
)

print(model)
```

```
MNISTMLP(
  (fc1): Linear(in_features=784, out_features=512, bias=True)
  (bn1): BatchNorm1d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (fc2): Linear(in_features=512, out_features=256, bias=True)
  (bn2): BatchNorm1d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (fc3): Linear(in_features=256, out_features=128, bias=True)
  (bn3): BatchNorm1d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (fc4): Linear(in_features=128, out_features=10, bias=True)
  (dropout): Dropout(p=0.3, inplace=False)
)
```

[10]:
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# ============================================================
# 3. Training + validation loop
# ============================================================

numEpochs = 100
```

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epochTrainLosses = []
valLosses = []
learningRates = []

for epoch in range(numEpochs):
    model.train()
    runningLoss = 0.0

    for images, labels in trainLoader:
        images, labels = images.to(device), labels.to(device)

        optimizer.zero_grad()
        logits = model(images)
        loss = criterion(logits, labels)
        loss.backward()
        optimizer.step()

        runningLoss += loss.item()

    epochLoss = runningLoss / len(trainLoader)
    epochTrainLosses.append(epochLoss)

    # ---- validation loss (no gradient, no augmentation) ----
    model.eval()
    valRunningLoss = 0.0
    with torch.no_grad():
        for images, labels in valLoader:
            images, labels = images.to(device), labels.to(device)
            logits = model(images)
            loss = criterion(logits, labels)
            valRunningLoss += loss.item()

    valLoss = valRunningLoss / len(valLoader)
    valLosses.append(valLoss)

    # Step scheduler on validation loss, then read scalar LR
    scheduler.step(valLoss)
    currentLr = optimizer.param_groups[0]["lr"]
    learningRates.append(currentLr)

    print(
        f"Epoch {epoch+1}/{numEpochs}, "
        f"Train Loss: {epochLoss:.4f}, Val Loss: {valLoss:.4f} "
        f"Learning Rate: {currentLr:.6f}"
    )

print("Training complete.")
```
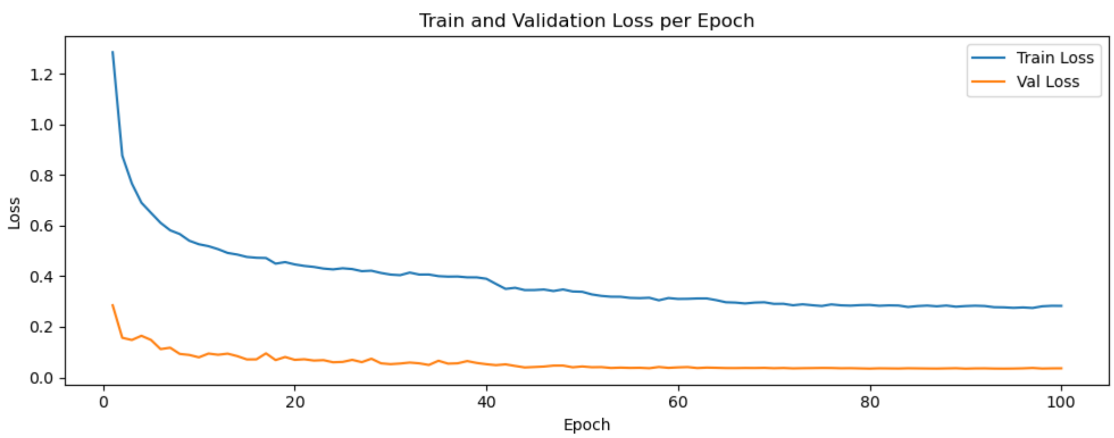
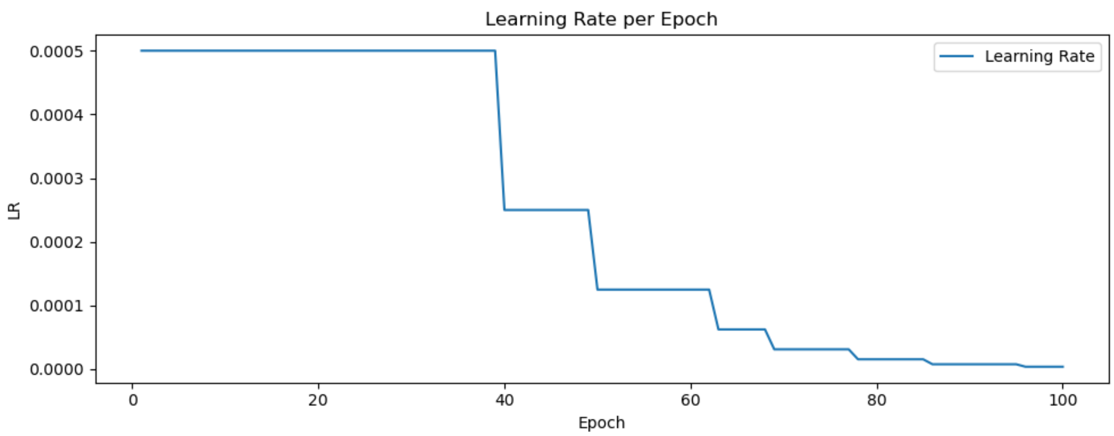

