NAME: PRATYUSH ABHI

CAMPUS: V.I.T VELLORE

We are building the project on Mnist Dataset

About Mnist data: The MNIST database contains 60,000 training images and 10,000 testing images. Half of the training set and half of the test set were taken from NIST's training dataset, while the other half of the training set and the other half of the test set were taken from NIST's testing dataset.

Here we would we using ANN and CNN models to train and test the data sets we are getting

an test accuracy of 97.73%

In [ ]:
```
import torch import torch.nn
as nn import
torch.nn.functional as
```

In [2]:
```
from torch.utils.data import DataLoader
from torchvision import
datasets,transforms
```

In [3]:
```
import numpy as np
import pandas as pd
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
%matplotlib inline
```

In [4]:
```
#MNIST image to tensor
```

In [5]:
```
transform=transforms.ToTensor()
```

In [6]:
```
train_data=datasets.MNIST(root='/Users/pratyushabhi/Desktop/3rd Year/
```

In [7]:
```
test_data=datasets.MNIST(root='/Users/pratyushabhi/Desktop/3rd Year/I
```

In [8]:
```
train_data
```

Out[8]:
```
Dataset MNIST
    Number of datapoints: 60000
    Root location: /Users/pratyushabhi/Desktop/3rd Year/Image process
ing/ANN
    Split: Train
    StandardTransform
Transform: ToTensor()
```

In [9]:
```
test_data
```

Out[9]:
```
Dataset MNIST
```

```
            Number of datapoints: 10000
            Root location: /Users/pratyushabhi/Desktop/3rd Year/Image process
        ing/ANN     Split: Test
            StandardTransform
        Transform: ToTensor()
```

```
In [10]: type(train_data)
```

```
Out[10]: torchvision.datasets.mnist.MNIST
```

```
In [11]: train_data[0]
```

```
Out[11]: (tensor([[[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000
        ,
                  0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
        0.0000 ,
                  0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
        0.0000 ,
                  0.0000, 0.0000, 0.0000, 0.0000],          [0.0000, 0.0000,
        0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
                  0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
        0.0000 ,
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        0.0000 ,
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        0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
                  0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
        0.0000 ,
                  0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
        0.0000 ,
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        0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
                  0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
        0.0000 ,
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        0.0000 ,
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        0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
                  0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
        0.0000 ,
                  0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
        0.0000 ,
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        0.0706 ,
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        0.4980
        ,
                  0.0000, 0.0000, 0.0000, 0.0000],          [0.0000, 0.0000,
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                  0.1176, 0.1412, 0.3686, 0.6039, 0.6667, 0.9922, 0.9922,
        0.9922 ,
```

```
          0.9922, 0.9922, 0.8824, 0.6745, 0.9922, 0.9490, 0.7647,
0.2510 ,
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0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.1922 ,
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0.9922 ,
          0.9922, 0.9843, 0.3647, 0.3216, 0.3216, 0.2196, 0.1529,
0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000],          [0.0000, 0.0000,
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0706 ,
          0.8588, 0.9922, 0.9922, 0.9922, 0.9922, 0.9922, 0.7765,
0.7137 ,
          0.9686, 0.9451, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000],          [0.0000, 0.0000,
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
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0.0000 ,
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0.0000 ,
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0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
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0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000],          [0.0000, 0.0000,
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
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0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000],          [0.0000, 0.0000,
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
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0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000],          [0.0000, 0.0000,
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
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0.6275 ,
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0.0000 ,
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0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
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0.9922 ,
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0.0000 ,
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0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.1765,
0.7294 ,
```

```
          0.9922, 0.9922, 0.5882, 0.1059, 0.0000, 0.0000, 0.0000,
0.0000 ,
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0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
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0.0000 ,
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0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
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0.0000 ,
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0.0000 ,
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0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
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0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000],          [0.0000, 0.0000,
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
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0.9922 ,
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0.0000 ,
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0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
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0.9922 ,
          0.9922, 0.7882, 0.3059, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000],          [0.0000, 0.0000,
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
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0.7765 ,
          0.3176, 0.0078, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000],
         [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0706,
0.6706 ,
          0.8588, 0.9922, 0.9922, 0.9922, 0.9922, 0.7647, 0.3137,
0.0353 ,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000],          [0.0000, 0.0000,
0.0000, 0.0000, 0.2157, 0.6745, 0.8863, 0.9922 ,
          0.9922, 0.9922, 0.9922, 0.9569, 0.5216, 0.0431, 0.0000,
0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
          0.0000, 0.0000, 0.0000, 0.0000],          [0.0000, 0.0000,
0.0000, 0.0000, 0.5333, 0.9922, 0.9922, 0.9922 ,
          0.8314, 0.5294, 0.5176, 0.0627, 0.0000, 0.0000, 0.0000,
0.0000 ,
```

```
                 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
                 0.0000, 0.0000, 0.0000, 0.0000],           [0.0000, 0.0000,
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
                 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
                 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
                 0.0000, 0.0000, 0.0000, 0.0000],           [0.0000, 0.0000,
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
                 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
                 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
                 0.0000, 0.0000, 0.0000, 0.0000],           [0.0000, 0.0000,
0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000 ,
                 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
                 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
0.0000 ,
                 0.0000, 0.0000, 0.0000, 0.0000]]]),
5)
```

