Assignment 4

Jason Wong

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Objective: Handwritten Digit Recognition

In this assignment, you are asked to design and develop artificial neural network models that can classify handwritten digits from the MNIST dataset. The MNIST dataset consists of 60,000 training images and 10,000 testing images. Each image is a small 28x28 (784) pixels grayscale digit between 0 and 9. You can use a Python library to download this dataset.

From this assignment, you will also learn how to process and compute images, and design multilayer backpropagation perceptron (MLP) and Convolutional Neural Network (CNN) architectures.

1 Project Setup

1.1 Import relevant libraries

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as AF
import matplotlib.pyplot as plt

from torchvision import datasets, transforms
from torch.utils.data import DataLoader
```

1.2 Download the dataset

For this project, we will be using the MNIST dataset. However, before using the dataset we have to preprocess the data. Specifically, converting the images to tensors and scaling the pixel values from 0-255 down to 0-1.

[2]:
```
mini_batch_size = 1000

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

train_dataset = datasets.MNIST(
    root="./data", train=True, transform=transformer, download=True
```

```
)
test_dataset = datasets.MNIST(
    root="./data", train=False, transform=transformer, download=False
)

train_dataloader = DataLoader(
    dataset=train_dataset, batch_size=mini_batch_size, shuffle=True
)
test_dataloader = DataLoader(
    dataset=test_dataset, batch_size=mini_batch_size, shuffle=True
)

print(f"Mini batch size: {mini_batch_size}")
print(f"Number of batches loaded for training: {len(train_dataloader)}")
print(f"Number of batches loaded for testing: {len(test_dataloader)}")
```

```
Mini batch size: 1000
Number of batches loaded for training: 60
Number of batches loaded for testing: 10
```

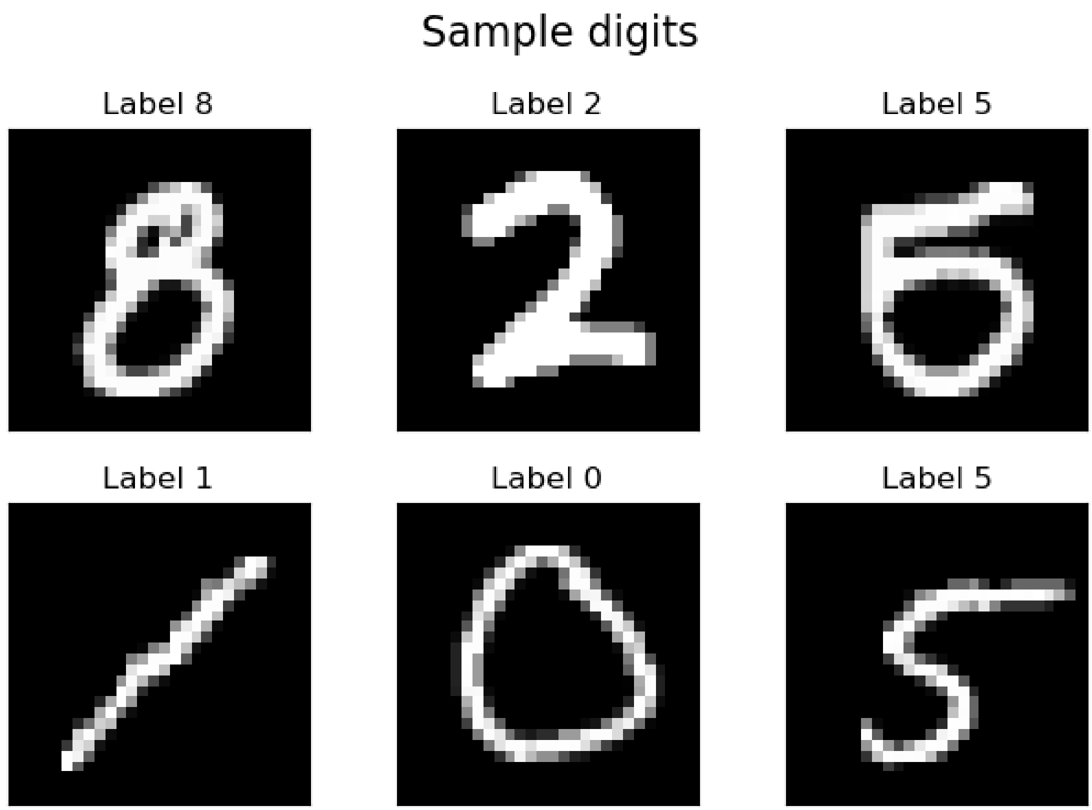
1.3 Visualizing the dataset

[3]:
```
# Dataloader that only loads 1 image at a time for the purposes of sampling
# individual images
sample_dataloader = DataLoader(dataset=test_dataset, batch_size=1, shuffle=True)