```python
epochs = range(1, numEpochs + 1)

plt.figure(figsize=(10, 4))
plt.plot(epochs, epochTrainLosses, label="Train Loss")
plt.plot(epochs, valLosses, label="Val Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("Train and Validation Loss per Epoch")
plt.legend()
plt.tight_layout()
plt.show(block=False)
plt.pause(0.001)


# Learning rate per epoch
plt.figure(figsize=(10, 4))
plt.plot(epochs, learningRates, label="Learning Rate")
plt.xlabel("Epoch")
plt.ylabel("LR")
plt.title("Learning Rate per Epoch")
plt.legend()
plt.tight_layout()
plt.show(block=False)
plt.pause(0.001)
```

```
Epoch 1/100, Train Loss: 1.2849, Val Loss: 0.2852 Learning Rate: 0.000500
Epoch 2/100, Train Loss: 0.8765, Val Loss: 0.1568 Learning Rate: 0.000500
Epoch 3/100, Train Loss: 0.7665, Val Loss: 0.1481 Learning Rate: 0.000500
Epoch 4/100, Train Loss: 0.6905, Val Loss: 0.1647 Learning Rate: 0.000500
Epoch 5/100, Train Loss: 0.6503, Val Loss: 0.1482 Learning Rate: 0.000500
Epoch 6/100, Train Loss: 0.6108, Val Loss: 0.1119 Learning Rate: 0.000500
Epoch 7/100, Train Loss: 0.5815, Val Loss: 0.1175 Learning Rate: 0.000500
Epoch 8/100, Train Loss: 0.5666, Val Loss: 0.0931 Learning Rate: 0.000500
Epoch 9/100, Train Loss: 0.5401, Val Loss: 0.0890 Learning Rate: 0.000500
Epoch 10/100, Train Loss: 0.5263, Val Loss: 0.0795 Learning Rate: 0.000500
Epoch 11/100, Train Loss: 0.5188, Val Loss: 0.0944 Learning Rate: 0.000500
Epoch 12/100, Train Loss: 0.5068, Val Loss: 0.0898 Learning Rate: 0.000500
Epoch 13/100, Train Loss: 0.4920, Val Loss: 0.0941 Learning Rate: 0.000500
Epoch 14/100, Train Loss: 0.4857, Val Loss: 0.0843 Learning Rate: 0.000500
Epoch 15/100, Train Loss: 0.4762, Val Loss: 0.0712 Learning Rate: 0.000500
Epoch 16/100, Train Loss: 0.4729, Val Loss: 0.0715 Learning Rate: 0.000500
Epoch 17/100, Train Loss: 0.4720, Val Loss: 0.0952 Learning Rate: 0.000500
Epoch 18/100, Train Loss: 0.4497, Val Loss: 0.0686 Learning Rate: 0.000500
Epoch 19/100, Train Loss: 0.4558, Val Loss: 0.0808 Learning Rate: 0.000500
Epoch 20/100, Train Loss: 0.4467, Val Loss: 0.0696 Learning Rate: 0.000500
Epoch 21/100, Train Loss: 0.4407, Val Loss: 0.0719 Learning Rate: 0.000500
Epoch 22/100, Train Loss: 0.4367, Val Loss: 0.0668 Learning Rate: 0.000500
```

