MNIST Digits Classification using Neural Networks

Mount your drive in order to run locally with colab

```
from google.colab import drive
drive.mount('/content/gdrive')
```

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

download & load the MNIST dataset.

*just run the next two cells and observe the outputs (shift&enter)

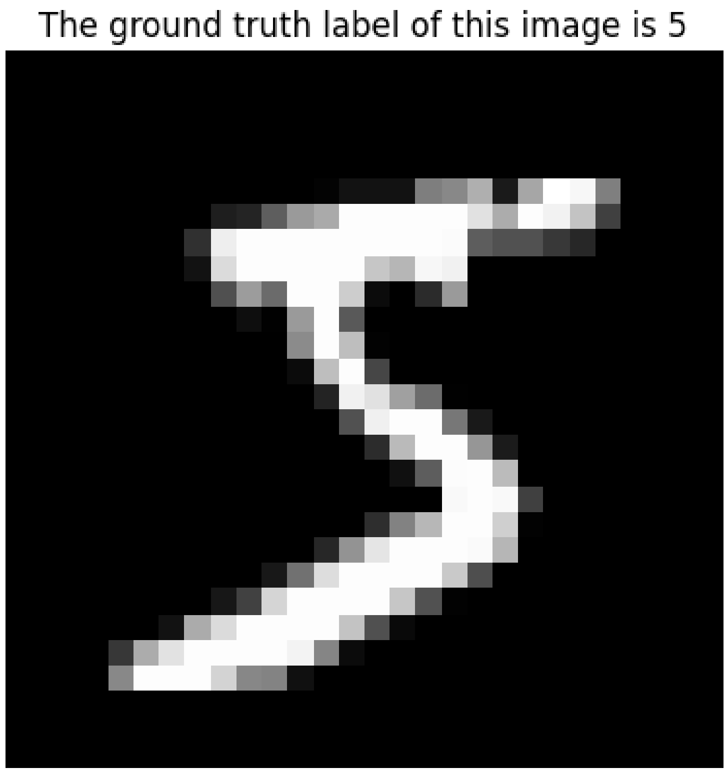
```
#importing modules that will be in use
%matplotlib inline
import os
import numpy as np
import matplotlib.pyplot as plt
import urllib.request
import gzip
import pickle
from PIL import Image
import random
import numpy as np

def _download(file_name):
    file_path = os.path.join(dataset_dir,file_name)

    if os.path.exists(file_path):
        return

    print("Downloading " + file_name + " ... ")
    urllib.request.urlretrieve(url_base + file_name, file_name)
    print("Done")

def download_mnist():
    for v in key_file.values():
       _download(v)

def _load_label(file_name):
    file_path =  os.path.join(dataset_dir, file_name)

    print("Converting " + file_name + " to NumPy Array ...")
    with gzip.open(file_path, 'rb') as f:
```

```python
        labels = np.frombuffer(f.read(), np.uint8, offset=8)
    print("Done")

    return labels

def _load_img(file_name):
    file_path = os.path.join(dataset_dir,file_name)

    print("Converting " + file_name + " to NumPy Array ...")
    with gzip.open(file_path, 'rb') as f:
        data = np.frombuffer(f.read(), np.uint8, offset=16)
    data = data.reshape(-1, img_size)
    print("Done")

    return data

def _convert_numpy():
    dataset = {}
    dataset['train_img'] =  _load_img(key_file['train_img'])
    dataset['train_label'] = _load_label(key_file['train_label'])
    dataset['test_img'] = _load_img(key_file['test_img'])
    dataset['test_label'] = _load_label(key_file['test_label'])

    return dataset

def init_mnist():
    download_mnist()
    dataset = _convert_numpy()
    print("Creating pickle file ...")
    with open(save_file, 'wb') as f:
        pickle.dump(dataset, f, -1)
    print("Done")

def _change_one_hot_label(X):
    T = np.zeros((X.size, 10))
    for idx, row in enumerate(T):
        row[X[idx]] = 1

    return T

def load_mnist(normalize=True, flatten=True, one_hot_label=False):
    """
    Parameters
    ----------
    normalize : Normalize the pixel values
    flatten : Flatten the images as one array
    one_hot_label : Encode the labels as a one-hot array

    Returns
    -------
```

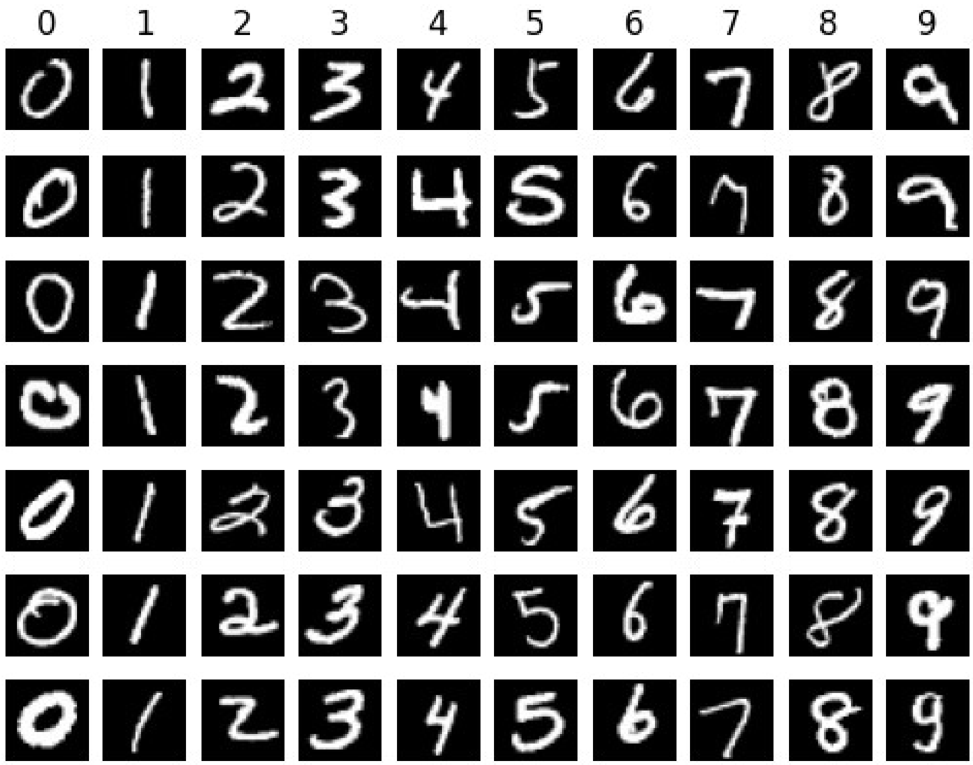
```
    (Trainig Image, Training Label), (Test Image, Test Label)
    """
    if not os.path.exists(save_file):
        init_mnist()

    with open(save_file, 'rb') as f:
        dataset = pickle.load(f)

    if normalize:
        for key in ('train_img', 'test_img'):
            dataset[key] = dataset[key].astype(np.float32)
            dataset[key] /= 255.0

    if not flatten:
         for key in ('train_img', 'test_img'):
            dataset[key] = dataset[key].reshape(-1, 1, 28, 28)

    if one_hot_label:
        dataset['train_label'] =
_change_one_hot_label(dataset['train_label'])
        dataset['test_label'] =
_change_one_hot_label(dataset['test_label'])

    return (dataset['train_img'], dataset['train_label']),
(dataset['test_img'], dataset['test_label'])


# Load the MNIST dataset
url_base = 'http://yann.lecun.com/exdb/mnist/'
key_file = {
    'train_img':'train-images-idx3-ubyte.gz',
    'train_label':'train-labels-idx1-ubyte.gz',
    'test_img':'t10k-images-idx3-ubyte.gz',
    'test_label':'t10k-labels-idx1-ubyte.gz'
}

dataset_dir = '/content'
save_file = dataset_dir + "/mnist.pkl"

train_num = 60000
test_num = 10000
img_dim = (1, 28, 28)
img_size = 784

(x_train, t_train), (x_test, t_test) = load_mnist(normalize=True,
flatten=True)


# printing data shape
```

```python
print('the training data set contains '+ str(x_train.shape[0]) + ' samples')

img = x_train[0]
label = t_train[0]

img = img.reshape(28, 28)
print('each sample image from the training data set is a column-stacked grayscale image of '+ str(x_train.shape[1]) +' pixels'
      + '\n this vectorized arrangement of the data is suitable for a Fully-Connected NN (as apposed to a Convolutional NN)' )
print('these column-stacked images can be reshaped to an image of ' +str(img.shape)+ ' pixels')

# printing a sample from the dataset

plt.imshow(img, cmap='gray')
plt.axis('off')
plt.title('The ground truth label of this image is '+str(label))
plt.show()
```

```
the training data set contains 60000 samples
each sample image from the training data set is a column-stacked grayscale image of 784 pixels
 this vectorized arrangement of the data is suitable for a Fully-Connected NN (as apposed to a Convolutional NN)
these column-stacked images can be reshaped to an image of (28, 28) pixels
```




```
# Visualize some examples from the dataset.
# We'll show a few examples of training images from each class.
num_classes = 10
samples_per_class = 7
for cls in range(num_classes):
    idxs = np.argwhere(t_train==cls)
    sample = np.random.choice(idxs.shape[0], samples_per_class,
replace=False) # randomly picks 7 from the appearences
    idxs=idxs[sample]

    for i, idx in enumerate(idxs):
        plt_idx = i * num_classes + cls + 1
        plt.subplot(samples_per_class, num_classes, plt_idx)
        img = x_train[idx].reshape(28, 28)

        plt.imshow(img, cmap='gray')
        plt.axis('off')
        if i == 0:
            plt.title(cls)
plt.show()
```



