model

December 11, 2025

[8]:
```python
# ============================================================
# Final Project: Train neural net on MNIST and evaluate on local digits
# ============================================================

DEMO = True

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
```

[9]:
```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)
        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(
```

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


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)
```

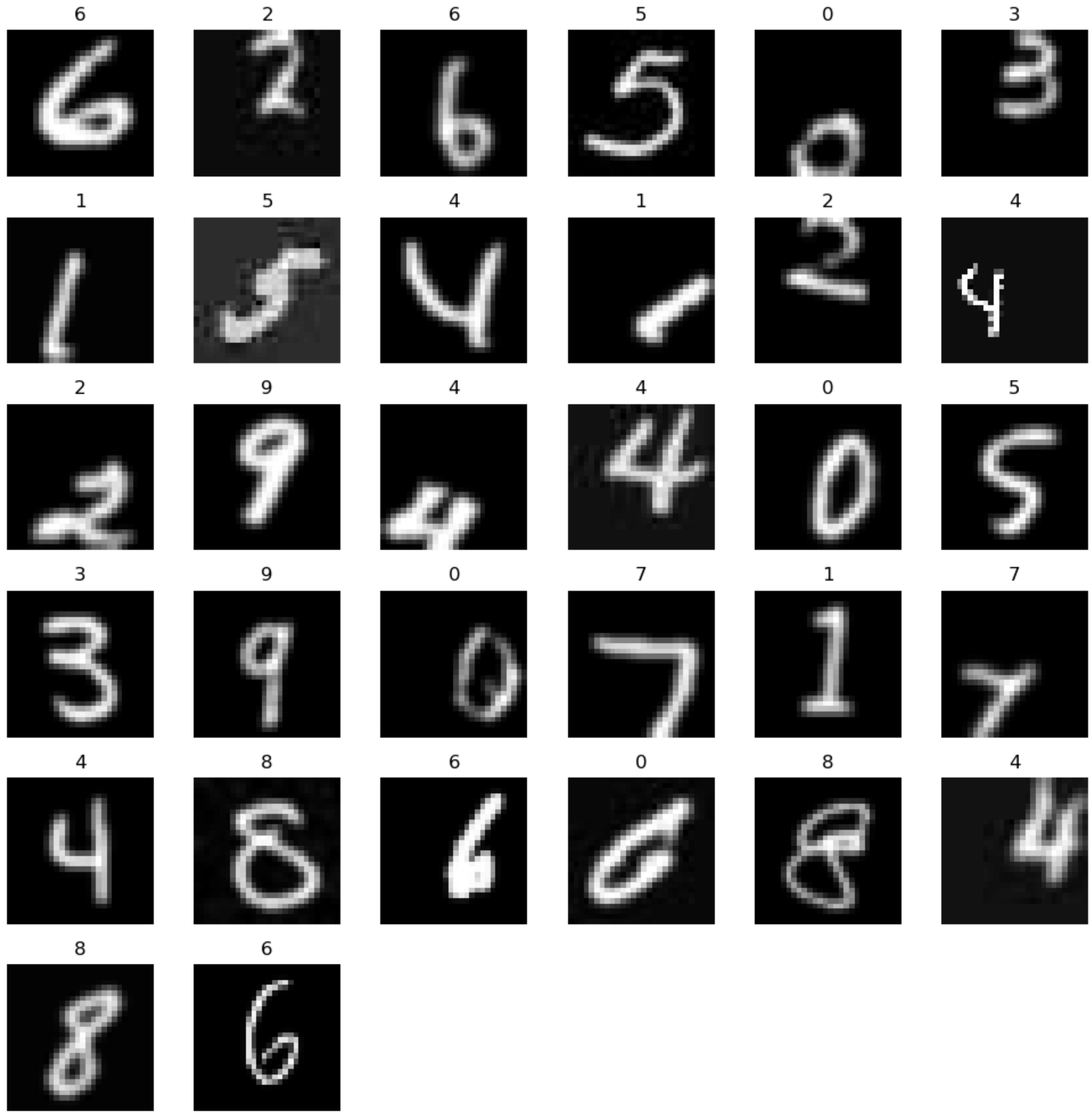
```python
testSet = datasets.MNIST(
    "~/.pytorch/MNIST_data/", download=True, train=False, transform=transform
)
testLoader = torch.utils.data.DataLoader(testSet, batch_size=64, shuffle=False)

