model

December 12, 2025

[15]:
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# ============================================================
# Final Project
# ============================================================

DEMO = False

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
```

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# ============================================================
# 1. Data and augmentation setup
# ============================================================


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

```python
    def __call__(self, img):
        arr = np.array(img).astype(np.float32)
        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
```

```python
class JPEGCompression(object):
    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(
```

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    [transforms.ToTensor(), transforms.Normalize((0.5,), (0.5,))]
)


def ColorStretch(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)
```

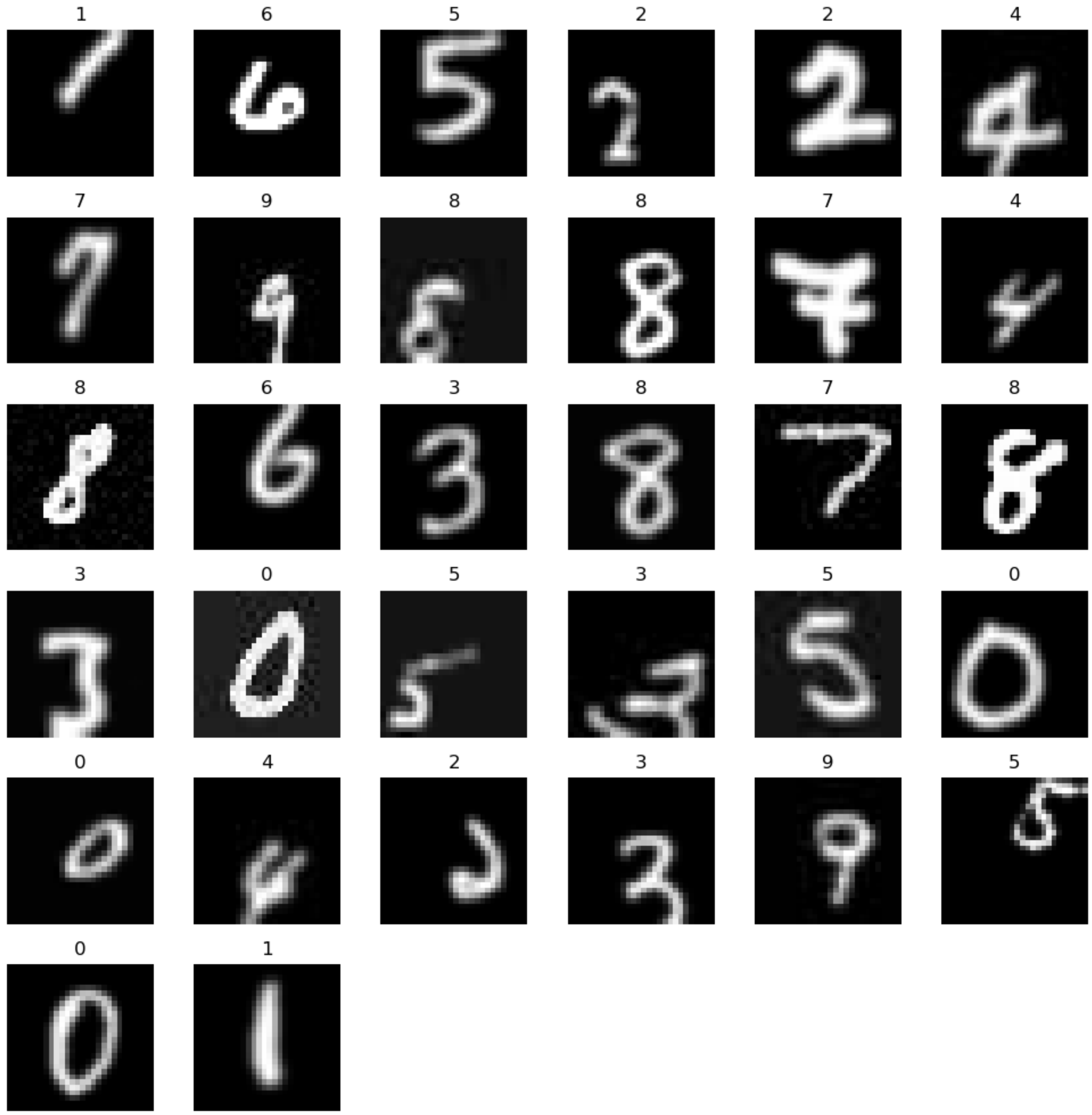
```python
testSet = datasets.MNIST(
    "~/.pytorch/MNIST_data/", download=True, train=False, transform=transform
)
testLoader = torch.utils.data.DataLoader(testSet, batch_size=64, shuffle=False)

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
```



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# ==============================================================
# 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)
```

```python
        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)
)
```

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```python
# ============================================================
# 3. Training + validation loop
# ============================================================

if not DEMO:
```

```python
numEpochs = 100
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
    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)

    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)


    torch.save(model.state_dict(), "model.pth")
else:
    # DEMO mode
    model.load_state_dict(torch.load("model.pth", map_location=device))
    model.eval()
    print("Loaded model.pth (DEMO mode)")
```

```
Epoch 1/100, Train Loss: 1.2846, Val Loss: 0.2421 Learning Rate: 0.000500
Epoch 2/100, Train Loss: 0.8823, Val Loss: 0.1809 Learning Rate: 0.000500
Epoch 3/100, Train Loss: 0.7666, Val Loss: 0.1505 Learning Rate: 0.000500
Epoch 4/100, Train Loss: 0.6978, Val Loss: 0.1815 Learning Rate: 0.000500
Epoch 5/100, Train Loss: 0.6495, Val Loss: 0.1450 Learning Rate: 0.000500
Epoch 6/100, Train Loss: 0.6134, Val Loss: 0.1483 Learning Rate: 0.000500
Epoch 7/100, Train Loss: 0.5873, Val Loss: 0.1116 Learning Rate: 0.000500
Epoch 8/100, Train Loss: 0.5641, Val Loss: 0.1211 Learning Rate: 0.000500
Epoch 9/100, Train Loss: 0.5418, Val Loss: 0.0778 Learning Rate: 0.000500
Epoch 10/100, Train Loss: 0.5210, Val Loss: 0.0787 Learning Rate: 0.000500
Epoch 11/100, Train Loss: 0.5187, Val Loss: 0.0878 Learning Rate: 0.000500
Epoch 12/100, Train Loss: 0.5076, Val Loss: 0.0991 Learning Rate: 0.000500
Epoch 13/100, Train Loss: 0.4917, Val Loss: 0.0768 Learning Rate: 0.000500
Epoch 14/100, Train Loss: 0.4822, Val Loss: 0.0852 Learning Rate: 0.000500
```