images, labels = next(iter(sample_dataloader))
print(images.shape)
```

```
torch.Size([1, 1, 28, 28])
```

As we can see, the shape of each image is 28x28, meaning there are 784 inputs for our model. Let's display some of the images from the dataset

[4]:
```
fig = plt.figure()
fig.suptitle("Sample digits", fontsize=16)
for i in range(6):
    images, labels = next(iter(sample_dataloader))
    plt.subplot(2, 3, i + 1)
    plt.tight_layout()
    plt.imshow(images[0][0].reshape(28, 28), cmap="gray", interpolation="none")
    plt.title(f'Label {labels[0]}')
    plt.xticks([])
    plt.yticks([])
    fig
```



2 Part 1: Multi Layer Perceptron (MLP)

2.1 Model Construction

Our MLP model used 4 linear layers for a total of 2330 neurons and the activation function we used was the Rectified Linear Unit (ReLU) with the LogSoftMax activation as the output activation function because this is a classification problem.

[5]:
```
model = nn.Sequential(
    nn.Linear(784, 512),
    nn.ReLU(),
    nn.Linear(512, 512),
    nn.ReLU(),
    nn.Linear(512, 512),
    nn.ReLU(),
    nn.Linear(512, 10),
    nn.LogSoftmax(dim=1),
)
print(model)
```

```
Sequential(
  (0): Linear(in_features=784, out_features=512, bias=True)
  (1): ReLU()
  (2): Linear(in_features=512, out_features=512, bias=True)
  (3): ReLU()
  (4): Linear(in_features=512, out_features=512, bias=True)
  (5): ReLU()
  (6): Linear(in_features=512, out_features=10, bias=True)
  (7): LogSoftmax(dim=1)
)
```

For our loss function we used the Cross Entropy Loss function

[6]:
```
loss_function = nn.CrossEntropyLoss()
```

For our gradient method we used the Adam optimizer with a learning rate of 0.003

[7]:
```
optimizer = optim.Adam(model.parameters(), lr=0.003)
```

[8]:
```
import time

time0 = time.perf_counter()
num_epochs = 20

# use gpu if available
device = torch.device(
    "cuda:0"
    if torch.cuda.is_available()
    else "mps"
    if torch.backends.mps.is_available() and torch.backends.mps.is_built()
    else "cpu"
)
if torch.cuda.is_available():
    print("The CUDA version is", torch.version.cuda)
    cuda_id = torch.cuda.current_device()
    print("ID of the CUDA device:", cuda_id)
    print("The name of the CUDA device:", torch.cuda.get_device_name(cuda_id))

    print("Training with CUDA")
    model = model.to(device=device)

elif device.type == "mps" or device.type == "cuda":
    print("Training with Apple Silicon")
    device = torch.device("mps")
    model = model.to(device)
else:
    print("Training with CPU")
```

```
for e in range(num_epochs):
    running_loss = 0
    for images, labels in train_dataloader:
        if device.type == "mps" or device.type == "cuda":
            images = images.to(device)
            labels = labels.to(device)
        images = images.view(images.shape[0], -1)

        # set the cumulated gradient to zero
        optimizer.zero_grad()

        # feedforward images as input to the network
        output = model(images)
        loss = loss_function(output, labels)

        # calculating gradients backward using Autograd
        loss.backward()

        # updating all parameters after every iteration through backpropagation
        optimizer.step()

        running_loss += loss.item()
    else:
        print(f"Epoch {e} - Training loss: {running_loss /
 ↪len(train_dataloader)}")
print(f"Training Time: {time.perf_counter() - time0}")
```

