Task 1: Manual code for forward pass and backward pass

```
import torch
import torchvision.datasets as datasets
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
train_dataset=datasets.MNIST(root="./data",train=True,download=True,tr
ansform=transforms.ToTensor())
test_dataset=datasets.MNIST(root="./data",train=False,download=True,tr
ansform=transforms.ToTensor())
from torch.utils.data import DataLoader
from torch.utils.data import random_split
from google.colab import drive
drive.mount('/content/drive')
```

```
100%|██████████| 9.91M/9.91M [00:00<00:00, 12.7MB/s]
100%|██████████| 28.9k/28.9k [00:00<00:00, 499kB/s]
100%|██████████| 1.65M/1.65M [00:00<00:00, 3.90MB/s]
100%|██████████| 4.54k/4.54k [00:00<00:00, 5.53MB/s]
```

```
Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).
```

```
def sigmoid(x):
  return 1/(1+torch.exp(-x))
def relu(x):
  return torch.max(x,torch.tensor([0]))
def tanh(x):
  return (torch.exp(x)-torch.exp(-x))/(torch.exp(x)+torch.exp(-x))
def softmax(x):
  return torch.exp(x)/torch.sum(torch.exp(x),dim=0)
def der_sigmoid(x):
  return sigmoid(x)*(1-sigmoid(x))
def der_relu(x):
  return (x > 0).float()
def der_tanh(x):
  return 1-tanh(x)**2

# forward pass
class hand_network():
  def
__init__(self,input_dim,hidden_layer_1,hidden_layer_2,hidden_layer_3,o
utput,activation_function):

self.w1=torch.rand(hidden_layer_1,input_dim)*2*((6.0/(input_dim+hidden
_layer_1))**0.5)-(6.0/(input_dim+hidden_layer_1))**0.5

self.w2=torch.rand(hidden_layer_2,hidden_layer_1)*2*((6.0/(hidden_laye
r_1+hidden_layer_2))**0.5)-(6/(hidden_layer_1+hidden_layer_2))**0.5
```

```
self.w3=torch.rand(hidden_layer_3,hidden_layer_2)*2*((6.0/(hidden_laye
r_2+hidden_layer_3))**0.5)-(6/(hidden_layer_2+hidden_layer_3))**0.5

self.w4=torch.rand(output,hidden_layer_3)*2*((6.0/(hidden_layer_3+outp
ut))**0.5)-(6.0/(hidden_layer_3+output))**0.5
    self.b1=torch.zeros(hidden_layer_1,1)
    self.b2=torch.zeros(hidden_layer_2,1)
    self.b3=torch.zeros(hidden_layer_3,1)
    self.b4=torch.zeros(output,1)
    self.act=activation_function
    self.out_act=softmax

  def forward_pass(self,x):
    self.layer_1_output=torch.matmul(self.w1,x)+self.b1
    self.layer_1_ac_output=self.act(self.layer_1_output)
    self.layer_2_output=torch.matmul(self.w2,self.layer_1_ac_output)
+self.b2
    self.layer_2_ac_output=self.act(self.layer_2_output)
    self.layer_3_output=torch.matmul(self.w3,self.layer_2_ac_output)
+self.b3
    self.layer_3_ac_output=self.act(self.layer_3_output)
    self.layer_4_output=torch.matmul(self.w4,self.layer_3_ac_output)
+self.b4
    self.layer_4_ac_output=self.out_act(self.layer_4_output)
    self.one_hot_rep_output=torch.zeros(self.layer_4_ac_output.shape)
    for i,data in enumerate(self.layer_4_ac_output):
      self.one_hot_rep_output[i][torch.argmax(data)]=1
    self.result=torch.argmax(self.layer_4_ac_output,dim=0)
    return self.layer_4_ac_output,self.result,self.one_hot_rep_output


#dataset with one hot encoding
new_train_dataset=[]
for data in train_dataset:
  data_1=data[0].squeeze(0)
  one_hot=torch.zeros(10)
  one_hot[data[1]]=1
  new_train_dataset.append((data_1,one_hot))

train_loader=DataLoader(new_train_dataset,batch_size=64,shuffle=True)
test_loader=DataLoader(test_dataset,batch_size=64,shuffle=False)

print(len(new_train_dataset))

60000

def loss_fn(y,p):
  eps=1e-7
  loss=-torch.sum(y*torch.log(p+eps))/y.shape[0]
  # if torch.isnan(loss):
  #   print(y)
```

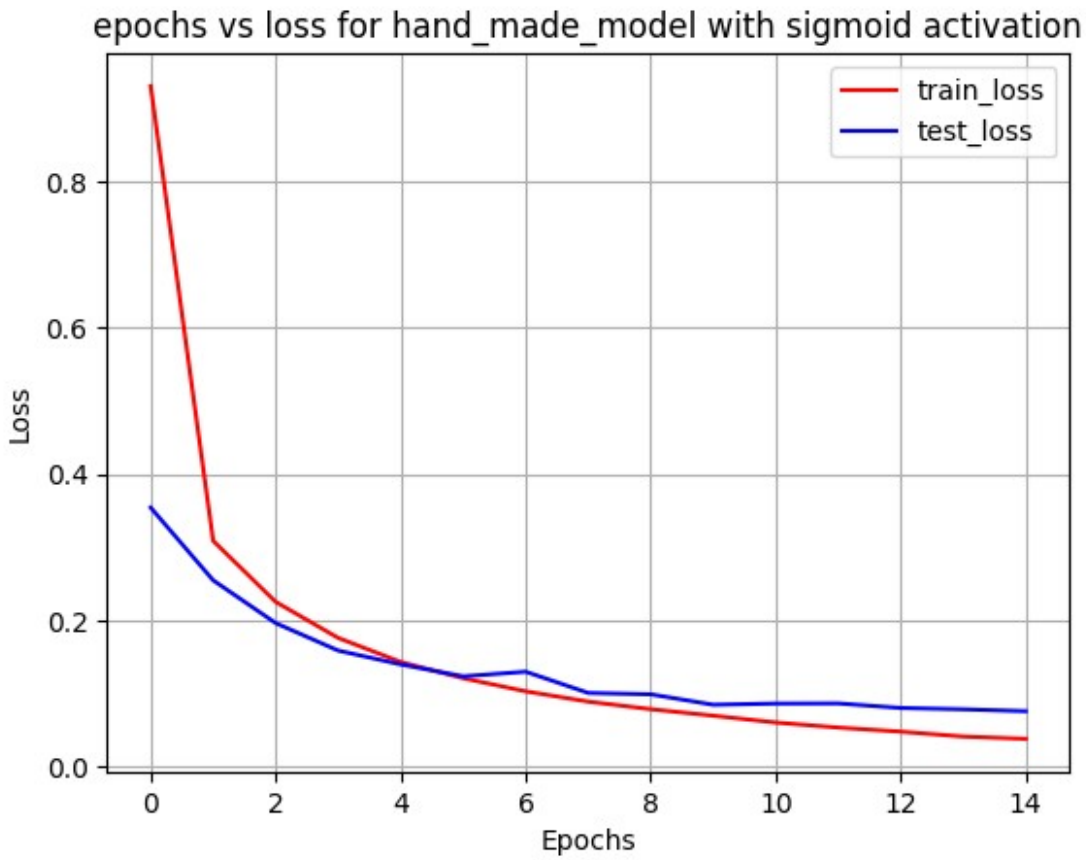
```
  #   print(p)
  #   print(torch.log(p))
  return loss

def training_loop_sigmoid(model,train_loader,test_loader,epochs,lr):
  train_loss=[]
  test_acc=[]
  test_loss=[]
  for i in range(epochs):
    correct=0
    total=0
    runn_loss=0
    for data in train_loader:
      x,y=data[0],data[1]
      x=x.reshape(x.shape[0],784)
      x=x.T
      # print(model.b1.shape)
      # print(torch.matmul(model.w1,x).shape)
      # print(y.shape)
      output,_,_=model.forward_pass(x)
      output=output.T
      loss=loss_fn(y,output)
      runn_loss+=loss.item()
      delta_4=output-y

delta_3=torch.matmul(delta_4,model.w4)*(model.layer_3_ac_output.T)*(1-
model.layer_3_ac_output.T)

delta_2=torch.matmul(delta_3,model.w3)*(model.layer_2_ac_output.T)*(1-
model.layer_2_ac_output.T)

delta_1=torch.matmul(delta_2,model.w2)*(model.layer_1_ac_output.T)*(1-
model.layer_1_ac_output.T)
      # for i in range(y.shape[0]):
      #   delta_3[i]=torch.matmul(delta_4[i],model.w4)*(torch.exp(-
model.layer_3_output)).T[i]*(1/((1+torch.exp(-
model.layer_3_output))**2).T[i])
      # print(delta_4.shape)
      # print(delta_3.shape)
      # print(delta_2.shape)
      # print(delta_1.shape)
      model.w1=model.w1-lr*torch.matmul(delta_1.T,x.T)
      model.w2=model.w2-
lr*torch.matmul(delta_2.T,model.layer_1_ac_output.T)
      model.w3=model.w3-
lr*torch.matmul(delta_3.T,model.layer_2_ac_output.T)
      model.w4=model.w4-
lr*torch.matmul(delta_4.T,model.layer_3_ac_output.T)
      # print(delta_1.T.mean(dim=1).shape)
      model.b1=model.b1-
```

```
lr*delta_1.T.mean(dim=1).reshape(model.b1.shape)
      model.b2=model.b2-
lr*delta_2.T.mean(dim=1).reshape(model.b2.shape)
      model.b3=model.b3-
lr*delta_3.T.mean(dim=1).reshape(model.b3.shape)
      model.b4=model.b4-
lr*delta_4.T.mean(dim=1).reshape(model.b4.shape)
    train_loss.append(runn_loss/len(train_loader))
    test_loss_val=0
    for test_data in test_loader:
      x_test,y_test=test_data
      x_test=x_test.reshape(x_test.shape[0],784)
      x_test=x_test.T
      y_test=y_test.reshape(y_test.shape[0],1)
      val_result,result,_=model.forward_pass(x_test)
      val_result=val_result.T
      for j in range(y_test.shape[0]):
        test_loss_val+=-torch.log(val_result[j][y_test[j].item()])
        if result[j].item() == y_test[j].item():
          correct+=1
      total+=y_test.shape[0]
    test_acc.append(correct/total)
    test_loss.append(test_loss_val/total)
    print(f'Epoch [{i+1}/{epochs}], train_Loss: {train_loss[i]} ,
test_acc: {correct/total}, test_loss: {test_loss[i]} ')
  return train_loss,test_acc,test_loss

  hand_model_sigmoid=hand_network(784,500,250,100,10,sigmoid)
  epochs=15
  n=0.01

train_loss,test_acc,test_loss=training_loop_sigmoid(hand_model_sigmoid
,train_loader,test_loader,epochs,0.01)
```

```
Epoch [1/15], train_Loss: 0.9304670484176577 , test_acc: 0.892,
test_loss: 0.35451439023017883
Epoch [2/15], train_Loss: 0.30909573700604664 , test_acc: 0.92,
test_loss: 0.25518175959587097
Epoch [3/15], train_Loss: 0.22569719962934567 , test_acc: 0.9399,
test_loss: 0.19671058654785156
Epoch [4/15], train_Loss: 0.17643207698059615 , test_acc: 0.9498,
test_loss: 0.15914525091648102
Epoch [5/15], train_Loss: 0.14356709632879572 , test_acc: 0.9569,
test_loss: 0.14025060832500458
Epoch [6/15], train_Loss: 0.1213627538588176 , test_acc: 0.9616,
test_loss: 0.12394356727600098
Epoch [7/15], train_Loss: 0.10347983197195888 , test_acc: 0.9594,
test_loss: 0.13030192255973816
Epoch [8/15], train_Loss: 0.08943464695366779 , test_acc: 0.9684,
test_loss: 0.1012841984629631
```