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
```



[10]:
```python
# ============================================================
# 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)
)
```

[11]:
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# ============================================================
# 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 (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.")

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

```
Loaded model.pth (DEMO mode)
```

[12]:
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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")
```

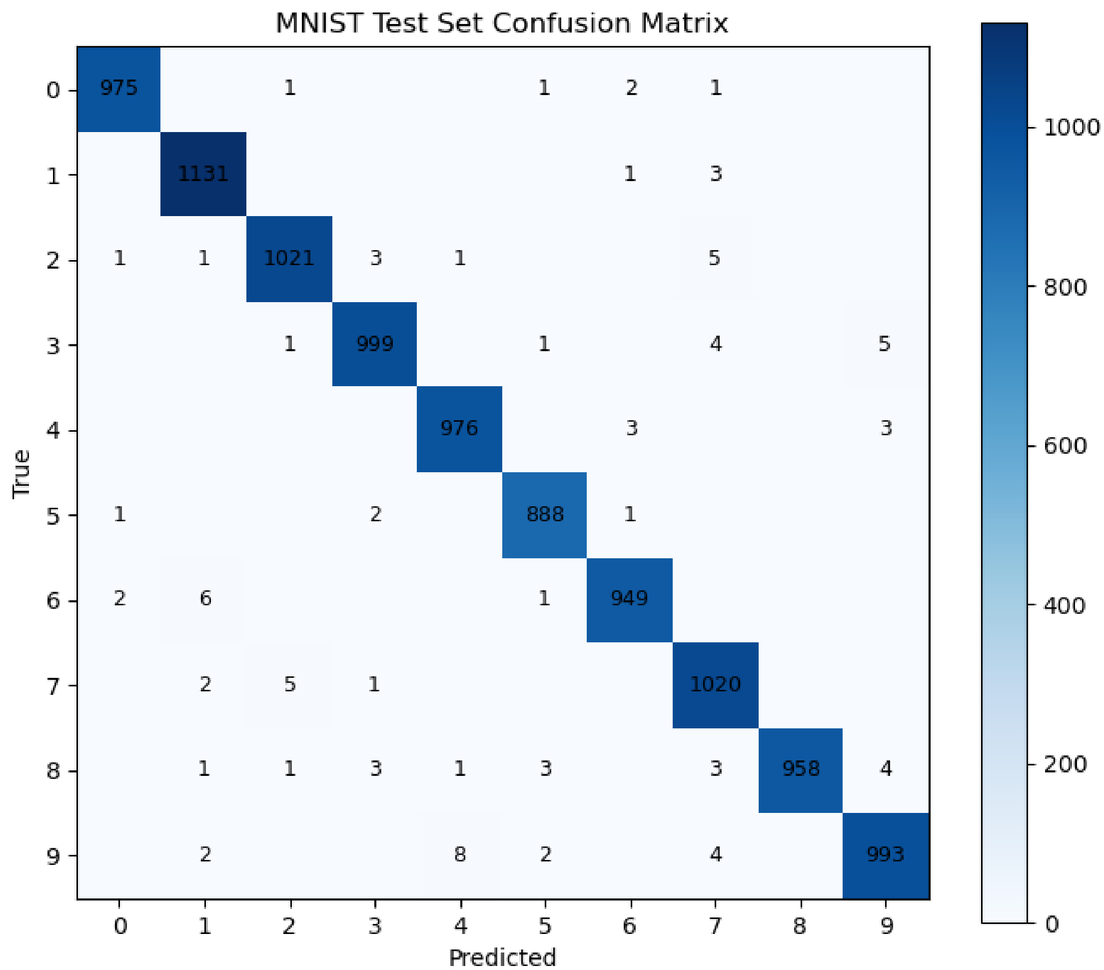
```python
    plt.xticks(range(10))
    plt.yticks(range(10))
    plt.colorbar()
    for r in range(cm.shape[0]):
        for c in range(cm.shape[1]):
            v = cm[r, c]
            if v != 0:
                plt.text(c, r, str(v), ha="center", va="center", fontsize=9)
    plt.tight_layout()
    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()
```

