MA22M006_MLP_1

September 3, 2023

Here I will create a Neural Network and train using "back propogation" to recognise the hand written digits using MNIST Dataset. Taken Some Ideas rather Code for last leg of this assignment from Here. Also Uses ChatGPT for plotting the confusion matrix, Surprisingly it has given the accurate response. Also I would like to thank **Rohan (MA22M025)** for helping me in backpropagation part.

1 Importing The Usefull Libraries

[ ]:
```
#Importing the libraries that will be helpful during calculation
import numpy as np
import pandas as pd
import torch
import matplotlib.pyplot as plt
from torchvision.transforms import ToTensor
```

2 Loading DataSet From Pytorch

[ ]:
```
from torchvision import datasets
training_data = datasets.MNIST(
    root="data",
    train=True,
    download=True,
    transform=ToTensor()   # it converts PIL image into pytorch tensor and also␣
 ↪normalise it
)

test_data = datasets.MNIST(
    root="data",
    train=False,
    download=True,
    transform=ToTensor()  # it converts PIL image into pytorch tensor and also␣
 ↪normalise it
)
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to
```

```
data/MNIST/raw/train-images-idx3-ubyte.gz

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Extracting data/MNIST/raw/train-images-idx3-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
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data/MNIST/raw/train-labels-idx1-ubyte.gz

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Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to
data/MNIST/raw/t10k-images-idx3-ubyte.gz


100%|          | 1648877/1648877 [00:00<00:00, 30874101.67it/s]

Extracting data/MNIST/raw/t10k-images-idx3-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to
data/MNIST/raw/t10k-labels-idx1-ubyte.gz

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Extracting data/MNIST/raw/t10k-labels-idx1-ubyte.gz to data/MNIST/raw
```

2.1 Preproccesing The DATA

[ ]:
```python
VALID_RATIO = 0.9
# Spilliting the data into train and validation sets
n_train_examples = int(len(training_data) * VALID_RATIO)
n_valid_examples = len(training_data) - n_train_examples
train_data, valid_data = torch.utils.data.random_split(training_data,
                                                       [n_train_examples, n_valid_examples])
```

[ ]:
```python
def Data(Train,Valid,Test,Batch_Size=64):
    train_iterator = torch.utils.data.DataLoader(Train,
                                    shuffle=True,
                                    batch_size=Batch_Size,
                                    drop_last=True)

    valid_iterator =torch.utils.data.DataLoader(Valid,
                                    batch_size=6000)

    test_iterator =torch.utils.data.DataLoader(Test,
```

```
                                        batch_size=10000)
    return train_iterator,valid_iterator,test_iterator
```

[ ]:
```
train_iterator,valid_iterator,test_iterator =␣
 ↪Data(train_data,valid_data,test_data)
```

2.1.1 Visualisation of data

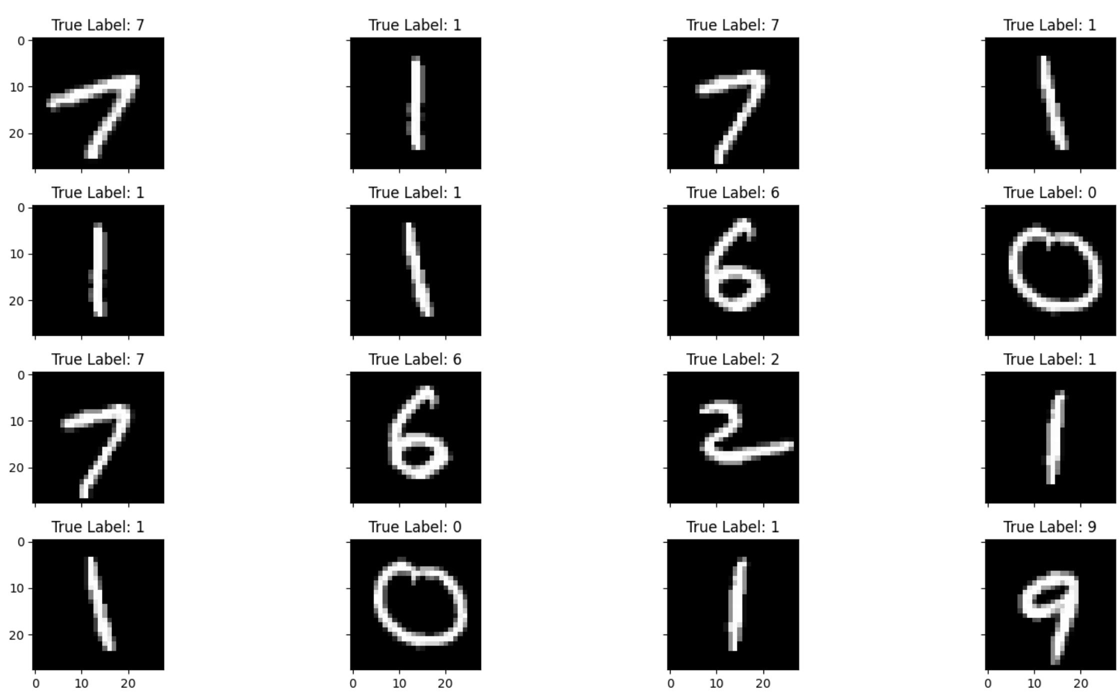
[ ]:
```
for data in train_iterator:
  print(data[0].shape,data[1].shape)
  break # It contains 60000 images
```

```
torch.Size([64, 1, 28, 28]) torch.Size([64])
```

[ ]:
```
for data in valid_iterator:
  print(data[0].shape,data[1])
  break # It contains 60000 images
```

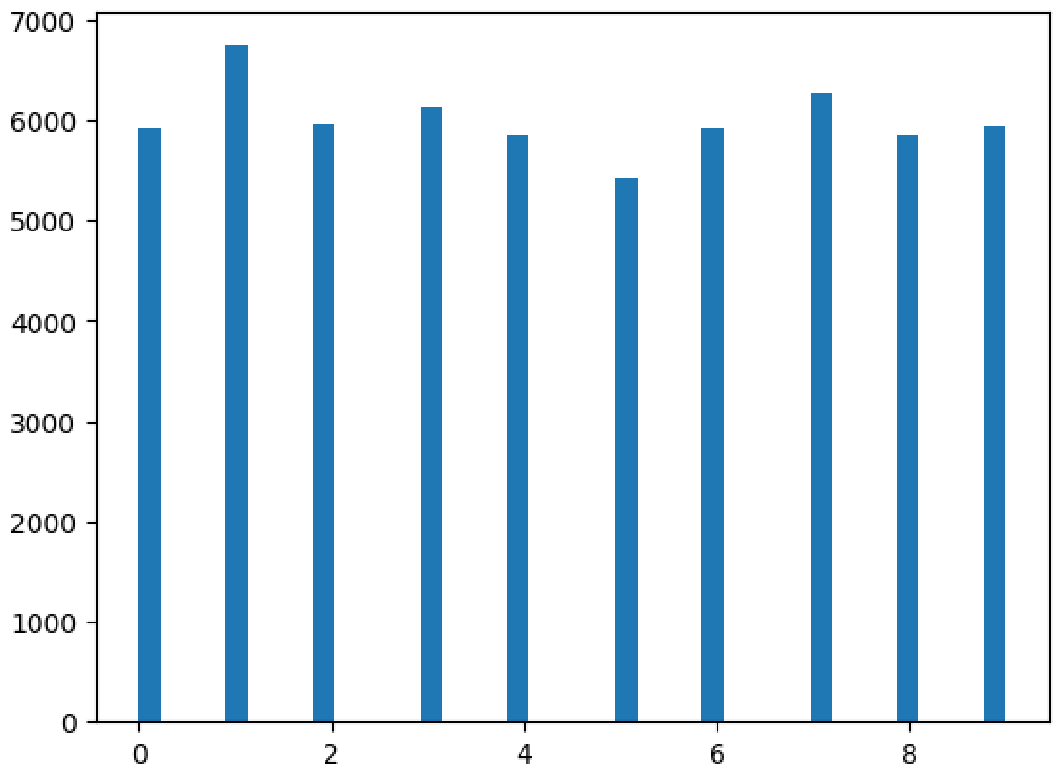
```
torch.Size([6000, 1, 28, 28]) tensor([3, 6, 0,  …, 2, 9, 6])
```

[ ]:
```
fig,ax= plt.subplots(nrows=4,ncols=4,figsize=(16,8),sharex=True,sharey=True)
for i in range(4):
  for j in range(4):
    k=(i+1)*(j+1)+100
    ax[i,j].imshow(training_data.data[k],cmap='gray')
    ax[i,j].set_title(f'True Label: {training_data.targets[k]}')
plt.tight_layout()
```



2.1.2 Distribution of Training Data into different classes. We can see data is uniformly distributed

[ ]:
```
plt.hist(train_iterator.dataset.dataset.targets,bins=40)
plt.show()
```



3 Changing the dimensions of data in order to use it for training.

[ ]:
```
# Creates one hot vectors out of given targets
def one_hot(Y):
    one_hot_Y = torch.zeros(len(Y), 10)
    one_hot_Y[range(len(Y)), Y] = 1
    one_hot_Y = one_hot_Y.T
    return one_hot_Y    # 10X64
```

[ ]:
```
# Flattening the images for training the model
X_train=[]
Y_train=[]
```

```
for X, Y in train_iterator:
    X=torch.flatten(X,start_dim=1)
    Y=one_hot(Y) # 10X 64
    X_train.append(X)
    Y_train.append(Y)
```

[ ]:
```
X_train[0].shape
```

[ ]:
```
torch.Size([64, 784])
```

[ ]:
```
Y_train[0].shape
```

[ ]:
```
torch.Size([10, 64])
```

[ ]:
```
X_valid = [torch.flatten(x[0],start_dim=1) for x in valid_iterator]
Y_valid = [y[1] for y in valid_iterator]
```

[ ]:
```
X_valid[0].shape
```

[ ]:
```
torch.Size([6000, 784])
```

[ ]:
```
X_test = [torch.flatten(x[0],start_dim=1) for x in test_iterator]
Y_test = [y[1] for y in test_iterator]
```

[ ]:
```
print(X_test[0].shape,Y_test[0].shape)
```

```
torch.Size([10000, 784]) torch.Size([10000])
```