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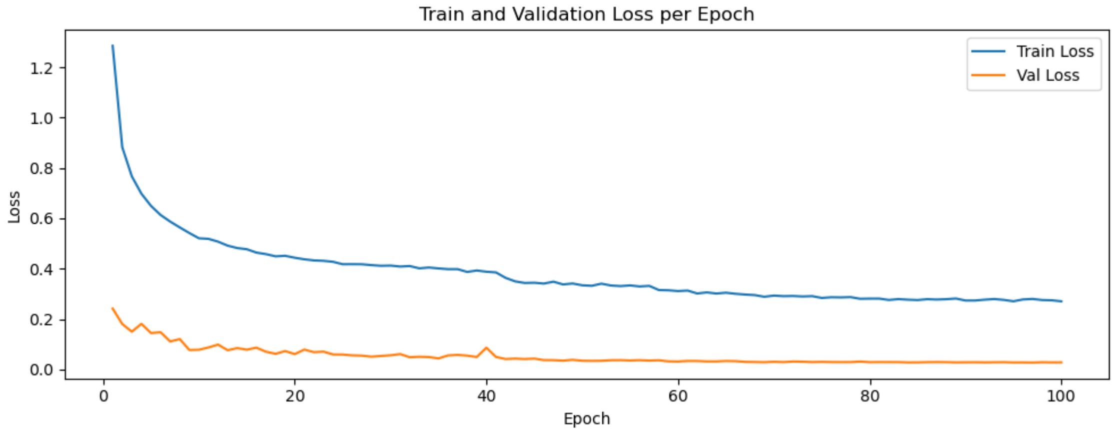
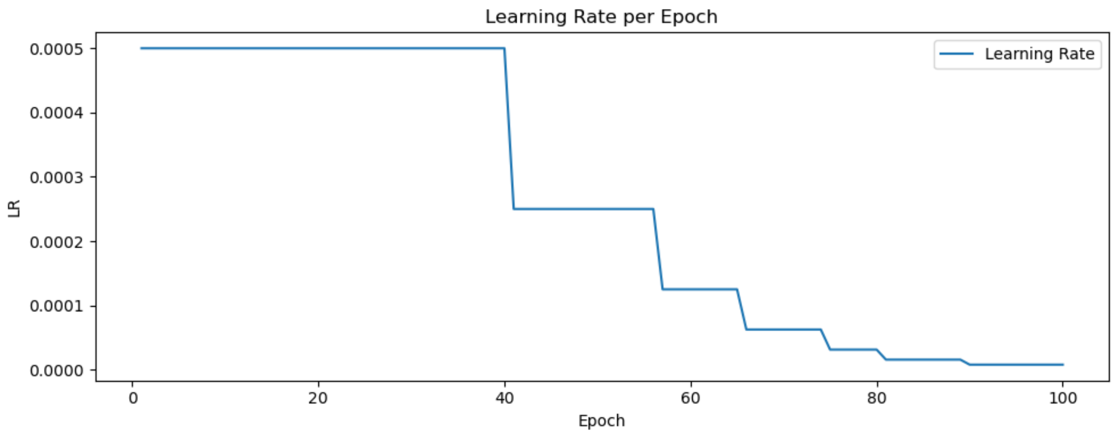
Epoch 15/100, Train Loss: 0.4775, Val Loss: 0.0791 Learning Rate: 0.000500
Epoch 16/100, Train Loss: 0.4642, Val Loss: 0.0870 Learning Rate: 0.000500
Epoch 17/100, Train Loss: 0.4581, Val Loss: 0.0707 Learning Rate: 0.000500
Epoch 18/100, Train Loss: 0.4494, Val Loss: 0.0625 Learning Rate: 0.000500
Epoch 19/100, Train Loss: 0.4515, Val Loss: 0.0735 Learning Rate: 0.000500
Epoch 20/100, Train Loss: 0.4438, Val Loss: 0.0613 Learning Rate: 0.000500
Epoch 21/100, Train Loss: 0.4376, Val Loss: 0.0794 Learning Rate: 0.000500
Epoch 22/100, Train Loss: 0.4332, Val Loss: 0.0691 Learning Rate: 0.000500
Epoch 23/100, Train Loss: 0.4315, Val Loss: 0.0712 Learning Rate: 0.000500
Epoch 24/100, Train Loss: 0.4277, Val Loss: 0.0599 Learning Rate: 0.000500
Epoch 25/100, Train Loss: 0.4181, Val Loss: 0.0596 Learning Rate: 0.000500
Epoch 26/100, Train Loss: 0.4183, Val Loss: 0.0564 Learning Rate: 0.000500
Epoch 27/100, Train Loss: 0.4179, Val Loss: 0.0553 Learning Rate: 0.000500
Epoch 28/100, Train Loss: 0.4145, Val Loss: 0.0513 Learning Rate: 0.000500
Epoch 29/100, Train Loss: 0.4119, Val Loss: 0.0541 Learning Rate: 0.000500
Epoch 30/100, Train Loss: 0.4127, Val Loss: 0.0566 Learning Rate: 0.000500
Epoch 31/100, Train Loss: 0.4089, Val Loss: 0.0615 Learning Rate: 0.000500
Epoch 32/100, Train Loss: 0.4108, Val Loss: 0.0491 Learning Rate: 0.000500
Epoch 33/100, Train Loss: 0.4018, Val Loss: 0.0508 Learning Rate: 0.000500
Epoch 34/100, Train Loss: 0.4050, Val Loss: 0.0497 Learning Rate: 0.000500
Epoch 35/100, Train Loss: 0.4014, Val Loss: 0.0443 Learning Rate: 0.000500
Epoch 36/100, Train Loss: 0.3985, Val Loss: 0.0562 Learning Rate: 0.000500
Epoch 37/100, Train Loss: 0.3985, Val Loss: 0.0584 Learning Rate: 0.000500
Epoch 38/100, Train Loss: 0.3875, Val Loss: 0.0552 Learning Rate: 0.000500
Epoch 39/100, Train Loss: 0.3932, Val Loss: 0.0500 Learning Rate: 0.000500
Epoch 40/100, Train Loss: 0.3883, Val Loss: 0.0868 Learning Rate: 0.000500
Epoch 41/100, Train Loss: 0.3856, Val Loss: 0.0502 Learning Rate: 0.000250
Epoch 42/100, Train Loss: 0.3641, Val Loss: 0.0419 Learning Rate: 0.000250
Epoch 43/100, Train Loss: 0.3501, Val Loss: 0.0437 Learning Rate: 0.000250
Epoch 44/100, Train Loss: 0.3437, Val Loss: 0.0419 Learning Rate: 0.000250
Epoch 45/100, Train Loss: 0.3446, Val Loss: 0.0436 Learning Rate: 0.000250
Epoch 46/100, Train Loss: 0.3413, Val Loss: 0.0376 Learning Rate: 0.000250
Epoch 47/100, Train Loss: 0.3488, Val Loss: 0.0374 Learning Rate: 0.000250
Epoch 48/100, Train Loss: 0.3379, Val Loss: 0.0354 Learning Rate: 0.000250
Epoch 49/100, Train Loss: 0.3416, Val Loss: 0.0387 Learning Rate: 0.000250
Epoch 50/100, Train Loss: 0.3345, Val Loss: 0.0351 Learning Rate: 0.000250
Epoch 51/100, Train Loss: 0.3325, Val Loss: 0.0346 Learning Rate: 0.000250
Epoch 52/100, Train Loss: 0.3409, Val Loss: 0.0350 Learning Rate: 0.000250
Epoch 53/100, Train Loss: 0.3336, Val Loss: 0.0371 Learning Rate: 0.000250
Epoch 54/100, Train Loss: 0.3313, Val Loss: 0.0374 Learning Rate: 0.000250
Epoch 55/100, Train Loss: 0.3340, Val Loss: 0.0361 Learning Rate: 0.000250
Epoch 56/100, Train Loss: 0.3299, Val Loss: 0.0373 Learning Rate: 0.000250
Epoch 57/100, Train Loss: 0.3322, Val Loss: 0.0358 Learning Rate: 0.000125
Epoch 58/100, Train Loss: 0.3156, Val Loss: 0.0369 Learning Rate: 0.000125
Epoch 59/100, Train Loss: 0.3147, Val Loss: 0.0326 Learning Rate: 0.000125
Epoch 60/100, Train Loss: 0.3116, Val Loss: 0.0320 Learning Rate: 0.000125
Epoch 61/100, Train Loss: 0.3135, Val Loss: 0.0342 Learning Rate: 0.000125
Epoch 62/100, Train Loss: 0.3019, Val Loss: 0.0341 Learning Rate: 0.000125
```