```
Training with Apple Silicon
Epoch 0 - Training loss: 0.7062971264123916
Epoch 1 - Training loss: 0.1836504850536585
Epoch 2 - Training loss: 0.12555630256732306
Epoch 3 - Training loss: 0.09297069745759169
Epoch 4 - Training loss: 0.07332255734751622
Epoch 5 - Training loss: 0.06508577490846316
Epoch 6 - Training loss: 0.05327987528095643
Epoch 7 - Training loss: 0.04592210249975324
Epoch 8 - Training loss: 0.041200701426714656
Epoch 9 - Training loss: 0.04915759799381097
Epoch 10 - Training loss: 0.0353595116486152
Epoch 11 - Training loss: 0.028985522609824937
Epoch 12 - Training loss: 0.029948636097833513
Epoch 13 - Training loss: 0.03318087127991021
Epoch 14 - Training loss: 0.024575960356742144
Epoch 15 - Training loss: 0.026748089166358114
Epoch 16 - Training loss: 0.019111777616975207
Epoch 17 - Training loss: 0.01769401797403892
Epoch 18 - Training loss: 0.01990034426562488
```

```
Epoch 19 - Training loss: 0.017190352315083146
Training Time: 51.388005125
```

[9]:
```
# torch.no_grad() is a decorator for the step method
# making "require_grad" false since no need to keeping track of gradients
predicted_digits = []
num_samples = 0
num_correct = 0
# torch.no_grad() deactivates Autogra engine (for weight updates)
with torch.no_grad():
    # set the model in testing mode
    model.eval()
    for batch_cnt, (images, labels) in enumerate(test_dataloader):
        images = images.reshape(-1, 784)

        if device.type == "mps" or device.type == "cuda":
            images = images.to(device)
            labels = labels.to(device)