3.1 Loss Function:

[ ]:
```
def Cross_entropy(Y, pred,lambda1=0,params_sum=0):
    J = Y * pred
    J=torch.sum(J,0)
    return -torch.sum(torch.log(J))+ lambda1*params_sum
```

3.1.1 Activation Functions

Relu Activation Function:

$$ReLU(x) = max(0, x)$$

[ ]:
```
def ReLU(x):
  return torch.maximum(torch.zeros_like(x),x)

def ReLU_deriv(Z):
    return Z > 0
```

Sigmoid Activationn Function:

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

```
[ ]: def Sigmoid(x):
       return 1/(1+torch.exp(-x))
```

```
[ ]: def Grad_Sigmoid(x):
       return Sigmoid(x)*(1-Sigmoid(x))
```

Tanh Activation Function:

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

```
[ ]: def Tanh(x):
       return torch.div((torch.exp(x)-torch.exp(-x)),(torch.exp(x)+torch.exp(-x)))
```

```
[ ]: def Grad_Tanh(x):
       return 1-Tanh(x)*Tanh(x)
```

Softmax Function:

$$Softmax(X_{n*1}) = \left(\frac{e^{x_i}}{\sum_j e^j}\right)_{n*1}$$

```
[ ]: def Softmax(X,dim=0):
       Y=torch.zeros_like(X)
       if dim==0:
         i=0
         for x in X.T:
           Y.T[i]=torch.exp(x)/sum(torch.exp(x))
           i+=1
       else:
         i=0
         for x in X:
           Y[i]=torch.exp(x)/sum(torch.exp(x))
           i+=1
       return Y
```

4 The Model

4.1 Defining The Architecture

```
[ ]: torch.seed()
     def init_params(In = [784,500,250,100],Out = [500,250,100,10]):
         param=[]
         for I,O in zip(In,Out):
           M=np.sqrt(6/(I+O))
```

```
    W=torch.FloatTensor(O, I).uniform_(-M,M)
    b=torch.FloatTensor(O,1).uniform_(-M,M)
    param.append(W)
    param.append(b)
  return param
```

[ ]:
```
params=init_params()
for a in params:
  print(a.shape)
```

```
torch.Size([500, 784])
torch.Size([500, 1])
torch.Size([250, 500])
torch.Size([250, 1])
torch.Size([100, 250])
torch.Size([100, 1])
torch.Size([10, 100])
torch.Size([10, 1])
```

4.1.1 Forward Propagation

[ ]:
```
def forward_prop(param, X,Activation=Sigmoid,OutAct=Softmax):␣
 ↪#hiddenacti,outacti
    #print('X',X)
    Z1=torch.mm(param[0],X.T)+param[1]
    #print('Z1',Z1)
    Activations=[X.T, Z1,Activation(Z1)]
    #print('A1',Activations[-1])
    for i in range(2,len(param),2):
      Z = torch.mm(param[i],Activations[-1])+param[i+1]
      Activations.append(Z)
      #print('Z',Z)
      if i!=len(param)-2:
        Activations.append(Activation(Z))
       # print("A",torch.nn.functional.sigmoid(Z))
      else:
        Activations.append(OutAct(Z,dim=0))
        #print("A",torch.nn.functional.softmax(Z,dim=0))
    return Activations
```

[ ]:
```
Activ=forward_prop(params,X_train[0])
```

[ ]:
```
for a in Activ:
  print(a.shape)
```

```
torch.Size([784, 64])
torch.Size([500, 64])
```

```
torch.Size([500, 64])
torch.Size([250, 64])
torch.Size([250, 64])
torch.Size([100, 64])
torch.Size([100, 64])
torch.Size([10, 64])
torch.Size([10, 64])
```

[ ]:
```
Activ[-1].T[0]  # Looking into output from softmax
```

[ ]:
```
tensor([0.0832, 0.0293, 0.1133, 0.1879, 0.1275, 0.1134, 0.0691, 0.0290, 0.1510,
        0.0964])
```

4.1.2 Back Ward Propagation

[ ]:
```
def backward_pass(X, Y, activations, parameters, grad_act = Grad_Sigmoid):
    grads = {}
    m = X.shape[1]
    dZ = activations[-1] - Y  #10X64
    dZ=dZ/m
    #print(dZ.shape)
    #print(activations[-3].shape)
    grads[f'db{len(parameters) // 2}'] = torch.sum(dZ, dim=1, keepdim=True)
    grads[f'dW{len(parameters) // 2}'] = torch.mm(dZ, activations[-3].T)

    for i in reversed(range(1, len(parameters) // 2)):
        dZ = torch.mm(parameters[2*i].T, dZ) *(grad_act(activations[2*i]))

        grads[f'db{i}'] = torch.sum(dZ, dim=1, keepdim=True)
        grads[f'dW{i}'] = torch.mm(dZ, activations[2*i-2].T)
    return grads
```

[ ]:
```
grad=backward_pass(X_train[0],Y_train[0],Activ,params)
```

[ ]:
```
for a in reversed(grad):
  print(a)
  print(grad[a].shape)
```

```
dW1
torch.Size([500, 784])
db1
torch.Size([500, 1])
dW2
torch.Size([250, 500])
db2
torch.Size([250, 1])
dW3
```

```
torch.Size([100, 250])
db3
torch.Size([100, 1])
dW4
torch.Size([10, 100])
db4
torch.Size([10, 1])
```

4.1.3 Updation of Parameters

[ ]:
```
def update_params(param,gradp, alpha, lambda1=0):
    r=0
    for i ,j in zip(param,reversed(gradp)):
      #print(i.shape,gradp[j].shape)
      if r%2+1:
        param[r]=(1-lambda1*alpha)*i-alpha*gradp[j]
      else:
        param[r]=i-alpha*gradp[j]
      r+=1
    return param
```

[ ]:
```
uparam=update_params(params,grad,0.01)
```

4.1.4 Predictions and Accuracy functions

[ ]:
```
def get_predictions(A4):
    return torch.argmax(A4, 0)

def get_accuracy(predictions, Y):
    #print(predictions, Y)
    X=torch.argmax(Y,0)
    #print(X.shape)
    #print(predictions.shape)
    return torch.sum(predictions == X) / len(X)
```

4.2 Gradient Descent Algorithm

[ ]:
```
def gradient_descent(X_train,Y_train, X_test, Y_test , X_valid, Y_valid,␣
 ↪Activation=Sigmoid,
                     grad_act=Grad_Sigmoid, OutAct = Softmax,  alpha=0.01,␣
 ↪epoch= 20,lambda1=0):
    params = init_params()
    #print('weight_Initialised.....')
    EpochLoss_train=[]
    EpochLoss_valid=[]
    for epo in range(epoch):
```

```
    for X,Y in zip(X_train,Y_train):

      activations = forward_prop(params,X, Activation, OutAct)

      gradp = backward_pass(X,Y, activations, params,grad_act)

      params = update_params(params, gradp, alpha,lambda1)

      #predictions = get_predictions(activations[-1])
    param_sum = sum([torch.sum(params[i]) for i in range(0,8,2)])
    #EpochLoss_train.
↪append(Cross_entropy(Y,activations[-1],lambda1,params_sum=param_sum))

    Activ1=forward_prop(params, X_valid[0], Activation, OutAct)

    EpochLoss_valid.append(Cross_entropy(one_hot(Y_valid[0]),Activ1[-1])/6000)
    train_true=0
    loss=0
    for X,Y in zip(X_train,Y_train):

      activt=forward_prop(params, X, Activation, OutAct)
      Y_hat_train = get_predictions(activt[-1])
      loss += Cross_entropy(Y,activt[-1],lambda1,params_sum=param_sum)
      train_true += torch.sum(Y_hat_train==torch.argmax(Y,0))

    EpochLoss_train.append(loss/54000)
 #activations = forward_prop(params, X)
    Y_hat_val=get_predictions(Activ1[-1])
    #Y_hat_train = get_predictions(activations[-1])
    print(f'**************************** Epoch {epo+1}␣
↪***********************************')
    print('Training Accuracy: ',(train_true/54000).item()*100)
    print('Validation Accuracy: ',(torch.sum(Y_hat_val==Y_valid[0])/6000).
↪item()*100)
    ␣
↪print('------------------------------------------------------------------------')
  Activ2=forward_prop(params, X_test[0], Activation, OutAct)
  Y_hat_test = get_predictions(Activ2[-1])
  print('Test Accuracy: ',(torch.sum(Y_hat_test==Y_test[0])/10000).item()*100)
  return params,EpochLoss_train,EpochLoss_valid , Y_hat_test
```

4.3 Confusion Matrix

```
[ ]: def Confusion_Matrix(Y_pre, Y):
         number_of_classes = 10
         conf_matrix = np.zeros((number_of_classes, number_of_classes),dtype=int)
         for true_label, prediction in zip(Y_pre ,Y):
           conf_matrix[true_label, prediction] += 1
         return conf_matrix
```

```
[ ]: def plot_confusion_matrix(confusion_matrix):
         plt.imshow(confusion_matrix, interpolation='nearest', cmap=plt.cm.Blues)
         plt.title("Confusion Matrix")
         plt.colorbar()

         num_classes = confusion_matrix.shape[0]

         plt.xticks(np.arange(num_classes), range(num_classes))
         plt.yticks(np.arange(num_classes), range(num_classes))

         plt.ylabel('True label')
         plt.xlabel('Predicted label')

         # Add text annotations for each cell
         for i in range(num_classes):
             for j in range(num_classes):
                 plt.text(j, i, str(confusion_matrix[i, j]),␣
      ↪horizontalalignment="center", color="black")

         plt.show()
```

4.4 (1) Using Sigmoid and softmax

Here I am using sigmoid activation in hidden layers and softmax at the output layer doing gradient descent with learning rate 1 and runs for 15 epoch