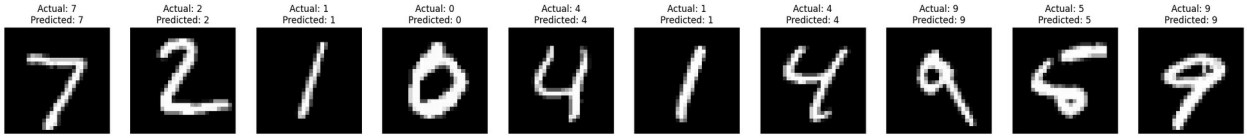
```
Epoch [9/15], train_Loss: 0.07906118924044438 , test_acc: 0.9701,
test_loss: 0.09942213445901871
Epoch [10/15], train_Loss: 0.0701833017334751 , test_acc: 0.9734,
test_loss: 0.08513518422842026
Epoch [11/15], train_Loss: 0.060859620070972564 , test_acc: 0.9732,
test_loss: 0.08679500222206116
Epoch [12/15], train_Loss: 0.053965689367684186 , test_acc: 0.9713,
test_loss: 0.08698272705078125
Epoch [13/15], train_Loss: 0.04839959201479414 , test_acc: 0.9747,
test_loss: 0.0807376280426979
Epoch [14/15], train_Loss: 0.04168831685104711 , test_acc: 0.9754,
test_loss: 0.07891304045915604
Epoch [15/15], train_Loss: 0.03857251420995143 , test_acc: 0.9766,
test_loss: 0.07637413591146469
```

```python
import matplotlib.pyplot as plt
plt.plot(range(15),train_loss,c="r",label="train_loss")
plt.plot(range(15),test_loss,c="b",label="test_loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.grid(True)
plt.title("epochs vs loss for hand_made_model with sigmoid
activation")
plt.legend()
plt.show()
```




```
plt.figure(figsize=(30, 3))
for i in range(10):
  img,actual_value=test_dataset[i]

_,predicted_value,_=hand_model_sigmoid.forward_pass(img.reshape(784,1)
)
  print(predicted_value)
  plt.subplot(1, 10, i + 1)
  plt.imshow(img.squeeze(), cmap="gray")
  plt.title(f"Actual: {actual_value}\nPredicted:
{predicted_value.item()}")
  plt.axis('off')
```

```
tensor([7])
tensor([2])
tensor([1])
tensor([0])
tensor([4])
tensor([1])
tensor([4])
tensor([9])
tensor([5])
tensor([9])
```




```
hand_param={"w1":hand_model_sigmoid.w1,"w2":hand_model_sigmoid.w2,"w3"
:hand_model_sigmoid.w3,"w4":hand_model_sigmoid.w4,"b1":hand_model_sigm
oid.b1,"b2":hand_model_sigmoid.b2,"b3":hand_model_sigmoid.b3,"b4":hand
_model_sigmoid.b4}

save_path="/content/drive/MyDrive/hand_model_sigmoid"
torch.save(hand_param, save_path)

path="/content/drive/MyDrive/hand_model_sigmoid"
hand_load_model=hand_network(784,500,250,100,10,sigmoid)
params=torch.load(path)
hand_load_model.w1=params["w1"]
hand_load_model.w2=params["w2"]
hand_load_model.w3=params["w3"]
hand_load_model.w4=params["w4"]
hand_load_model.b1=params["b1"]
hand_load_model.b2=params["b2"]
hand_load_model.b3=params["b3"]
hand_load_model.b4=params["b4"]

def generate_confusion_matrix_test(hand_load_model,test_loader):
  confusion_matrix=torch.zeros(10,10)
  correct=0
  total=0
  for test_data in test_loader:
      x_test,y_test=test_data
      x_test=x_test.reshape(x_test.shape[0],784)
      x_test=x_test.T
      y_test=y_test.reshape(y_test.shape[0],1)
      _,result,_=hand_load_model.forward_pass(x_test)
      for j in range(y_test.shape[0]):
        if result[j].item() == y_test[j].item():
          correct+=1
          confusion_matrix[y_test[j].item()][y_test[j].item()]+=1
        else:
          confusion_matrix[y_test[j].item()][result[j].item()]+=1
      total+=y_test.shape[0]
  return confusion_matrix,correct/total

import numpy as np
confusion_matrix,acc=generate_confusion_matrix_test(hand_load_model,te
st_loader)
torch.set_printoptions(sci_mode=False)
np.set_printoptions(suppress=True)
```

```
print(confusion_matrix.detach().numpy())
print(f"accuracy of test_data using sigmoid {acc*100}")
```

```
[[ 970.    0.    2.    0.    1.    4.    1.    1.    1.    0.]
 [   0. 1121.    7.    2.    0.    1.    2.    1.    1.    0.]
 [   3.    0. 1015.    4.    1.    0.    0.    4.    5.    0.]
 [   0.    0.    4.  990.    0.    5.    0.    4.    5.    2.]
 [   1.    0.    2.    1.  957.    1.    4.    3.    3.   10.]
 [   3.    0.    0.    3.    2.  878.    2.    0.    2.    2.]
 [   6.    3.    2.    1.    6.    7.  929.    0.    4.    0.]
 [   1.    3.   13.    4.    1.    1.    0.  998.    3.    4.]
 [   3.    0.    4.    3.    1.    3.    2.    2.  955.    1.]
 [   5.    4.    1.    9.   15.    9.    0.    5.    8.  953.]]
accuracy of test_data using sigmoid 97.66
```

```
def generate_confusion_matrix_train(hand_load_model,train_loader):
  confusion_matrix=torch.zeros(10,10)
  correct=0
  total=0
  for data in train_loader:
      x_train,y_train=data
      x_train=x_train.reshape(x_train.shape[0],784)
      x_train=x_train.T
      y_train=y_train.reshape(y_train.shape[0],10)
      _,result,_=hand_load_model.forward_pass(x_train)
      for j in range(y_train.shape[0]):
        if result[j].item() == torch.argmax(y_train[j]).item():
          correct+=1
          confusion_matrix[result[j].item()][result[j].item()]+=1
        else:
          confusion_matrix[torch.argmax(y_train[j]).item()]
[result[j].item()]+=1
      total+=y_train.shape[0]
  return confusion_matrix,correct/total

confusion_matrix,acc=generate_confusion_matrix_train(hand_load_model,t
rain_loader)
torch.set_printoptions(sci_mode=False)
np.set_printoptions(suppress=True)
print(confusion_matrix.detach().numpy())
print(f"accuracy of train_data using sigmoid {acc*100}")
```

```
[[5911.    0.    5.    0.    0.    1.    0.    1.    2.    3.]
 [   1. 6694.   19.    7.    3.    1.    3.   13.    1.    0.]
 [   3.    2. 5936.    3.    3.    1.    1.    7.    2.    0.]
 [   1.    0.   10. 6077.    0.   26.    0.    4.   10.    3.]
 [   5.    1.    7.    0. 5807.    2.    4.    3.    5.    8.]
 [   2.    0.    1.   10.    0. 5401.    5.    1.    1.    0.]
 [  26.    1.    5.    0.    8.   16. 5859.    0.    3.    0.]
 [   2.    5.   26.    2.    6.    2.    0. 6219.    1.    2.]
```

```
 [   6.    5.    6.    6.    0.    4.    3.    1. 5817.    3.]
 [  13.    1.    1.   15.   58.   49.    0.   28.   15. 5769.]]
accuracy of train_data using sigmoid 99.15
```

1. Using Relu as activation

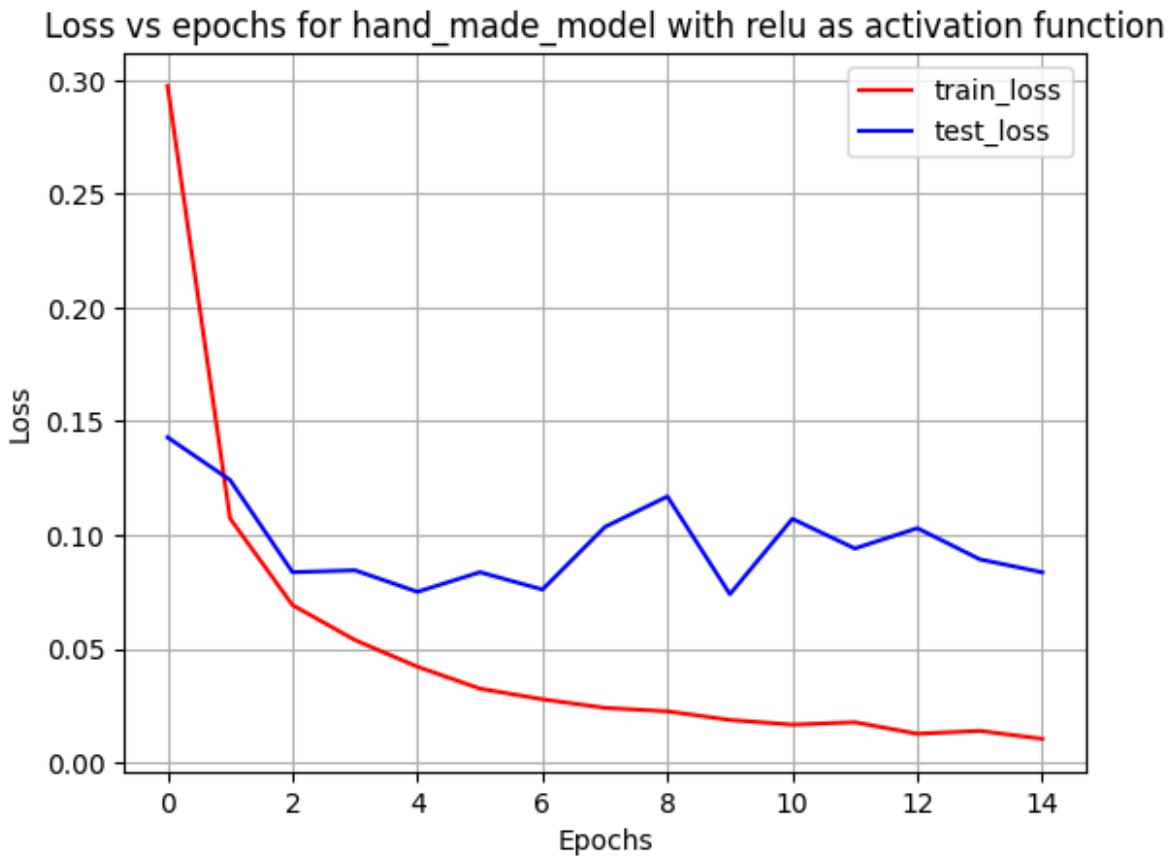
```
def training_loop_relu(model,train_loader,test_loader,epochs,lr):
  train_loss=[]
  test_acc=[]
  test_loss=[]
  for i in range(epochs):
    correct=0
    total=0
    runn_loss=0
    for data in train_loader:
      x,y=data[0],data[1]
      x=x.reshape(x.shape[0],784)
      x=x.T
      # print(model.b1.shape)
      # print(torch.matmul(model.w1,x).shape)
      # print(y.shape)
      output,_,_=model.forward_pass(x)
      output=output.T
      loss=loss_fn(y,output)

      runn_loss+=loss.item()
      delta_4=output-y

delta_3=torch.matmul(delta_4,model.w4)*(der_relu(model.layer_3_output.
T))

delta_2=torch.matmul(delta_3,model.w3)*(der_relu(model.layer_2_output.
T))

delta_1=torch.matmul(delta_2,model.w2)*(der_relu(model.layer_1_output.
T))
      # for i in range(y.shape[0]):
      #   delta_3[i]=torch.matmul(delta_4[i],model.w4)*(torch.exp(-
model.layer_3_output)).T[i]*(1/((1+torch.exp(-
model.layer_3_output))**2).T[i])
      # print(delta_4.shape)
      # print(delta_3.shape)
      # print(delta_2.shape)
      # print(delta_1.shape)
      model.w1=model.w1-lr*torch.matmul(delta_1.T,x.T)
      model.w2=model.w2-
lr*torch.matmul(delta_2.T,model.layer_1_ac_output.T)
      model.w3=model.w3-
lr*torch.matmul(delta_3.T,model.layer_2_ac_output.T)
      model.w4=model.w4-
```

```
lr*torch.matmul(delta_4.T,model.layer_3_ac_output.T)
      # print(delta_1.T.mean(dim=1).shape)
      model.b1=model.b1-
lr*delta_1.T.mean(dim=1).reshape(model.b1.shape)
      model.b2=model.b2-
lr*delta_2.T.mean(dim=1).reshape(model.b2.shape)
      model.b3=model.b3-
lr*delta_3.T.mean(dim=1).reshape(model.b3.shape)
      model.b4=model.b4-
lr*delta_4.T.mean(dim=1).reshape(model.b4.shape)
    train_loss.append(runn_loss/len(train_loader))
    test_loss_val=0
    for test_data in test_loader:
      x_test,y_test=test_data
      x_test=x_test.reshape(x_test.shape[0],784)
      x_test=x_test.T
      y_test=y_test.reshape(y_test.shape[0],1)
      val_result,result,_=model.forward_pass(x_test)
      val_result=val_result.T
      for j in range(y_test.shape[0]):
        test_loss_val+=-torch.log(val_result[j][y_test[j].item()])
        if result[j].item() == y_test[j].item():
          correct+=1
      total+=y_test.shape[0]
    test_loss.append(test_loss_val/total)
    print(f'Epoch [{i+1}/{epochs}], train_Loss: {train_loss[i]} ,
test_acc: {correct/total}, test_loss: {test_loss[i]} ')
  return train_loss,test_acc,test_loss

  hand_model_relu=hand_network(784,500,250,100,10,relu)
  epochs=15
  n=0.01

train_loss,test_acc,test_loss=training_loop_relu(hand_model_relu,train
_loader,test_loader,epochs,0.01)
```

```
Epoch [1/15], train_Loss: 0.2973913132756162 , test_acc: 0.957,
test_loss: 0.14293062686920166
Epoch [2/15], train_Loss: 0.10726802326145092 , test_acc: 0.9591,
test_loss: 0.12418217957019806
Epoch [3/15], train_Loss: 0.06916286049697147 , test_acc: 0.9746,
test_loss: 0.08363868296146393
Epoch [4/15], train_Loss: 0.053792993725984416 , test_acc: 0.9763,
test_loss: 0.08446674793958664
Epoch [5/15], train_Loss: 0.042069826356821265 , test_acc: 0.9788,
test_loss: 0.07500720769166946
Epoch [6/15], train_Loss: 0.03242176107118782 , test_acc: 0.9791,
test_loss: 0.08363514393568039
Epoch [7/15], train_Loss: 0.02775084805611679 , test_acc: 0.9804,
test_loss: 0.07601866126060486
```