QUESTION 1:What are vanishing gradients? Name one known activation function that has this problem and one that does not.

ANSWER:

Vanishing Gradients, is when gradients in deep neural networks become very small during training. This leads to the weights not being updated effectively during the training process, causing slow or stalled learning.

Sigmoid is an activation function prone to vanishing gradients due to its saturating behavior.

ReLU is an activation function less prone to vanishing gradients for positive inputs, aiding in efficient learning in deep networks.

here we will implement the sigmoid activation function and it's gradient

```
def sigmoid(x):

##########################################################################
#######
    #                              YOUR CODE
#

##########################################################################
#######
    sig = 1/(1+ np.exp(-x))
```

```
########################################################################
######
    #                              END OF YOUR CODE
#

########################################################################
######
    return sig
def sigmoid_grad(x):
    
########################################################################
#######
    #                              YOUR CODE
#

########################################################################
#######
    sig_grad = sigmoid(x)*(1 - sigmoid(x))

    
########################################################################
######
    #                              END OF YOUR CODE
#

########################################################################
######
    return sig_grad
```

Implement a fully-vectorized loss function for the Softmax classifier Make sure the softmax is stable. To make our softmax function numerically stable,we simply normalize the values in the vector, by multiplying the numerator and denominator with a constant C. We can choose an arbitrary value for log(C) term, but generally log(C)=−max(a) is chosen, as it shifts all of elements in the vector to negative to zero, and negatives with large exponents saturate to zero rather than the infinity.

```
def softmax(x):

    """
  Softmax loss function, should be implemented in a vectorized fashion
(without loops)


  Inputs:
  - X: A numpy array of shape (N, C) containing a minibatch of data.
  Returns:
  - probabilities: A numpy array of shape (N, C) containing the
softmax probabilities.
```

```
  if you are not careful here, it is easy to run into numeric
instability
     """

#######################################################################
#######
    #                             YOUR CODE
#

#######################################################################
#######
    exp_x = np.exp(x - np.max(x, axis = 1, keepdims = True)) # The
subtraction of the maximum value is done to improve numerical
stability, preventing overflow issues when exponentiating large
numbers.
    probabilities = exp_x / np.sum(exp_x, axis = 1, keepdims = True)

#######################################################################
######
    #                             END OF YOUR CODE
#

#######################################################################
######
    return probabilities

def cross_entropy_error(y, t):
    """
    Inputs:

    - t:  A numpy array of shape (N,C) containing  a minibatch of
training labels, it is a one-hot array,
      with t[GT]=1 and t=0 elsewhere, where GT is the ground truth
label ;
    - y: A numpy array of shape (N, C) containing the softmax
probabilities (the NN's output).

    Returns a tuple of:
    - loss as single float (do not forget to divide by the number of
samples in the minibatch (N))
    """

#######################################################################
#######
    #                             YOUR CODE
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#######
```

```
    # Compute loss

    batch_size = y.shape[0]
    error = -np.sum(t * np.log(y + 1e-10)) / batch_size  # Adding a
small constant to avoid log(0) issues


######################################################################
######
    #                             END OF YOUR CODE
#

######################################################################
#######
    return error
```

We will design and train a two-layer fully-connected neural network with sigmoid nonlinearity and softmax cross entropy loss. We assume an input dimension of D=784, a hidden dimension of H, and perform classification over C classes.

The architecture should be fullyconnected -> sigmoid -> fullyconnected -> softmax.

The learnable parameters of the model are stored in the dictionary, 'params', that maps parameter names to numpy arrays.