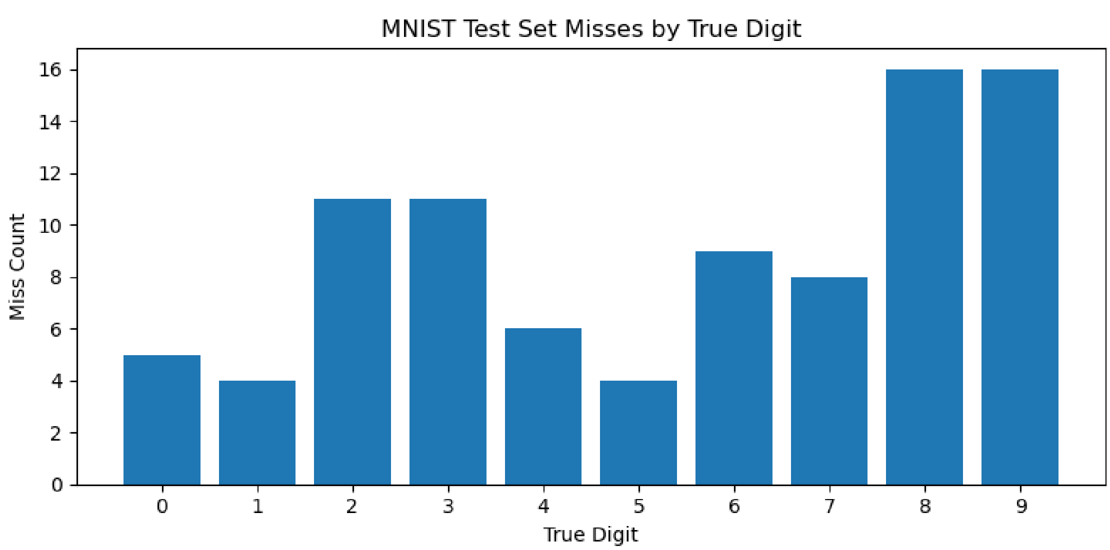
```python
    plt.show(block=False)
    plt.pause(0.001)

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)
```

```python
            allPreds.extend(preds.cpu().numpy())
            allLabels.extend(labels.cpu().numpy())

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

    # preserve old behavior: MNIST call expects a float accuracy
    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 Set Confusion Matrix
True
Predicted
975 1 1 2 1
1131 1 3
1 1 1021 3 1 5
1 999 1 4 5
976 3 3
1 2 888 1
2 6 1 949
2 5 1 1020
1 1 3 1 3 3 958 4
2 8 2 4 993
0 1 2 3 4 5 6 7 8 9
0 200 400 600 800 1000

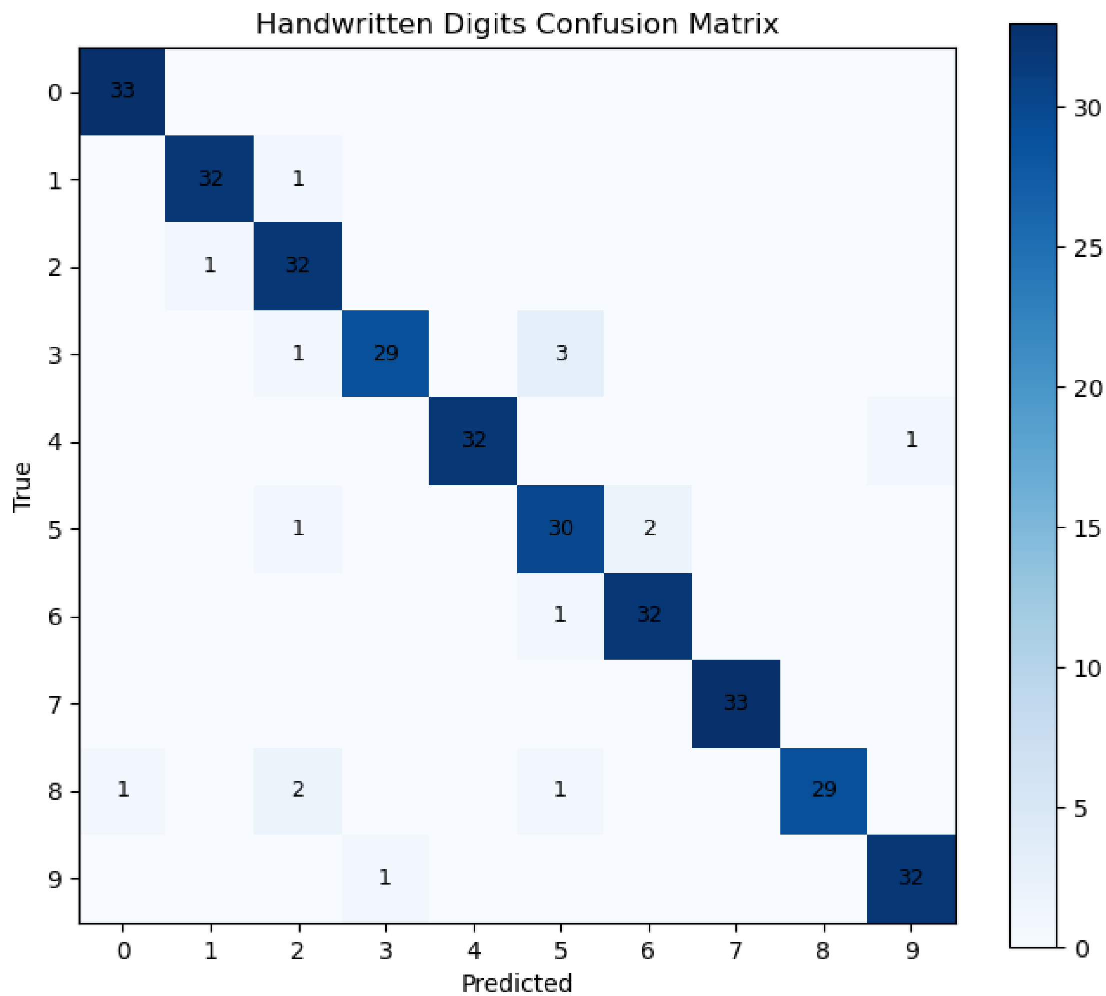

MNIST Test Set Misses by True Digit
Miss Count
True Digit
0 2 4 6 8 10 12 14 16
0 1 2 3 4 5 6 7 8 9