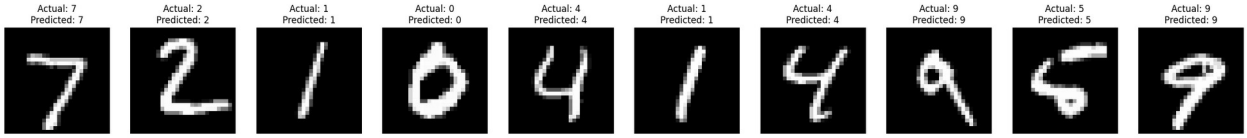
```
Epoch [8/15], train_Loss: 0.02398440495960028 , test_acc: 0.9746,
test_loss: 0.1035461574792862
Epoch [9/15], train_Loss: 0.022460525226829314 , test_acc: 0.9716,
test_loss: 0.11693689972162247
Epoch [10/15], train_Loss: 0.018669086343174046 , test_acc: 0.9824,
test_loss: 0.07395844161510468
Epoch [11/15], train_Loss: 0.016611815107886608 , test_acc: 0.9766,
test_loss: 0.10711568593978882
Epoch [12/15], train_Loss: 0.017653193512551936 , test_acc: 0.9804,
test_loss: 0.09405014663934708
Epoch [13/15], train_Loss: 0.012593698219555952 , test_acc: 0.9788,
test_loss: 0.10299405455589294
Epoch [14/15], train_Loss: 0.013874487181379734 , test_acc: 0.9825,
test_loss: 0.08929786831140518
Epoch [15/15], train_Loss: 0.010365686152715395 , test_acc: 0.9829,
test_loss: 0.08356443047523499
```

```
import matplotlib.pyplot as plt
plt.plot(range(15),train_loss,c="r",label="train_loss")
plt.plot(range(15),test_loss,c="b",label="test_loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("Loss vs epochs for hand_made_model with relu as activation
function")
plt.grid(True)
plt.legend()
plt.show()
```




```
plt.figure(figsize=(30, 3))
for i in range(10):
  img,actual_value=test_dataset[i]
  _,predicted_value,_=hand_model_relu.forward_pass(img.reshape(784,1))
  print(predicted_value)
  plt.subplot(1, 10, i + 1)
  plt.imshow(img.squeeze(), cmap="gray")
  plt.title(f"Actual: {actual_value}\nPredicted:
{predicted_value.item()}")
  plt.axis('off')
```

```
tensor([7])
tensor([2])
tensor([1])
tensor([0])
tensor([4])
tensor([1])
tensor([4])
tensor([9])
tensor([5])
tensor([9])
```




```
import numpy as np
confusion_matrix,acc=generate_confusion_matrix_test(hand_model_relu,te
st_loader)
torch.set_printoptions(sci_mode=False)
np.set_printoptions(suppress=True)
print(confusion_matrix.detach().numpy())
print(f"accuracy of test_data using relu {acc*100}")
```

```
[[ 967.    1.    0.    1.    1.    1.    6.    1.    1.    1.]
 [   0. 1127.    2.    0.    0.    1.    2.    2.    1.    0.]
 [   2.    1. 1014.    3.    3.    1.    1.    4.    3.    0.]
 [   0.    0.    5.  990.    0.    3.    0.    4.    4.    4.]
 [   0.    2.    0.    0.  967.    0.    5.    2.    0.    6.]
 [   2.    0.    0.   10.    0.  872.    1.    1.    3.    3.]
 [   3.    3.    0.    1.    3.    8.  937.    0.    3.    0.]
 [   0.    2.    8.    1.    1.    0.    0. 1010.    1.    5.]
 [   1.    1.    1.    4.    1.    5.    1.    2.  956.    2.]
 [   1.    2.    0.    1.    6.    1.    1.    6.    2.  989.]]
accuracy of test_data using relu 98.29
```

```
confusion_matrix,acc=generate_confusion_matrix_train(hand_model_relu,t
rain_loader)
torch.set_printoptions(sci_mode=False)
np.set_printoptions(suppress=True)
print(confusion_matrix.detach().numpy())
print(f"accuracy of train_data using relu {acc*100}")
```

```
[[5893.    0.    1.    0.    0.    3.   24.    1.    1.    0.]
 [   0. 6738.    2.    0.    0.    0.    0.    2.    0.    0.]
 [   0.    0. 5948.    1.    3.    0.    1.    1.    4.    0.]
 [   0.    0.    0. 6120.    0.    5.    0.    0.    3.    3.]
 [   0.    2.    0.    0. 5837.    0.    1.    1.    1.    0.]
 [   0.    0.    0.    3.    0. 5418.    0.    0.    0.    0.]
 [   0.    5.    3.    0.    0.   17. 5889.    0.    4.    0.]
 [   0.    3.    0.    0.    1.    0.    0. 6259.    0.    2.]
 [   0.    2.    1.    1.    0.   14.    0.    0. 5833.    0.]
 [   0.    0.    0.    0.    7.    0.    0.    4.    4. 5934.]]
accuracy of train_data using relu 99.78166666666667
```

3.Using tanh as activation

```
def training_loop_tanh(model,train_loader,test_loader,epochs,lr):
  test_loss=[]
  train_loss=[]
  test_acc=[]
```