In [12]:
```
image,label=train_data[0]
```

In [13]:
```
image.shape
```

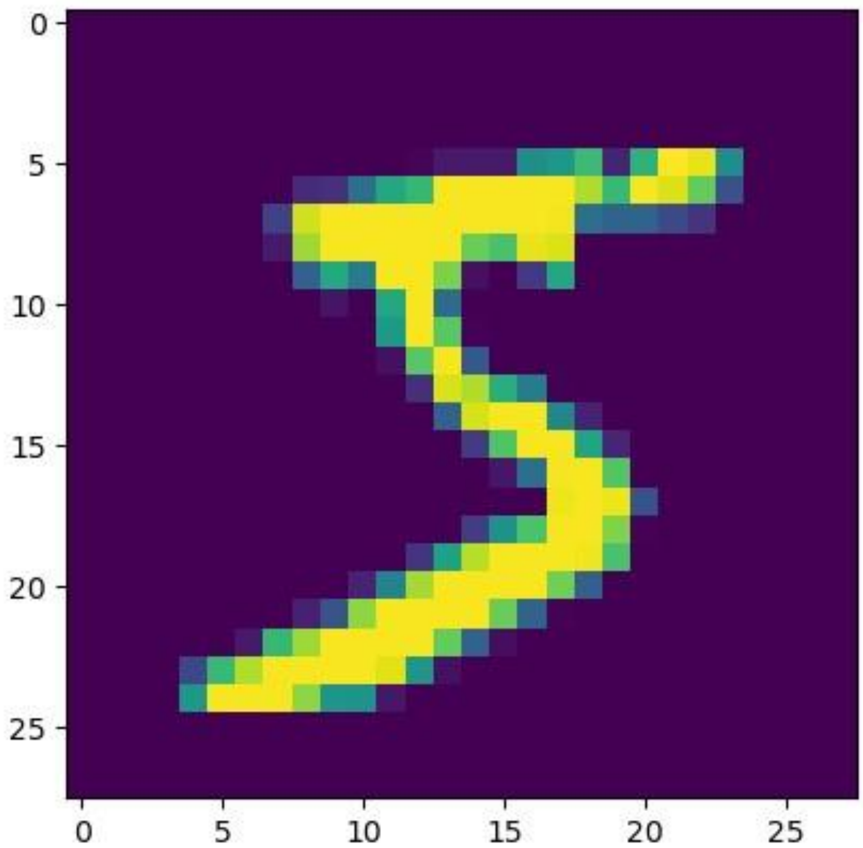
Out[13]: torch.Size([1, 28, 28])

In [14]:
```
label
```

Out[14]: 5

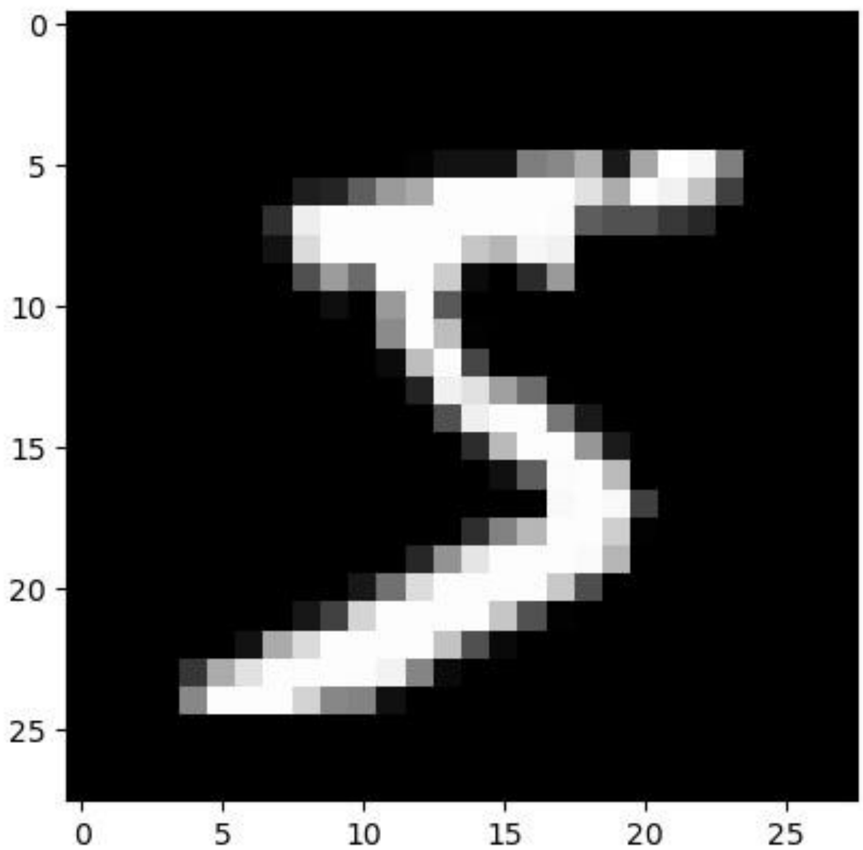
In [15]:
```
plt.imshow(image.reshape((28,28)))
```

Out[15]: <matplotlib.image.AxesImage at 0x163a81ed0>



In [16]:
```
plt.imshow(image.reshape((28,28)),cmap='gray')
```

Out[16]: <matplotlib.image.AxesImage at 0x163ae6710>



In [17]:
```
torch.manual_seed(101)

train_loader=DataLoader(train_data,batch_size=100,shuffle=True)
test_loader=DataLoader(test_data,batch_size=500,shuffle=False)
```

In [18]:
```
from torchvision.utils import make_grid
np.set_printoptions(formatter=dict(int=lambda x:f'{x:4}')) #FORMATTING
```

In [19]:
```
#First Batch for images,labels in
train_loader:
    break
```

In [20]:
```
images.shape  # 1->Means it is a grey scale image,(28,28)->width,length o
```