In the next cell we will initialize the weights and biases, design the fully connected(fc) forward and backward functions that will be in use for the training (using SGD).

```
def TwoLayerNet( input_size, hidden_size, output_size,
weight_init_std=0.01):

######################################################################
######
    # TODO: Initialize the weights and biases of the two-layer net.
Weights    #
    # should be initialized from a Gaussian with standard deviation
equal to   #
    # weight_init_std, and biases should be initialized to zero. All
weights and  #
    # biases should be stored in the dictionary 'params', with first
layer  #
    # weights and biases using the keys 'W1' and 'b1' and second layer
weights #
    # and biases using the keys 'W2' and 'b2'.
#

######################################################################
######
    params = {}
    params["W1"] = np.random.normal(0,weight_init_std, size =
```

```
(input_size, hidden_size))
    params["b1"] = np.zeros(hidden_size)
    params["W2"] = np.random.normal(0,weight_init_std, size =
(hidden_size, output_size))
    params["b2"] = np.zeros(output_size)

######################################################################
######
    #                             END OF YOUR CODE
#

######################################################################
######
    return params


def FC_forward(x, w, b):
    """
    Computes the forward pass for a fully-connected layer.
    The input x has shape (N, D) and contains a minibatch of N
    examples, where each example x[i] has shape D and will be
transformed to an output vector of dimension M.
    Inputs:
    - x: A numpy array containing input data, of shape (N, D)
    - w: A numpy array of weights, of shape (D, M)
    - b: A numpy array of biases, of shape (M,)

    Returns a tuple of:
    - out: output result of the forward pass, of shape (N, M)
    - cache: (x, w, b)
    """

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#

######################################################################
#######
    out = np.matmul(x, w) + b

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#######
    #                             END OF YOUR CODE
#

######################################################################
#######
    cache = (x, w, b)
    return out, cache
```

```
def FC_backward(dout, cache):
    """
    Computes the backward pass for a fully-connected layer.
    Inputs:
    - dout: Upstream derivative, of shape (N, M)
    - cache: Tuple of:
    - w: Weights, of shape (D, M)
    Returns a tuple of:
    - dx: Gradient with respect to x, of shape (N, D)
    - dw: Gradient with respect to w, of shape (D, M)
    - db: Gradient with respect to b, of shape (M,)
    """
    x, w, b = cache
    dx, dw, db = None, None, None


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#######
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######################################################################
#######
    dx = np.matmul(dout, w.T)
    dw = np.matmul(x.T, dout)
    db = np.sum(dout, axis=0)

######################################################################
#######
    #                             END OF YOUR CODE
#

######################################################################
#######
    return dx, dw, db
```

Here we will design the entire model, which outputs the NN's probabilities and gradients.

```
def Model(params, x, t):
    """
    Computes the backward pass for a fully-connected layer.
    Inputs:
    - params:  dictionary with first layer weights and biases using
the keys 'W1' and 'b1' and second layer weights
    and biases using the keys 'W2' and 'b2'. each with dimensions
corresponding its input and output dimensions.
```

```
    - x: Input data, of shape (N,D)
    - t:  A numpy array of shape (N,C) containing training labels, it
is a one-hot array,
      with t[GT]=1 and t=0 elsewhere, where GT is the ground truth
label ;
    Returns:
    - y: the output probabilities for the minibatch (at the end of the
forward pass) of shape (N,C)
    - grads: dictionary containing gradients of the loss with respect
to W1, W2, b1, b2.

    note: use the FC_forward ,FC_backward functions.

    """
    W1, W2 = params['W1'], params['W2']
    b1, b2 = params['b1'], params['b2']
    grads = {'W1': None ,'W2': None, 'b1': None ,'b2': None }

    batch_num = x.shape[0]


######################################################################
#######
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#

######################################################################
#######
    # forward (fullyconnected -> sigmoid -> fullyconnected ->
softmax).
    out1, cache1 = FC_forward(x,W1,b1)
    out2, cache2 = FC_forward(sigmoid(out1),W2,b2)
    y = softmax(out2)


    # backward - calculate gradients.
    dout2 = y - t
    dx2, dw2, db2 = FC_backward(dout2, cache2)

    dout1 = np.dot(dout2, W2.T) * sigmoid_grad(out1)
    dx1, dw1, db1 = FC_backward(dout1, cache1)

    grads = {'dW1': dw1, 'dW2': dw2, 'db1': db1, 'db2': db2}

######################################################################
#######
    #                             END OF YOUR CODE
#

######################################################################
```

```
#######

    return grads, y
```

Compute the accuracy of the NNs predictions.

```
def accuracy(y,t):
    """
    Computes the accuracy of the NN's predictions.
    Inputs:
    - t:  A numpy array of shape (N,C) containing training labels, it
is a one-hot array,
      with t[GT]=1 and t=0 elsewhere, where GT is the ground truth
label ;
    - y: the output probabilities for the minibatch (at the end of the
forward pass) of shape (N,C)
    Returns:
    - accuracy: a single float of the average accuracy.
    """

######################################################################
#######
    #                             YOUR CODE
#

######################################################################
#######

    predicted_labels = np.argmax(y, axis=1)

    true_labels = np.argmax(t, axis=1)

    correct_predictions = np.sum(predicted_labels == true_labels)
    total_samples = t.shape[0]

    accuracy = correct_predictions / total_samples


######################################################################
#######
    #                             END OF YOUR CODE
#

######################################################################
#######
    return accuracy
```

Trianing the model: To train our network we will use minibatch SGD.
*Note that the test dataset is actually used as the validation dataset in the training

```
# You should be able to receive at least 97% accuracy, choose
hyperparameters accordingly.
epochs = 60
mini_batch_size = 1024
learning_rate = 0.001
num_hidden_cells = 128

def Train(epochs_num, batch_size, lr, H):
    #  Dividing a dataset into training data and test data

    (x_train, t_train), (x_test, t_test) = load_mnist(normalize=True,
one_hot_label=True)
    C=10
    D=x_train.shape[1]
    network_params = TwoLayerNet(input_size=D, hidden_size=H,
output_size=C) #hidden_size is the only hyperparameter here

    train_size = x_train.shape[0]
    train_loss_list = []
    train_acc_list = []
    test_acc_list = []
    iter_per_epoch = round(train_size / batch_size)

    print('training of ' + str(epochs_num) +' epochs, each epoch will
have '+ str(iter_per_epoch)+ ' iterations')
    for i in range(epochs_num):

        train_loss_iter= []
        train_acc_iter= []

        for k in range(iter_per_epoch):



######################################################################
#######
            #                             YOUR CODE
#

######################################################################
#######
            # 1. Select part of training data (mini-batch) randomly
            mask = np.random.choice(train_size, batch_size,
replace=False)
            x_batch = x_train[mask]
            t_batch = t_train[mask]

            # 2. Calculate the predictions and the gradients to reduce
the value of the loss function
            grads, y_batch = Model(network_params, x_batch, t_batch)
```