```
MNIST Test Set mispredictions: 90 / 10000
(No file paths available to print per-image misses.)
MNIST test accuracy (float): 0.991
```

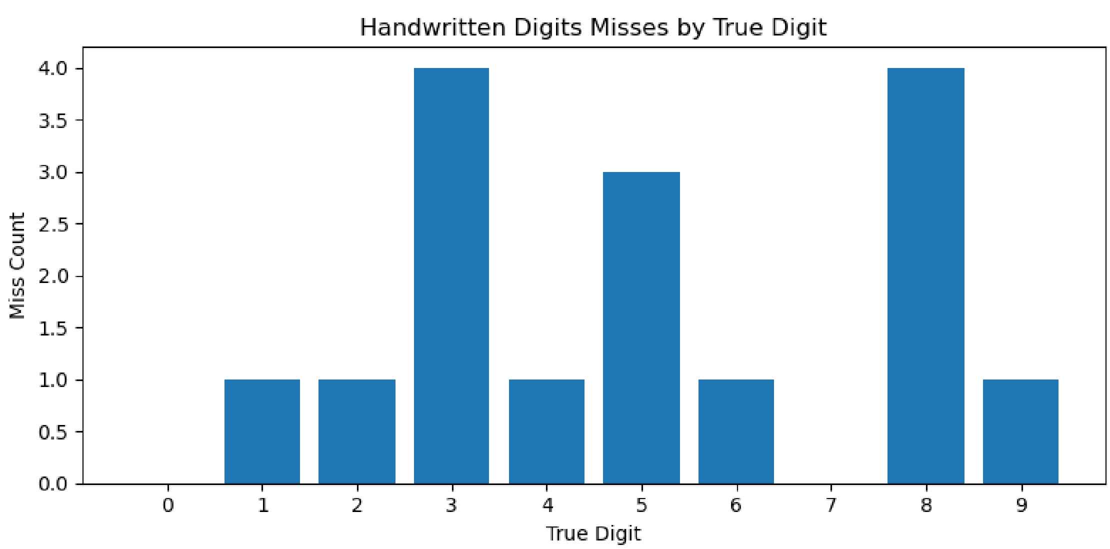
[13]:
```
# ============================================================
# 5. Local handwritten digit dataset
# ============================================================