        # returns the max value of all elements in the input tensor
        output = model(images)
        _, prediction = torch.max(output, 1)
        predicted_digits.append(prediction)
        num_samples += labels.shape[0]
        num_correct += (prediction == labels).sum().item()
    accuracy = num_correct / num_samples
    print(f"Number of samples: {num_samples}")
    print(f"Number of correct prediction: {num_correct}")
    print(f"Accuracy: {accuracy}")
```

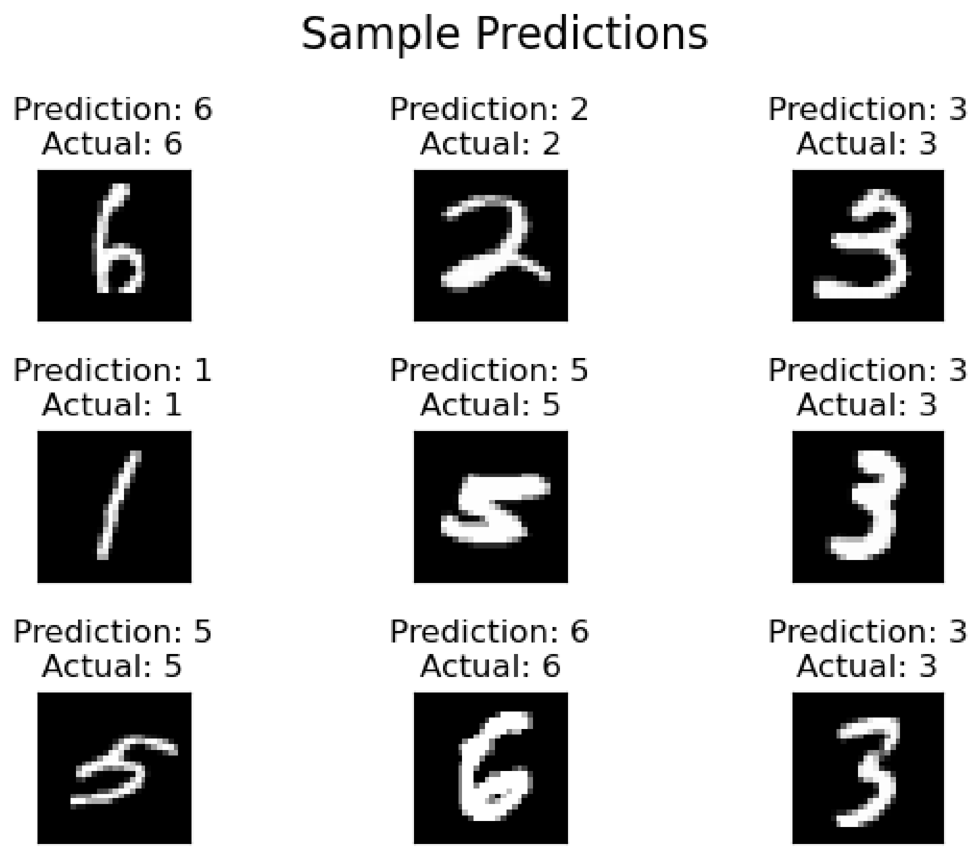
```
Number of samples: 10000
Number of correct prediction: 9784
Accuracy: 0.9784
```

2.2 Results

Our MLP model yielded a classification accuracy of 97.84% after 20 epoches and 51 seconds of training

[10]:
```
fig = plt.figure()
fig.suptitle('Sample Predictions', fontsize=16)
for i in range(9):
    images, labels = next(iter(sample_dataloader))
    plt.subplot(3, 3, i + 1)
    plt.tight_layout()
    plt.imshow(images[0][0].reshape(28, 28), cmap="gray", interpolation="none")
    images = images.to(device)
    images = images.reshape(-1, 784)
```

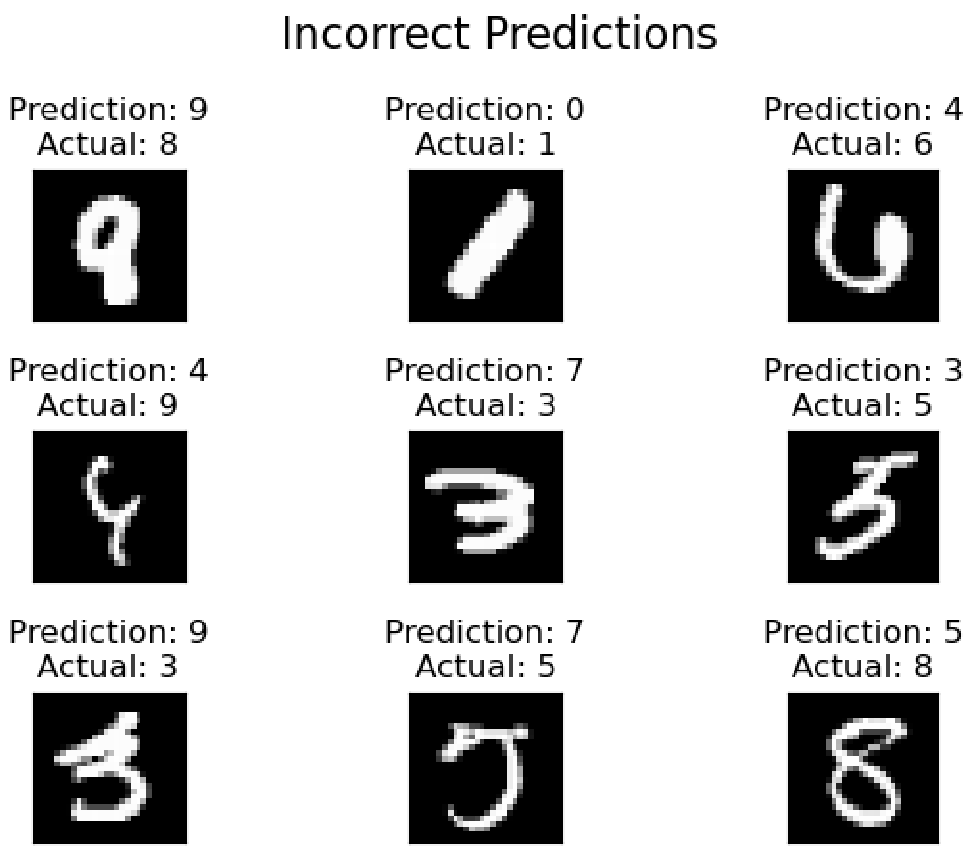
```
    model.eval()
    output = model(images)
    _, prediction = torch.max(output, 1)
    plt.title(f"Prediction: {prediction[0]}\nActual: {labels[0]}")
    plt.xticks([])
    plt.yticks([])
    fig
```



As we can see, it tends to correctly classify most digits in the testing set. Let's take a look at what digits it failed to properly classify

[11]:
```
fig = plt.figure()
fig.suptitle("Incorrect Predictions", fontsize=16)
i = 0
while i < 9:
    images, labels = next(iter(sample_dataloader))
    images_ = images.to(device)
    images_ = images_.reshape(-1, 784)
    model.eval()
    output = model(images_)
```