```
Epoch 63/100, Train Loss: 0.3063, Val Loss: 0.0323 Learning Rate: 0.000125
Epoch 64/100, Train Loss: 0.3018, Val Loss: 0.0323 Learning Rate: 0.000125
Epoch 65/100, Train Loss: 0.3051, Val Loss: 0.0341 Learning Rate: 0.000125
Epoch 66/100, Train Loss: 0.3007, Val Loss: 0.0334 Learning Rate: 0.000063
Epoch 67/100, Train Loss: 0.2978, Val Loss: 0.0306 Learning Rate: 0.000063
Epoch 68/100, Train Loss: 0.2956, Val Loss: 0.0300 Learning Rate: 0.000063
Epoch 69/100, Train Loss: 0.2889, Val Loss: 0.0293 Learning Rate: 0.000063
Epoch 70/100, Train Loss: 0.2936, Val Loss: 0.0310 Learning Rate: 0.000063
Epoch 71/100, Train Loss: 0.2914, Val Loss: 0.0298 Learning Rate: 0.000063
Epoch 72/100, Train Loss: 0.2920, Val Loss: 0.0320 Learning Rate: 0.000063
Epoch 73/100, Train Loss: 0.2901, Val Loss: 0.0312 Learning Rate: 0.000063
Epoch 74/100, Train Loss: 0.2914, Val Loss: 0.0298 Learning Rate: 0.000063
Epoch 75/100, Train Loss: 0.2842, Val Loss: 0.0306 Learning Rate: 0.000031
Epoch 76/100, Train Loss: 0.2870, Val Loss: 0.0299 Learning Rate: 0.000031
Epoch 77/100, Train Loss: 0.2864, Val Loss: 0.0297 Learning Rate: 0.000031
Epoch 78/100, Train Loss: 0.2876, Val Loss: 0.0297 Learning Rate: 0.000031
Epoch 79/100, Train Loss: 0.2810, Val Loss: 0.0319 Learning Rate: 0.000031
Epoch 80/100, Train Loss: 0.2817, Val Loss: 0.0294 Learning Rate: 0.000031
Epoch 81/100, Train Loss: 0.2817, Val Loss: 0.0298 Learning Rate: 0.000016
Epoch 82/100, Train Loss: 0.2763, Val Loss: 0.0297 Learning Rate: 0.000016
Epoch 83/100, Train Loss: 0.2797, Val Loss: 0.0296 Learning Rate: 0.000016
Epoch 84/100, Train Loss: 0.2774, Val Loss: 0.0284 Learning Rate: 0.000016
Epoch 85/100, Train Loss: 0.2759, Val Loss: 0.0286 Learning Rate: 0.000016
Epoch 86/100, Train Loss: 0.2794, Val Loss: 0.0294 Learning Rate: 0.000016
Epoch 87/100, Train Loss: 0.2780, Val Loss: 0.0298 Learning Rate: 0.000016
Epoch 88/100, Train Loss: 0.2793, Val Loss: 0.0294 Learning Rate: 0.000016
Epoch 89/100, Train Loss: 0.2820, Val Loss: 0.0286 Learning Rate: 0.000016
Epoch 90/100, Train Loss: 0.2740, Val Loss: 0.0288 Learning Rate: 0.000008
Epoch 91/100, Train Loss: 0.2741, Val Loss: 0.0290 Learning Rate: 0.000008
Epoch 92/100, Train Loss: 0.2774, Val Loss: 0.0285 Learning Rate: 0.000008
Epoch 93/100, Train Loss: 0.2800, Val Loss: 0.0290 Learning Rate: 0.000008
Epoch 94/100, Train Loss: 0.2766, Val Loss: 0.0293 Learning Rate: 0.000008
Epoch 95/100, Train Loss: 0.2711, Val Loss: 0.0282 Learning Rate: 0.000008