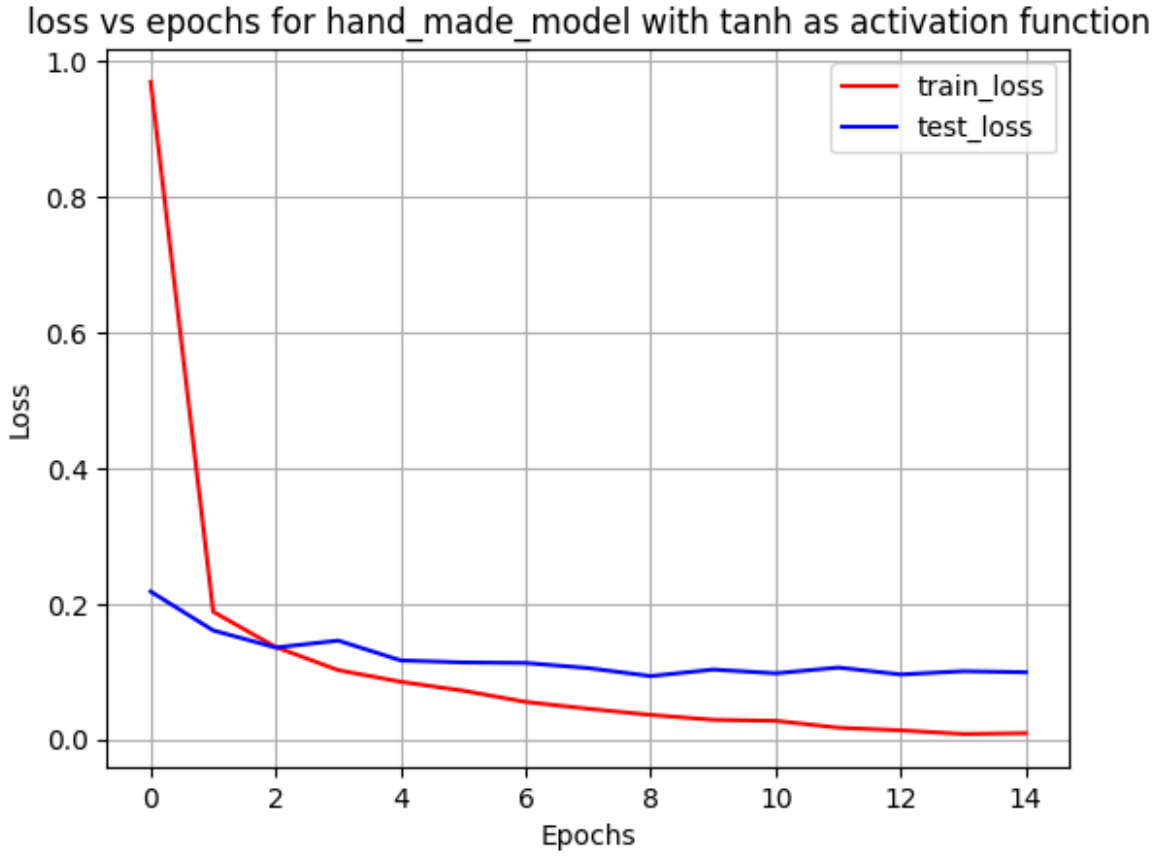
```
  for i in range(epochs):
    correct=0
    total=0
    runn_loss=0
    for data in train_loader:
      x,y=data[0],data[1]
      x=x.reshape(x.shape[0],784)
      x=x.T
      output,_,_=model.forward_pass(x)
      output=output.T
      loss=loss_fn(y,output)
      runn_loss+=loss.item()
      delta_4=output-y

delta_3=torch.matmul(delta_4,model.w4)*(der_tanh(model.layer_3_output.
T))

delta_2=torch.matmul(delta_3,model.w3)*(der_tanh(model.layer_2_output.
T))

delta_1=torch.matmul(delta_2,model.w2)*(der_tanh(model.layer_1_output.
T))

      model.w1=model.w1-lr*torch.matmul(delta_1.T,x.T)
      model.w2=model.w2-
lr*torch.matmul(delta_2.T,model.layer_1_ac_output.T)
      model.w3=model.w3-
lr*torch.matmul(delta_3.T,model.layer_2_ac_output.T)
      model.w4=model.w4-
lr*torch.matmul(delta_4.T,model.layer_3_ac_output.T)
      # print(delta_1.T.mean(dim=1).shape)
      model.b1=model.b1-
lr*delta_1.T.mean(dim=1).reshape(model.b1.shape)
      model.b2=model.b2-
lr*delta_2.T.mean(dim=1).reshape(model.b2.shape)
      model.b3=model.b3-
lr*delta_3.T.mean(dim=1).reshape(model.b3.shape)
      model.b4=model.b4-
lr*delta_4.T.mean(dim=1).reshape(model.b4.shape)
    train_loss.append(runn_loss/len(train_loader))
    test_loss_val=0
    for test_data in test_loader:
      x_test,y_test=test_data
      x_test=x_test.reshape(x_test.shape[0],784)
      x_test=x_test.T
      y_test=y_test.reshape(y_test.shape[0],1)
      val_result,result,_=model.forward_pass(x_test)
      val_result=val_result.T
      for j in range(y_test.shape[0]):
        test_loss_val+=-torch.log(val_result[j][y_test[j].item()]+1e-
```

```
7)
        if result[j].item() == y_test[j].item():
          correct+=1
      total+=y_test.shape[0]
    test_loss.append(test_loss_val/total)
    print(f'Epoch [{i+1}/{epochs}], train_Loss: {train_loss[i]} ,
test_acc: {correct/total}, test_loss: {test_loss[i]} ')
  return train_loss,test_acc,test_loss

  hand_model_tanh=hand_network(784,500,250,100,10,tanh)
  epochs=15
  n=0.01

train_loss,test_acc,test_loss=training_loop_tanh(hand_model_tanh,train
_loader,test_loader,epochs,0.01)
```

```
Epoch [1/15], train_Loss: 0.970053078570981 , test_acc: 0.937,
test_loss: 0.21826450526714325
Epoch [2/15], train_Loss: 0.18847140802273046 , test_acc: 0.9529,
test_loss: 0.16094304621219635
Epoch [3/15], train_Loss: 0.13637853729755067 , test_acc: 0.9624,
test_loss: 0.1357092410326004
Epoch [4/15], train_Loss: 0.10227910689721659 , test_acc: 0.9572,
test_loss: 0.14594240486621857
Epoch [5/15], train_Loss: 0.08513366093294127 , test_acc: 0.9667,
test_loss: 0.11668404191732407
Epoch [6/15], train_Loss: 0.07200185846036443 , test_acc: 0.9695,
test_loss: 0.11376301199197769
Epoch [7/15], train_Loss: 0.055425893835428515 , test_acc: 0.968,
test_loss: 0.1129351556301117
Epoch [8/15], train_Loss: 0.04535225620825908 , test_acc: 0.9727,
test_loss: 0.10535168647766113
Epoch [9/15], train_Loss: 0.036277195690593164 , test_acc: 0.9752,
test_loss: 0.09358508139848709
Epoch [10/15], train_Loss: 0.02903597684565193 , test_acc: 0.9733,
test_loss: 0.10319551825523376
Epoch [11/15], train_Loss: 0.02758454892315593 , test_acc: 0.9771,
test_loss: 0.09765905141830444
Epoch [12/15], train_Loss: 0.01745553213300239 , test_acc: 0.9748,
test_loss: 0.10617908835411072
Epoch [13/15], train_Loss: 0.013536553732621526 , test_acc: 0.9775,
test_loss: 0.09596466273069382
Epoch [14/15], train_Loss: 0.008155885030627067 , test_acc: 0.9777,
test_loss: 0.10077302157878876
Epoch [15/15], train_Loss: 0.009334008482542745 , test_acc: 0.978,
test_loss: 0.09924246370792389
```

```
import matplotlib.pyplot as plt
plt.plot(range(15),train_loss,c="r",label="train_loss")
plt.plot(range(15),test_loss,c="b",label="test_loss")
```

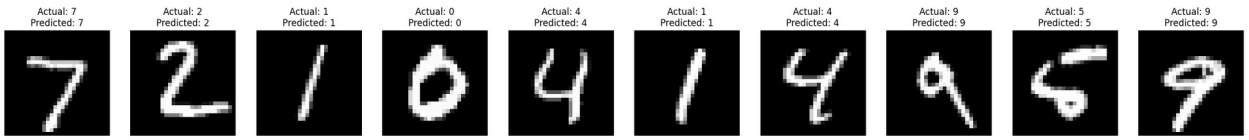
```
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("loss vs epochs for hand_made_model with tanh as activation
function")
plt.grid(True)
plt.legend()
plt.show()
```




```
plt.figure(figsize=(30, 3))
for i in range(10):
  img,actual_value=test_dataset[i]
  _,predicted_value,_=hand_model_tanh.forward_pass(img.reshape(784,1))
  print(predicted_value)
  plt.subplot(1, 10, i + 1)
  plt.imshow(img.squeeze(), cmap="gray")
  plt.title(f"Actual: {actual_value}\nPredicted:
{predicted_value.item()}")
  plt.axis('off')
```

```
tensor([7])
tensor([2])
tensor([1])
```

```
tensor([0])
tensor([4])
tensor([1])
tensor([4])
tensor([9])
tensor([5])
tensor([9])
```




```
confusion_matrix,acc=generate_confusion_matrix_test(hand_model_tanh,te
st_loader)
torch.set_printoptions(sci_mode=False)
np.set_printoptions(suppress=True)
print(confusion_matrix.detach().numpy())
print(f"accuracy of test_data using tanh {acc*100}")
```

```
[[ 972.    0.    2.    0.    1.    1.    1.    1.    1.    1.]
 [   1. 1126.    1.    1.    0.    1.    2.    1.    2.    0.]
 [   3.    2. 1006.    6.    1.    0.    3.    5.    5.    1.]
 [   0.    0.    1.  996.    0.    3.    0.    4.    3.    3.]
 [   0.    1.    3.    0.  964.    0.    5.    2.    0.    7.]
 [   4.    0.    0.   13.    2.  858.    6.    1.    4.    4.]
 [   4.    2.    2.    1.    3.    2.  940.    0.    4.    0.]
 [   1.    5.    7.    8.    1.    0.    0.  998.    1.    7.]
 [   2.    0.    6.    8.    1.    8.    1.    3.  942.    3.]
 [   0.    4.    0.    4.   13.    1.    1.    8.    0.  978.]]
accuracy of test_data using tanh 97.8
```

```
confusion_matrix,acc=generate_confusion_matrix_train(hand_model_tanh,t
rain_loader)
torch.set_printoptions(sci_mode=False)
np.set_printoptions(suppress=True)
print(confusion_matrix.detach().numpy())
print(f"accuracy of train_data using tanh {acc*100}")
```

```
[[5922.    0.    0.    0.    0.    0.    0.    0.    0.    1.]
 [   0. 6739.    0.    0.    2.    0.    0.    0.    1.    0.]
 [   0.    0. 5953.    3.    0.    0.    0.    1.    1.    0.]
 [   0.    0.    0. 6129.    0.    0.    0.    0.    2.    0.]
 [   0.    0.    2.    0. 5831.    0.    4.    2.    0.    3.]
 [   1.    0.    0.    1.    0. 5416.    3.    0.    0.    0.]
 [   1.    0.    0.    0.    0.    0. 5917.    0.    0.    0.]
 [   0.    8.    2.    3.    1.    0.    0. 6248.    0.    3.]
 [   1.    4.    1.    4.    0.    2.    1.    0. 5838.    0.]
 [   0.    4.    0.    3.   15.    0.    0.    5.    1. 5921.]]
accuracy of train_data using tanh 99.85666666666667
```

Relu activation function performs the best when compared to sigmoid and tanh

Problem 4 : creating MLP using pytorch library

```
import torch
import torchvision.datasets as datasets
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
from torch.utils.data import DataLoader
from torch.utils.data import random_split
from google.colab import drive
drive.mount('/content/drive')
import torch.nn as nn
import os
```

```
Mounted at /content/drive
```