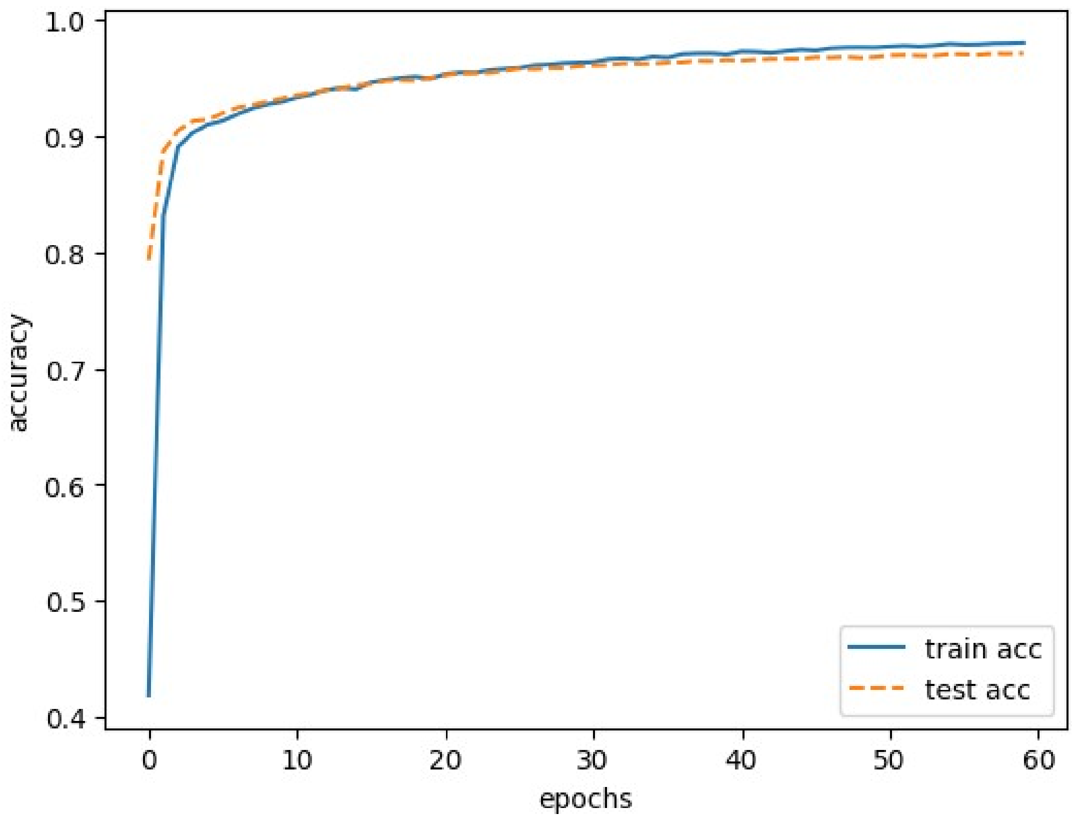
```
            # 3. Update weights and biases with the gradients
            for key in network_params.keys():
              if key.startswith('W'):
                  network_params[key] -= lr * grads['d' + key]
              elif key.startswith('b'):
                  network_params[key] -= lr * grads['d' + key]



######################################################################
#######
            #                             END OF YOUR CODE
#

######################################################################
#######

            # Calculate the loss and accuracy for visalizaton

            error=cross_entropy_error(y_batch, t_batch)
            train_loss_iter.append(error)
            acc_iter=accuracy(y_batch, t_batch)
            train_acc_iter.append(acc_iter)
            if k == iter_per_epoch-1:
                train_acc = np.mean(train_acc_iter)
                train_acc_list.append(train_acc)
                train_loss_list.append(np.mean(train_loss_iter))

                _, y_test = Model(network_params, x_test, t_test)
                test_acc = accuracy(y_test, t_test)
                test_acc_list.append(test_acc)
                print("train acc: " + str(train_acc)[:5] + "% |  test
acc: "   + str(test_acc) + "% |  loss for epoch " + str(i) +": "+
str(np.mean(train_loss_iter)))
    return train_acc_list, test_acc_list, train_loss_list,
network_params

train_acc, test_acc, train_loss, net_params = Train(epochs,
mini_batch_size, learning_rate, num_hidden_cells)

markers = {'train': 'o', 'test': 's'}
x = np.arange(len(train_acc))
plt.plot(x, train_acc, label='train acc')
plt.plot(x, test_acc, label='test acc', linestyle='--')
plt.xlabel("epochs")
plt.ylabel("accuracy")
plt.legend(loc='lower right')
plt.show()
```

```python
markers = {'train': 'o'}
x = np.arange(len(train_loss))
plt.plot(x, train_loss, label='train loss')
plt.xlabel("epochs")
plt.ylabel("Loss")
plt.legend(loc='lower right')
plt.show()
```