Epoch 96/100, Train Loss: 0.2784, Val Loss: 0.0284 Learning Rate: 0.000008
Epoch 97/100, Train Loss: 0.2803, Val Loss: 0.0278 Learning Rate: 0.000008
Epoch 98/100, Train Loss: 0.2760, Val Loss: 0.0291 Learning Rate: 0.000008
Epoch 99/100, Train Loss: 0.2750, Val Loss: 0.0285 Learning Rate: 0.000008
Epoch 100/100, Train Loss: 0.2709, Val Loss: 0.0286 Learning Rate: 0.000008
Training complete.
```





[19]:

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# ============================================================
# 4. Evaluation helpers
# ============================================================

def PlotConfusionMatrix(cm, title):
    plt.figure(figsize=(7, 6))
    plt.imshow(cm, interpolation="nearest", cmap="Blues")
    plt.title(f"{title} Confusion Matrix")
    plt.xlabel("Predicted")
    plt.ylabel("True")
    plt.xticks(range(10))
    plt.yticks(range(10))
    plt.colorbar()
    for r in range(cm.shape[0]):
        for c in range(cm.shape[1]):
            v = cm[r, c]
```
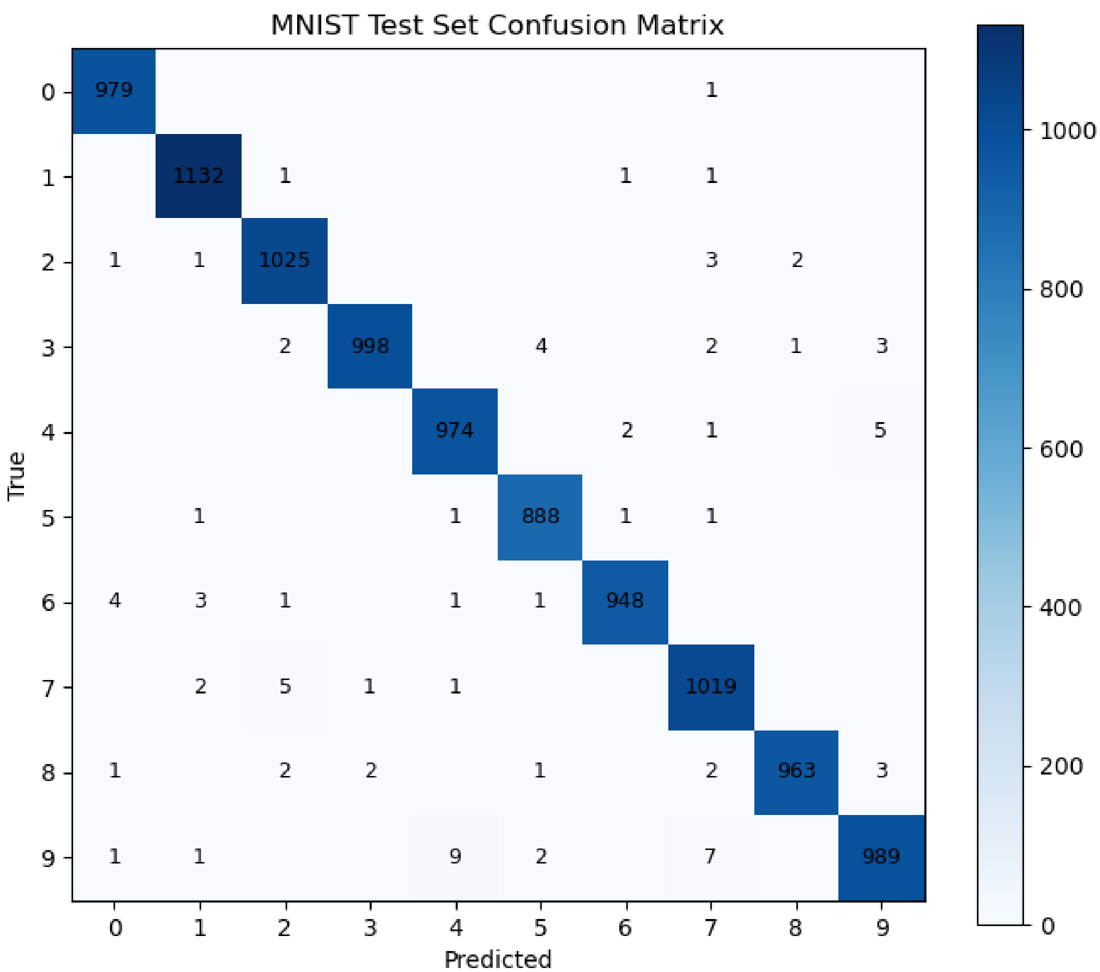

```python
            if v != 0:
                plt.text(c, r, str(v), ha="center", va="center", fontsize=9)
    plt.tight_layout()
    plt.show(block=False)
    plt.pause(0.001)

def PlotMissesByDigit(allPreds, allLabels, title):
    misses = []
    for d in range(10):
        misses.append(int(np.sum((allLabels == d) & (allPreds != d))))

    plt.figure(figsize=(8, 4))
    plt.bar(range(10), misses)
    plt.title(f"{title} Misses by True Digit")
    plt.xlabel("True Digit")
    plt.ylabel("Miss Count")
    plt.xticks(range(10))
    plt.tight_layout()
    plt.show(block=False)
    plt.pause(0.001)

def PlotGroupAccuracy(allPreds, allLabels, allGroupIDs, title):
    valid = allGroupIDs >= 0
    if not np.any(valid):
        return

    groupAcc = {}
    for gid in np.unique(allGroupIDs[valid]):
        mask = (allGroupIDs == gid)
        groupAcc[gid] = float(np.mean(allPreds[mask] == allLabels[mask]))

    groups = list(groupAcc.keys())
    accs = [groupAcc[g] for g in groups]

    plt.figure(figsize=(10, 5))
    plt.bar([str(g) for g in groups], accs)
    plt.ylim(0, 1.05)
    plt.xlabel("Group ID")
    plt.ylabel("Accuracy")
    plt.title(f"{title} Accuracy by Group")
    plt.tight_layout()
    plt.show(block=False)
    plt.pause(0.001)

def PrintMispredictions(allPreds, allLabels, allPaths, title, maxMisses=None):
    missIdx = np.where(allPreds != allLabels)[0]
    print(f"\n{title} mispredictions: {len(missIdx)} / {len(allLabels)}")
```