Out[20]:
```
torch.Size([100, 1, 28, 28])
```

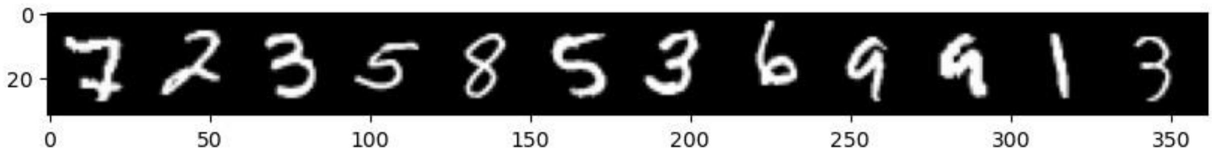
In [21]:
```
labels.shape
```

Out[21]:
```

#Print first 12 labels
print('Labels:',labels[:12].numpy())

#Print the first 12 images
im=make_grid(images[:12],nrow=12)#default nrow is 8
plt.figure(figsize=(10,4))
plt.imshow(np.transpose(im.numpy(),(1,2,0)));
```

```
torch.Size([100])
```

In [22]:

```
Labels: [   7    2    3    5    8    5    3    6    9    9    1    3]
```



In [23]:
```
class MultilayerPerceptron(nn.Module):     def
__init__(self,in_sz=784,out_sz=10,layers=[120,84]):
        super().__init__()

        self.fc1=nn.Linear(in_sz,layers[0])
self.fc2=nn.Linear(layers[0],layers[1])
self.fc3=nn.Linear(layers[1],out_sz)

    def forward(self,x): #x->data
features         x=F.relu(self.fc1(x))
x=F.relu(self.fc2(x))
x=self.fc3(x)

        return F.log_softmax(x,dim=1) #Multi-class classification
```

In [24]:
```
torch.manual_seed(101)
model=MultilayerPerceptron()
model
```

Out[24]:
```
MultilayerPerceptron(
  (fc1): Linear(in_features=784, out_features=120, bias=True)
  (fc2): Linear(in_features=120, out_features=84,
bias=True)   (fc3): Linear(in_features=84, out_features=10,
bias=True) )
```

In [25]:
```
criterion=nn.CrossEntropyLoss()
optimizer=torch.optim.Adam(model.parameters(),lr=0.001)
```

In [26]:
```
images.shape
```

Out[26]:
```
torch.Size([100, 1, 28, 28])
```

In [27]:
```
images.view(100,-1)
```

Out[27]:
```
tensor([[0., 0., 0.,  ..., 0., 0., 0.],
 [0., 0., 0.,  ..., 0., 0., 0.],
 [0., 0., 0.,  ..., 0., 0., 0.],
 ...,
        [0., 0., 0.,  ..., 0., 0., 0.],
        [0., 0., 0.,  ..., 0., 0., 0.],
        [0., 0., 0.,  ..., 0., 0., 0.]])
```

In [28]:
```
import time
start_time = time.time()

epochs = 10
train_losses = []
test_losses = []
train_correct = []
test_correct = []

for i in range(epochs):
    trn_corr = 0
tst_corr = 0

    # Run the training batches      for b, (X_train, 
y_train) in enumerate(train_loader):
        b+=1

        # Apply the model
        y_pred = model(X_train.view(100, -1))  # Here we flatten X_train
loss = criterion(y_pred, y_train)

        # Tally the number of correct predictions
predicted = torch.max(y_pred.data, 1)[1]
batch_corr = (predicted == y_train).sum()
trn_corr += batch_corr

        # Update parameters
optimizer.zero_grad()
loss.backward()
optimizer.step()

        # Print interim results
if b%200 == 0:
            print(f'epoch: {i:2}  batch: {b:4} [{100*b:6}/60000]  loss:
{ accuracy: {trn_corr.item()*100/(100*b):7.3f}%')

    # Update train loss & accuracy for the epoch
train_losses.append(loss.item())
train_correct.append(trn_corr.item())

    # Run the testing batches      with torch.no_grad():
for b, (X_test, y_test) in enumerate(test_loader):

            # Apply the model
            y_val = model(X_test.view(500, -1))  # Here we flatten X_test

            # Tally the number of correct predictions
predicted = torch.max(y_val.data, 1)[1]
```