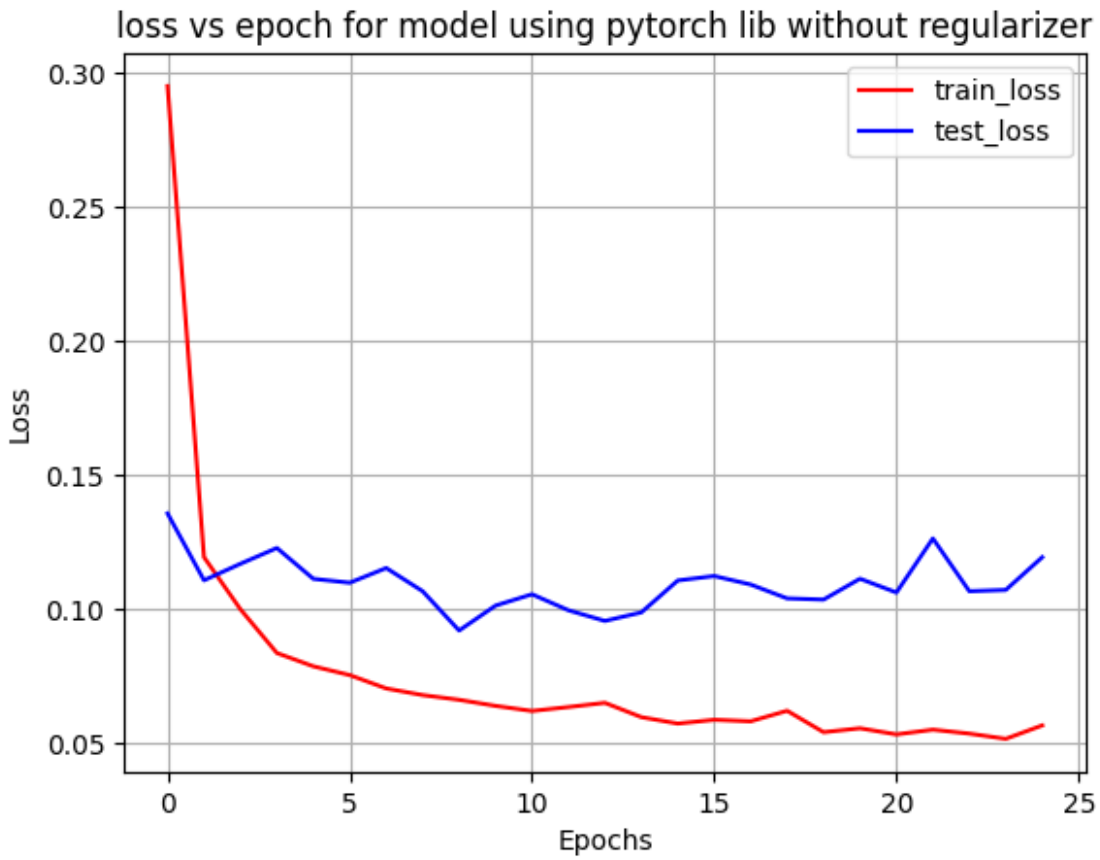
```
class network(nn.Module):
  def
__init__(self,input_dim=784,hid_1=500,hid_2=250,hid_3=100,out=10):
    super().__init__()
    self.layer_1=nn.Linear(input_dim,hid_1)
    self.act=nn.Sigmoid()
    self.out_act=nn.Softmax()
    self.layer_2=nn.Linear(hid_1,hid_2)
    self.layer_3=nn.Linear(hid_2,hid_3)
    self.out=nn.Linear(hid_3,out)

  def forward(self,x):
    out_1=self.act(self.layer_1(x))
    out_2=self.act(self.layer_2(out_1))
    out_3=self.act(self.layer_3(out_2))
    real_out=self.out_act(self.out(out_3))
    real_value=torch.argmax(real_out,dim=1)
    return real_out,real_value

def
train_model(model,train_loader,test_loader,loss_fn,optimizer,epochs):
  train_loss=[]
  test_acc=[]
  test_loss=[]
  for i in range(epochs):
    model.train()
    runn_loss=0
    for data in train_loader:
      data[0]=data[0].reshape(len(data[0]),784)
      optimizer.zero_grad()
      prediction,_=model(data[0])
      loss=-torch.sum(torch.log(prediction)*data[1],dim=1)
      loss=loss.mean()
      runn_loss+=loss.item()
```

```
      loss.backward()
      optimizer.step()
    train_loss.append(runn_loss/len(train_loader))
    model.eval()
    correct=0
    total=0
    test_val_loss=0
    with torch.no_grad():
      for test_data in test_loader:
        test_data[0]=test_data[0].reshape(len(test_data[0]),784)
        real_out,prediction=model(test_data[0])
        for j in range(test_data[0].shape[0]):
          test_val_loss+=-torch.log(real_out[j][test_data[1]
[j].item()])
          if prediction[j].item() == test_data[1][j].item():
            correct+=1
        total+=test_data[0].shape[0]
      test_acc.append(correct/total)
      test_loss.append(test_val_loss/total)
    print(f'Epoch [{i+1}/{epochs}], train_Loss: {train_loss[i]},
test_acc: {test_acc[i]}, test_loss: {test_loss[i]}')
  return train_loss,test_acc,test_loss

model=network()
loss_fn=nn.CrossEntropyLoss()
optimizer=torch.optim.Adam(model.parameters(),lr=0.01)
train_loss,test_acc,test_loss=train_model(model,train_loader,test_load
er,loss_fn,optimizer,epochs=25)
```

```
/usr/local/lib/python3.12/dist-packages/torch/nn/modules/
module.py:1773: UserWarning: Implicit dimension choice for softmax has
been deprecated. Change the call to include dim=X as an argument.
  return self._call_impl(*args, **kwargs)

Epoch [1/25], train_Loss: 0.2953312905120062, test_acc: 0.9622,
test_loss: 0.13582780957221985
Epoch [2/25], train_Loss: 0.11952807266922441, test_acc: 0.9677,
test_loss: 0.11089611798524857
Epoch [3/25], train_Loss: 0.10007646361287477, test_acc: 0.964,
test_loss: 0.11705946177244186
Epoch [4/25], train_Loss: 0.08376102344376712, test_acc: 0.9627,
test_loss: 0.12295734882354736
Epoch [5/25], train_Loss: 0.07880370134995607, test_acc: 0.9693,
test_loss: 0.11144453287124634
Epoch [6/25], train_Loss: 0.07551967263021178, test_acc: 0.969,
test_loss: 0.10998397320508957
Epoch [7/25], train_Loss: 0.07054081062331045, test_acc: 0.966,
test_loss: 0.1154792457818985
Epoch [8/25], train_Loss: 0.06806222970216676, test_acc: 0.9697,
test_loss: 0.10681157559156418
```

```
Epoch [9/25], train_Loss: 0.06630276207492422, test_acc: 0.9746,
test_loss: 0.09215966612100601
Epoch [10/25], train_Loss: 0.06403395434236353, test_acc: 0.9732,
test_loss: 0.10146181285381317
Epoch [11/25], train_Loss: 0.062137102342716084, test_acc: 0.9707,
test_loss: 0.10568328946828842
Epoch [12/25], train_Loss: 0.0636053284142923, test_acc: 0.9701,
test_loss: 0.0997098758816719
Epoch [13/25], train_Loss: 0.06517570735581382, test_acc: 0.9699,
test_loss: 0.09573553502559662
Epoch [14/25], train_Loss: 0.05982965344775603, test_acc: 0.972,
test_loss: 0.09891427308320999
Epoch [15/25], train_Loss: 0.057440188273897706, test_acc: 0.9687,
test_loss: 0.11083044111728668
Epoch [16/25], train_Loss: 0.05884624227632219, test_acc: 0.97,
test_loss: 0.1124875396490097
Epoch [17/25], train_Loss: 0.058281265040075206, test_acc: 0.9694,
test_loss: 0.10932065546512604
Epoch [18/25], train_Loss: 0.062213663963962405, test_acc: 0.9711,
test_loss: 0.10414837300777435
Epoch [19/25], train_Loss: 0.05422051794791489, test_acc: 0.9717,
test_loss: 0.10369685292243958
Epoch [20/25], train_Loss: 0.05568474815280459, test_acc: 0.9714,
test_loss: 0.11148262023925781
Epoch [21/25], train_Loss: 0.05339301423647993, test_acc: 0.9702,
test_loss: 0.10633949935436249
Epoch [22/25], train_Loss: 0.05516350663745893, test_acc: 0.9662,
test_loss: 0.12651443481445312
Epoch [23/25], train_Loss: 0.05368769135201292, test_acc: 0.97,
test_loss: 0.1068328395485878
Epoch [24/25], train_Loss: 0.05173792091703642, test_acc: 0.9722,
test_loss: 0.10730842500925064
Epoch [25/25], train_Loss: 0.0567522426758871, test_acc: 0.9704,
test_loss: 0.11951230466365814
```

```
plt.plot(range(25),train_loss,c="r",label="train_loss")
plt.plot(range(25),test_loss,c="b",label="test_loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("loss vs epoch for model using pytorch lib without
regularizer")
plt.grid(True)
plt.legend()
plt.show()
```




```
def generate_confusion_matrix_test(hand_load_model,test_loader):
  confusion_matrix=torch.zeros(10,10)
  correct=0
  total=0
  model.eval()
  with torch.no_grad():
    for test_data in test_loader:
      test_data[0]=test_data[0].reshape(len(test_data[0]),784)
      _,prediction=model(test_data[0])
      for j in range(test_data[0].shape[0]):
        if prediction[j].item() == test_data[1][j].item():
          correct+=1
          confusion_matrix[test_data[1][j].item()][test_data[1]
[j].item()]+=1
        else:
          confusion_matrix[test_data[1][j].item()]
[prediction[j].item()]+=1
      total+=test_data[0].shape[0]
  return confusion_matrix,correct/total

confusion_matrix,acc=generate_confusion_matrix_test(model,test_loader)
torch.set_printoptions(sci_mode=False)
np.set_printoptions(suppress=True)
```

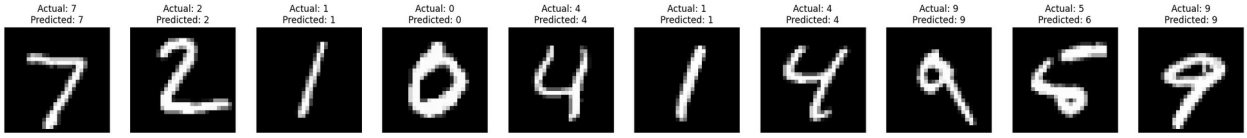
```
print(confusion_matrix.detach().numpy())
print(f"accuracy of test_data using libraries without regularizer
{acc*100}")
```

```
[[ 972.    1.    1.    1.    0.    0.    1.    2.    2.    0.]
 [   0. 1117.    5.    3.    2.    0.    3.    0.    5.    0.]
 [   8.    1. 1002.    4.    2.    0.    1.   12.    2.    0.]
 [   2.    0.   10.  976.    0.    5.    0.    7.    8.    2.]
 [   1.    0.    8.    0.  956.    0.    1.    2.    1.   13.]
 [   4.    0.    0.   14.    1.  857.    9.    1.    4.    2.]
 [   4.    2.    3.    1.    2.    5.  939.    0.    1.    1.]
 [   1.    3.    6.    2.    3.    0.    0. 1006.    0.    7.]
 [   9.    3.   13.    6.    3.    5.    7.    6.  917.    5.]
 [   5.    5.    1.    7.   16.    0.    0.    7.    6.  962.]]
accuracy of test_data using libraries without regularizer 97.04
```

```
def generate_confusion_matrix_train(hand_load_model,train_loader):
  confusion_matrix=torch.zeros(10,10)
  correct=0
  total=0
  model.eval()
  with torch.no_grad():
    for data in train_loader:
      x_train,y_train=data
      x_train=x_train.reshape(x_train.shape[0],784)
      y_train=y_train.reshape(y_train.shape[0],10)
      _,prediction=model(x_train)
      for j in range(y_train.shape[0]):
        if prediction[j].item() == torch.argmax(y_train[j]).item():
          correct+=1
          confusion_matrix[prediction[j].item()][prediction[j].item()]
+=1
        else:
          confusion_matrix[torch.argmax(y_train[j]).item()]
[prediction[j].item()]+=1
      total+=y_train.shape[0]
  return confusion_matrix,correct/total

confusion_matrix,acc=generate_confusion_matrix_train(model,train_loade
r)
torch.set_printoptions(sci_mode=False)
np.set_printoptions(suppress=True)
print(confusion_matrix.detach().numpy())
print(f"accuracy of train_data using libraries without
regularizer{acc*100}")
```

```
[[5904.    3.    8.    0.    0.    1.    2.    1.    3.    1.]
 [   1. 6690.   15.    7.   10.    0.    3.    2.    8.    6.]
 [  25.    6. 5884.    4.   11.    0.    5.   18.    3.    2.]
 [   4.    6.   55. 5981.    0.   16.    0.   17.   36.   16.]
```

```
 [   5.    4.    6.    0. 5805.    0.    1.    2.    1.   18.]
 [  12.    2.    3.   35.    2. 5293.   34.    4.   13.   23.]
 [  29.    0.    6.    0.    5.    4. 5870.    0.    4.    0.]
 [   1.   17.    5.    4.   15.    0.    0. 6202.    0.   21.]
 [  15.   49.   43.    8.    1.    6.   25.    5. 5690.    9.]
 [  11.    6.    2.   18.   59.    3.    0.   32.   27. 5791.]]
accuracy of train_data using libraries without
regularizer98.51666666666667

plt.figure(figsize=(30, 3))
for i in range(10):
  img,actual_value=test_dataset[i]
  _,predicted_value=model(img.reshape(1,784))
  print(predicted_value)
  plt.subplot(1, 10, i + 1)
  plt.imshow(img.squeeze(), cmap="gray")
  plt.title(f"Actual: {actual_value}\nPredicted:
{predicted_value.item()}")
  plt.axis('off')

tensor([7])
tensor([2])
tensor([1])
tensor([0])
tensor([4])
tensor([1])
tensor([4])
tensor([9])
tensor([6])
tensor([9])
```