```
    _, prediction = torch.max(output, 1)
    if prediction[0] == labels[0]:
        continue;
    plt.subplot(3, 3, i + 1)
    plt.tight_layout()
    plt.imshow(images[0][0].reshape(28, 28), cmap="gray", interpolation="none")
    plt.title(f"Prediction: {prediction[0]}\nActual: {labels[0]}")
    plt.xticks([])
    plt.yticks([])
    i = i + 1
    fig
```



3 Part 2: Convolutional Neural Network

3.1 Model Construction

Our CNN model used only 1 Conv2d layer with 1 MaxPool2d layer and an additional hidden linear layer. It uses the ReLU activation function.

[12]:

```
class CNN(nn.Module):
    def __init__(self):
        super(CNN, self).__init__()
        self.conv1 = nn.Conv2d(1, 28, kernel_size=3)
        self.pool1 = nn.MaxPool2d(2)
        self.dropout_conv1 = nn.Dropout(0.2)
        self.fc1 = nn.Linear(128, 10)
        self.hidden = nn.Linear(28 * 13 * 13, 128)
        self.out = nn.ReLU()

    def forward(self, x):
        x = self.out(self.conv1(x))
        x = self.pool1(x)
        x = x.view(x.size(0), -1)
        x = self.out(self.hidden(x))
        x = self.dropout_conv1(x)
        x = self.fc1(x)
        return x


model = CNN()
print(model)
```

```
CNN(
  (conv1): Conv2d(1, 28, kernel_size=(3, 3), stride=(1, 1))
  (pool1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (dropout_conv1): Dropout(p=0.2, inplace=False)
  (fc1): Linear(in_features=128, out_features=10, bias=True)
  (hidden): Linear(in_features=4732, out_features=128, bias=True)
  (out): ReLU()
)
```

Our loss function and optimizer used the same parameters as the MLP model. Cross Entropy Loss and Adam respectively.

[13]:

```
loss_function = nn.CrossEntropyLoss()
```

[14]:

```
optimizer = optim.Adam(model.parameters(), lr=0.003)
```

[15]:

```
import time

time0 = time.perf_counter()
num_epochs = 20

# use gpu if available
device = torch.device(
    "cuda:0"
```

```
    if torch.cuda.is_available()
    else "mps"
    if torch.backends.mps.is_available() and torch.backends.mps.is_built()
    else "cpu"
)
if torch.cuda.is_available():
    print("The CUDA version is", torch.version.cuda)
    cuda_id = torch.cuda.current_device()
    print("ID of the CUDA device:", cuda_id)
    print("The name of the CUDA device:", torch.cuda.get_device_name(cuda_id))

    print("Training with CUDA")
    model = model.to(device=device)

elif torch.backends.mps.is_available() and torch.backends.mps.is_built():
    print("Training with Apple Silicon")
    device = torch.device("mps")
    model = model.to(device)
else:
    print("Training with CPU")

for e in range(num_epochs):
    running_loss = 0
    for images, labels in train_dataloader:
        if device.type == "mps" or device.type == "cuda":
            images = images.to(device)
            labels = labels.to(device)

        # set the cumulated gradient to zero
        optimizer.zero_grad()

        # feedforward images as input to the network
        output = model(images)
        loss = loss_function(output, labels)

        # calculating gradients backward using Autograd
        loss.backward()

        # updating all parameters after every iteration through backpropagation
        optimizer.step()

        running_loss += loss.item()
    else:
        print(f"Epoch {e} - Training loss: {running_loss /
 ↪len(train_dataloader)}")
print(f"Training Time: {time.perf_counter() - time0}")
```