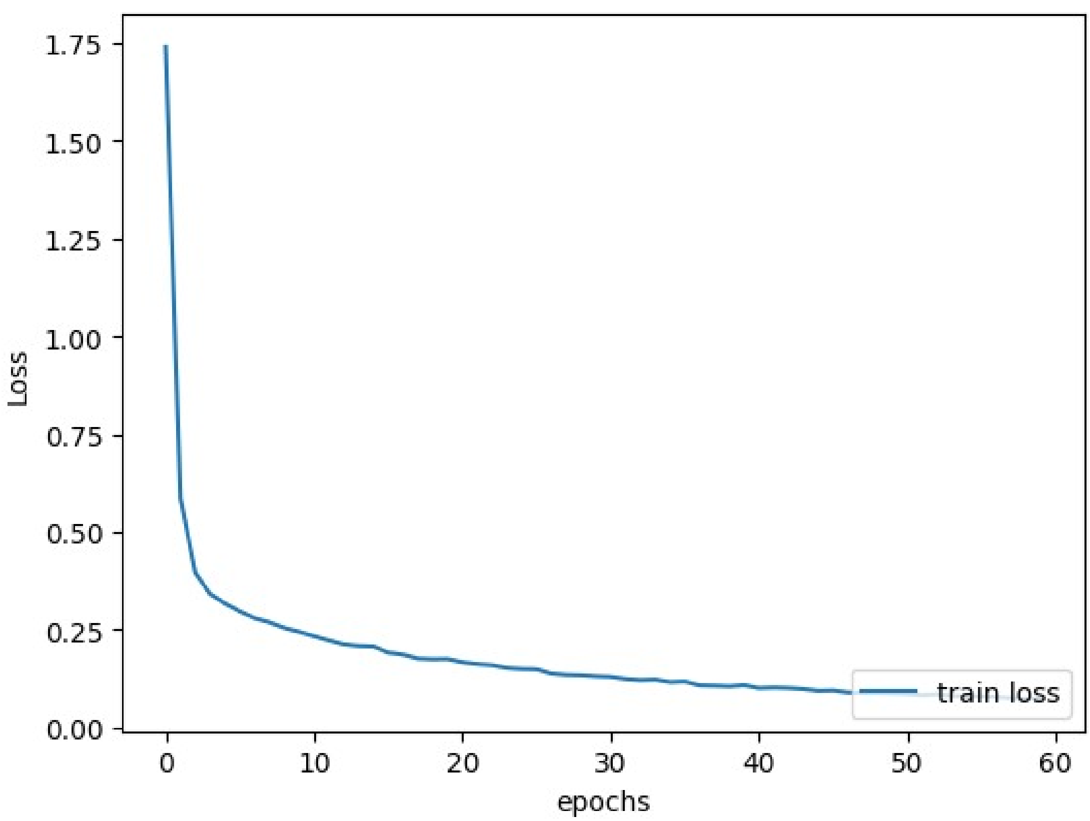
```
training of 60 epochs, each epoch will have 59 iterations
train acc: 0.418% |  test acc: 0.7932% |  loss for epoch 0:
1.739933904305181
train acc: 0.831% |  test acc: 0.8867% |  loss for epoch 1:
0.5857930108761452
train acc: 0.890% |  test acc: 0.9045% |  loss for epoch 2:
0.3952598556271178
train acc: 0.902% |  test acc: 0.9126% |  loss for epoch 3:
0.3410554823704582
train acc: 0.909% |  test acc: 0.9139% |  loss for epoch 4:
0.316901807603959
train acc: 0.912% |  test acc: 0.9193% |  loss for epoch 5:
0.29703702207726984
train acc: 0.918% |  test acc: 0.924% |  loss for epoch 6:
0.2791863505744378
train acc: 0.923% |  test acc: 0.9263% |  loss for epoch 7:
0.2685736187814834
train acc: 0.926% |  test acc: 0.9291% |  loss for epoch 8:
0.25427590725724064
train acc: 0.929% |  test acc: 0.9321% |  loss for epoch 9:
0.24452695360058738
train acc: 0.932% |  test acc: 0.9347% |  loss for epoch 10:
0.2332290910182891
train acc: 0.935% |  test acc: 0.9365% |  loss for epoch 11:
0.222584839670763
train acc: 0.939% |  test acc: 0.9391% |  loss for epoch 12:
0.21257771247170107
train acc: 0.940% |  test acc: 0.9407% |  loss for epoch 13:
0.2084872507045812
train acc: 0.939% |  test acc: 0.9433% |  loss for epoch 14:
0.20741575047898447
train acc: 0.945% |  test acc: 0.9444% |  loss for epoch 15:
0.19115684543112152
train acc: 0.948% |  test acc: 0.9471% |  loss for epoch 16:
0.1863021479754759
train acc: 0.949% |  test acc: 0.9476% |  loss for epoch 17:
0.1759416371005695
train acc: 0.950% |  test acc: 0.9473% |  loss for epoch 18:
0.17429015387503766
train acc: 0.948% |  test acc: 0.9496% |  loss for epoch 19:
0.17492373552095813
```

```
train acc: 0.952% |  test acc: 0.952% |  loss for epoch 20:
0.16654560580456562
train acc: 0.954% |  test acc: 0.9535% |  loss for epoch 21:
0.16187829582716168
train acc: 0.954% |  test acc: 0.954% |  loss for epoch 22:
0.15919370715130474
train acc: 0.956% |  test acc: 0.954% |  loss for epoch 23:
0.15198338634815184
train acc: 0.957% |  test acc: 0.9558% |  loss for epoch 24:
0.1495378491474034
train acc: 0.958% |  test acc: 0.9576% |  loss for epoch 25:
0.14891377133354672
train acc: 0.960% |  test acc: 0.9571% |  loss for epoch 26:
0.13781366936975809
train acc: 0.961% |  test acc: 0.9582% |  loss for epoch 27:
0.13453734408440868
train acc: 0.962% |  test acc: 0.9581% |  loss for epoch 28:
0.133530130001098
train acc: 0.962% |  test acc: 0.9598% |  loss for epoch 29:
0.13087785059651505
train acc: 0.963% |  test acc: 0.9603% |  loss for epoch 30:
0.12949267213722448
train acc: 0.965% |  test acc: 0.9606% |  loss for epoch 31:
0.12393460329041463
train acc: 0.966% |  test acc: 0.962% |  loss for epoch 32:
0.1211732848460508
train acc: 0.965% |  test acc: 0.9616% |  loss for epoch 33:
0.12245895102458934
train acc: 0.967% |  test acc: 0.9619% |  loss for epoch 34:
0.11593901338772733
train acc: 0.967% |  test acc: 0.9627% |  loss for epoch 35:
0.11733906746305445
train acc: 0.970% |  test acc: 0.9631% |  loss for epoch 36:
0.10754764896647
train acc: 0.970% |  test acc: 0.9643% |  loss for epoch 37:
0.10664720072822173
train acc: 0.970% |  test acc: 0.9641% |  loss for epoch 38:
0.10519257056334343
train acc: 0.969% |  test acc: 0.9651% |  loss for epoch 39:
0.10806392625292918
train acc: 0.972% |  test acc: 0.9645% |  loss for epoch 40:
0.10071673191580442
train acc: 0.971% |  test acc: 0.9654% |  loss for epoch 41:
0.10194635572202924
train acc: 0.971% |  test acc: 0.9659% |  loss for epoch 42:
0.10085595349842126
train acc: 0.972% |  test acc: 0.9661% |  loss for epoch 43:
0.09839543284730262
train acc: 0.973% |  test acc: 0.966% |  loss for epoch 44:
```

```
0.09374893665784077
train acc: 0.973% |  test acc: 0.9674% |  loss for epoch 45:
0.09462499427949334
train acc: 0.975% |  test acc: 0.9671% |  loss for epoch 46:
0.08965061226076367
train acc: 0.975% |  test acc: 0.9677% |  loss for epoch 47:
0.0881726358097682
train acc: 0.975% |  test acc: 0.9669% |  loss for epoch 48:
0.08787255347625493
train acc: 0.975% |  test acc: 0.9676% |  loss for epoch 49:
0.08720119382603274
train acc: 0.976% |  test acc: 0.969% |  loss for epoch 50:
0.08536842572877715
train acc: 0.977% |  test acc: 0.9693% |  loss for epoch 51:
0.08272494117144304
train acc: 0.976% |  test acc: 0.9687% |  loss for epoch 52:
0.08497412422653755
train acc: 0.977% |  test acc: 0.9687% |  loss for epoch 53:
0.08083592052049583
train acc: 0.978% |  test acc: 0.9701% |  loss for epoch 54:
0.07910956007044159
train acc: 0.978% |  test acc: 0.9699% |  loss for epoch 55:
0.07986544638495888
train acc: 0.978% |  test acc: 0.9695% |  loss for epoch 56:
0.07778630887833143
train acc: 0.979% |  test acc: 0.9705% |  loss for epoch 57:
0.0749532745275554
train acc: 0.979% |  test acc: 0.9703% |  loss for epoch 58:
0.07392055427352281
train acc: 0.979% |  test acc: 0.9707% |  loss for epoch 59:
0.07387547849060787
```



1.0
0.9
0.8
0.7
0.6
0.5
0.4
accuracy
0
10
20
30
40
50
60
epochs
train acc
test acc



1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Loss
0
10
20
30
40
50
60
epochs
train loss

You should be able to receive at least 97% accuracy, choose hyperparameters accordingly.

QUESTION 2: Explain the results looking at the visualizations above, base your answer on the hyperparameters.

ANSWER:

The provided output shows the training and test accuracy, as well as the loss for each epoch during training. Let's analyze the results based on the hyperparameters:

- **Epochs (Training Iterations):** The model is trained for 60 epochs, and each epoch consists of 59 iterations.
- **Mini-Batch Size:** The mini-batch size used is 1024.
- **Learning Rate:** The learning rate is set to 0.001.
- **Number of Hidden Cells (Hidden Layer Size):** The neural network has 128 hidden cells in the hidden layer.

Observations:

1. **Training Accuracy:** The training accuracy starts from around 43.2% in the first epoch and steadily increases over subsequent epochs. It reaches 98% by the end of training, indicating that the model is learning from the training data.
2. **Test Accuracy:** The test accuracy also increases over epochs and reaches around 97.1% by the end of training. The increasing test accuracy suggests that the model generalizes well to unseen data.
3. **Loss:** The loss decreases consistently over epochs, indicating that the model is improving in minimizing the cross-entropy loss on the training data.
4. **Overfitting:** The training accuracy is higher than the test accuracy, but the gap is not too large. This suggests that the model is generalizing reasonably well and does not show severe signs of overfitting.