Problem 4.1: Model using library with regularizer

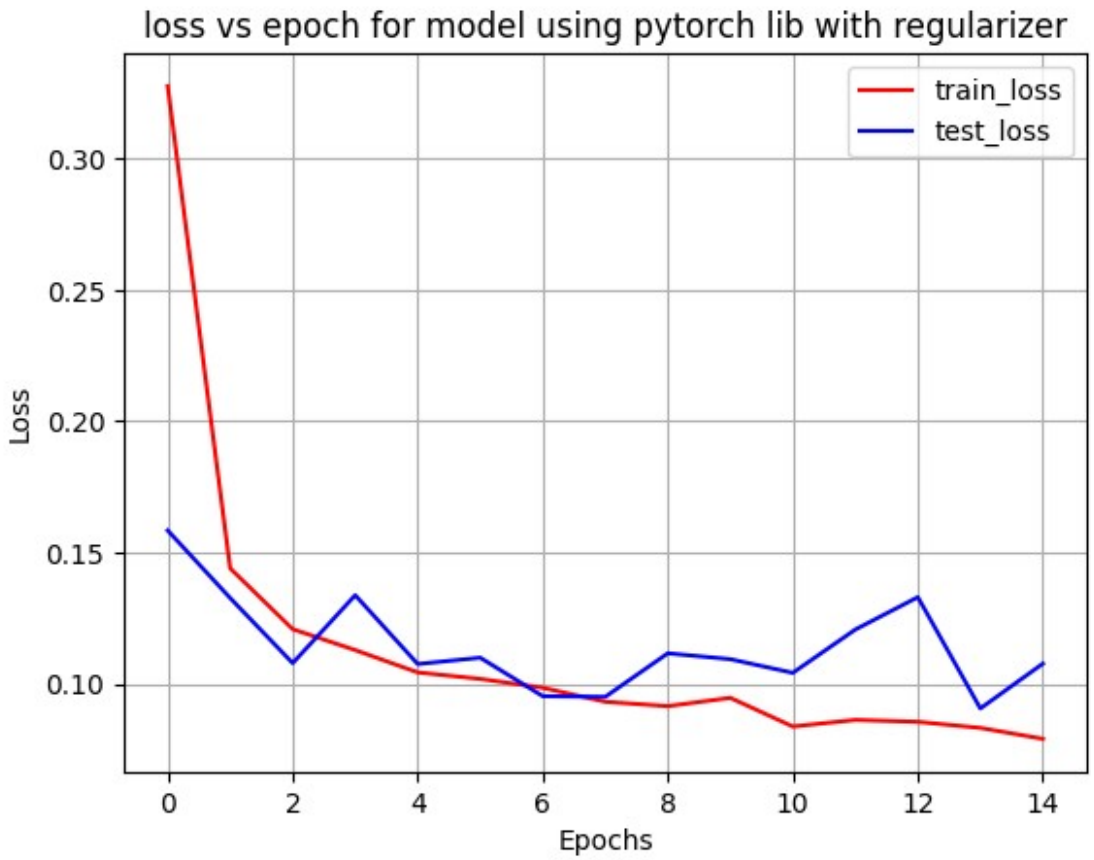
```
def
train_model_regularizer(model,train_loader,test_loader,loss_fn,optimiz
er,epochs,z=1e-5):
  train_loss=[]
  test_acc=[]
  test_loss=[]
  for i in range(epochs):
    model.train()
    runn_loss=0
    for data in train_loader:
      data[0]=data[0].reshape(len(data[0]),784)
      optimizer.zero_grad()
```

```
      prediction,_=model(data[0])
      loss=-torch.sum(torch.log(prediction)*data[1],dim=1)
      loss=loss.mean()
      runn_loss+=loss.item()
      sum_weights=torch.tensor(0.)
      for index,param in enumerate(model.parameters()):
        if index%2==0:
          sum_weights+=torch.sum(param.pow(2))
      loss+=z*sum_weights
      loss.backward()
      optimizer.step()
    train_loss.append(runn_loss/len(train_loader))
    model.eval()
    correct=0
    total=0
    test_val_loss=0
    with torch.no_grad():
      for test_data in test_loader:
        test_data[0]=test_data[0].reshape(len(test_data[0]),784)
        real_out,prediction=model(test_data[0])
        for j in range(test_data[0].shape[0]):
          test_val_loss+=-torch.log(real_out[j][test_data[1]
[j].item()])
          if prediction[j].item() == test_data[1][j].item():
            correct+=1
        total+=test_data[0].shape[0]
      test_acc.append(correct/total)
      test_loss.append(test_val_loss/total)
    print(f'Epoch [{i+1}/{epochs}], train_Loss: {train_loss[i]},
test_acc: {test_acc[i]}, test_loss: {test_loss[i]}')
  return train_loss,test_acc,test_loss

model=network()
loss_fn=nn.CrossEntropyLoss()
optimizer=torch.optim.Adam(model.parameters(),lr=0.01)
train_loss,test_acc,test_loss=train_model_regularizer(model,train_load
er,test_loader,loss_fn,optimizer,epochs=15)
```

```
/usr/local/lib/python3.12/dist-packages/torch/nn/modules/
module.py:1773: UserWarning: Implicit dimension choice for softmax has
been deprecated. Change the call to include dim=X as an argument.
  return self._call_impl(*args, **kwargs)

Epoch [1/15], train_Loss: 0.32755340398676486, test_acc: 0.9518,
test_loss: 0.15846118330955505
Epoch [2/15], train_Loss: 0.14402822494459178, test_acc: 0.9609,
test_loss: 0.13274110853672028
Epoch [3/15], train_Loss: 0.12089664053851004, test_acc: 0.966,
test_loss: 0.1079661026597023
Epoch [4/15], train_Loss: 0.11292806573198247, test_acc: 0.9583,
```

```
test_loss: 0.13381707668304443
Epoch [5/15], train_Loss: 0.10443114639738443, test_acc: 0.9677,
test_loss: 0.10762298852205276
Epoch [6/15], train_Loss: 0.10196523959520085, test_acc: 0.9655,
test_loss: 0.11003317683935165
Epoch [7/15], train_Loss: 0.09859677061050344, test_acc: 0.9712,
test_loss: 0.0953945443034172
Epoch [8/15], train_Loss: 0.09327012918510241, test_acc: 0.9701,
test_loss: 0.09514673054218292
Epoch [9/15], train_Loss: 0.09159331496105964, test_acc: 0.9658,
test_loss: 0.11170314997434616
Epoch [10/15], train_Loss: 0.09476178354059439, test_acc: 0.9658,
test_loss: 0.10946915298700333
Epoch [11/15], train_Loss: 0.08385002005995233, test_acc: 0.9694,
test_loss: 0.10427110642194748
Epoch [12/15], train_Loss: 0.08635482899988614, test_acc: 0.9638,
test_loss: 0.12074622511863708
Epoch [13/15], train_Loss: 0.08563012180940262, test_acc: 0.959,
test_loss: 0.1330767124891281
Epoch [14/15], train_Loss: 0.08331738265334511, test_acc: 0.9724,
test_loss: 0.09071307629346848
Epoch [15/15], train_Loss: 0.0791597874931443, test_acc: 0.9687,
test_loss: 0.1077822744846344
```

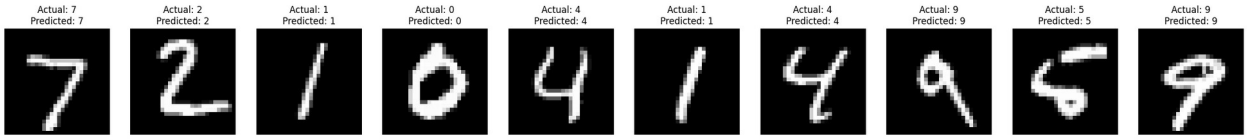
```
plt.plot(range(15),train_loss,c="r",label="train_loss")
plt.plot(range(15),test_loss,c="b",label="test_loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("loss vs epoch for model using pytorch lib with
regularizer")
plt.grid(True)
plt.legend()
plt.show()
```




```
plt.figure(figsize=(30, 3))
for i in range(10):
  img,actual_value=test_dataset[i]
  _,predicted_value=model(img.reshape(1,784))
  print(predicted_value)
  plt.subplot(1, 10, i + 1)
  plt.imshow(img.squeeze(), cmap="gray")
  plt.title(f"Actual: {actual_value}\nPredicted:
{predicted_value.item()}")
  plt.axis('off')
```

```
/usr/local/lib/python3.12/dist-packages/torch/nn/modules/
module.py:1773: UserWarning: Implicit dimension choice for softmax has
been deprecated. Change the call to include dim=X as an argument.
  return self._call_impl(*args, **kwargs)

tensor([7])
tensor([2])
tensor([1])
tensor([0])
tensor([4])
tensor([1])
tensor([4])
```

```
tensor([9])
tensor([5])
tensor([9])
```




```
import numpy as np
confusion_matrix,acc=generate_confusion_matrix_test(model,test_loader)
torch.set_printoptions(sci_mode=False)
np.set_printoptions(suppress=True)
print(confusion_matrix.detach().numpy())
print(f"accuracy of test_data using pytorch lib with regularizer
{acc*100}")
```

```
[[ 972.    0.    0.    0.    1.    0.    2.    2.    3.    0.]
 [   0. 1125.    1.    2.    0.    0.    0.    1.    6.    0.]
 [   7.    0.  993.    9.    3.    2.    1.   10.    6.    1.]
 [   0.    0.    3.  984.    0.    4.    0.    8.    5.    6.]
 [   5.    0.    1.    0.  944.    0.    6.    4.    0.   22.]
 [   4.    1.    0.   25.    2.  839.    2.    3.    4.   12.]
 [  15.    3.    0.    1.    4.   13.  916.    0.    6.    0.]
 [   2.    3.    8.    0.    3.    0.    0. 1001.    0.   11.]
 [   3.    0.    2.    9.    5.    4.    2.    7.  925.   17.]
 [   3.    3.    0.    2.    7.    1.    0.    5.    0.  988.]]
accuracy of test_data using pytorch lib with regularizer 96.87
```

```
confusion_matrix,acc=generate_confusion_matrix_train(model,train_loade
r)
torch.set_printoptions(sci_mode=False)
np.set_printoptions(suppress=True)
print(confusion_matrix.detach().numpy())
print(f"accuracy of train_data using using pytorch lib with
regularizer {acc*100}")
```

```
[[5868.    1.    1.    2.    4.    7.   10.    1.   16.   13.]
 [   0. 6681.    9.    1.    7.    0.    0.   23.   13.    8.]
 [  18.   12. 5788.   52.    8.    1.    3.   42.   25.    9.]
 [   4.    5.   17. 5975.    1.   19.    0.   36.   19.   55.]
 [   6.    4.    4.    3. 5696.    1.   12.   12.    2.  102.]
 [  14.    2.    2.  102.    5. 5165.    5.    6.   45.   75.]
 [  41.   23.   10.    0.   11.   59. 5756.    0.   17.    1.]
 [   2.    5.   10.    2.   11.    0.    0. 6191.    1.   43.]
 [  12.   15.    8.   45.   14.   15.    1.    7. 5606.  128.]
 [   5.    3.    1.   15.    8.   11.    1.   35.    4. 5866.]]
accuracy of train_data using using pytorch lib with regularizer
97.65333333333334
```