```
Training with Apple Silicon
Epoch 0 - Training loss: 0.7130954526364803
Epoch 1 - Training loss: 0.19142543996373812
Epoch 2 - Training loss: 0.12121491432189942
Epoch 3 - Training loss: 0.09439456276595592
Epoch 4 - Training loss: 0.0749340392028292
Epoch 5 - Training loss: 0.06489987994233767
Epoch 6 - Training loss: 0.0552262614791592
Epoch 7 - Training loss: 0.049915183894336225
Epoch 8 - Training loss: 0.04406964086617033
Epoch 9 - Training loss: 0.039694247239579754
Epoch 10 - Training loss: 0.03653611990933617
Epoch 11 - Training loss: 0.03266819203272462
Epoch 12 - Training loss: 0.02937838526753088
Epoch 13 - Training loss: 0.026868577348068357
Epoch 14 - Training loss: 0.024683859742557008
Epoch 15 - Training loss: 0.02322738996396462
Epoch 16 - Training loss: 0.022761528038730224
Epoch 17 - Training loss: 0.02116626452965041
Epoch 18 - Training loss: 0.01855914629995823
Epoch 19 - Training loss: 0.016913721803575754
Training Time: 74.36753841699999
```

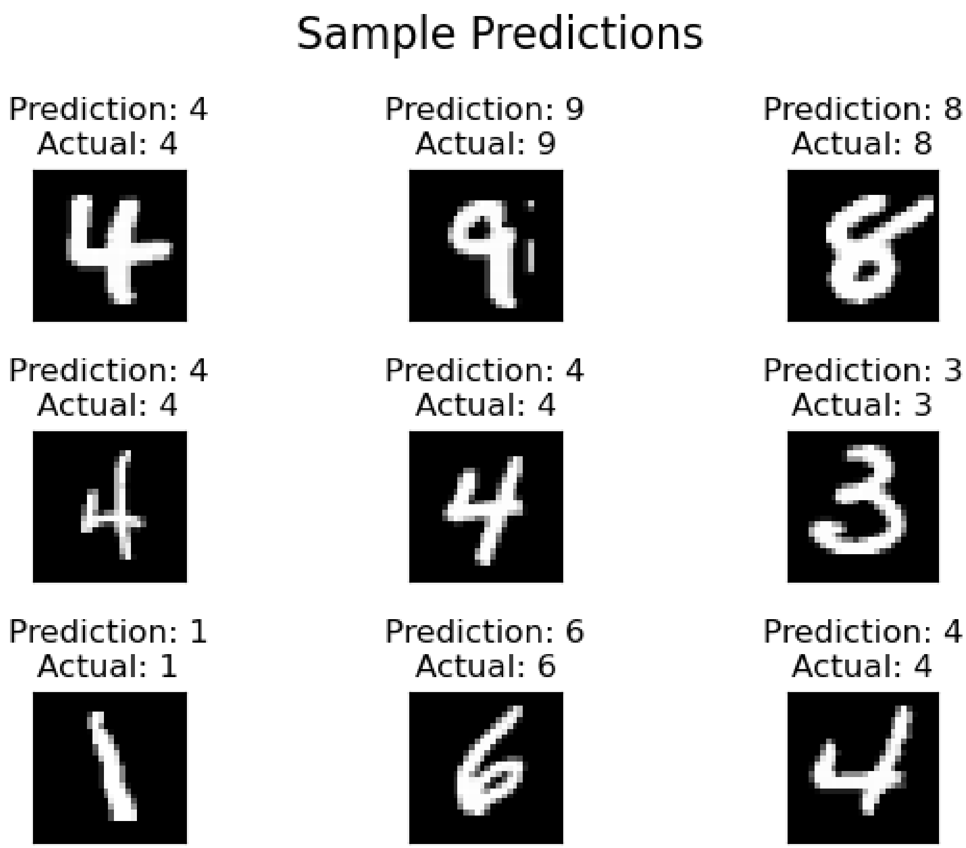
[16]:
```
# torch.no_grad() is a decorator for the step method
# making "require_grad" false since no need to keeping track of gradients
predicted_digits = []
num_samples = 0
num_correct = 0
# torch.no_grad() deactivates Autogra engine (for weight updates)
with torch.no_grad():
    # set the model in testing mode
    model.eval()
    for batch_cnt, (images, labels) in enumerate(test_dataloader):
        if device.type == "mps" or device.type == "cuda":
            images = images.to(device)
            labels = labels.to(device)

        # returns the max value of all elements in the input tensor
        output = model(images)
        _, prediction = torch.max(output, 1)
        predicted_digits.append(prediction)
        num_samples += labels.shape[0]
        num_correct += (prediction == labels).sum().item()
    accuracy = num_correct / num_samples
    print(f"Number of samples: {num_samples}")
    print(f"Number of correct prediction: {num_correct}")
    print(f"Accuracy: {accuracy}")
```