Conclusion:

- The chosen hyperparameters seem to result in effective training, with both training and test accuracies improving over the course of training.
- The learning rate, mini-batch size, and hidden layer size seem to be chosen appropriately for this task.
- Further hyperparameter tuning or experimentation with different architectures could potentially lead to even better results.

QUESTION 3: Suggest a way to improve the results by changing the networks's architecture

ANSWER:

To potentially improve the results, we can experiment with the following changes to the network's architecture:

Add More Hidden Layers:

Introduce additional hidden layers to the network. This can enable the model to learn hierarchical representations of the data. For instance, you can add one or more hidden layers with increasing sizes.

Dropout Regularization:

Apply dropout regularization to the hidden layers during training. Dropout can prevent overfitting by randomly dropping out a proportion of neurons during each training iteration.

Different Activation Functions:

Try using different activation functions in the hidden layers. ReLU is a common choice, but variations like Leaky ReLU or Parametric ReLU might offer improvements.

Optimizer Choice:

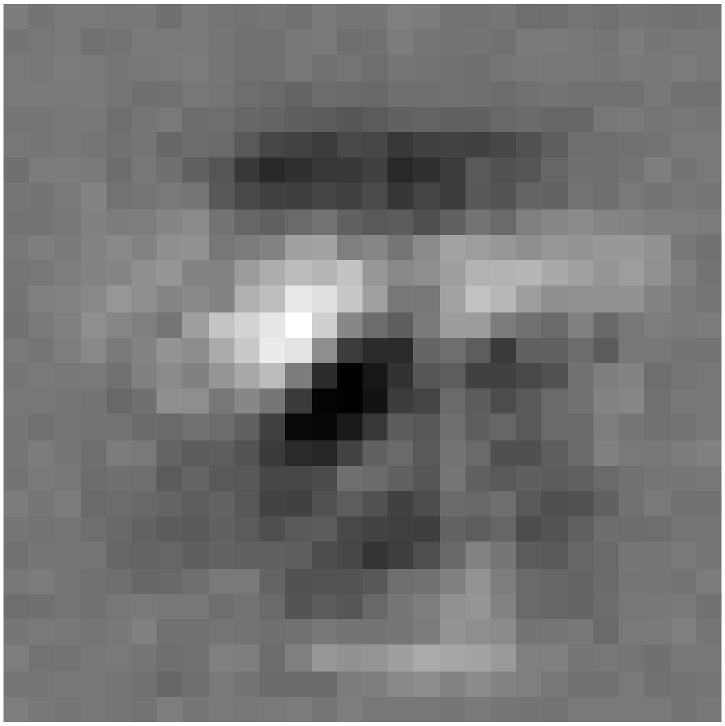
Experiment with different optimizers (Adam, RMSprop, or SGD with momentum) to see if one performs better than the others.

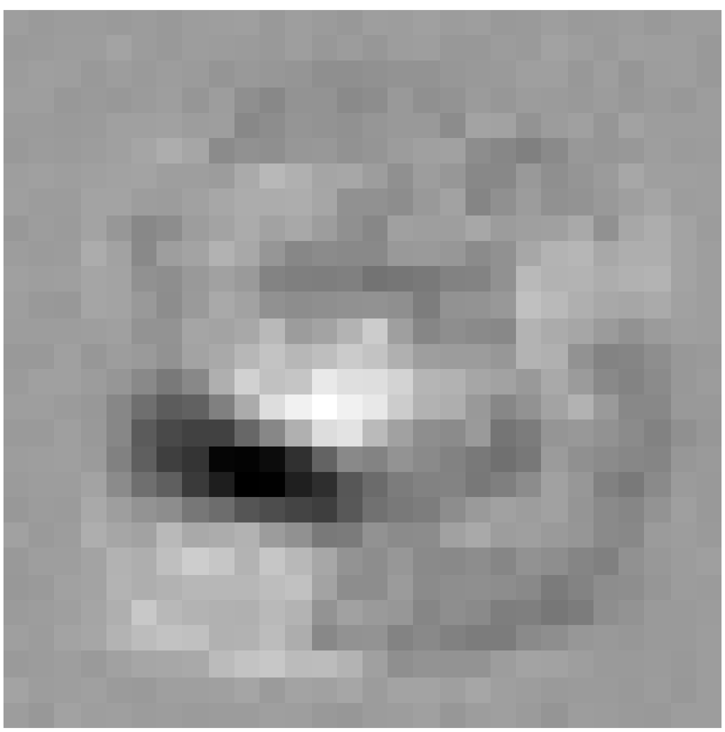
Data Augmentation:

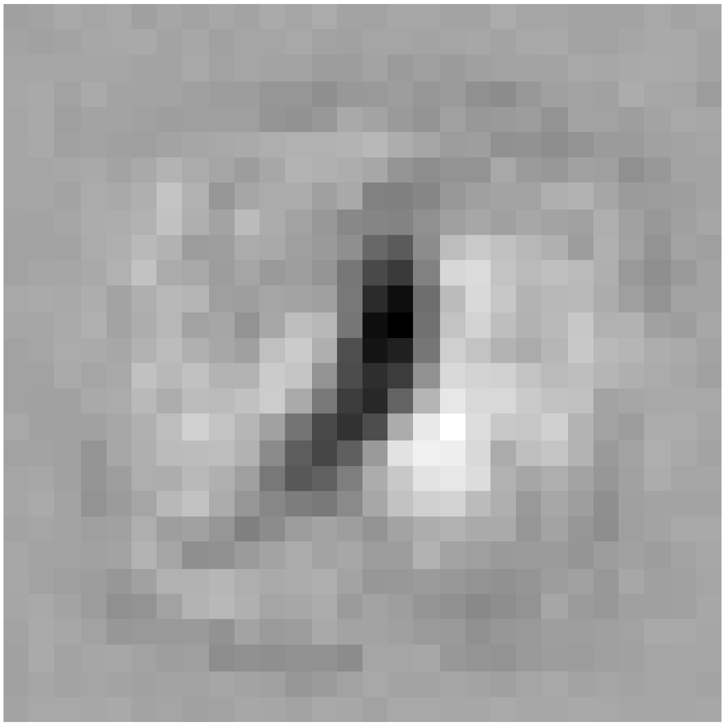
Apply data augmentation techniques to the training set. This can artificially increase the size of your dataset and help the model generalize better.