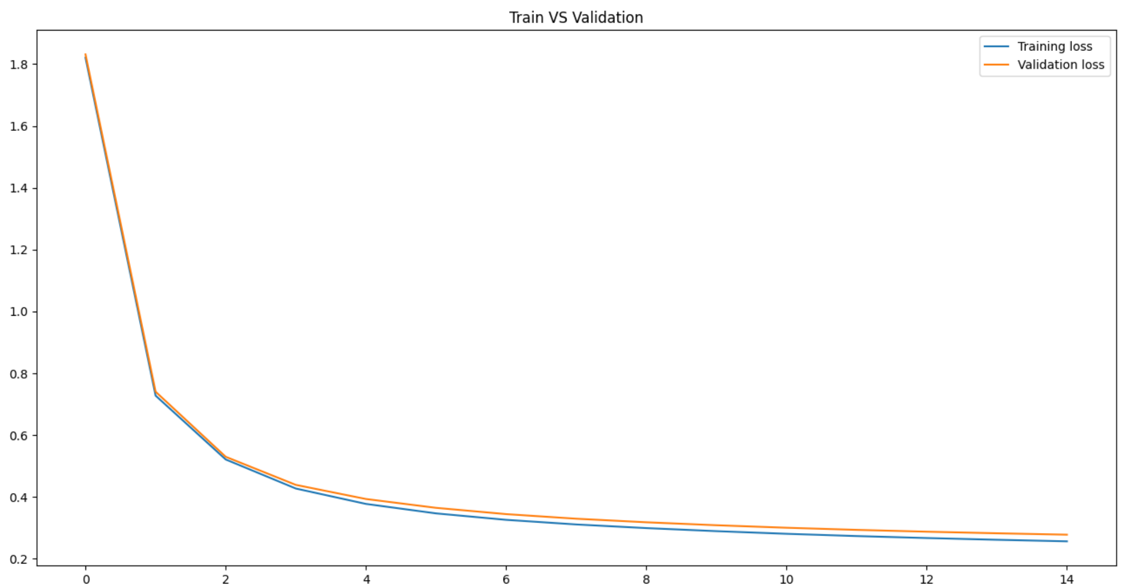
```
[ ]: # For differen learning rate please change alpha
     Params = gradient_descent(X_train,Y_train, X_test, Y_test , X_valid, Y_valid,␣
      ↪Activation=Sigmoid,
                          grad_act=Grad_Sigmoid, OutAct = Softmax,  alpha=1, epoch=␣
      ↪15)
```

```
**************************** Epoch 1 ***********************************
Training Accuracy:  41.93703830242157
Validation Accuracy:  41.11666679382324
--------------------------------------------------------------------------
**************************** Epoch 2 ***********************************
Training Accuracy:  78.2537043094635
Validation Accuracy:  78.29999923706055
```

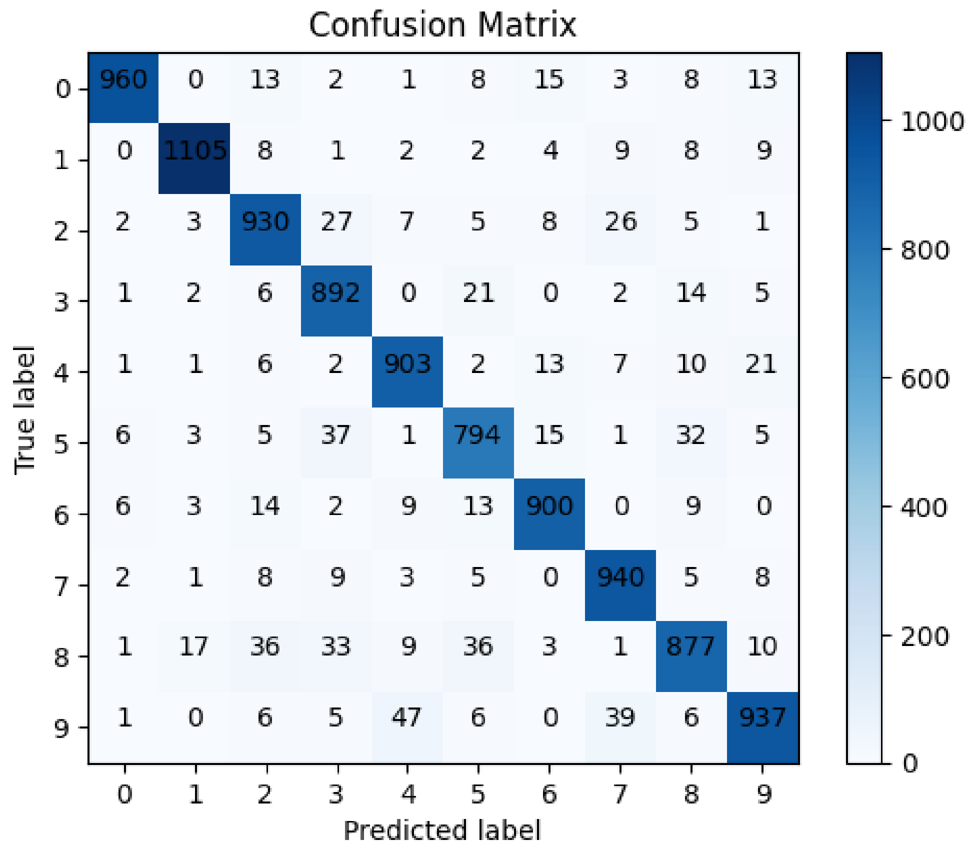
```
-----------------------------------------------------------------------
**************************** Epoch 3 ***********************************
Training Accuracy:  84.62036848068237
Validation Accuracy:  84.26666855812073
-----------------------------------------------------------------------
**************************** Epoch 4 ***********************************
Training Accuracy:  87.37407326698303
Validation Accuracy:  87.23333477973938
-----------------------------------------------------------------------
**************************** Epoch 5 ***********************************
Training Accuracy:  88.80741000175476
Validation Accuracy:  88.40000033378601
-----------------------------------------------------------------------
**************************** Epoch 6 ***********************************
Training Accuracy:  89.71666693687439
Validation Accuracy:  89.13333415985107
-----------------------------------------------------------------------
**************************** Epoch 7 ***********************************
Training Accuracy:  90.39815068244934
Validation Accuracy:  89.81666564941406
-----------------------------------------------------------------------
**************************** Epoch 8 ***********************************
Training Accuracy:  90.82221984863281
Validation Accuracy:  90.16666412353516
-----------------------------------------------------------------------
**************************** Epoch 9 ***********************************
Training Accuracy:  91.15926027297974
Validation Accuracy:  90.56666493415833
-----------------------------------------------------------------------
**************************** Epoch 10 ***********************************
Training Accuracy:  91.39629602432251
Validation Accuracy:  90.88333249092102
-----------------------------------------------------------------------
**************************** Epoch 11 ***********************************
Training Accuracy:  91.61296486854553
Validation Accuracy:  90.9666657447815
-----------------------------------------------------------------------
**************************** Epoch 12 ***********************************
Training Accuracy:  91.79444313049316
Validation Accuracy:  91.18333458900452
-----------------------------------------------------------------------
**************************** Epoch 13 ***********************************
Training Accuracy:  91.95926189422607
Validation Accuracy:  91.33333563804626
-----------------------------------------------------------------------
**************************** Epoch 14 ***********************************
Training Accuracy:  92.08333492279053
Validation Accuracy:  91.56666398048401
```

```
-----------------------------------------------------------------------
*************************** Epoch 15 **********************************
Training Accuracy:  92.25555658340454
Validation Accuracy:  91.60000085830688
-----------------------------------------------------------------------
Test Accuracy:  92.3799991607666
```

[ ]:
```
plt.figure(figsize=(16,8))
plt.plot(Params[1],label='Training loss')
plt.plot(Params[2],label='Validation loss')
plt.title('Train VS Validation')
plt.legend()
plt.show()
```



[ ]:
```
Mat = Confusion_Matrix(Params[-1],Y_test[0])
plot_confusion_matrix(Mat)
```



4.5 (1) Using ReLU and softmax

Here I am using ReLu activation in hidden layers and softmax at the output layer doing gradient descent with learning rate 0.1 and runs for 15 epoch

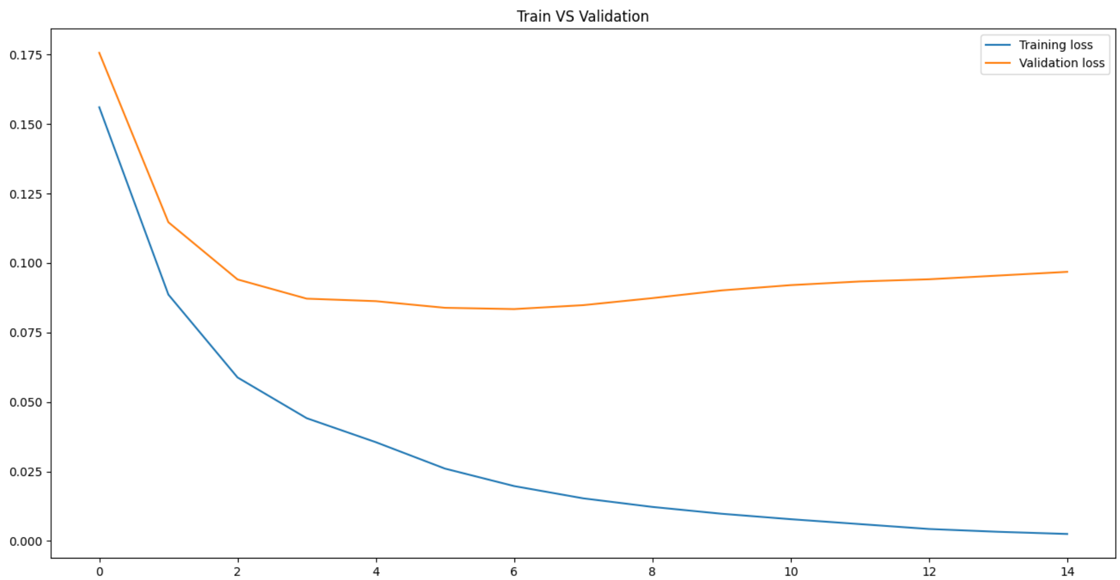
```
[ ]: Params = gradient_descent(X_train,Y_train, X_test, Y_test , X_valid, Y_valid,␣
     ↪Activation=ReLU,
                         grad_act=ReLU_deriv, OutAct = Softmax,  alpha=1, epoch= 15)
```

```
**************************** Epoch 1 ***********************************
Training Accuracy:  95.2129602432251
Validation Accuracy:  94.81666684150696
------------------------------------------------------------------------
**************************** Epoch 2 ***********************************
Training Accuracy:  97.25925922393799
Validation Accuracy:  96.66666388511658
------------------------------------------------------------------------
**************************** Epoch 3 ***********************************
Training Accuracy:  98.14444184303284
Validation Accuracy:  97.2166657447815
```