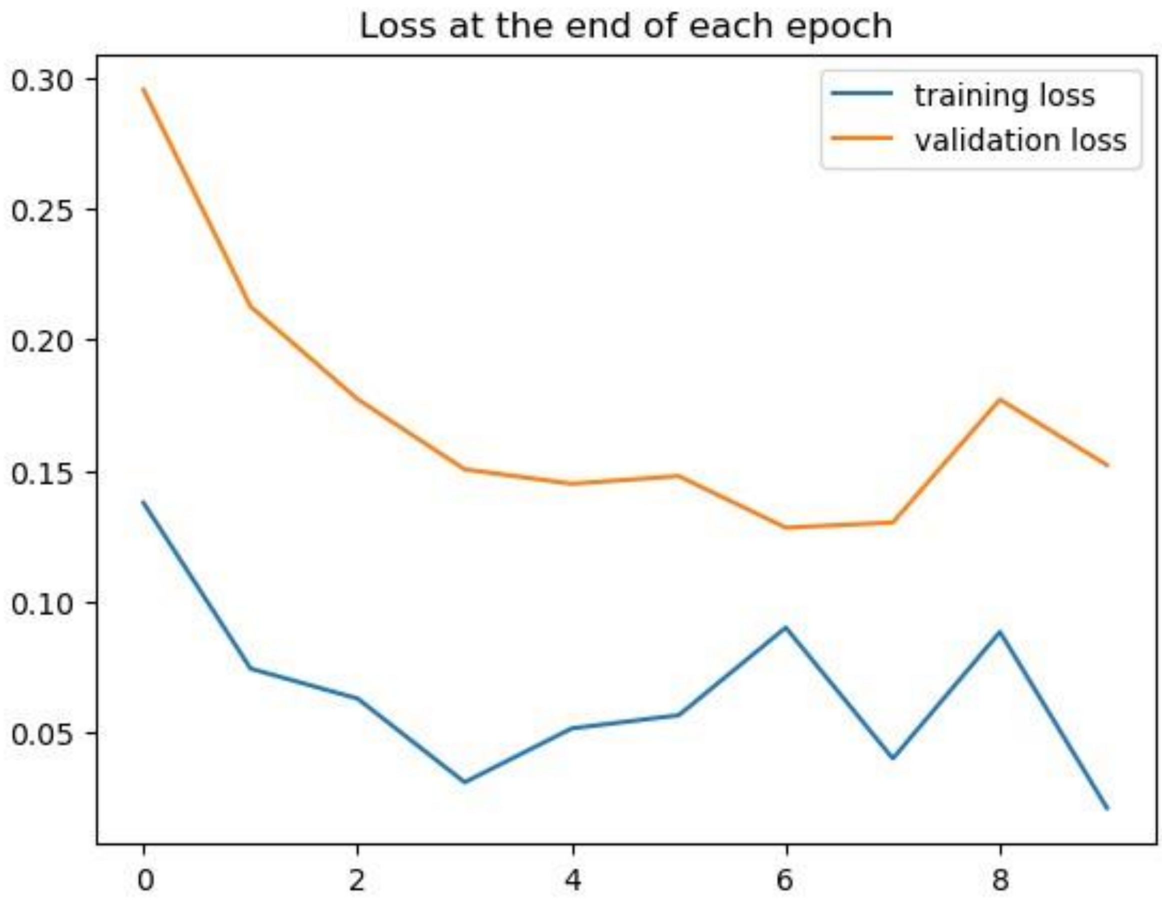
```
            tst_corr += (predicted == y_test).sum()

    # Update test loss & accuracy for the epoch
loss = criterion(y_val, y_test)
test_losses.append(loss)
test_correct.append(tst_corr)

print(f'\nDuration: {time.time() - start_time:.0f} seconds') # print the




#total_time=time.time()-start_time
#print(f'Duration:{Total time/60}mins')
```

```
epoch:  0  batch:  200 [ 20000/60000]  loss: 0.23562382  accuracy:
83.24
5%
epoch:  0  batch:  400 [ 40000/60000]  loss: 0.35330707  accuracy:
87.53
2%
epoch:  0  batch:  600 [ 60000/60000]  loss: 0.13765770  accuracy:
89.58
2%
epoch:  1  batch:  200 [ 20000/60000]  loss: 0.24507998  accuracy:
94.88
0%
epoch:  1  batch:  400 [ 40000/60000]  loss: 0.14064841  accuracy:
95.11
0%
epoch:  1  batch:  600 [ 60000/60000]  loss: 0.07430533  accuracy:
95.37
7%
epoch:  2  batch:  200 [ 20000/60000]  loss: 0.08479684  accuracy:
96.57
0%
epoch:  2  batch:  400 [ 40000/60000]  loss: 0.06338982  accuracy:
96.67
2%
epoch:  2  batch:  600 [ 60000/60000]  loss: 0.06284785  accuracy:
96.73
7%
epoch:  3  batch:  200 [ 20000/60000]  loss: 0.11593810  accuracy:
97.65
0%
epoch:  3  batch:  400 [ 40000/60000]  loss: 0.05100821  accuracy:
97.46
8%
epoch:  3  batch:  600 [ 60000/60000]  loss: 0.03086828  accuracy:
97.49
3%
epoch:  4  batch:  200 [ 20000/60000]  loss: 0.11303577  accuracy:
98.17
0%
```

```
epoch:  4  batch:  400 [ 40000/60000]  loss: 0.04967898  accuracy:
98.01
3%
epoch:  4  batch:  600 [ 60000/60000]  loss: 0.05145194  accuracy:
98.01
0%
epoch:  5  batch:  200 [ 20000/60000]  loss: 0.00721604  accuracy:
98.41
0%
epoch:  5  batch:  400 [ 40000/60000]  loss: 0.03383062  accuracy:
98.46
8%
epoch:  5  batch:  600 [ 60000/60000]  loss: 0.05648751  accuracy:
98.38
0%
epoch:  6  batch:  200 [ 20000/60000]  loss: 0.02997145  accuracy:
98.82
0%
epoch:  6  batch:  400 [ 40000/60000]  loss: 0.06433750  accuracy:
98.69
0%
epoch:  6  batch:  600 [ 60000/60000]  loss: 0.08998419  accuracy:
98.67 0%
epoch:  7  batch:  200 [ 20000/60000]  loss: 0.07536934  accuracy:
99.10
5%
epoch:  7  batch:  400 [ 40000/60000]  loss: 0.09858016  accuracy:
98.91
0%
epoch:  7  batch:  600 [ 60000/60000]  loss: 0.03994036  accuracy:
98.86
5%
epoch:  8  batch:  200 [ 20000/60000]  loss: 0.00415698  accuracy:
99.22
0%
epoch:  8  batch:  400 [ 40000/60000]  loss: 0.00953338  accuracy:
99.13
5%
epoch:  8  batch:  600 [ 60000/60000]  loss: 0.08832055  accuracy:
99.11
0%
epoch:  9  batch:  200 [ 20000/60000]  loss: 0.00536544  accuracy:
99.34
0%
epoch:  9  batch:  400 [ 40000/60000]  loss: 0.01200775  accuracy:
99.26
5%
epoch:  9  batch:  600 [ 60000/60000]  loss: 0.02104353  accuracy:
99.24 2%

Duration: 39 seconds
```

```
In [29]: plt.plot(train_losses, label='training loss')
         plt.plot(test_losses, label='validation loss')
```

```
        plt.title('Loss at the end of each epoch')
        plt.legend();
```




```
print(test_correct) # contains the results of all 10 epochs
print()
print(f'Test accuracy: {test_correct[-1].item()*100/10000:.3f}%') # print
```