```
Epoch 23/100, Train Loss: 0.4302, Val Loss: 0.0684 Learning Rate: 0.000500
Epoch 24/100, Train Loss: 0.4270, Val Loss: 0.0601 Learning Rate: 0.000500
Epoch 25/100, Train Loss: 0.4314, Val Loss: 0.0614 Learning Rate: 0.000500
Epoch 26/100, Train Loss: 0.4283, Val Loss: 0.0695 Learning Rate: 0.000500
Epoch 27/100, Train Loss: 0.4200, Val Loss: 0.0605 Learning Rate: 0.000500
Epoch 28/100, Train Loss: 0.4218, Val Loss: 0.0740 Learning Rate: 0.000500
Epoch 29/100, Train Loss: 0.4129, Val Loss: 0.0559 Learning Rate: 0.000500
Epoch 30/100, Train Loss: 0.4064, Val Loss: 0.0526 Learning Rate: 0.000500
Epoch 31/100, Train Loss: 0.4041, Val Loss: 0.0551 Learning Rate: 0.000500
Epoch 32/100, Train Loss: 0.4144, Val Loss: 0.0589 Learning Rate: 0.000500
Epoch 33/100, Train Loss: 0.4065, Val Loss: 0.0558 Learning Rate: 0.000500
Epoch 34/100, Train Loss: 0.4067, Val Loss: 0.0494 Learning Rate: 0.000500
Epoch 35/100, Train Loss: 0.4003, Val Loss: 0.0660 Learning Rate: 0.000500
Epoch 36/100, Train Loss: 0.3984, Val Loss: 0.0546 Learning Rate: 0.000500
Epoch 37/100, Train Loss: 0.3989, Val Loss: 0.0559 Learning Rate: 0.000500
Epoch 38/100, Train Loss: 0.3955, Val Loss: 0.0647 Learning Rate: 0.000500
Epoch 39/100, Train Loss: 0.3954, Val Loss: 0.0573 Learning Rate: 0.000500
Epoch 40/100, Train Loss: 0.3900, Val Loss: 0.0523 Learning Rate: 0.000250
Epoch 41/100, Train Loss: 0.3695, Val Loss: 0.0486 Learning Rate: 0.000250
Epoch 42/100, Train Loss: 0.3499, Val Loss: 0.0518 Learning Rate: 0.000250
Epoch 43/100, Train Loss: 0.3543, Val Loss: 0.0455 Learning Rate: 0.000250
Epoch 44/100, Train Loss: 0.3452, Val Loss: 0.0395 Learning Rate: 0.000250
Epoch 45/100, Train Loss: 0.3454, Val Loss: 0.0413 Learning Rate: 0.000250
Epoch 46/100, Train Loss: 0.3476, Val Loss: 0.0430 Learning Rate: 0.000250
Epoch 47/100, Train Loss: 0.3415, Val Loss: 0.0468 Learning Rate: 0.000250
Epoch 48/100, Train Loss: 0.3478, Val Loss: 0.0469 Learning Rate: 0.000250
Epoch 49/100, Train Loss: 0.3397, Val Loss: 0.0402 Learning Rate: 0.000250
Epoch 50/100, Train Loss: 0.3384, Val Loss: 0.0434 Learning Rate: 0.000125
Epoch 51/100, Train Loss: 0.3281, Val Loss: 0.0404 Learning Rate: 0.000125
Epoch 52/100, Train Loss: 0.3223, Val Loss: 0.0409 Learning Rate: 0.000125
Epoch 53/100, Train Loss: 0.3191, Val Loss: 0.0375 Learning Rate: 0.000125
Epoch 54/100, Train Loss: 0.3189, Val Loss: 0.0388 Learning Rate: 0.000125
Epoch 55/100, Train Loss: 0.3144, Val Loss: 0.0377 Learning Rate: 0.000125
Epoch 56/100, Train Loss: 0.3134, Val Loss: 0.0382 Learning Rate: 0.000125
Epoch 57/100, Train Loss: 0.3150, Val Loss: 0.0364 Learning Rate: 0.000125
Epoch 58/100, Train Loss: 0.3048, Val Loss: 0.0414 Learning Rate: 0.000125
Epoch 59/100, Train Loss: 0.3137, Val Loss: 0.0379 Learning Rate: 0.000125
Epoch 60/100, Train Loss: 0.3103, Val Loss: 0.0398 Learning Rate: 0.000125
Epoch 61/100, Train Loss: 0.3107, Val Loss: 0.0410 Learning Rate: 0.000125
Epoch 62/100, Train Loss: 0.3121, Val Loss: 0.0372 Learning Rate: 0.000125
Epoch 63/100, Train Loss: 0.3122, Val Loss: 0.0389 Learning Rate: 0.000063
Epoch 64/100, Train Loss: 0.3053, Val Loss: 0.0381 Learning Rate: 0.000063
Epoch 65/100, Train Loss: 0.2971, Val Loss: 0.0371 Learning Rate: 0.000063
Epoch 66/100, Train Loss: 0.2958, Val Loss: 0.0370 Learning Rate: 0.000063
Epoch 67/100, Train Loss: 0.2924, Val Loss: 0.0375 Learning Rate: 0.000063
Epoch 68/100, Train Loss: 0.2958, Val Loss: 0.0373 Learning Rate: 0.000063
Epoch 69/100, Train Loss: 0.2970, Val Loss: 0.0379 Learning Rate: 0.000031
Epoch 70/100, Train Loss: 0.2909, Val Loss: 0.0365 Learning Rate: 0.000031
```