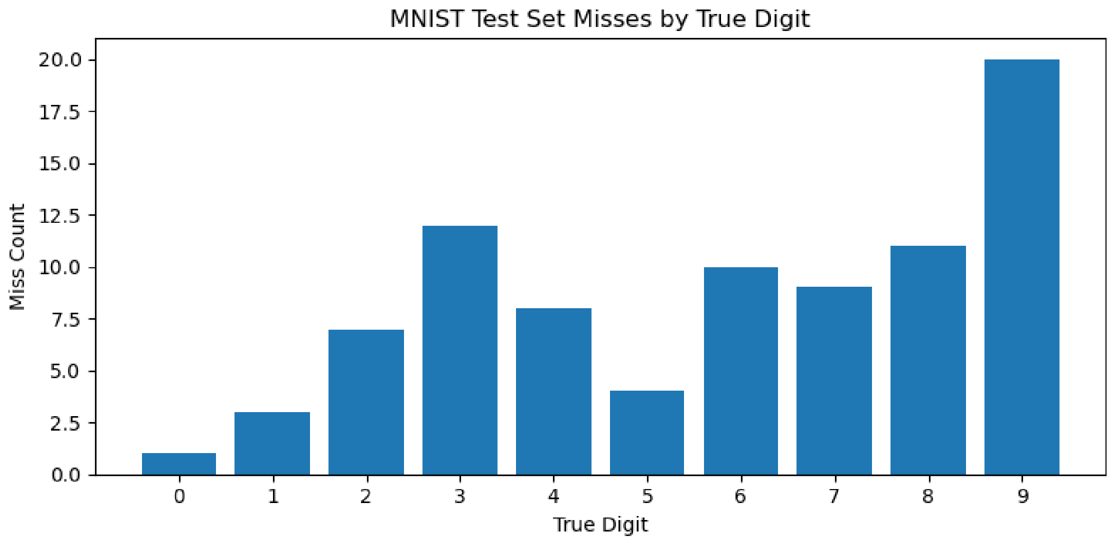
```
    if len(allPaths) != len(allLabels):
        print("(No file paths available to print per-image misses.)")
        return

    shown = 0
    for i in missIdx:
        print(f"- {allPaths[i]} | true={int(allLabels[i])}␣
↪pred={int(allPreds[i])}")
        shown += 1
        if maxMisses is not None and shown >= maxMisses:
            print(f"... truncated at {maxMisses} misses")
            break



def EvaluateWithDetails(loader, name="Dataset", plot=True, printMisses=True,␣
↪maxMisses=None):
    model.eval()
    allPreds, allLabels = [], []
    allGroupIDs = []
    allPaths = []

    with torch.no_grad():
        for data in loader:
            if len(data) == 4:
                images, labels, group_ids, paths = data
                allGroupIDs.extend(group_ids.cpu().numpy())
                allPaths.extend(list(paths))
            elif len(data) == 3:
                images, labels, group_ids = data
                allGroupIDs.extend(group_ids.cpu().numpy())
            elif len(data) == 2:
                images, labels = data
            else:
                continue

            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)
```

```python
    allGroupIDs = np.array(allGroupIDs) if len(allGroupIDs) == len(allLabels) else None

    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))

    cm = confusion_matrix(allLabels, allPreds)
    print("Confusion Matrix:")
    print(cm)

    if plot:
        PlotConfusionMatrix(cm, name)
        PlotMissesByDigit(allPreds, allLabels, name)
        if allGroupIDs is not None and np.any(allGroupIDs >= 0):
            PlotGroupAccuracy(allPreds, allLabels, allGroupIDs, name)

    if printMisses:
        PrintMispredictions(allPreds, allLabels, allPaths, name, maxMisses=maxMisses)

    return accuracy


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