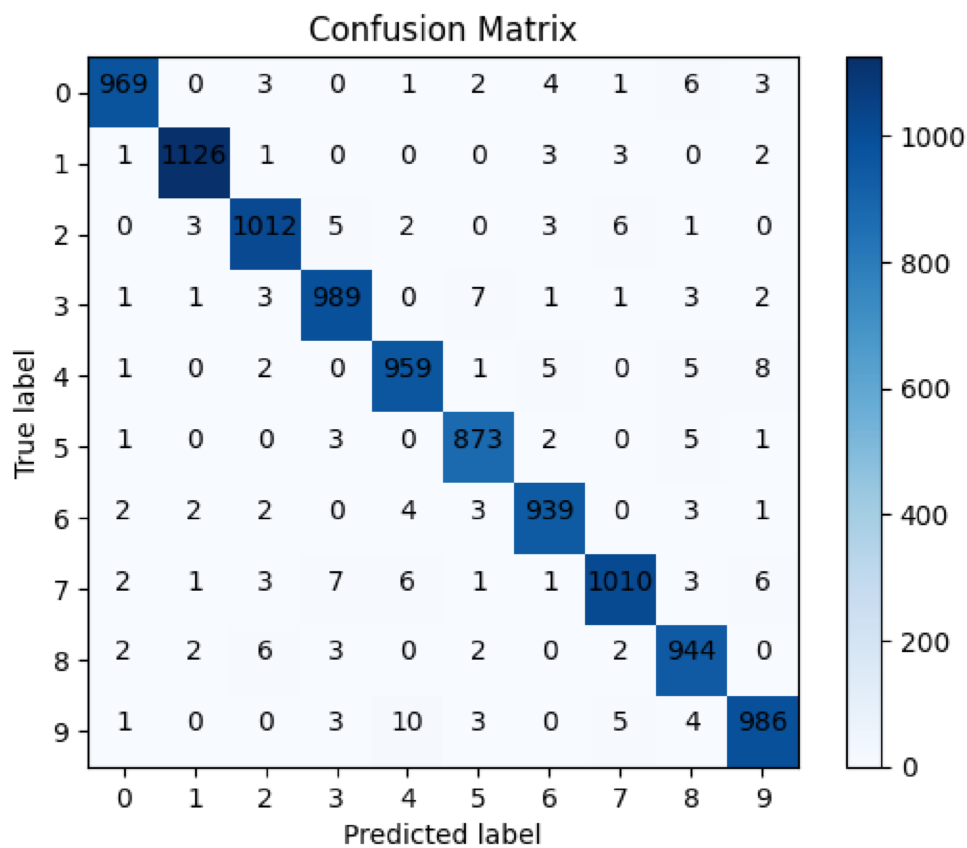
```
--------------------------------------------------------------------------
**************************** Epoch 4 ***********************************
Training Accuracy:  98.56851696968079
Validation Accuracy:  97.46666550636292
--------------------------------------------------------------------------
**************************** Epoch 5 ***********************************
Training Accuracy:  98.78518581390381
Validation Accuracy:  97.38333225250244
--------------------------------------------------------------------------
**************************** Epoch 6 ***********************************
Training Accuracy:  99.14259314537048
Validation Accuracy:  97.53333330154419
--------------------------------------------------------------------------
**************************** Epoch 7 ***********************************
Training Accuracy:  99.33518767356873
Validation Accuracy:  97.60000109672546
--------------------------------------------------------------------------
**************************** Epoch 8 ***********************************
Training Accuracy:  99.4962990283966
Validation Accuracy:  97.61666655540466
--------------------------------------------------------------------------
**************************** Epoch 9 ***********************************
Training Accuracy:  99.58703517913818
Validation Accuracy:  97.66666889190674
--------------------------------------------------------------------------
**************************** Epoch 10 ***********************************
Training Accuracy:  99.65925812721252
Validation Accuracy:  97.56666421890259
--------------------------------------------------------------------------
**************************** Epoch 11 ***********************************
Training Accuracy:  99.71296191215515
Validation Accuracy:  97.66666889190674
--------------------------------------------------------------------------
**************************** Epoch 12 ***********************************
Training Accuracy:  99.77592825889587
Validation Accuracy:  97.63333201408386
--------------------------------------------------------------------------
**************************** Epoch 13 ***********************************
Training Accuracy:  99.83333349227905
Validation Accuracy:  97.73333072662354
--------------------------------------------------------------------------
**************************** Epoch 14 ***********************************
Training Accuracy:  99.86110925674438
Validation Accuracy:  97.73333072662354
--------------------------------------------------------------------------
**************************** Epoch 15 ***********************************
Training Accuracy:  99.88333582878113
Validation Accuracy:  97.75000214576721
```

```
------------------------------------------------------------------------
Test Accuracy:  98.07000160217285
```

[ ]:
```
plt.figure(figsize=(16,8))
plt.plot(Params[1],label='Training loss')
plt.plot(Params[2],label='Validation loss')
plt.title('Train VS Validation')
plt.legend()
plt.show()
```



[ ]:
```
Mat = Confusion_Matrix(Params[-1],Y_test[0])
plot_confusion_matrix(Mat)
```



[ ]:

```

```

4.6 (1) Using Tanh and softmax

Here I am using Tanh activation in hidden layers and softmax at the output layer doing gradient descent with learning rate 0.1 and runs for 15 epoch

[ ]:

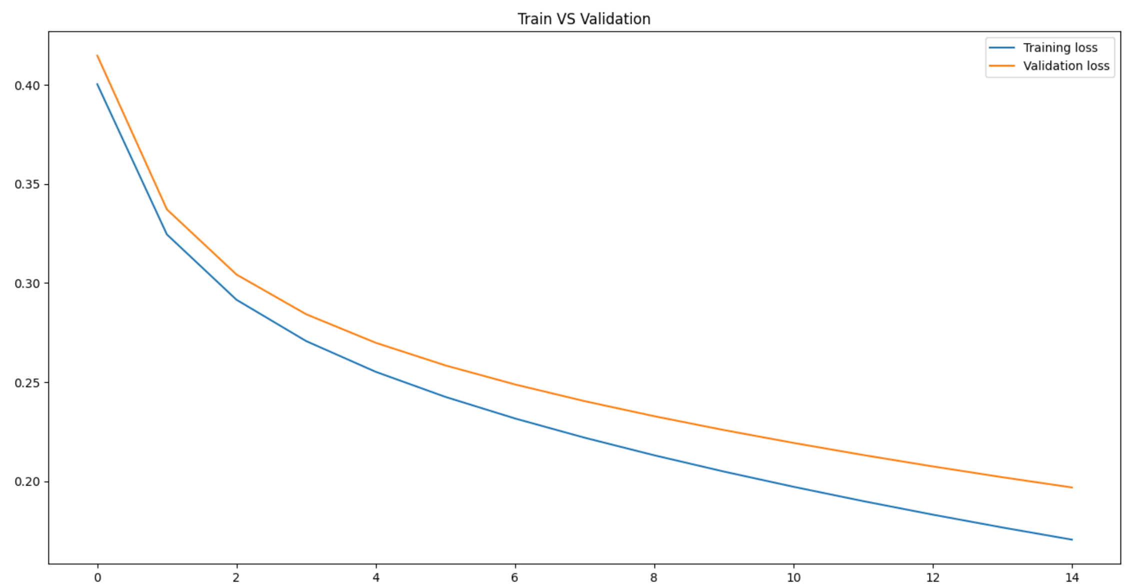
```
Params = gradient_descent(X_train,Y_train, X_test, Y_test , X_valid, Y_valid,␣
 ↪Activation=Tanh,
                         grad_act=Grad_Tanh, OutAct = Softmax,  alpha=0.1, epoch=␣
 ↪15)
```

```
**************************** Epoch 1 ***********************************
Training Accuracy:  89.08148407936096
Validation Accuracy:  88.84999752044678
------------------------------------------------------------------------
**************************** Epoch 2 ***********************************
Training Accuracy:  90.65740704536438
Validation Accuracy:  90.6499981880188
------------------------------------------------------------------------
```