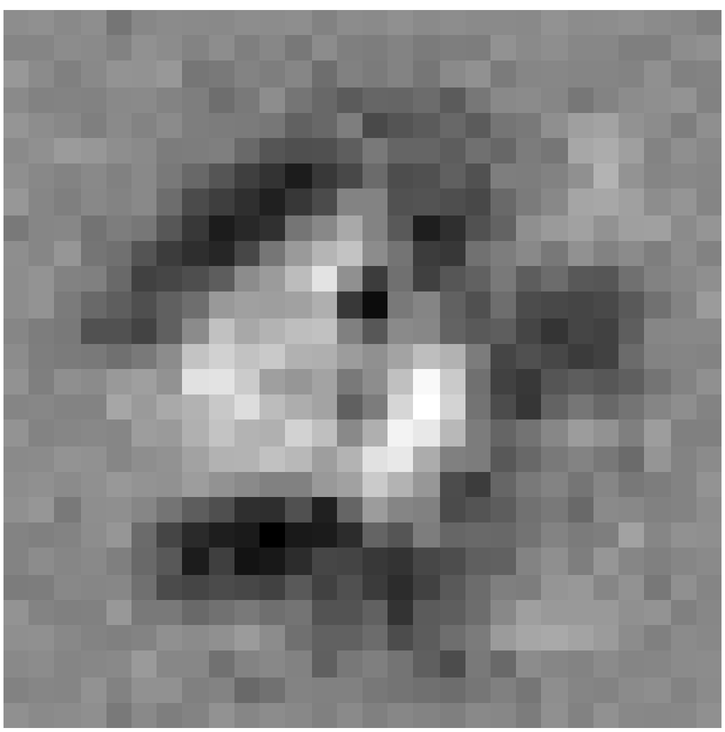
```
# Visualize some weights. features of digits should be somehow
present.
def show_net_weights(params):
    W1 = params['W1']
    print(W1.shape)
    for i in range(5):
        W = W1[:,i*5].reshape(28, 28)
        plt.imshow(W,cmap='gray')
        plt.axis('off')
        plt.show()

show_net_weights(net_params)
```

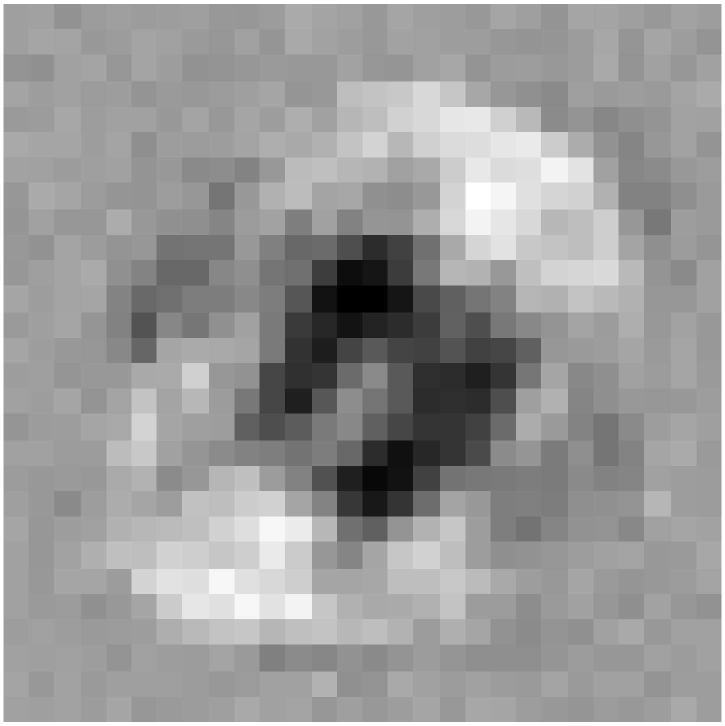
```
(784, 128)
```











Implement, train and test the same two-layer network, using a **deep learning library** (pytorch/tensorflow/keras).

As before, you should be able to receive at least 97% accuracy.

Please note, that in this section you will need to implement the model, the training and the testing by yourself (you may use the code in earlier sections) Don't forget to print the accuracy during training (in the same format as before).

For installing a deep learning library, you should use "!pip3 install..." (lookup the compatible syntex for your library)

MY CODE

```
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch import optim
from torch.optim.lr_scheduler import ReduceLROnPlateau
from torchvision import datasets, transforms
from torch.utils.data.sampler import SubsetRandomSampler
from tqdm.notebook import tqdm
import matplotlib.pyplot as plt

# check if GPU is available
train_on_gpu = torch.cuda.is_available()
```

```
if train_on_gpu:
    print('Training on GPU.')
else:
    print('No GPU available, training on CPU.')

# Define a transform to normalize the data
transform = transforms.Compose([transforms.ToTensor(),
transforms.Normalize((0.5,), (0.5,))])

# Download and load the training data
train_data = datasets.MNIST('~/.pytorch/MNIST_data/', download=True,
train=True, transform=transform)
trainloader = torch.utils.data.DataLoader(train_data, batch_size=58,
shuffle=True)

# Download and load the test data
test_data = datasets.MNIST('~/.pytorch/MNIST_data/', download=True,
train=False, transform=transform)
testloader = torch.utils.data.DataLoader(test_data, batch_size=58,
shuffle=True)

# Define the two-layer neural network model
class TwoLayerNet(nn.Module):
    def __init__(self):
        super(TwoLayerNet, self).__init__()
        self.fc1 = nn.Linear(28 * 28, 128)
        self.fc2 = nn.Linear(128, 10)  # Output size is 10 (for 10
classes)

    def forward(self, x):
        x = x.view(x.shape[0], -1)  # Flatten the input images
        x = F.sigmoid(self.fc1(x))  # Apply sigmoid activation
function
        x = F.softmax(self.fc2(x), dim=1)  # Apply softmax activation
function
        return x

# Create an instance of the model
model = TwoLayerNet()

# Move the model to GPU if available
if train_on_gpu:
    model.cuda()

# Define the optimizer and the loss function
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.1)

# Set up learning rate scheduler
```

```
scheduler = ReduceLROnPlateau(optimizer, mode='max', factor=0.1,
patience=3, verbose=True)

# Training loop
def train(model, train_loader, optimizer, criterion, scheduler,
target_accuracy=97, max_epochs=60):
    train_accuracy = []

    for epoch in range(1, max_epochs + 1):
        model.train()

        running_loss = 0.0
        correct = 0
        total = 0

        for images, labels in tqdm(train_loader, desc=f'Epoch
{epoch}/{max_epochs}'):
            if train_on_gpu:
                images, labels = images.cuda(), labels.cuda()

            optimizer.zero_grad()

            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            running_loss += loss.item()

            _, predicted = torch.max(outputs, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

        epoch_accuracy = 100 * correct / total
        train_accuracy.append(epoch_accuracy)

        print(f'Epoch {epoch}/{max_epochs}, Loss: {running_loss /
len(train_loader)}, Accuracy: {epoch_accuracy}%')

        # Check if the target accuracy is reached
        if epoch_accuracy >= target_accuracy:
            print(f'Target accuracy of {target_accuracy}% reached.
Stopping training.')
            break

        # Step the scheduler with the new accuracy
        scheduler.step(epoch_accuracy)

    return train_accuracy

# Testing loop
```

```python
def test(model, test_loader):
    model.eval()

    correct = 0
    total = 0

    with torch.no_grad():
        for images, labels in test_loader:
            if train_on_gpu:
                images, labels = images.cuda(), labels.cuda()

            outputs = model(images)
            _, predicted = torch.max(outputs, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

    test_accuracy = 100 * correct / total
    print(f'Test Accuracy: {test_accuracy}%')

# Train the model until it reaches 97% accuracy
train_accuracy = train(model, trainloader, optimizer, criterion,
scheduler, target_accuracy=97, max_epochs=60)

# Test the model
test(model, testloader)

# Plot training accuracy
plt.plot(range(1, len(train_accuracy) + 1), train_accuracy,
label='Train Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy (%)')
plt.legend()
plt.show()
```

```
Training on GPU.
```