```
==== MNIST Test Set RESULTS ====
Accuracy: 0.9915
Error Rate: 0.0085

Classification Report:
              precision    recall  f1-score   support

           0     0.9929    0.9990    0.9959       980
           1     0.9930    0.9974    0.9952      1135
           2     0.9894    0.9932    0.9913      1032
           3     0.9970    0.9881    0.9925      1010
           4     0.9878    0.9919    0.9898       982
           5     0.9911    0.9955    0.9933       892
           6     0.9958    0.9896    0.9927       958
```

```
           7     0.9826    0.9912    0.9869      1028
           8     0.9969    0.9887    0.9928       974
           9     0.9890    0.9802    0.9846      1009

    accuracy                         0.9915     10000
   macro avg     0.9916    0.9915    0.9915     10000
weighted avg     0.9915    0.9915    0.9915     10000

Confusion Matrix:
[[ 979    0    0    0    0    0    0    1    0    0]
 [   0 1132    1    0    0    0    1    1    0    0]
 [   1    1 1025    0    0    0    0    3    2    0]
 [   0    0    2  998    0    4    0    2    1    3]
 [   0    0    0    0  974    0    2    1    0    5]
 [   0    1    0    0    1  888    1    1    0    0]
 [   4    3    1    0    1    1  948    0    0    0]
 [   0    2    5    1    1    0    0 1019    0    0]
 [   1    0    2    2    0    1    0    2  963    3]
 [   1    1    0    0    9    2    0    7    0  989]]
```






```
MNIST Test Set mispredictions: 85 / 10000
(No file paths available to print per-image misses.)
MNIST test accuracy (float): 0.9915
```

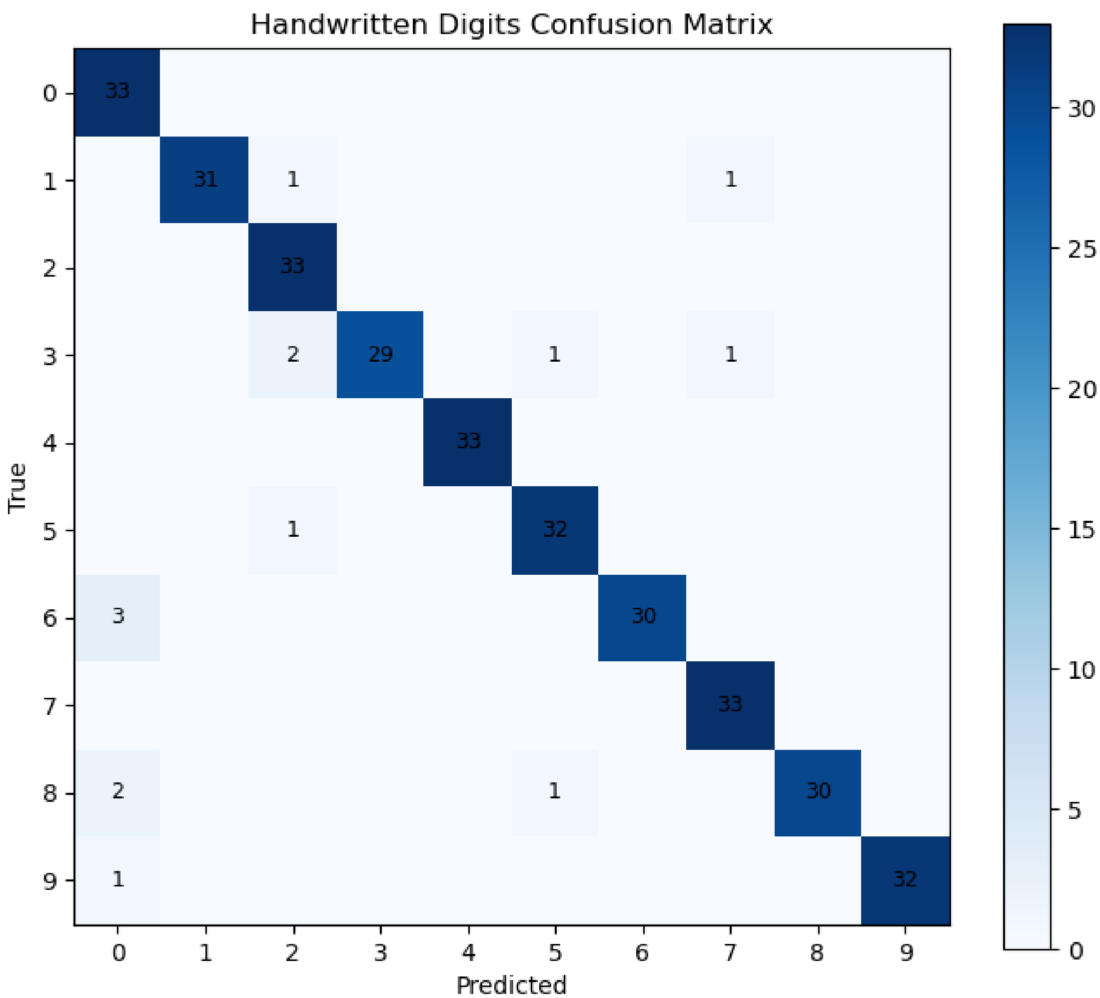
[20]:

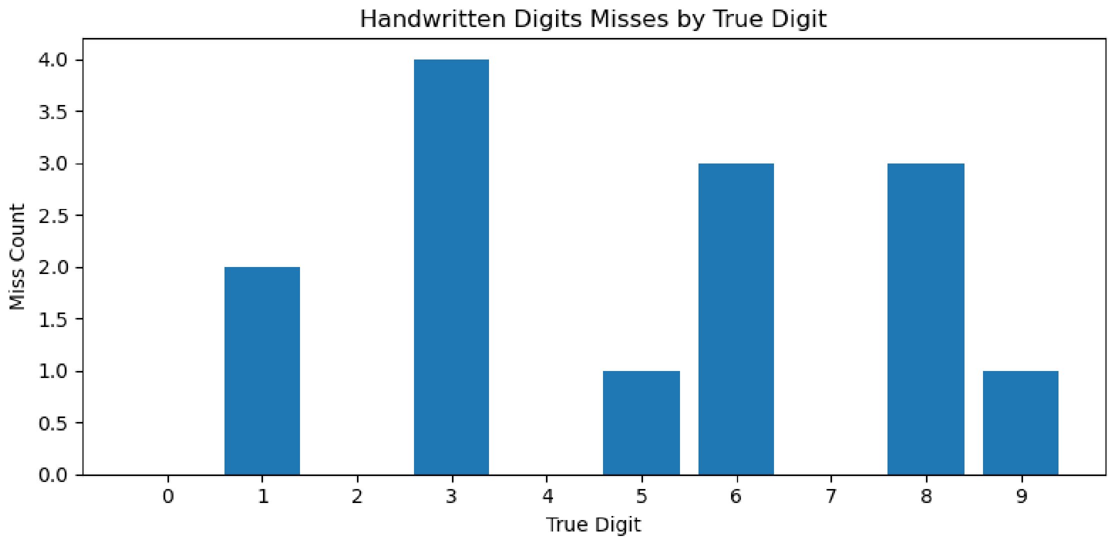
```python
# ============================================================
# 5. Local handwritten digit dataset
# ============================================================