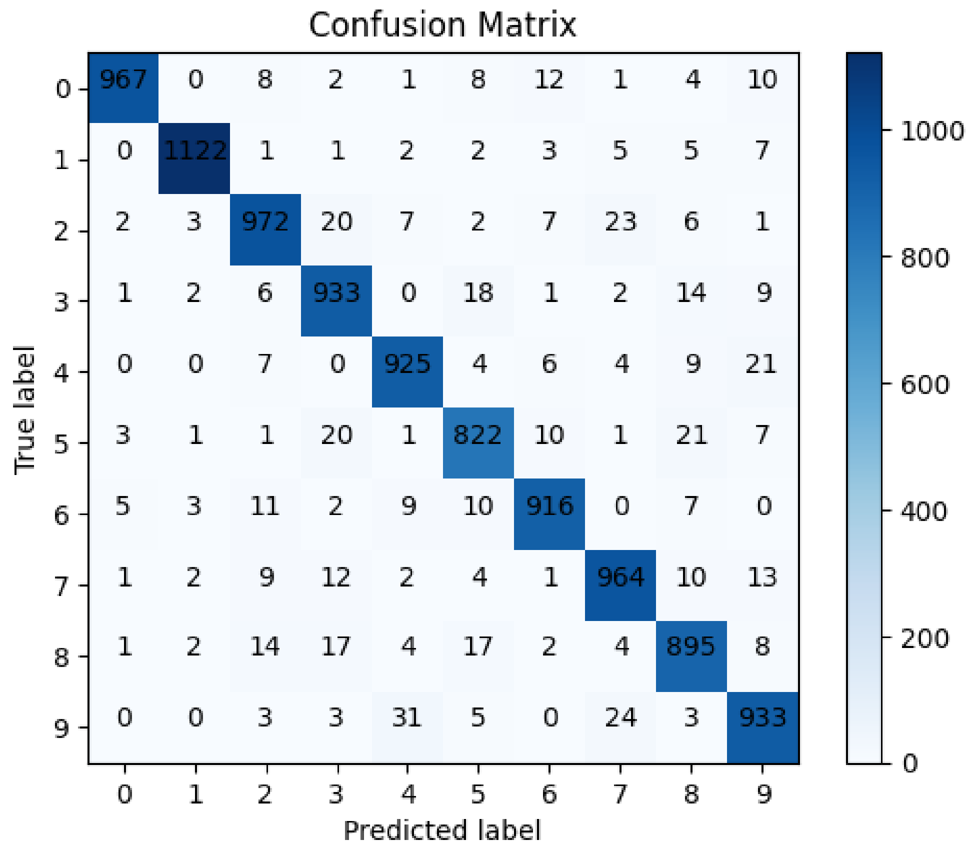
```
**************************** Epoch 3 ***********************************
Training Accuracy:  91.55185222625732
Validation Accuracy:  91.50000214576721
------------------------------------------------------------------------
**************************** Epoch 4 ***********************************
Training Accuracy:  92.08518266677856
Validation Accuracy:  91.81666374206543
------------------------------------------------------------------------
**************************** Epoch 5 ***********************************
Training Accuracy:  92.57592558860779
Validation Accuracy:  92.1999990940094
------------------------------------------------------------------------
**************************** Epoch 6 ***********************************
Training Accuracy:  92.91852116584778
Validation Accuracy:  92.58333444595337
------------------------------------------------------------------------
**************************** Epoch 7 ***********************************
Training Accuracy:  93.20926070213318
Validation Accuracy:  92.91666746139526
------------------------------------------------------------------------
**************************** Epoch 8 ***********************************
Training Accuracy:  93.47962737083435
Validation Accuracy:  93.08333396911621
------------------------------------------------------------------------
**************************** Epoch 9 ***********************************
Training Accuracy:  93.73703598976135
Validation Accuracy:  93.31666827201843
------------------------------------------------------------------------
**************************** Epoch 10 ***********************************
Training Accuracy:  93.99259090423584
Validation Accuracy:  93.56666803359985
------------------------------------------------------------------------
**************************** Epoch 11 ***********************************
Training Accuracy:  94.24999952316284
Validation Accuracy:  93.69999766349792
------------------------------------------------------------------------
**************************** Epoch 12 ***********************************
Training Accuracy:  94.45740580558777
Validation Accuracy:  93.94999742507935
------------------------------------------------------------------------
**************************** Epoch 13 ***********************************
Training Accuracy:  94.67407464981079
Validation Accuracy:  94.0999984741211
------------------------------------------------------------------------
**************************** Epoch 14 ***********************************
Training Accuracy:  94.862961769104
Validation Accuracy:  94.23333406448364
------------------------------------------------------------------------
```

```
**************************** Epoch 15 ***********************************
Training Accuracy:  95.02037167549133
Validation Accuracy:  94.38333511352539
------------------------------------------------------------------------
Test Accuracy:  94.48999762535095
```

```
[ ]: plt.figure(figsize=(16,8))
     plt.plot(Params[1],label='Training loss')
     plt.plot(Params[2],label='Validation loss')
     plt.title('Train VS Validation')
     plt.legend()
     plt.show()
```




```
[ ]: Mat = Confusion_Matrix(Params[-1],Y_test[0])
     plot_confusion_matrix(Mat)
```



5 With Regularisation

5.0.1 Sigmoid

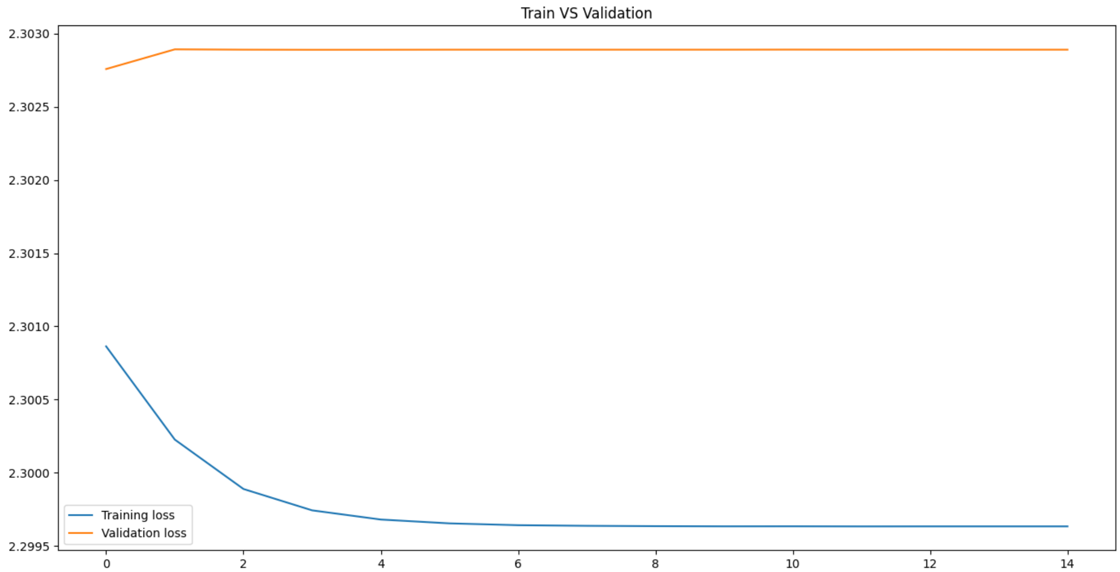
[ ]:
```
Params = gradient_descent(X_train,Y_train, X_test, Y_test , X_valid, Y_valid,␣
↪Activation=Sigmoid,
                        grad_act=Grad_Sigmoid, OutAct = Softmax,  alpha=0.1,␣
↪epoch= 15,lambda1=0.01)
```

```
**************************** Epoch 1 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
------------------------------------------------------------------------
**************************** Epoch 2 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
------------------------------------------------------------------------
**************************** Epoch 3 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
```

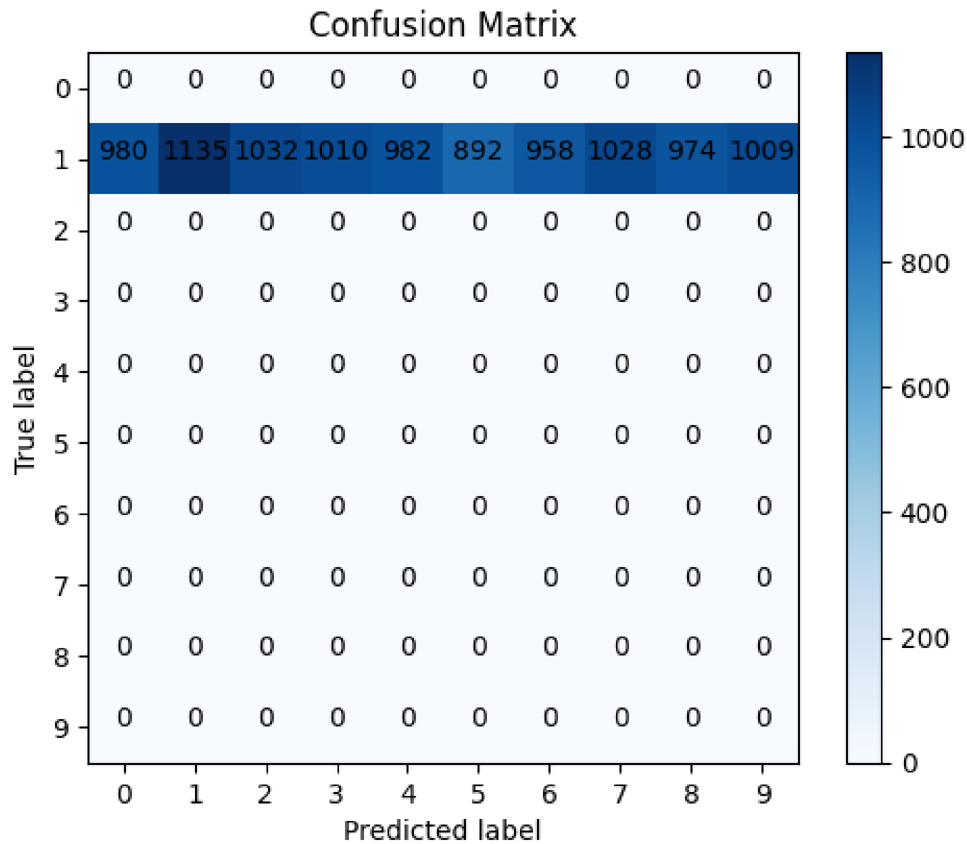
```
--------------------------------------------------------------------------
**************************** Epoch 4 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
--------------------------------------------------------------------------
**************************** Epoch 5 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
--------------------------------------------------------------------------
**************************** Epoch 6 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
--------------------------------------------------------------------------
**************************** Epoch 7 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
--------------------------------------------------------------------------
**************************** Epoch 8 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
--------------------------------------------------------------------------
**************************** Epoch 9 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
--------------------------------------------------------------------------
**************************** Epoch 10 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
--------------------------------------------------------------------------
**************************** Epoch 11 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
--------------------------------------------------------------------------
**************************** Epoch 12 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
--------------------------------------------------------------------------
**************************** Epoch 13 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
--------------------------------------------------------------------------
**************************** Epoch 14 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
--------------------------------------------------------------------------
**************************** Epoch 15 ***********************************
Training Accuracy:  11.299999803304672
Validation Accuracy:  10.649999976158142
```

```
------------------------------------------------------------------------
Test Accuracy:  11.349999904632568
```

[ ]:
```
plt.figure(figsize=(16,8))
plt.plot(Params[1],label='Training loss')
plt.plot(Params[2],label='Validation loss')
plt.title('Train VS Validation')
plt.legend()
plt.show()
```



[ ]:
```
Mat = Confusion_Matrix(Params[-1],Y_test[0])
plot_confusion_matrix(Mat)
```