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]

        # Try to parse group id like "digit-group-....png"
        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)  # no group present

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

    def __getitem__(self, idx):
        path = self.paths[idx]
        img = Image.open(path)
        img = PreprocessSingle(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.")
```

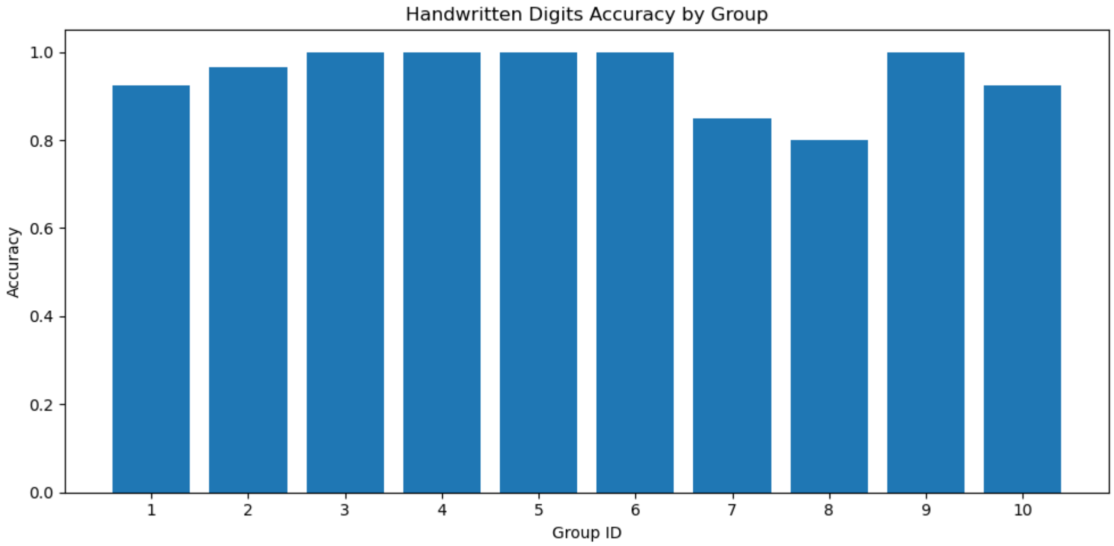
```
Handwritten digits found: 330

==== Handwritten Digits RESULTS ====
Accuracy: 0.9515
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]]
```



Handwritten Digits Confusion Matrix
True
Predicted
0
1
2
3
4
5
6
7
8
9
33
32
1
1
32
1
29
3
32
1
1
30
2
1
32
33
1
2
1
29
1
32
0
5
10
15
20
25
30



Handwritten Digits Misses by True Digit
Miss Count
True Digit
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
0
1
2
3
4
5
6
7
8
9




```
Handwritten Digits mispredictions: 16 / 330
- ./digits/1-8-2.png | true=1 pred=2
- ./digits/2-1-4.png | true=2 pred=1
- ./digits/3-1-4.png | true=3 pred=5
- ./digits/3-7-1.png | true=3 pred=5
- ./digits/3-7-2.png | true=3 pred=5
- ./digits/3-8-2.png | true=3 pred=2
- ./digits/4-2-4.png | true=4 pred=9
- ./digits/5-7-2.png | true=5 pred=6
- ./digits/5-8-1.png | true=5 pred=6
- ./digits/5-8-2.png | true=5 pred=2
- ./digits/6-8-2.png | true=6 pred=5
- ./digits/8-1-1.png | true=8 pred=5
- ./digits/8-10-1.png | true=8 pred=0
- ./digits/8-10-3.png | true=8 pred=2
- ./digits/8-8-2.png | true=8 pred=2
- ./digits/9-10-3.png | true=9 pred=3
```