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]

        self.group_ids = []
        for p in self.paths:
            parts = os.path.basename(p).split("-")
            if len(parts) > 1 and parts[1].isdigit():
                self.group_ids.append(int(parts[1]))
            else:
                self.group_ids.append(-1)

    def __len__(self):
```

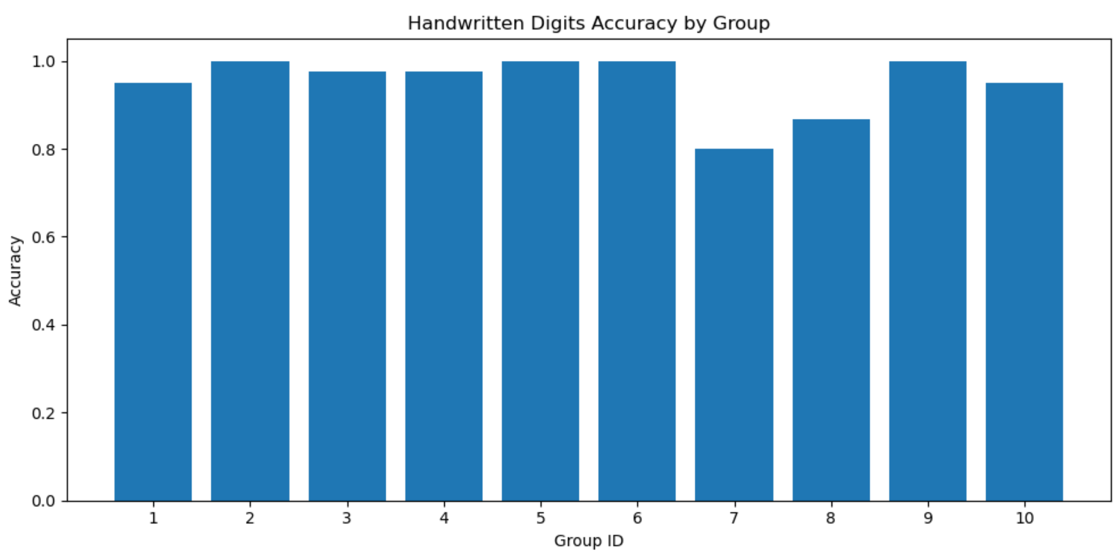
```python
        return len(self.paths)

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

        return img, self.labels[idx], torch.tensor(self.group_ids[idx]), path


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", plot=True,␣
 ↪printMisses=True, maxMisses=50)
else:
    print("No handwritten digits found.")
```

```
Handwritten digits found: 330

==== Handwritten Digits RESULTS ====
Accuracy: 0.9576
Error Rate: 0.0424

Classification Report:
              precision    recall  f1-score   support

           0     0.8462    1.0000    0.9167        33
           1     1.0000    0.9394    0.9688        33
           2     0.8919    1.0000    0.9429        33
           3     1.0000    0.8788    0.9355        33
           4     1.0000    1.0000    1.0000        33
           5     0.9412    0.9697    0.9552        33
           6     1.0000    0.9091    0.9524        33
           7     0.9429    1.0000    0.9706        33
           8     1.0000    0.9091    0.9524        33
           9     1.0000    0.9697    0.9846        33

    accuracy                         0.9576       330
   macro avg     0.9622    0.9576    0.9579       330
```