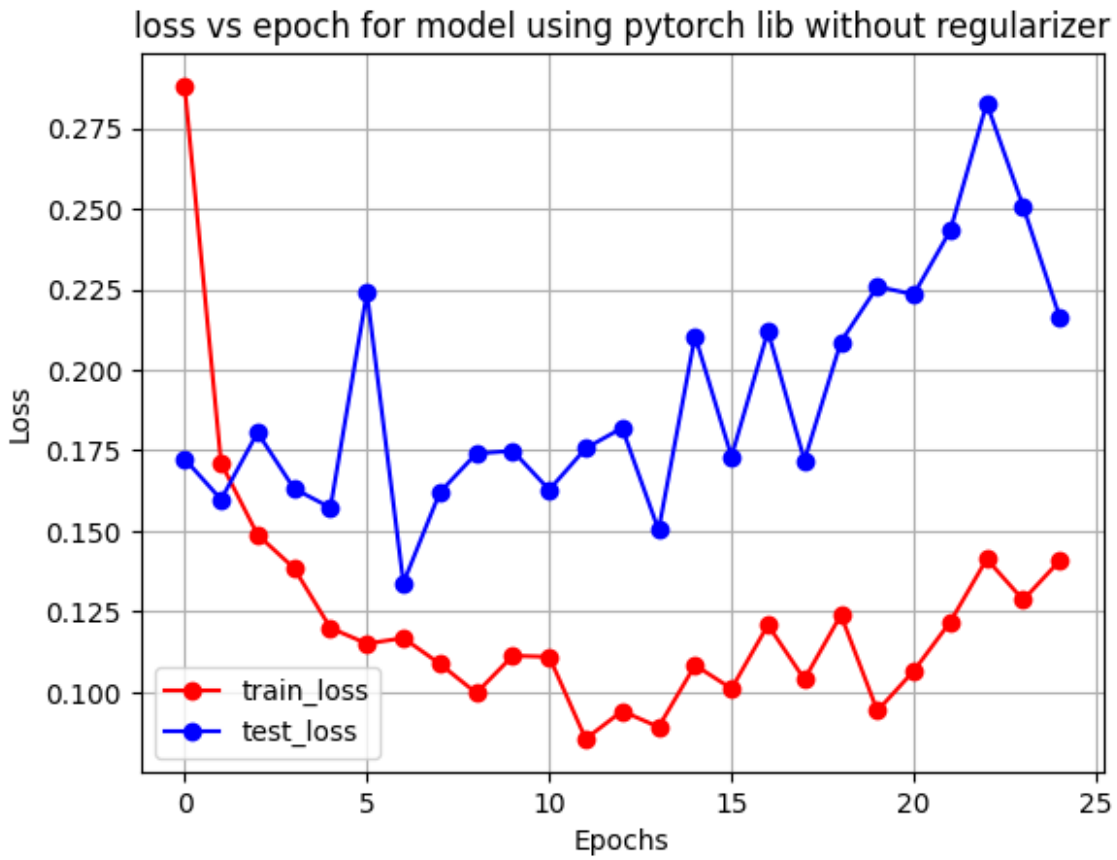
Building model using pytorch lib and relu as hidden layer activation

```
class network_1(nn.Module):
  def
__init__(self,input_dim=784,hid_1=500,hid_2=250,hid_3=100,out=10):
    super().__init__()
    self.layer_1=nn.Linear(input_dim,hid_1)
    self.act=nn.ReLU()
    self.out_act=nn.Softmax()
    self.layer_2=nn.Linear(hid_1,hid_2)
    self.layer_3=nn.Linear(hid_2,hid_3)
    self.out=nn.Linear(hid_3,out)

  def forward(self,x):
    out_1=self.act(self.layer_1(x))
    out_2=self.act(self.layer_2(out_1))
    out_3=self.act(self.layer_3(out_2))
    real_out=self.out_act(self.out(out_3))
    real_value=torch.argmax(real_out,dim=1)
    return real_out,real_value

def
train_model(model,train_loader,test_loader,loss_fn,optimizer,epochs):
  train_loss=[]
  test_acc=[]
  test_loss=[]
  for i in range(epochs):
    model.train()
    runn_loss=0
    for data in train_loader:
      data[0]=data[0].reshape(len(data[0]),784)
      optimizer.zero_grad()
      prediction,_=model(data[0])
      loss=-torch.sum(torch.log(prediction+1e-7)*data[1],dim=1)
      loss=loss.mean()
      runn_loss+=loss.item()
      loss.backward()
      optimizer.step()
    train_loss.append(runn_loss/len(train_loader))
    model.eval()
    correct=0
    total=0
    test_val_loss=0
    with torch.no_grad():
      for test_data in test_loader:
        test_data[0]=test_data[0].reshape(len(test_data[0]),784)
        real_out,prediction=model(test_data[0])
        for j in range(test_data[0].shape[0]):
          test_val_loss+=-torch.log(real_out[j][test_data[1]
[j].item()]+1e-7)
```

```
          if prediction[j].item() == test_data[1][j].item():
            correct+=1
        total+=test_data[0].shape[0]
      test_acc.append(correct/total)
      test_loss.append(test_val_loss/total)
    print(f'Epoch [{i+1}/{epochs}], train_Loss: {train_loss[i]},
test_acc: {test_acc[i]}, test_loss: {test_loss[i]}')
  return train_loss,test_acc,test_loss

model=network_1()
loss_fn=nn.CrossEntropyLoss()
optimizer=torch.optim.Adam(model.parameters(),lr=0.01)
train_loss,test_acc,test_loss=train_model(model,train_loader,test_load
er,loss_fn,optimizer,epochs=25)
```

```
/usr/local/lib/python3.12/dist-packages/torch/nn/modules/
module.py:1773: UserWarning: Implicit dimension choice for softmax has
been deprecated. Change the call to include dim=X as an argument.
  return self._call_impl(*args, **kwargs)

Epoch [1/25], train_Loss: 0.28816513981181646, test_acc: 0.9535,
test_loss: 0.1723804622888565
Epoch [2/25], train_Loss: 0.17110116101343678, test_acc: 0.9587,
test_loss: 0.15977732837200165
Epoch [3/25], train_Loss: 0.1488430953785918, test_acc: 0.9604,
test_loss: 0.18058817088603973
Epoch [4/25], train_Loss: 0.1384930900816343, test_acc: 0.9615,
test_loss: 0.16317413747310638
Epoch [5/25], train_Loss: 0.11987012304722576, test_acc: 0.9641,
test_loss: 0.15723547339439392
Epoch [6/25], train_Loss: 0.11502789675882623, test_acc: 0.9538,
test_loss: 0.22394335269927979
Epoch [7/25], train_Loss: 0.11674691758876635, test_acc: 0.9703,
test_loss: 0.13388395309448242
Epoch [8/25], train_Loss: 0.1087527096287401, test_acc: 0.963,
test_loss: 0.16198426485061646
Epoch [9/25], train_Loss: 0.09966953644216352, test_acc: 0.9633,
test_loss: 0.17404887080192566
Epoch [10/25], train_Loss: 0.11125836078757555, test_acc: 0.9648,
test_loss: 0.17489735782146454
Epoch [11/25], train_Loss: 0.110922239548572, test_acc: 0.9666,
test_loss: 0.16277998685836792
Epoch [12/25], train_Loss: 0.08545430334293776, test_acc: 0.9674,
test_loss: 0.17566072940826416
Epoch [13/25], train_Loss: 0.09408117558227602, test_acc: 0.9648,
test_loss: 0.18200159072875977
Epoch [14/25], train_Loss: 0.08913424381784729, test_acc: 0.9687,
test_loss: 0.1502791941165924
Epoch [15/25], train_Loss: 0.10832305731000544, test_acc: 0.9619,
test_loss: 0.21057341992855072
```

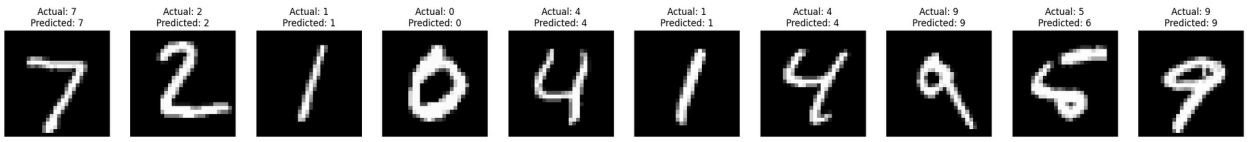
```
Epoch [16/25], train_Loss: 0.10103629958700071, test_acc: 0.9697,
test_loss: 0.17311519384384155
Epoch [17/25], train_Loss: 0.120836227816949, test_acc: 0.968,
test_loss: 0.2120409905910492
Epoch [18/25], train_Loss: 0.10392626795691032, test_acc: 0.97,
test_loss: 0.17192082107067108
Epoch [19/25], train_Loss: 0.1239540890760596, test_acc: 0.9669,
test_loss: 0.20871926844120026
Epoch [20/25], train_Loss: 0.09416366362645481, test_acc: 0.9626,
test_loss: 0.2258656919002533
Epoch [21/25], train_Loss: 0.10657324266061229, test_acc: 0.9519,
test_loss: 0.2234731912612915
Epoch [22/25], train_Loss: 0.12177960422668781, test_acc: 0.9518,
test_loss: 0.2432805895805359
Epoch [23/25], train_Loss: 0.14128304820638413, test_acc: 0.9529,
test_loss: 0.28277212381362915
Epoch [24/25], train_Loss: 0.12859212794218383, test_acc: 0.9495,
test_loss: 0.250743567943573
Epoch [25/25], train_Loss: 0.14075682150203536, test_acc: 0.9658,
test_loss: 0.21648381650447845

plt.plot(range(25),train_loss,c="r",marker="o",label="train_loss")
plt.plot(range(25),test_loss,c="b",marker="o",label="test_loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("loss vs epoch for model using pytorch lib without
regularizer")
plt.grid(True)
plt.legend()
plt.show()
```




```
plt.figure(figsize=(30, 3))
for i in range(10):
  img,actual_value=test_dataset[i]
  _,predicted_value=model(img.reshape(1,784))
  print(predicted_value)
  plt.subplot(1, 10, i + 1)
  plt.imshow(img.squeeze(), cmap="gray")
  plt.title(f"Actual: {actual_value}\nPredicted:
{predicted_value.item()}")
  plt.axis('off')
```

```
/usr/local/lib/python3.12/dist-packages/torch/nn/modules/
module.py:1773: UserWarning: Implicit dimension choice for softmax has
been deprecated. Change the call to include dim=X as an argument.
  return self._call_impl(*args, **kwargs)

tensor([7])
tensor([2])
tensor([1])
tensor([0])
tensor([4])
tensor([1])
tensor([4])
```

```
tensor([9])
tensor([6])
tensor([9])
```




```
import numpy as np
confusion_matrix,acc=generate_confusion_matrix_test(model,test_loader)
torch.set_printoptions(sci_mode=False)
np.set_printoptions(suppress=True)
print(confusion_matrix.detach().numpy())
print(f"accuracy of test_data using pytorch lib and relu activation
without regularizer {acc*100}")
```