Evaluating test data

In [30]:

```
[tensor(9437), tensor(9579), tensor(9691), tensor(9706), tensor(9746),
te nsor(9759), tensor(9777), tensor(9756), tensor(9751), tensor(9773)]

Test accuracy: 97.730%
```

```
In [31]: # Extract the data all at once, not in batches test_load_all =
         DataLoader(test_data, batch_size=10000, shuffle=False)
```

```
In [32]: with torch.no_grad():      correct = 0      for X_test, y_test in
         test_load_all:          y_val = model(X_test.view(len(X_test), -1))   #
         pass in a flattene          predicted = torch.max(y_val,1)[1]
         correct += (predicted == y_test).sum() print(f'Test accuracy:
         {correct.item()}/{len(test_data)} = {correct.item(
```

```
Test accuracy: 9773/10000 =  97.730%
```

Confusion

Matrix

In [33]:
```
# print a row of values for reference
np.set_printoptions(formatter=dict(int=lambda x: f'{x:4}'))
print(np.arange(10).reshape(1,10)) print()

# print the confusion matrix
print(confusion_matrix(predicted.view(-1), y_test.view(-1)))
```

```
[[   0    1    2    3    4    5    6    7    8    9]]

[[ 970    0    4    0    1    2    6    3    5    3]
 [   0 1124    4    0    0    0    3    7    0    2]
 [   1    3 1002    2    1    0    2   11    2    0]
 [   3    3    5  991    0   10    1    3    4    2]
 [   1    0    2    0  961    3    4    2    2    5]
 [   0    0    0    5    0  865    3    1    2    2]
 [   1    1    2    0    6    2  938    0    1    0]
 [   1    0    3    4    1    0    0  978    3    0]
 [   2    4   10    2    1    8    1    2  952    3]
 [   1    0    0    6   11    2    0   21    3  992]]
```

```
import torch import torch.nn as nn import
torch.nn.functional as F from
torch.utils.data import DataLoader from
torchvision import datasets, transforms
from torchvision.utils import make_grid

import numpy as np
import pandas as pd
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
%matplotlib inline
```

Using CNN for "Mnist" Dataset

In [34]:

In [36]:
```
transform = transforms.ToTensor()

train_data = datasets.MNIST(root='/Users/pratyushabhi/Desktop/3rd Yea
test_data = datasets.MNIST(root='/Users/pratyushabhi/Desktop/3rd Year
```

In [37]:
```
train_data
```

Out[37]:
```
Dataset MNIST
    Number of datapoints: 60000
    Root location: /Users/pratyushabhi/Desktop/3rd Year/Image process
ing/ANN
    Split: Train
    StandardTransform
Transform: ToTensor()
```

In [38]:
```
test_data
```

Out[38]:
```
Dataset MNIST
    Number of datapoints: 10000
    Root location: /Users/pratyushabhi/Desktop/3rd Year/Image process
ing/ANN     Split: Test
    StandardTransform
Transform: ToTensor()
```

In [39]:
```
train_loader = DataLoader(train_data, batch_size=10, shuffle=True)
test_loader = DataLoader(test_data, batch_size=10, shuffle=False)
```

In [40]:

In [41]:
```
#Defining CNN
```

In [42]:
```
conv1 = nn.Conv2d(1, 6, 3, 1)
conv2 = nn.Conv2d(6, 16, 3, 1)
```

In [43]:
```
# Grab the first MNIST record for i, (X_train,
y_train) in enumerate(train_data):
    break

# Create a rank-4 tensor to be passed into the model
# (train_loader will have done this
already) x = X_train.view(1,1,28,28)
print(x.shape)
```

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

In [44]:
```
# Perform the first
convolution/activation x =
F.relu(conv1(x)) print(x.shape)
```

```
torch.Size([1, 6, 26, 26])
```

In [45]:
```
# Run the first pooling layer
x = F.max_pool2d(x, 2, 2)
print(x.shape)
```

```
torch.Size([1, 6, 13, 13])
```

In [46]:
```
# Perform the second
convolution/activation x =
F.relu(conv2(x)) print(x.shape)
```

```
torch.Size([1, 16, 11, 11])
```

In [48]:
```
# Run the second pooling layer
x = F.max_pool2d(x, 2, 2)
print(x.shape)
```

```
torch.Size([1, 16, 5, 5])
```

In [49]:
```
# Flatten the data x
= x.view(-1, 5*5*16)
print(x.shape)
```

```
torch.Size([1, 400])
```

In [50]:
```
class ConvolutionalNetwork(nn.Module):
def __init__(self):
super().__init__()
        self.conv1 = nn.Conv2d(1, 6, 3, 1)
self.conv2 = nn.Conv2d(6, 16, 3, 1)
self.fc1 = nn.Linear(5*5*16, 120)
self.fc2 = nn.Linear(120, 84)
self.fc3 = nn.Linear(84,10)

    def forward(self, X):
        X = F.relu(self.conv1(X))
        X = F.max_pool2d(X, 2, 2)
        X = F.relu(self.conv2(X))
        X = F.max_pool2d(X, 2, 2)
        X = X.view(-1, 5*5*16)
        X = F.relu(self.fc1(X))
        X = F.relu(self.fc2(X))
        X = self.fc3(X)
        return F.log_softmax(X, dim=1)
```

In [51]:
```
torch.manual_seed(42) model =
ConvolutionalNetwork() model
```

Out[51]:
```
ConvolutionalNetwork(
  (conv1): Conv2d(1, 6, kernel_size=(3, 3), stride=(1, 1))
  (conv2): Conv2d(6, 16, kernel_size=(3, 3), stride=(1, 1))
  (fc1): Linear(in_features=400, out_features=120, bias=True)
  (fc2): Linear(in_features=120, out_features=84, bias=True)
  (fc3): Linear(in_features=84, out_features=10, bias=True)
)
```