```
weighted avg      0.9622     0.9576     0.9579        330

Confusion Matrix:
[[33  0  0  0  0  0  0  0  0  0]
 [ 0 31  1  0  0  0  0  1  0  0]
 [ 0  0 33  0  0  0  0  0  0  0]
 [ 0  0  2 29  0  1  0  1  0  0]
 [ 0  0  0  0 33  0  0  0  0  0]
 [ 0  0  1  0  0 32  0  0  0  0]
 [ 3  0  0  0  0  0 30  0  0  0]
 [ 0  0  0  0  0  0  0 33  0  0]
 [ 2  0  0  0  0  1  0  0 30  0]
 [ 1  0  0  0  0  0  0  0  0 32]]
```





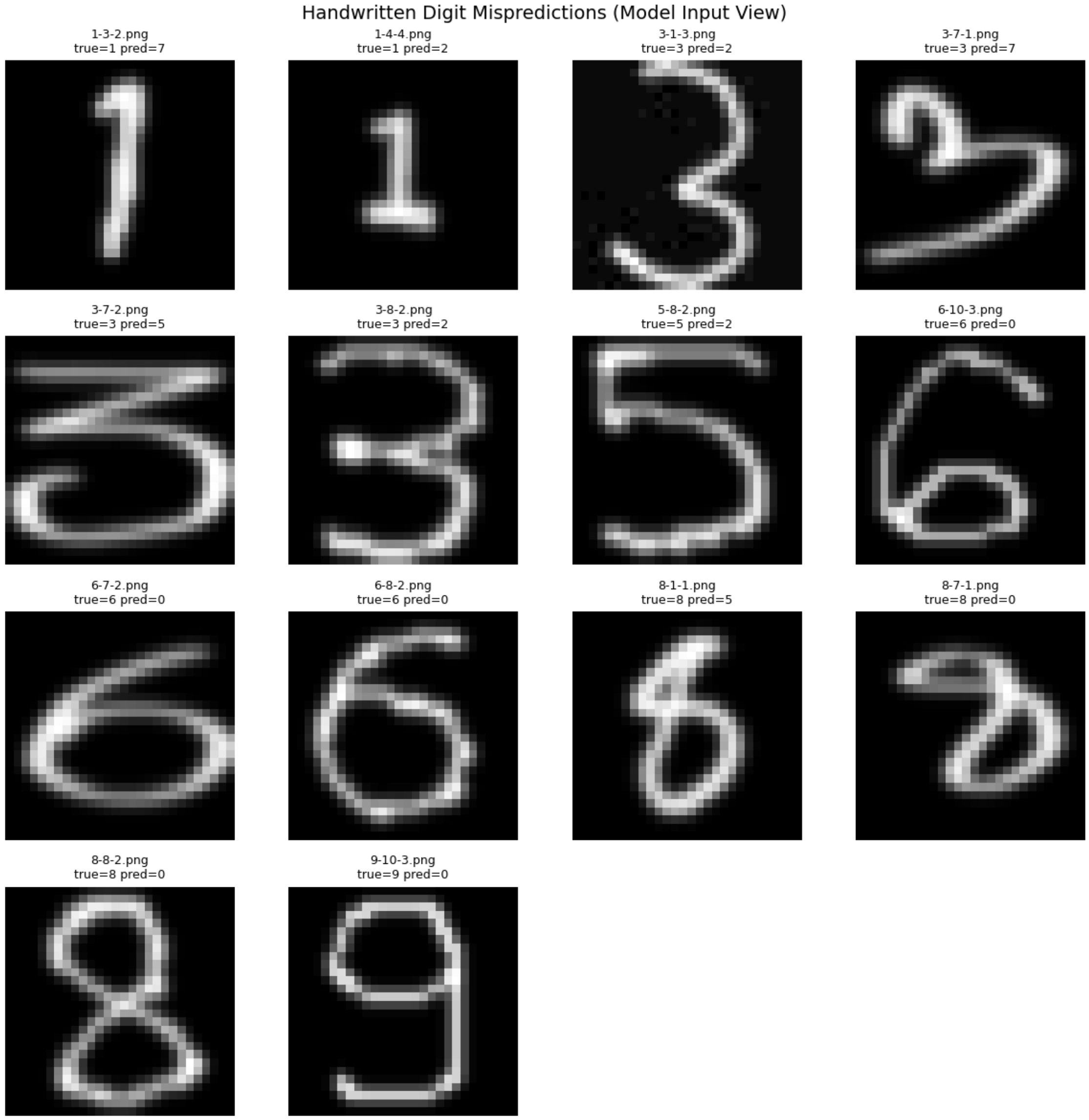



```
Handwritten Digits mispredictions: 14 / 330
- ./digits/1-3-2.png | true=1 pred=7
- ./digits/1-4-4.png | true=1 pred=2
- ./digits/3-1-3.png | true=3 pred=2
- ./digits/3-7-1.png | true=3 pred=7
- ./digits/3-7-2.png | true=3 pred=5
- ./digits/3-8-2.png | true=3 pred=2
- ./digits/5-8-2.png | true=5 pred=2
- ./digits/6-10-3.png | true=6 pred=0
- ./digits/6-7-2.png | true=6 pred=0
```

```
- ./digits/6-8-2.png | true=6 pred=0
- ./digits/8-1-1.png | true=8 pred=5
- ./digits/8-7-1.png | true=8 pred=0
- ./digits/8-8-2.png | true=8 pred=0
- ./digits/9-10-3.png | true=9 pred=0
```

[26]:
```python
import os, math
import numpy as np
import matplotlib.pyplot as plt
from PIL import Image

MISSES = [
    ("./digits/1-3-2.png", 1, 7),
    ("./digits/1-4-4.png", 1, 2),
    ("./digits/3-1-3.png", 3, 2),
    ("./digits/3-7-1.png", 3, 7),
    ("./digits/3-7-2.png", 3, 5),
    ("./digits/3-8-2.png", 3, 2),
    ("./digits/5-8-2.png", 5, 2),
    ("./digits/6-10-3.png", 6, 0),
    ("./digits/6-7-2.png", 6, 0),
    ("./digits/6-8-2.png", 6, 0),
    ("./digits/8-1-1.png", 8, 5),
    ("./digits/8-7-1.png", 8, 0),
    ("./digits/8-8-2.png", 8, 0),
    ("./digits/9-10-3.png", 9, 0),
]

def _tensor_to_display_uint8(x):
    x = x.detach().cpu()
    x = (x * 0.5 + 0.5).clamp(0, 1)  # de-normalize
    return (x.squeeze().numpy() * 255).astype(np.uint8)

def MakeMispredictionGallery(misses, out_path="mispredictions_gallery.png",␣
 ↪cols=4, dpi=300):
    n = len(misses)
    rows = math.ceil(n / cols)
    plt.figure(figsize=(cols * 3.0, rows * 3.0))

    for i, (path, y_true, y_pred) in enumerate(misses, start=1):
        ax = plt.subplot(rows, cols, i)

        if not os.path.exists(path):
            ax.set_title(f"Missing:\n{os.path.basename(path)}", fontsize=9)
            ax.axis("off")
            continue
```

```
        img = Image.open(path).convert("RGB")
        img = ColorStretch(img)
        img = img.resize((28, 28))
        x = transform(img)
        disp = _tensor_to_display_uint8(x)

        ax.imshow(disp, cmap="gray", vmin=0, vmax=255)
        ax.set_title(f"{os.path.basename(path)}\ntrue={y_true} pred={y_pred}", fontsize=9)
        ax.axis("off")

    plt.suptitle("Handwritten Digit Mispredictions (Model Input View)", fontsize=14)
    plt.tight_layout()
    plt.savefig(out_path, dpi=dpi, bbox_inches="tight")
    plt.show()
    print("Saved:", out_path)

MakeMispredictionGallery(MISSES, out_path="mispredictions_gallery.png", cols=4, dpi=300)
```




```
Saved: mispredictions_gallery.png
```