```
Epoch 71/100, Train Loss: 0.2911, Val Loss: 0.0374 Learning Rate: 0.000031
Epoch 72/100, Train Loss: 0.2852, Val Loss: 0.0359 Learning Rate: 0.000031
Epoch 73/100, Train Loss: 0.2892, Val Loss: 0.0366 Learning Rate: 0.000031
Epoch 74/100, Train Loss: 0.2855, Val Loss: 0.0370 Learning Rate: 0.000031
Epoch 75/100, Train Loss: 0.2824, Val Loss: 0.0376 Learning Rate: 0.000031
Epoch 76/100, Train Loss: 0.2887, Val Loss: 0.0374 Learning Rate: 0.000031
Epoch 77/100, Train Loss: 0.2850, Val Loss: 0.0363 Learning Rate: 0.000031
Epoch 78/100, Train Loss: 0.2838, Val Loss: 0.0366 Learning Rate: 0.000016
Epoch 79/100, Train Loss: 0.2858, Val Loss: 0.0358 Learning Rate: 0.000016
Epoch 80/100, Train Loss: 0.2866, Val Loss: 0.0349 Learning Rate: 0.000016
Epoch 81/100, Train Loss: 0.2833, Val Loss: 0.0361 Learning Rate: 0.000016
Epoch 82/100, Train Loss: 0.2849, Val Loss: 0.0357 Learning Rate: 0.000016
Epoch 83/100, Train Loss: 0.2843, Val Loss: 0.0353 Learning Rate: 0.000016
Epoch 84/100, Train Loss: 0.2785, Val Loss: 0.0363 Learning Rate: 0.000016
Epoch 85/100, Train Loss: 0.2821, Val Loss: 0.0358 Learning Rate: 0.000016
Epoch 86/100, Train Loss: 0.2840, Val Loss: 0.0354 Learning Rate: 0.000008
Epoch 87/100, Train Loss: 0.2811, Val Loss: 0.0351 Learning Rate: 0.000008
Epoch 88/100, Train Loss: 0.2841, Val Loss: 0.0358 Learning Rate: 0.000008
Epoch 89/100, Train Loss: 0.2796, Val Loss: 0.0365 Learning Rate: 0.000008
Epoch 90/100, Train Loss: 0.2821, Val Loss: 0.0348 Learning Rate: 0.000008
Epoch 91/100, Train Loss: 0.2835, Val Loss: 0.0357 Learning Rate: 0.000008
Epoch 92/100, Train Loss: 0.2823, Val Loss: 0.0359 Learning Rate: 0.000008
Epoch 93/100, Train Loss: 0.2776, Val Loss: 0.0351 Learning Rate: 0.000008
Epoch 94/100, Train Loss: 0.2770, Val Loss: 0.0348 Learning Rate: 0.000008
Epoch 95/100, Train Loss: 0.2751, Val Loss: 0.0352 Learning Rate: 0.000008
Epoch 96/100, Train Loss: 0.2766, Val Loss: 0.0360 Learning Rate: 0.000004
Epoch 97/100, Train Loss: 0.2745, Val Loss: 0.0375 Learning Rate: 0.000004
Epoch 98/100, Train Loss: 0.2812, Val Loss: 0.0352 Learning Rate: 0.000004
Epoch 99/100, Train Loss: 0.2831, Val Loss: 0.0359 Learning Rate: 0.000004
Epoch 100/100, Train Loss: 0.2829, Val Loss: 0.0361 Learning Rate: 0.000004
Training complete.
```





[11]:
```
# ============================================================
# 4. Evaluation helpers
# ============================================================


def EvaluateWithDetails(loader, name="Dataset"):
    model.eval()
    allPreds, allLabels = [], []

    with torch.no_grad():
        for images, labels in loader:
            images, labels = images.to(device), labels.to(device)
            logits = model(images)
            _, preds = torch.max(logits, 1)
            allPreds.extend(preds.cpu().numpy())
            allLabels.extend(labels.cpu().numpy())

    allPreds = np.array(allPreds)
    allLabels = np.array(allLabels)

    accuracy = (allPreds == allLabels).mean()
    errorRate = 1.0 - accuracy

    print(f"\n==== {name} RESULTS ====")
    print(f"Accuracy: {accuracy:.4f}")
    print(f"Error Rate: {errorRate:.4f}")

    print("\nClassification Report:")
    print(classification_report(allLabels, allPreds, digits=4))

    print("Confusion Matrix:")
```

```
    print(confusion_matrix(allLabels, allPreds))

    return accuracy


mnistAcc = EvaluateWithDetails(testLoader, "MNIST Test Set")
print("MNIST test accuracy (float):", float(mnistAcc))
```