In [52]:
```
#Loss function
```

In [53]:
```
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
```

In [54]:

```
#Train the model
import time
start_time = time.time()

epochs = 5
train_losses = []
test_losses = []
train_correct = []
test_correct = []

for i in range(epochs):
    trn_corr = 0
tst_corr = 0

    # Run the training batches      for b, (X_train,
y_train) in enumerate(train_loader):
        b+=1

        # Apply the model
        y_pred = model(X_train)  # we don't flatten X-train here
loss = criterion(y_pred, y_train)

        # Tally the number of correct predictions
predicted = torch.max(y_pred.data, 1)[1]
batch_corr = (predicted == y_train).sum()
trn_corr += batch_corr

        # Update parameters
optimizer.zero_grad()
loss.backward()
optimizer.step()

        # Print interim results
if b%600 == 0:
            print(f'epoch: {i:2}  batch: {b:4} [{10*b:6}/60000]  loss:
{l accuracy: {trn_corr.item()*100/(10*b):7.3f}%')

    train_losses.append(loss.item())
train_correct.append(trn_corr.item())

    # Run the testing batches      with torch.no_grad():
for b, (X_test, y_test) in enumerate(test_loader):

            # Apply the model
y_val = model(X_test)

            # Tally the number of correct predictions
predicted = torch.max(y_val.data, 1)[1]
tst_corr += (predicted == y_test).sum()

    loss = criterion(y_val, y_test)
test_losses.append(loss)
test_correct.append(tst_corr)

print(f'\nDuration: {time.time() - start_time:.0f} seconds') # print the
```