5.0.2 ReLU

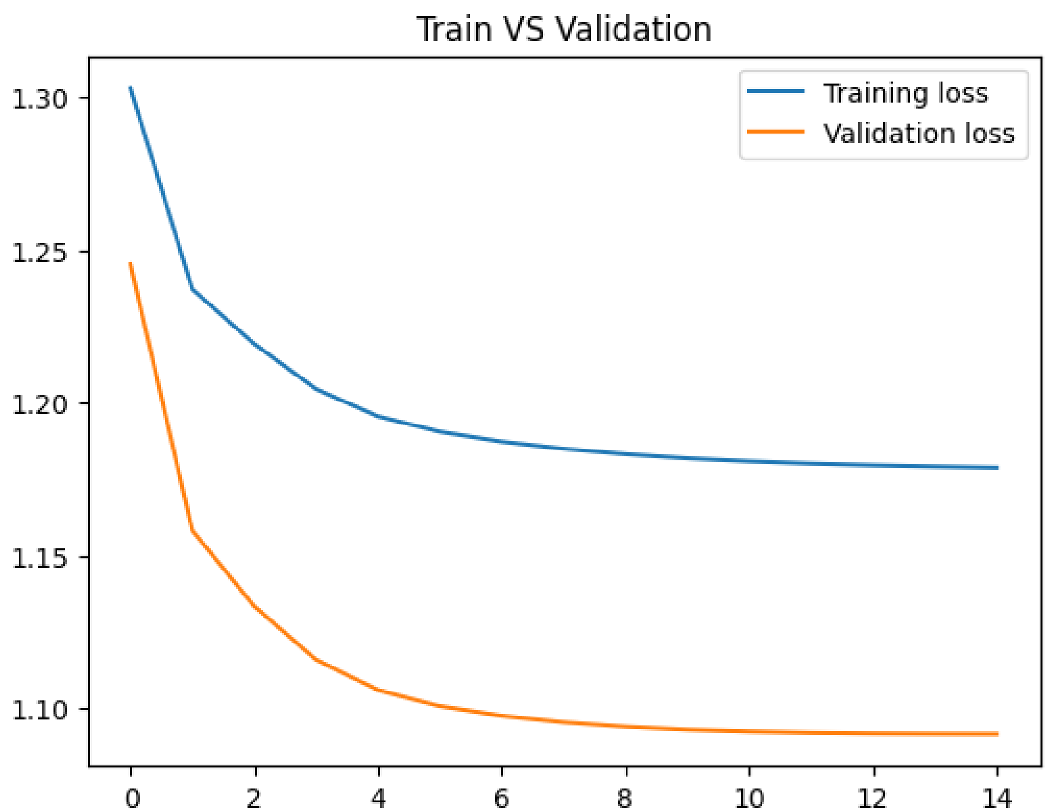
[ ]:
```
Params = gradient_descent(X_train,Y_train, X_test, Y_test , X_valid, Y_valid,␣
 ↪Activation=ReLU,
                        grad_act=ReLU_deriv, OutAct = Softmax,  alpha=0.1, epoch=␣
 ↪15,lambda1=0.01)
```

```
**************************** Epoch 1 ***********************************
Training Accuracy:  73.83888959884644
Validation Accuracy:  72.89999723434448
------------------------------------------------------------------------
**************************** Epoch 2 ***********************************
Training Accuracy:  71.65370583534241
Validation Accuracy:  71.48333191871643
------------------------------------------------------------------------
**************************** Epoch 3 ***********************************
Training Accuracy:  70.78889012336731
Validation Accuracy:  70.59999704360962
------------------------------------------------------------------------
**************************** Epoch 4 ***********************************
```

```
Training Accuracy:  71.11851572990417
Validation Accuracy:  70.86666822433472
------------------------------------------------------------------------
**************************** Epoch 5 ***********************************
Training Accuracy:  71.59073948860168
Validation Accuracy:  71.16666436195374
------------------------------------------------------------------------
**************************** Epoch 6 ***********************************
Training Accuracy:  71.85184955596924
Validation Accuracy:  71.5833306312561
------------------------------------------------------------------------
**************************** Epoch 7 ***********************************
Training Accuracy:  72.03333377838135
Validation Accuracy:  71.66666388511658
------------------------------------------------------------------------
**************************** Epoch 8 ***********************************
Training Accuracy:  72.13703989982605
Validation Accuracy:  71.63333296775818
------------------------------------------------------------------------
**************************** Epoch 9 ***********************************
Training Accuracy:  72.2333312034607
Validation Accuracy:  71.64999842643738
------------------------------------------------------------------------
**************************** Epoch 10 ***********************************
Training Accuracy:  72.28147983551025
Validation Accuracy:  71.73333168029785
------------------------------------------------------------------------
**************************** Epoch 11 ***********************************
Training Accuracy:  72.303706407547
Validation Accuracy:  71.73333168029785
------------------------------------------------------------------------
**************************** Epoch 12 ***********************************
Training Accuracy:  72.32592701911926
Validation Accuracy:  71.71666622161865
------------------------------------------------------------------------
**************************** Epoch 13 ***********************************
Training Accuracy:  72.3370373249054
Validation Accuracy:  71.70000076293945
------------------------------------------------------------------------
**************************** Epoch 14 ***********************************
Training Accuracy:  72.32407331466675
Validation Accuracy:  71.70000076293945
------------------------------------------------------------------------
**************************** Epoch 15 ***********************************
Training Accuracy:  72.31296300888062
Validation Accuracy:  71.70000076293945
------------------------------------------------------------------------
Test Accuracy:  72.99000024795532
```

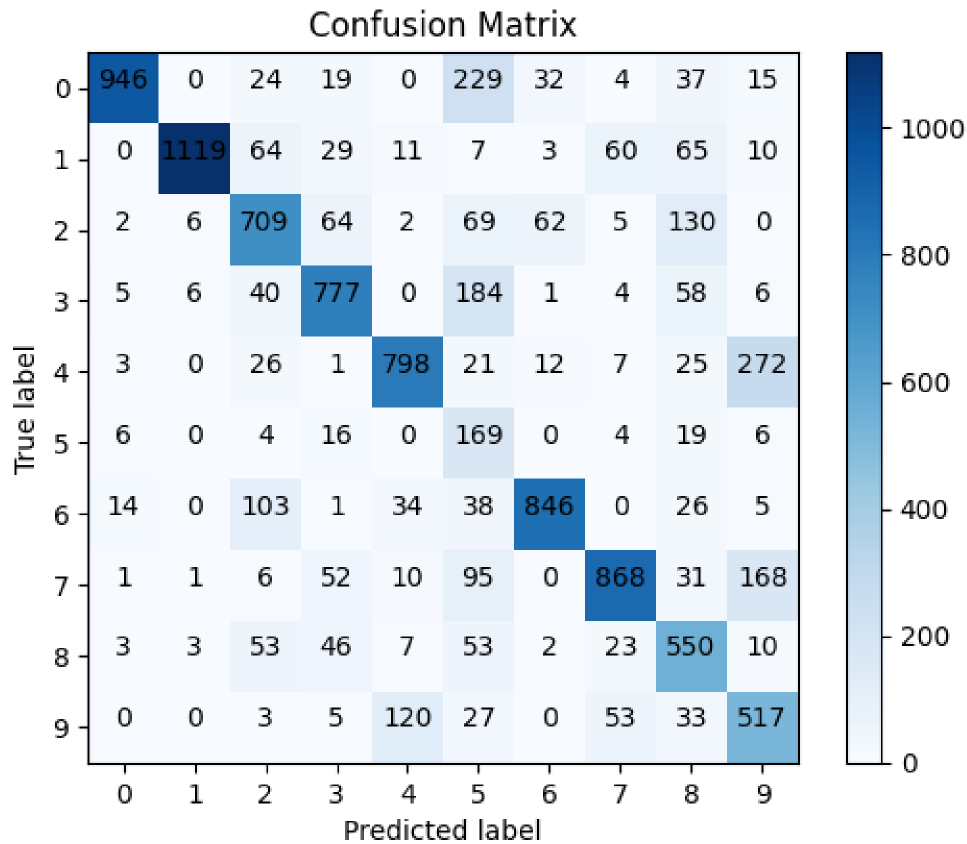
[ ]:

```
plt.plot(figsize=(16,8))
plt.plot(Params[1],label='Training loss')
plt.plot(Params[2],label='Validation loss')
plt.title('Train VS Validation')
plt.legend()
plt.show()
```



[ ]:

```
Mat = Confusion_Matrix(Params[-1],Y_test[0])
plot_confusion_matrix(Mat)
```