```
Number of samples: 10000
Number of correct prediction: 9869
Accuracy: 0.9869
```

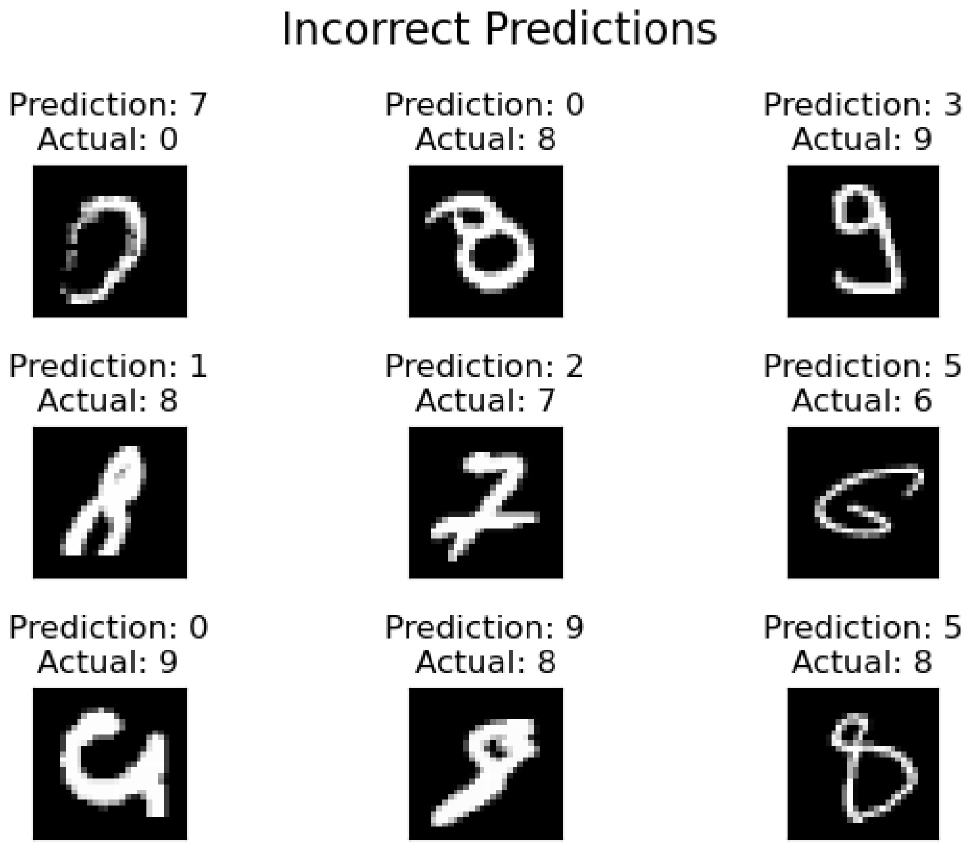
3.2 Results

Our CNN model yielded a classification accuracy of 98.69% after 20 epoches and 74 seconds of training.

[17]:
```
fig = plt.figure()
fig.suptitle("Sample Predictions", fontsize=16)
for i in range(9):
    images, labels = next(iter(sample_dataloader))
    plt.subplot(3, 3, i + 1)
    plt.tight_layout()
    plt.imshow(images[0][0].reshape(28, 28), cmap="gray", interpolation="none")
    images = images.to(device)
    model.eval()
    output = model(images)
    _, prediction = torch.max(output, 1)
    plt.title(f"Prediction: {prediction[0]}\nActual: {labels[0]}")
    plt.xticks([])
    plt.yticks([])
    fig
```



[18]:
```
fig = plt.figure()
fig.suptitle("Incorrect Predictions", fontsize=16)
i = 0
while i < 9:
    images, labels = next(iter(sample_dataloader))
    images_ = images.to(device)
    model.eval()
    output = model(images_)
    _, prediction = torch.max(output, 1)
    if prediction[0] == labels[0]:
        continue;
    plt.subplot(3, 3, i + 1)
    plt.tight_layout()
    plt.imshow(images[0][0].reshape(28, 28), cmap="gray", interpolation="none")
    plt.title(f"Prediction: {prediction[0]}\nActual: {labels[0]}")
    plt.xticks([])
    plt.yticks([])
    i = i + 1
    fig
```



4 Conclusion

We found that the Convolutional Neural Network model consistently out performs the Multi Layer Perceptron model in classification accuracy. However it is worth noting that the MLP model tended to have faster training times despite having more layers than the CNN. As such, we would recommend using a CNN for the classification of hand written digits