```
==== MNIST Test Set RESULTS ====
Accuracy: 0.9910
Error Rate: 0.0090

Classification Report:
              precision    recall  f1-score   support

           0     0.9959    0.9949    0.9954       980
           1     0.9895    0.9965    0.9930      1135
           2     0.9922    0.9893    0.9908      1032
           3     0.9911    0.9891    0.9901      1010
           4     0.9899    0.9939    0.9919       982
           5     0.9911    0.9955    0.9933       892
           6     0.9927    0.9906    0.9916       958
           7     0.9808    0.9922    0.9865      1028
           8     1.0000    0.9836    0.9917       974
           9     0.9881    0.9841    0.9861      1009

    accuracy                         0.9910     10000
   macro avg     0.9911    0.9910    0.9910     10000
weighted avg     0.9910    0.9910    0.9910     10000

Confusion Matrix:
[[ 975    0    1    0    0    1    2    1    0    0]
 [    0 1131    0    0    0    0    1    3    0    0]
 [    1    1 1021    3    1    0    0    5    0    0]
 [    0    0    1  999    0    1    0    4    0    5]
 [    0    0    0    0  976    0    3    0    0    3]
 [    1    0    0    2    0  888    1    0    0    0]
 [    2    6    0    0    0    1  949    0    0    0]
 [    0    2    5    1    0    0    0 1020    0    0]
 [    0    1    1    3    1    3    0    3  958    4]
 [    0    2    0    0    8    2    0    4    0  993]]
MNIST test accuracy (float): 0.991
```

[12]:
```
# ============================================================
# 5. Local handwritten digit dataset
# ============================================================
```

```python
class HandwrittenDigits(Dataset):
    def __init__(self, root, transform=None):
        self.paths = sorted(glob.glob(os.path.join(root, "*.png")))
        self.transform = transform
        self.labels = [int(os.path.basename(p).split("-")[0]) for p in self.
 ↪paths]

    def __len__(self):
        return len(self.paths)

    def __getitem__(self, idx):
        img = Image.open(self.paths[idx])
        img = PreprocessSingle(img)
        img = img.resize((28, 28))
        if self.transform is not None:
            img = self.transform(img)
        return img, self.labels[idx]


digitsRoot = "./digits"
handSet = HandwrittenDigits(digitsRoot, transform)

handLoader = torch.utils.data.DataLoader(handSet, batch_size=64, shuffle=False)

print("Handwritten digits found:", len(handSet))

if len(handSet) > 0:
    EvaluateWithDetails(handLoader, "Handwritten Digits")
else:
    print("No handwritten digits found.")

torch.save(model.state_dict(), "model.pth")
```

```
Handwritten digits found: 330

==== Handwritten Digits RESULTS ====
Accuracy: 0.9515
Error Rate: 0.0485

Classification Report:
              precision    recall  f1-score   support

           0     0.9706    1.0000    0.9851        33
           1     0.9697    0.9697    0.9697        33
           2     0.8649    0.9697    0.9143        33
           3     0.9667    0.8788    0.9206        33
```

```
           4     1.0000    0.9697    0.9846        33
           5     0.8571    0.9091    0.8824        33
           6     0.9412    0.9697    0.9552        33
           7     1.0000    1.0000    1.0000        33
           8     1.0000    0.8788    0.9355        33
           9     0.9697    0.9697    0.9697        33

    accuracy                         0.9515       330
   macro avg     0.9540    0.9515    0.9517       330
weighted avg     0.9540    0.9515    0.9517       330

Confusion Matrix:
[[33  0  0  0  0  0  0  0  0  0]
 [ 0 32  1  0  0  0  0  0  0  0]
 [ 0  1 32  0  0  0  0  0  0  0]
 [ 0  0  1 29  0  3  0  0  0  0]
 [ 0  0  0  0 32  0  0  0  0  1]
 [ 0  0  1  0  0 30  2  0  0  0]
 [ 0  0  0  0  0  1 32  0  0  0]
 [ 0  0  0  0  0  0  0 33  0  0]
 [ 1  0  2  0  0  1  0  0 29  0]
 [ 0  0  0  1  0  0  0  0  0 32]]
```