5.0.3 Tanh

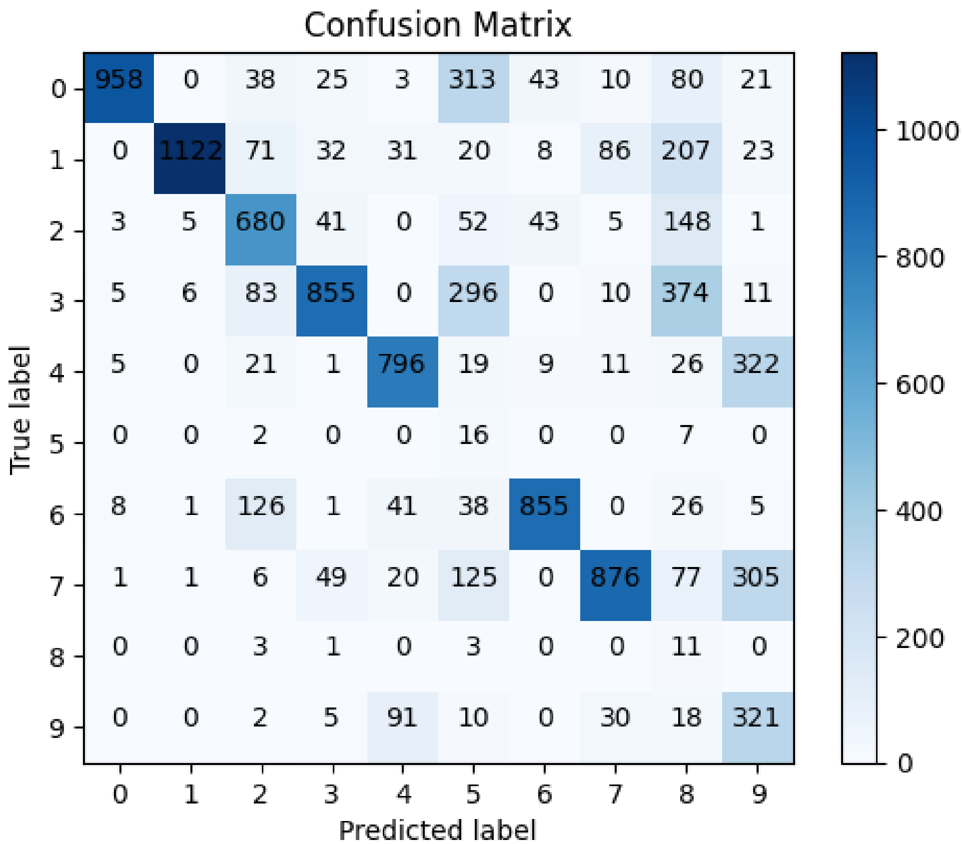
```
[ ]: Params = gradient_descent(X_train,Y_train, X_test, Y_test , X_valid, Y_valid,␣
      ↪Activation=Tanh,
                          grad_act=Grad_Tanh, OutAct = Softmax,  alpha=0.1, epoch=␣
      ↪15,lambda1=0.01)
```

```
**************************** Epoch 1 ***********************************
Training Accuracy:  81.77777528762817
Validation Accuracy:  81.30000233650208
-------------------------------------------------------------------------
**************************** Epoch 2 ***********************************
Training Accuracy:  75.61296224594116
Validation Accuracy:  75.3000020980835
-------------------------------------------------------------------------
**************************** Epoch 3 ***********************************
Training Accuracy:  72.20370173454285
Validation Accuracy:  72.28333353996277
-------------------------------------------------------------------------
**************************** Epoch 4 ***********************************
```

```
Training Accuracy:  70.30740976333618
Validation Accuracy:  70.20000219345093
------------------------------------------------------------------------
**************************** Epoch 5 ***********************************
Training Accuracy:  67.44258999824524
Validation Accuracy:  67.03333258628845
------------------------------------------------------------------------
**************************** Epoch 6 ***********************************
Training Accuracy:  65.14444351196289
Validation Accuracy:  64.78333473205566
------------------------------------------------------------------------
**************************** Epoch 7 ***********************************
Training Accuracy:  64.50185179710388
Validation Accuracy:  64.16666507720947
------------------------------------------------------------------------
**************************** Epoch 8 ***********************************
Training Accuracy:  64.39074277877808
Validation Accuracy:  63.91666531562805
------------------------------------------------------------------------
**************************** Epoch 9 ***********************************
Training Accuracy:  64.3240749835968
Validation Accuracy:  63.81666660308838
------------------------------------------------------------------------
**************************** Epoch 10 ***********************************
Training Accuracy:  64.25740718841553
Validation Accuracy:  63.78333568572998
------------------------------------------------------------------------
**************************** Epoch 11 ***********************************
Training Accuracy:  64.22777771949768
Validation Accuracy:  63.733333349227905
------------------------------------------------------------------------
**************************** Epoch 12 ***********************************
Training Accuracy:  64.22222256660461
Validation Accuracy:  63.716667890548706
------------------------------------------------------------------------
**************************** Epoch 13 ***********************************
Training Accuracy:  64.21852111816406
Validation Accuracy:  63.733333349227905
------------------------------------------------------------------------
**************************** Epoch 14 ***********************************
Training Accuracy:  64.21666741371155
Validation Accuracy:  63.68333101272583
------------------------------------------------------------------------
**************************** Epoch 15 ***********************************
Training Accuracy:  64.21296000480652
Validation Accuracy:  63.70000243186951
------------------------------------------------------------------------
Test Accuracy:  64.89999890327454
```

[ ]:
```
plt.figure(figsize=(16,8))
plt.plot(Params[1],label='Training loss')
plt.plot(Params[2],label='Validation loss')
plt.title('Train VS Validation')
plt.legend()
plt.show()
```

[ ]:
```
Mat = Confusion_Matrix(Params[-1],Y_test[0])
plot_confusion_matrix(Mat)
```



6 Using Pytorch

[ ]:
```
class MLP(torch.nn.Module):
    def __init__(self, input_dim, output_dim):
        super().__init__()

        self.input_fc = torch.nn.Linear(input_dim, 500)
        self.hidden1_fc = torch.nn.Linear(500, 250)
        self.hidden2_fc = torch.nn.Linear(250, 100)
        self.output_fc = torch.nn.Linear(100,output_dim)

    def forward(self, x):
        batch_size = x.shape[0]
        h_1 = torch.nn.functional.relu(self.input_fc(x))
        h_2 = torch.nn.functional.relu(self.hidden1_fc(h_1))
        h_3 = torch.nn.functional.relu(self.hidden2_fc(h_2))
        y_pred = self.output_fc(h_3)
        return y_pred, h_3
```

[ ]:
```python
model = MLP(784,10)
```

[ ]:
```python
def count_parameters(model):
    return sum(p.numel() for p in model.parameters() if p.requires_grad)
```

[ ]:
```python
optimizer = torch.optim.Adam(model.parameters(),lr=0.001)
criterion = torch.nn.CrossEntropyLoss()
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

[ ]:
```python
model = model.to(device)
criterion = criterion.to(device)
```

[ ]:
```python
def calculate_accuracy(y_pred, y):
    top_pred = y_pred.argmax(1, keepdim=True)
    correct = top_pred.eq(y.view_as(top_pred)).sum()
    acc = correct.float() / y.shape[0]
    return acc
```

[ ]:
```python
def train(model, iterator, optimizer, criterion, device):

    epoch_loss = 0
    epoch_acc = 0

    model.train()

    for data in iterator:
        x=torch.flatten(data[0],start_dim=1)
        y=data[1]
        x = x.to(device)
        y = y.to(device)

        optimizer.zero_grad()

        y_pred, _ = model(x)

        loss = criterion(y_pred, y)

        acc = calculate_accuracy(y_pred, y)

        loss.backward()

        optimizer.step()

        epoch_loss += loss.item()
        epoch_acc += acc.item()

    return epoch_loss / len(iterator), epoch_acc / len(iterator)
```

[ ]:
```
def evaluate(model, iterator, criterion, device):

    epoch_loss = 0
    epoch_acc = 0

    model.eval()

    with torch.no_grad():

        for data in iterator:
            x=torch.flatten(data[0],start_dim=1)
            y=data[1]
            x = x.to(device)
            y = y.to(device)

            y_pred, _ = model(x)

            loss = criterion(y_pred, y)

            acc = calculate_accuracy(y_pred, y)

            epoch_loss += loss.item()
            epoch_acc += acc.item()

    return epoch_loss / len(iterator), epoch_acc / len(iterator)
```

[ ]:
```
EPOCHS = 10

best_valid_loss = float('inf')

for epoch in range(EPOCHS):

    train_loss, train_acc = train(model, train_iterator, optimizer, criterion,␣
 ↪device)
    valid_loss, valid_acc = evaluate(model, valid_iterator, criterion, device)
# To Save the Model
    if valid_loss < best_valid_loss:
        best_valid_loss = valid_loss
        torch.save(model.state_dict(), 'tut1-model.pt')




    print(f'Epoch: {epoch+1:02} ')
    print(f'\tTrain Loss: {train_loss:.3f} | Train Acc: {train_acc*100:.2f}%')
    print(f'\t Val. Loss: {valid_loss:.3f} |  Val. Acc: {valid_acc*100:.2f}%')
```

```
Epoch: 01
        Train Loss: 0.275 | Train Acc: 91.88%
         Val. Loss: 0.145 |  Val. Acc: 95.88%
Epoch: 02
        Train Loss: 0.101 | Train Acc: 96.89%
         Val. Loss: 0.104 |  Val. Acc: 96.97%
Epoch: 03
        Train Loss: 0.065 | Train Acc: 97.93%
         Val. Loss: 0.095 |  Val. Acc: 97.30%
Epoch: 04
        Train Loss: 0.049 | Train Acc: 98.55%
         Val. Loss: 0.095 |  Val. Acc: 97.40%
Epoch: 05
        Train Loss: 0.038 | Train Acc: 98.80%
         Val. Loss: 0.105 |  Val. Acc: 97.58%
Epoch: 06
        Train Loss: 0.032 | Train Acc: 98.95%
         Val. Loss: 0.103 |  Val. Acc: 97.28%
Epoch: 07
        Train Loss: 0.026 | Train Acc: 99.21%
         Val. Loss: 0.110 |  Val. Acc: 97.37%
Epoch: 08
        Train Loss: 0.024 | Train Acc: 99.24%
         Val. Loss: 0.092 |  Val. Acc: 97.90%
Epoch: 09
        Train Loss: 0.021 | Train Acc: 99.31%
         Val. Loss: 0.092 |  Val. Acc: 97.98%
Epoch: 10
        Train Loss: 0.018 | Train Acc: 99.42%
         Val. Loss: 0.112 |  Val. Acc: 97.58%
```

[ ]:
```
test_loss, test_acc = evaluate(model, test_iterator, criterion, device)
```

[ ]:
```
print('Test Loss: ',test_loss)
print('Test Accuracy: ',test_acc)
```