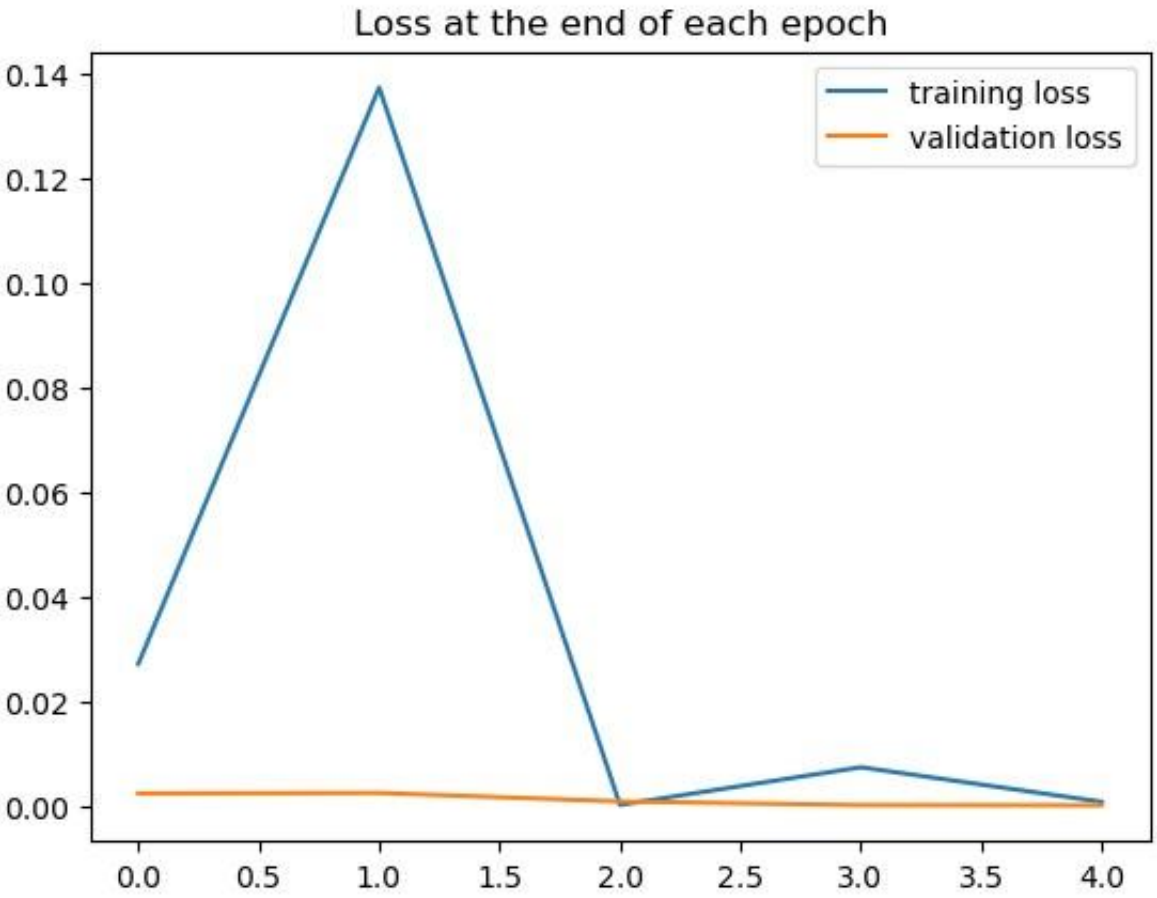
```
epoch:  0  batch:  600 [  6000/60000]  loss: 0.04055630  accuracy:
78.41
7%
epoch:  0  batch: 1200 [ 12000/60000]  loss: 0.08253471  accuracy:
85.80
0%
epoch:  0  batch: 1800 [ 18000/60000]  loss: 0.36470532  accuracy:
88.68
9%
epoch:  0  batch: 2400 [ 24000/60000]  loss: 0.01825019  accuracy:
90.52
5%
epoch:  0  batch: 3000 [ 30000/60000]  loss: 0.00806712  accuracy:
91.65
0%
epoch:  0  batch: 3600 [ 36000/60000]  loss: 0.00097706  accuracy:
92.49
2%
epoch:  0  batch: 4200 [ 42000/60000]  loss: 0.44326892  accuracy:
93.13
3%
epoch:  0  batch: 4800 [ 48000/60000]  loss: 0.03169333  accuracy:
93.61
5%
epoch:  0  batch: 5400 [ 54000/60000]  loss: 0.01946524  accuracy:
94.03
1%
epoch:  0  batch: 6000 [ 60000/60000]  loss: 0.02709320  accuracy:
94.33
3%
epoch:  1  batch:  600 [  6000/60000]  loss: 0.01472266  accuracy:
97.75
0%
epoch:  1  batch: 1200 [ 12000/60000]  loss: 0.04359249  accuracy:
97.87
5%
epoch:  1  batch: 1800 [ 18000/60000]  loss: 0.00124075  accuracy:
97.90
0%
epoch:  1  batch: 2400 [ 24000/60000]  loss: 0.03912879  accuracy:
97.85
4%
epoch:  1  batch: 3000 [ 30000/60000]  loss: 0.14564939  accuracy:
97.86
7%
epoch:  1  batch: 3600 [ 36000/60000]  loss: 0.00049980  accuracy:
97.87
8%
epoch:  1  batch: 4200 [ 42000/60000]  loss: 0.00076085  accuracy:
97.91
4%
epoch:  1  batch: 4800 [ 48000/60000]  loss: 0.00105086  accuracy:
97.91
2%
```

```
epoch:  1  batch: 5400 [ 54000/60000]  loss: 0.00745581  accuracy:
97.94
1%
epoch:  1  batch: 6000 [ 60000/60000]  loss: 0.13721663  accuracy:
97.94
3%
epoch:  2  batch:  600 [  6000/60000]  loss: 0.00099742  accuracy:
98.68
3%
epoch:  2  batch: 1200 [ 12000/60000]  loss: 0.00254112  accuracy:
98.65
0%
epoch:  2  batch: 1800 [ 18000/60000]  loss: 0.00188525  accuracy:
98.53
9%
epoch:  2  batch: 2400 [ 24000/60000]  loss: 0.00276521  accuracy:
98.59
6%
epoch:  2  batch: 3000 [ 30000/60000]  loss: 0.24948892  accuracy:
98.55
3%
epoch:  2  batch: 3600 [ 36000/60000]  loss: 0.03415573  accuracy:
98.54
4%
epoch:  2  batch: 4200 [ 42000/60000]  loss: 0.02346098  accuracy:
98.52
4%
epoch:  2  batch: 4800 [ 48000/60000]  loss: 0.01159347  accuracy:
98.54
6%
epoch:  2  batch: 5400 [ 54000/60000]  loss: 0.00048137  accuracy:
98.53 1%
epoch:  2  batch: 6000 [ 60000/60000]  loss: 0.00013920  accuracy:
98.53
5%
epoch:  3  batch:  600 [  6000/60000]  loss: 0.00057079  accuracy:
98.90
0%
epoch:  3  batch: 1200 [ 12000/60000]  loss: 0.00067071  accuracy:
98.80
0%
epoch:  3  batch: 1800 [ 18000/60000]  loss: 0.00059610  accuracy:
98.86
1%
epoch:  3  batch: 2400 [ 24000/60000]  loss: 0.00048164  accuracy:
98.81
7%
epoch:  3  batch: 3000 [ 30000/60000]  loss: 0.12320199  accuracy:
98.83
3%
epoch:  3  batch: 3600 [ 36000/60000]  loss: 0.00446792  accuracy:
98.83
3%
epoch:  3  batch: 4200 [ 42000/60000]  loss: 0.00079797  accuracy:
98.84
```

```
8%
epoch:  3  batch: 4800 [ 48000/60000]  loss: 0.12382223  accuracy:
98.842%
epoch:  3  batch: 5400 [ 54000/60000]  loss: 0.00634904  accuracy:
98.833%
epoch:  3  batch: 6000 [ 60000/60000]  loss: 0.00734646  accuracy:
98.853%
epoch:  4  batch:  600 [  6000/60000]  loss: 0.00278111  accuracy:
99.083%
epoch:  4  batch: 1200 [ 12000/60000]  loss: 0.17682204  accuracy:
99.067%
epoch:  4  batch: 1800 [ 18000/60000]  loss: 0.00004966  accuracy:
99.083%
epoch:  4  batch: 2400 [ 24000/60000]  loss: 0.00025236  accuracy:
99.067%
epoch:  4  batch: 3000 [ 30000/60000]  loss: 0.00490724  accuracy:
99.040%
epoch:  4  batch: 3600 [ 36000/60000]  loss: 0.05752410  accuracy:
99.044%
epoch:  4  batch: 4200 [ 42000/60000]  loss: 0.01335440  accuracy:
99.071%
epoch:  4  batch: 4800 [ 48000/60000]  loss: 0.00020917  accuracy:
99.065%
epoch:  4  batch: 5400 [ 54000/60000]  loss: 0.00006763  accuracy:
99.050%
epoch:  4  batch: 6000 [ 60000/60000]  loss: 0.00072345  accuracy:
99.057%

Duration: 74 seconds
```