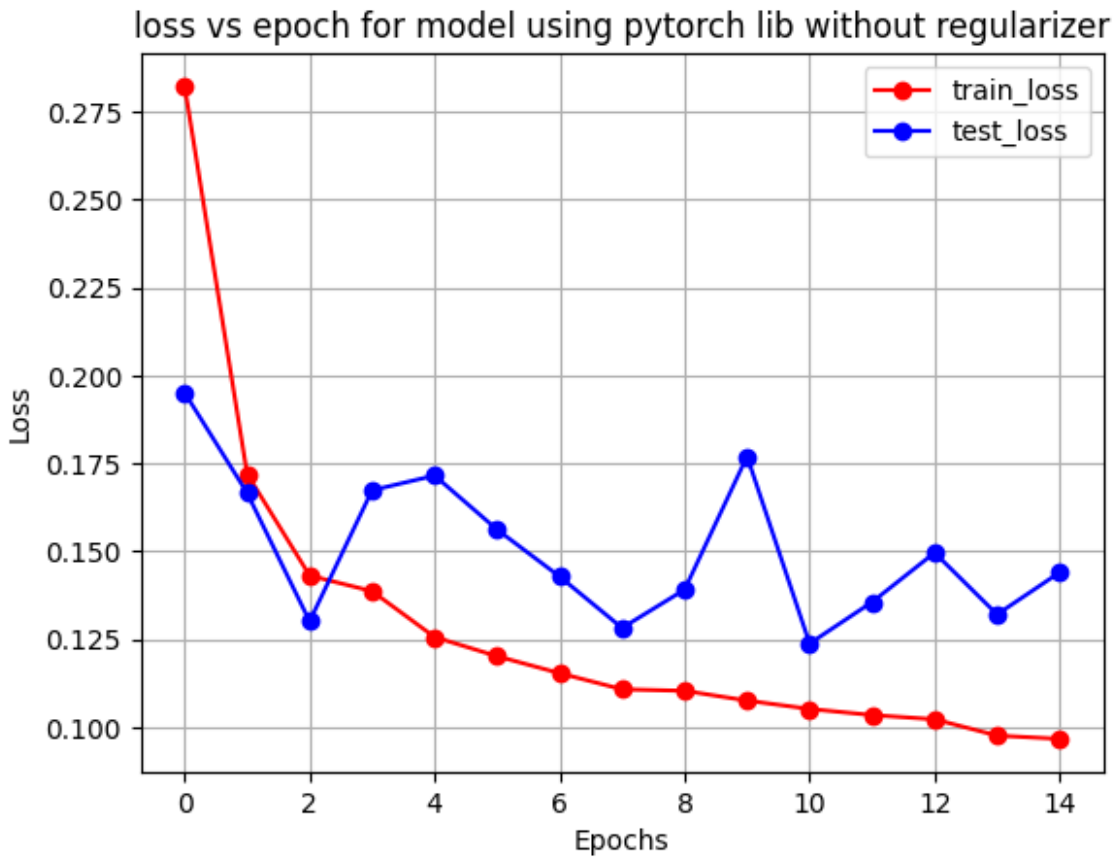
```
[[ 959.    0.   19.    0.    0.    1.    0.    1.    0.    0.]
 [   0. 1112.   11.    3.    0.    1.    1.    1.    6.    0.]
 [   1.    0. 1010.    6.    1.    0.    0.   10.    4.    0.]
 [   0.    0.    6.  993.    0.    1.    0.    2.    6.    2.]
 [   0.    0.   15.    0.  943.    0.    4.    2.    1.   17.]
 [   4.    0.   25.   17.    1.  820.    4.    1.   13.    7.]
 [   4.    1.   24.    0.    2.    2.  920.    0.    5.    0.]
 [   1.    0.   21.    3.    3.    1.    0.  987.    2.   10.]
 [   1.    0.   22.    6.    5.    2.    0.    2.  933.    3.]
 [   2.    2.    3.    5.    4.    2.    0.    6.    4.  981.]]
accuracy of test_data using pytorch lib and relu activation without
regularizer 96.58
```

```
confusion_matrix,acc=generate_confusion_matrix_train(model,train_loade
r)
torch.set_printoptions(sci_mode=False)
np.set_printoptions(suppress=True)
print(confusion_matrix.detach().numpy())
print(f"accuracy of train_data using pytorch lib and relu without
regularizer {acc*100}")
```

```
[[5771.    0.  141.    0.    0.    0.    3.    1.    4.    3.]
 [   0. 6654.   59.    4.    3.    0.    4.    3.    8.    7.]
 [   1.    1. 5918.   14.    1.    0.    0.   17.    6.    0.]
 [   0.    0.   59. 6024.    3.    7.    0.    7.   16.   15.]
 [   1.    0.   58.    0. 5693.    0.    4.    2.    1.   83.]
 [   7.    0.  120.   57.    0. 5179.   11.    0.   20.   27.]
 [   4.    0.  137.    0.    2.    4. 5756.    0.   15.    0.]
 [   1.    2.   66.   10.    6.    0.    0. 6157.    0.   23.]
 [   4.    7.   66.   16.    4.    9.    0.    2. 5730.   13.]
 [   4.    0.   16.   13.   14.    1.    0.   16.   12. 5873.]]
accuracy of train_data using pytorch lib and relu without regularizer
97.925
```

```
def
train_model_regularizer(model,train_loader,test_loader,loss_fn,optimiz
er,epochs,z=1e-5):
  train_loss=[]
  test_acc=[]
  test_loss=[]
  for i in range(epochs):
    model.train()
    runn_loss=0
    for data in train_loader:
      data[0]=data[0].reshape(len(data[0]),784)
      optimizer.zero_grad()
      prediction,_=model(data[0])
      loss=-torch.sum(torch.log(prediction+1e-7)*data[1],dim=1)
      loss=loss.mean()
      runn_loss+=loss.item()
      sum_weights=torch.tensor(0.)
      for index,param in enumerate(model.parameters()):
        if index%2==0:
          sum_weights+=torch.sum(param.pow(2))
      loss+=z*sum_weights
      loss.backward()
      optimizer.step()
    train_loss.append(runn_loss/len(train_loader))
    model.eval()
    correct=0
    total=0
    test_val_loss=0
    with torch.no_grad():
      for test_data in test_loader:
        test_data[0]=test_data[0].reshape(len(test_data[0]),784)
        real_out,prediction=model(test_data[0])
        for j in range(test_data[0].shape[0]):
          test_val_loss+=-torch.log(real_out[j][test_data[1]
[j].item()]+1e-7)
          if prediction[j].item() == test_data[1][j].item():
            correct+=1
        total+=test_data[0].shape[0]
      test_acc.append(correct/total)
      test_loss.append(test_val_loss/total)
    print(f'Epoch [{i+1}/{epochs}], train_Loss: {train_loss[i]},
test_acc: {test_acc[i]}, test_loss: {test_loss[i]}')
  return train_loss,test_acc,test_loss

model=network_1()
loss_fn=nn.CrossEntropyLoss()
optimizer=torch.optim.Adam(model.parameters(),lr=0.01)
train_loss,test_acc,test_loss=train_model_regularizer(model,train_load
er,test_loader,loss_fn,optimizer,epochs=15)
```

```
/usr/local/lib/python3.12/dist-packages/torch/nn/modules/
module.py:1773: UserWarning: Implicit dimension choice for softmax has
been deprecated. Change the call to include dim=X as an argument.
  return self._call_impl(*args, **kwargs)

Epoch [1/15], train_Loss: 0.28235834279258465, test_acc: 0.9489,
test_loss: 0.1951228678226471
Epoch [2/15], train_Loss: 0.17200414317824853, test_acc: 0.9558,
test_loss: 0.16659994423389435
Epoch [3/15], train_Loss: 0.1430871364703255, test_acc: 0.9671,
test_loss: 0.13006912171840668
Epoch [4/15], train_Loss: 0.13863967569656113, test_acc: 0.963,
test_loss: 0.16736020147800446
Epoch [5/15], train_Loss: 0.12559636930194396, test_acc: 0.9591,
test_loss: 0.1715407818555832
Epoch [6/15], train_Loss: 0.12013623332763627, test_acc: 0.965,
test_loss: 0.15617136657238007
Epoch [7/15], train_Loss: 0.11531585200775617, test_acc: 0.964,
test_loss: 0.1428222358226776
Epoch [8/15], train_Loss: 0.1107286206756367, test_acc: 0.9657,
test_loss: 0.1281892955303192
Epoch [9/15], train_Loss: 0.11029947231146894, test_acc: 0.9656,
test_loss: 0.13908681273460388
Epoch [10/15], train_Loss: 0.10751333723077054, test_acc: 0.9608,
test_loss: 0.1770131140947342
Epoch [11/15], train_Loss: 0.10514175113457352, test_acc: 0.9676,
test_loss: 0.12374365329742432
Epoch [12/15], train_Loss: 0.10339790306884104, test_acc: 0.9663,
test_loss: 0.13555513322353363
Epoch [13/15], train_Loss: 0.10219829512806212, test_acc: 0.9652,
test_loss: 0.14959439635276794
Epoch [14/15], train_Loss: 0.09755791191916183, test_acc: 0.9675,
test_loss: 0.1320391297340393
Epoch [15/15], train_Loss: 0.09663669735879334, test_acc: 0.9626,
test_loss: 0.14397773146629333

plt.plot(range(15),train_loss,c="r",marker="o",label="train_loss")
plt.plot(range(15),test_loss,c="b",marker="o",label="test_loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("loss vs epoch for model using pytorch lib without
regularizer")
plt.grid(True)
plt.legend()
plt.show()
```




```
import numpy as np
confusion_matrix,acc=generate_confusion_matrix_test(model,test_loader)
torch.set_printoptions(sci_mode=False)
np.set_printoptions(suppress=True)
print(confusion_matrix.detach().numpy())
print(f"accuracy of test_data using pytorch lib and relu with
regularizer {acc*100}")
```

```
[[ 975.    0.    1.    0.    0.    0.    1.    0.    2.    1.]
 [   0. 1112.   11.    3.    0.    0.    2.    0.    7.    0.]
 [   4.    0. 1019.    3.    0.    0.    2.    2.    2.    0.]
 [   0.    0.    7.  986.    0.    4.    0.    7.    4.    2.]
 [   1.    0.   15.    0.  925.    0.    7.    3.    6.   25.]
 [   6.    0.    2.   25.    0.  843.   10.    2.    4.    0.]
 [   5.    2.    4.    1.    3.    1.  940.    1.    1.    0.]
 [   3.    2.   27.    0.    2.    0.    0.  983.    3.    8.]
 [  15.    0.   16.    7.    3.   13.   13.    2.  904.    1.]
 [   4.    4.    1.    7.    4.   10.    2.   19.   19.  939.]]
accuracy of test_data using pytorch lib and relu with regularizer
96.26
```

```
confusion_matrix,acc=generate_confusion_matrix_train(model,train_loade
r)
```

```
torch.set_printoptions(sci_mode=False)
np.set_printoptions(suppress=True)
print(confusion_matrix.detach().numpy())
print(f"accuracy of train_data using pytorch lib and relu with
regularizer {acc*100}")
```

```
[[5878.    0.    9.    5.    0.    3.   17.    4.    7.    0.]
 [   1. 6613.   84.    3.    6.    0.    3.   10.   21.    1.]
 [   5.    2. 5920.   13.    1.    2.    3.    7.    5.    0.]
 [   5.    0.   60. 5998.    0.   25.    1.   19.   14.    9.]
 [   8.    9.   59.    2. 5568.    5.   30.   18.   28.  115.]
 [  10.    3.   12.   82.    0. 5243.   43.    6.   16.    6.]
 [  30.    3.   21.    0.    3.    5. 5854.    0.    2.    0.]
 [   3.    4.   74.    1.    3.    1.    0. 6155.    6.   18.]
 [  37.   10.   84.   33.    1.   40.   60.    1. 5579.    6.]
 [  20.    3.    6.   29.   35.   39.    4.   83.   49. 5681.]]
accuracy of train_data using pytorch lib and relu with regularizer
97.48166666666667
```

Observation and results:

The network coded from scratch performed slightly better than the model created using libraries, but overall the performance was almost similar.

When L2 regularization was applied, the models did not perform as well compared to the ones without regularization. One possible reason is that the training dataset may contain very little noise. In such cases, adding a regularization penalty can reduce the magnitude of weights unnecessarily, which may lead to the model losing some essential learning ability. As a result, both training and testing accuracy decreased.

Another possible explanation is that the chosen regularization strength (λ) might have been too high relative to the dataset size and complexity, causing underfitting. With further tuning of λ, it is possible that the regularized models could achieve a better balance between generalization and accuracy.

S.no	Model	Activation func	Train accuracy	Test accuracy
1	Without lib	sigmoid	99.15	97.66
2	Without lib	relu	99.78	98.29
3	Without lib	tanh	99.85	97.8
4	With lib and without regularizer	sigmoid	98.51	97.04
5	With lib and with regularizer	sigmoid	97.65	96.87
6	With lib and without regularizer	relu	97.925	96.58
7	With lib and with regularizer	relu	97.48	96.26