```
Test Loss:  0.10441038757562637
Test Accuracy:  0.9795999526977539
```

[ ]:
```
def get_predictions(model, iterator, device):

    model.eval()

    images = []
    labels = []
    probs = []

```

```python
    with torch.no_grad():

        for data in iterator:
            x=torch.flatten(data[0],start_dim=1)
            y=data[1]
            x = x.to(device)

            y_pred, _ = model(x)

            y_prob = torch.nn.functional.softmax(y_pred, dim=-1)

            images.append(x.cpu())
            labels.append(y.cpu())
            probs.append(y_prob.cpu())

    images = torch.cat(images, dim=0)
    labels = torch.cat(labels, dim=0)
    probs = torch.cat(probs, dim=0)

    return images, labels, probs
```

[ ]:
```python
from sklearn import metrics
```

[ ]:
```python
def plot_confusion_matrix(labels, pred_labels):

    fig = plt.figure(figsize=(10, 10))
    ax = fig.add_subplot(1, 1, 1)
    cm = metrics.confusion_matrix(labels, pred_labels)
    cm = metrics.ConfusionMatrixDisplay(cm, display_labels=range(10))
    cm.plot(values_format='d', cmap='Blues', ax=ax)
```

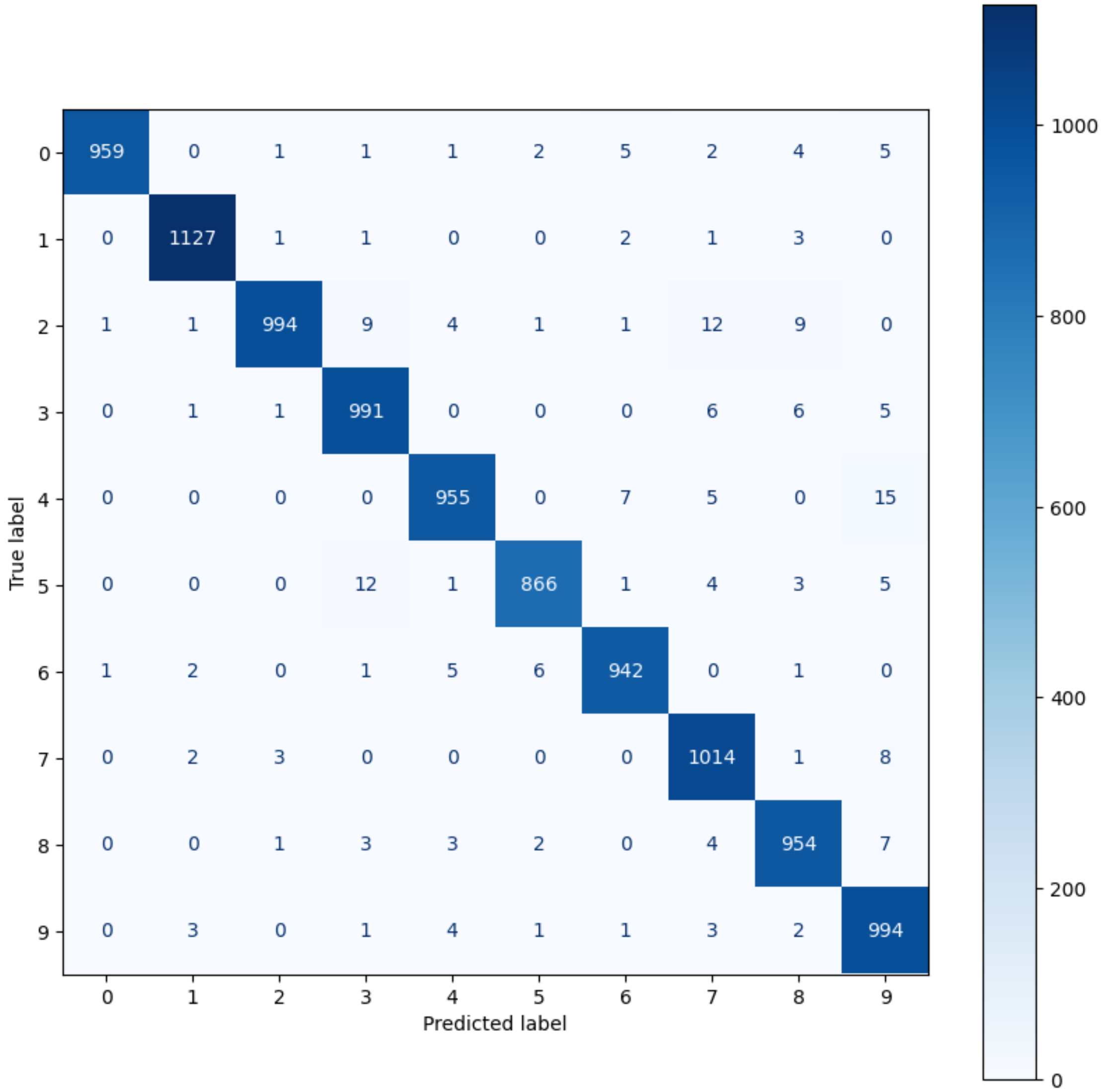
[ ]:
```python

```

[ ]:
```python
images, labels, probs = get_predictions(model, test_iterator, device)

pred_labels = torch.argmax(probs, 1)
```

[ ]:
```python
plot_confusion_matrix(labels, pred_labels)
```




```
[ ]: corrects = torch.eq(labels, pred_labels)
     incorrect_examples = []

     for image, label, prob, correct in zip(images, labels, probs, corrects):
         if not correct:
             incorrect_examples.append((image, label, prob))

     incorrect_examples.sort(reverse=True,
                             key=lambda x: torch.max(x[2], dim=0).values)
```

```
[ ]: def plot_most_incorrect(incorrect, n_images):

         rows = int(np.sqrt(n_images))
```

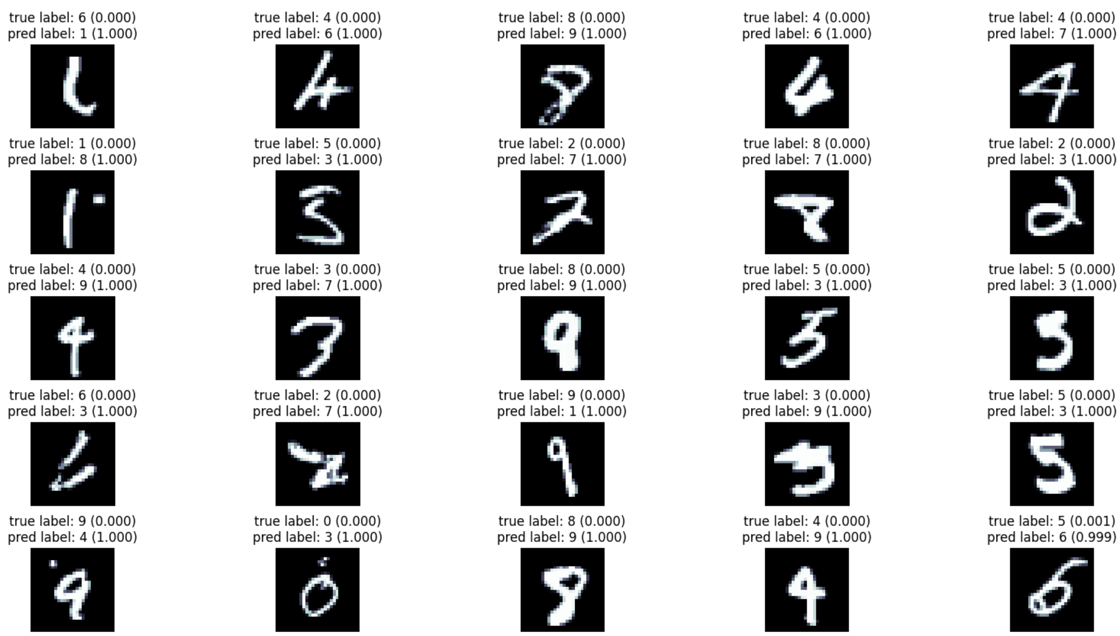
```
    cols = int(np.sqrt(n_images))

    fig = plt.figure(figsize=(20, 10))
    for i in range(rows*cols):
        ax = fig.add_subplot(rows, cols, i+1)
        image, true_label, probs = incorrect[i]
        true_prob = probs[true_label]
        incorrect_prob, incorrect_label = torch.max(probs, dim=0)
        ax.imshow(image.view(28, 28).cpu().numpy(), cmap='bone')
        ax.set_title(f'true label: {true_label} ({true_prob:.3f})\n'
                     f'pred label: {incorrect_label} ({incorrect_prob:.3f})')
        ax.axis('off')
    fig.subplots_adjust(hspace=0.5)
```

6.1 In Reality Model had done a good job as we can see the following:

[ ]:
```
N_IMAGES = 25

plot_most_incorrect(incorrect_examples, N_IMAGES)
```



[ ]:
```

```

7 Summary

1. **Sigmoid** With *Epoch* = 15 Here are the Details: > * *Learning rate* = 0.01

- Train Accuracy : 67.13%
- Validation Accuracy: 66.39%
- Test Accuracy: 67.45%
- Time: $4m10sec > *Learning\ rate = 0.01$
- Train Accuracy : Not Learning
- Validation Accuracy: —-
- Test Accuracy: —-
- Time: — $> *Learning\ rate = 1$
- Train Accuracy : 92.17%
- Validation Accuracy: 91.85%
- Test Accuracy: 92.14%
- Time: $4m10sec$

---

2. **ReLU** With $Epoch = 15$ Here are the Details: > * $Learning\ rate = 0.01$
   - Train Accuracy : 90.47%
   - Validation Accuracy: 90.20%
   - Test Accuracy: 91.00%
   - Time: $4m1sec > *Learning\ rate = 0.1$
   - Train Accuracy : 97.33%
   - Validation Accuracy: 96.1%
   - Test Accuracy:96.64%
   - Time: 3m55s $> *Learning\ rate = 1$
   - Train Accuracy : 99.83
   - Validation Accuracy: 97.75
   - Test Accuracy: 98.07
   - Time: $3m0sec$

#Regularisation penality=0.01 1. **ReLU** With $Epoch = 15$ Here are the Details: > * $Learning\ rate = 0.01$ * Train Accuracy :—– * Validation Accuracy: —- * Test Accuracy: —– * Time: $4m10sec$ 2. **Tanh** > $Learning\ rate = 0.01$ Train Accuracy : 65.04 * Validation Accuracy: 63.07 * Test Accuracy: 64.70 * Time: — —

1. **Pytorch** With $Epoch = 10$ and Adam optimizer Here are the Details: > * $Learning\ rate = 0.01$
   - Train Accuracy : 97.95
   - Validation Accuracy: 95.07
   - Test Accuracy: 95.20
   - Time: $3m45s > *Learning\ rate = 0.01$
   - Train Accuracy : Not doing good job
   - Validation Accuracy: —-
   - Test Accuracy: —-
   - Time: — $> *Learning\ rate = 0.001$
   - Train Accuracy : 99.48
   - Validation Accuracy: 97.85
   - Test Accuracy: 97.75
   - Time: $2m55sec$