In [55]:
```
## Plot the loss and accuracy comparisons
```

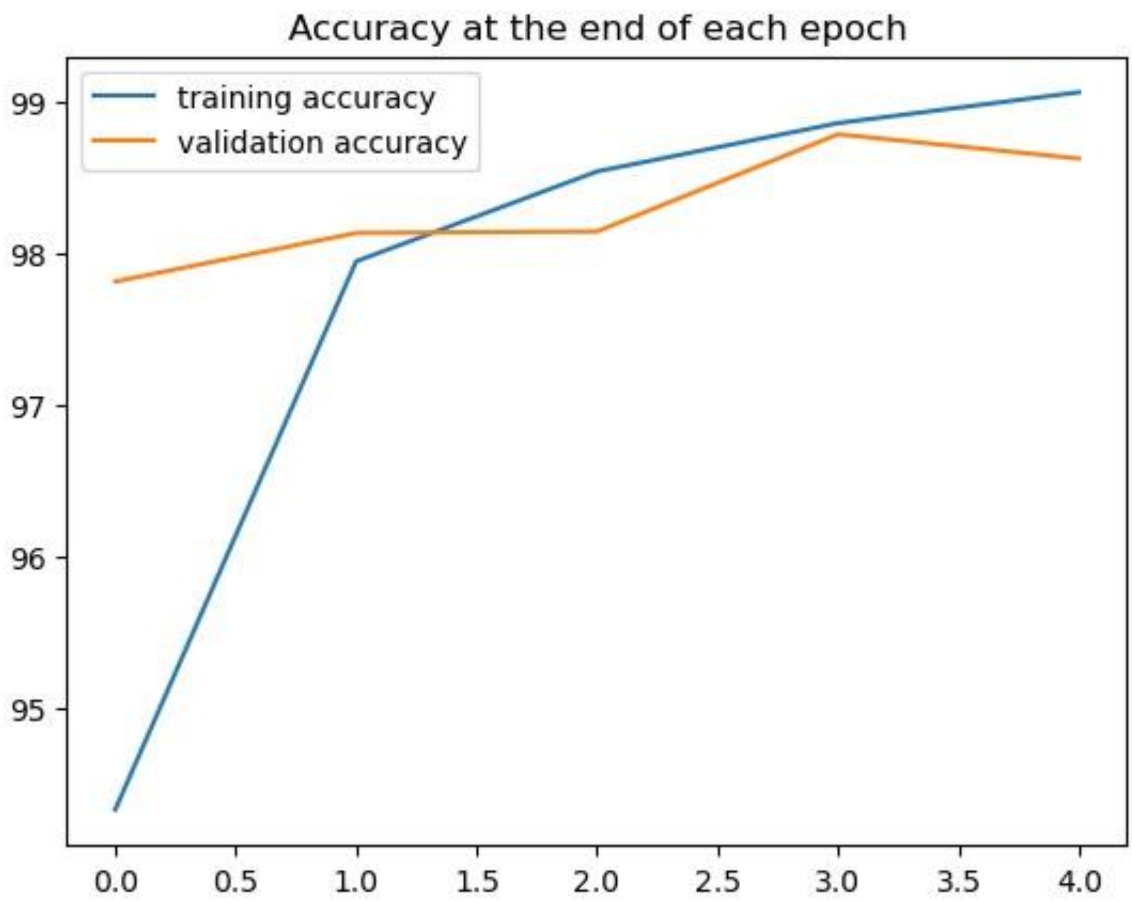
In [56]:
```
plt.plot(train_losses, label='training loss')
plt.plot(test_losses, label='validation loss')
plt.title('Loss at the end of each epoch')
plt.legend();
```



In [57]:
```
test_losses
```

Out[57]:
```
[tensor(0.0023),
 tensor(0.0024),
 tensor(0.0008),
 tensor(0.0001),
 tensor(6.7299e-05)]
```

In [58]:
```
plt.plot([t/600 for t in train_correct], label='training accuracy')
plt.plot([t/100 for t in test_correct], label='validation accuracy')
plt.title('Accuracy at the end of each epoch')
plt.legend();
```



In [59]:

```
#Evaluate Test data
test_load_all = DataLoader(test_data, batch_size=10000, shuffle=False)
with torch.no_grad():
    correct = 0     for X_test, y_test in test_load_all:
y_val = model(X_test)  # we don't flatten the data this time
predicted = torch.max(y_val,1)[1]         correct += (predicted ==
y_test).sum()
print(f'Test accuracy: {correct.item()}/{len(test_data)} = {correct.item(
```

```
Test accuracy: 9862/10000 =  98.620%
```

In [64]:

```
#Confusion Matrix
# print a row of values for reference
np.set_printoptions(formatter=dict(int=lambda x:
f'{x:4}')) print(np.arange(10).reshape(1,10)) print()

# print the confusion matrix
print(confusion_matrix(predicted.view(-1), y_test.view(-1)))
```

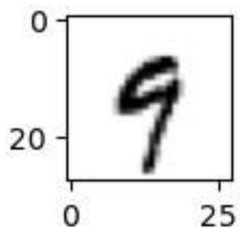
```
[[   0    1    2    3    4    5    6    7    8    9]]

[[ 975    0    0    0    0    3    4    0    4    0]
 [   0 1134    4    1    1    0    4    5    0    3]
 [   2    0 1019    1    0    0    0    5    2    0]
 [   0    1    0 1002    0   19    0    0    1    0]
 [   0    0    1    0  978    0    2    0    1   16]
 [   0    0    0    2    0  858    0    0    0    2]
```

```
 [   1    0    0    0    2    2  947    0    0    1]
 [   1    0    6    2    0    0    0 1015    3    6]
 [   1    0    2    2    0    3    1    1  962    9]
 [   0    0    0    0    1    7    0    2    1  972]]
```

Run a new image through the model.

We can also pass a single image through the model to obtain a prediction. Pick a number from 0 to 9999, assign it to "x", and we'll use that value to select a number from the MNIST test set.

In [61]:
```
x = 2019
plt.figure(figsize=(1,1))
plt.imshow(test_data[x][0].reshape((28,28)), cmap="gist_yarg");
```



In [62]:
```
model.eval() with
torch.no_grad():
    new_pred = model(test_data[x][0].view(1,1,28,28)).argmax()
print("Predicted value:",new_pred.item())
```

```
Predicted value: 9
```