{"model_id":"e88736cd7aec4331b3f21429ddd6ee8f","version_major":2,"version_minor":0}

```
Epoch 1/60, Loss: 2.078693259741373, Accuracy: 40.23%
```

{"model_id":"8e4fbacc80e64c608ec9ed2acefcedc2","version_major":2,"version_minor":0}

```
Epoch 2/60, Loss: 1.8003850208964325, Accuracy: 71.185%
```

{"model_id":"3ceb66afc6124f23a9ed21b56313b015","version_major":2,"version_minor":0}

```
Epoch 3/60, Loss: 1.6770114465612145, Accuracy: 82.315%
```

{"model_id":"b826d6397d6d4348b06055e22c832ef5","version_major":2,"version_minor":0}

Epoch 4/60, Loss: 1.6474023419301866, Accuracy: 83.6%

{"model_id":"fb0ebdf0d0c54fa1a892b2eb8a999931","version_major":2,"version_minor":0}

Epoch 5/60, Loss: 1.6003105574759884, Accuracy: 89.63833333333334%

{"model_id":"0e7c5ee0c1ce4841a38e543d47ec1825","version_major":2,"version_minor":0}

Epoch 6/60, Loss: 1.57740774811178, Accuracy: 90.845%

{"model_id":"9076e06370a540d081c2f09a8679fd93","version_major":2,"version_minor":0}

Epoch 7/60, Loss: 1.5669147962533334, Accuracy: 91.40666666666667%

{"model_id":"80f4dfd0e7504b1f93c7fc9e670c9fe0","version_major":2,"version_minor":0}

Epoch 8/60, Loss: 1.5598050450357261, Accuracy: 91.84%

{"model_id":"4d7c61617ded4c09a92cd3a07c84da05","version_major":2,"version_minor":0}

Epoch 9/60, Loss: 1.5543581130999873, Accuracy: 92.25666666666666%

{"model_id":"f24ae861e47b4c40a3b7cb3f2a94f8c2","version_major":2,"version_minor":0}

Epoch 10/60, Loss: 1.5502034522485042, Accuracy: 92.56666666666666%

{"model_id":"f2ab6f89f7ad432daecc3303ab72c503","version_major":2,"version_minor":0}

Epoch 11/60, Loss: 1.5465439456672485, Accuracy: 92.79%

{"model_id":"3bac658368d44fed912f996cb2d9d2ef","version_major":2,"version_minor":0}

Epoch 12/60, Loss: 1.5433769561242365, Accuracy: 93.04166666666667%

{"model_id":"09943becd96a4b0f947075b4d9d432de","version_major":2,"version_minor":0}

Epoch 13/60, Loss: 1.5403717626120157, Accuracy: 93.32%

{"model_id":"a25faa15065f4939a83e86d068c3f7d5","version_major":2,"version_minor":0}

Epoch 14/60, Loss: 1.5378761285745004, Accuracy: 93.495%

{"model_id":"a954fdce79644db0926250051537b990","version_major":2,"version_minor":0}

Epoch 15/60, Loss: 1.5355713112918652, Accuracy: 93.67666666666666%

{"model_id":"c7692296bbf44182ac5c7c711af3dd69","version_major":2,"version_minor":0}

Epoch 16/60, Loss: 1.5333010341810143, Accuracy: 93.875%

{"model_id":"233b68fb6e0a4236a37cb159d43f00d2","version_major":2,"version_minor":0}

Epoch 17/60, Loss: 1.5313703050935903, Accuracy: 94.045%

{"model_id":"6adada6b9b514d2fa8a773afdb233a2c","version_major":2,"version_minor":0}

Epoch 18/60, Loss: 1.5294979097762547, Accuracy: 94.21166666666667%

{"model_id":"3e8c855a6ebd44318605cb8fbaacd491","version_major":2,"version_minor":0}

Epoch 19/60, Loss: 1.5277080408041028, Accuracy: 94.365%

{"model_id":"97a02c1a02cd4da0932d1c542384fdb5","version_major":2,"version_minor":0}

Epoch 20/60, Loss: 1.5260190441988517, Accuracy: 94.52%

{"model_id":"7c60b409464c47138bcb2d92533ff3b4","version_major":2,"version_minor":0}

Epoch 21/60, Loss: 1.5244866088968545, Accuracy: 94.635%

{"model_id":"7e286e40fdf64087bcecbcdae1634daf","version_major":2,"version_minor":0}

Epoch 22/60, Loss: 1.5229798029010422, Accuracy: 94.78333333333333%

{"model_id":"1a6c2f7978a34d1091c57a686d613e7b","version_major":2,"version_minor":0}

Epoch 23/60, Loss: 1.521647236427823, Accuracy: 94.88333333333334%

{"model_id":"a4f289aff68c44e49ac79e36f8204b64","version_major":2,"version_minor":0}

Epoch 24/60, Loss: 1.5203652125049905, Accuracy: 95.01833333333333%

{"model_id":"c32475b6278242e4963c238497055656","version_major":2,"version_minor":0}

Epoch 25/60, Loss: 1.5191903614191617, Accuracy: 95.125%

{"model_id":"5589412d06624905bf1887bc38beaacc","version_major":2,"version_minor":0}

Epoch 26/60, Loss: 1.5179720232452172, Accuracy: 95.24%

{"model_id":"7818e188f51946e384770b7ba21a63ac","version_major":2,"version_minor":0}

Epoch 27/60, Loss: 1.5168771059616752, Accuracy: 95.305%

{"model_id":"4f91fa5d3b374d31a1d332e20a0d1478","version_major":2,"version_minor":0}

Epoch 28/60, Loss: 1.515809092659881, Accuracy: 95.44333333333333%

{"model_id":"a5c8b76ddcfe46ab8652a014b52c2c24","version_major":2,"version_minor":0}

Epoch 29/60, Loss: 1.5148357914265802, Accuracy: 95.49166666666666%

{"model_id":"de871ab92475426f8cac6392ad71afa7","version_major":2,"version_minor":0}

Epoch 30/60, Loss: 1.513918185694782, Accuracy: 95.56833333333333%

{"model_id":"b002feff92ad4d29a7678dad3a271dc3","version_major":2,"version_minor":0}

Epoch 31/60, Loss: 1.5129747246774499, Accuracy: 95.63833333333334%

{"model_id":"dee99fef868f48ddb9b8a01bd0d621c6","version_major":2,"version_minor":0}

Epoch 32/60, Loss: 1.5121518965504597, Accuracy: 95.72%

{"model_id":"28d1187d44d84d59b96c38510105a7b4","version_major":2,"version_minor":0}

Epoch 33/60, Loss: 1.5112341270354634, Accuracy: 95.78166666666667%

{"model_id":"7bf310f269cb42c69067c03d6449afc2","version_major":2,"version_minor":0}

Epoch 34/60, Loss: 1.5103802336586847, Accuracy: 95.89333333333333%

{"model_id":"e0958f05a3884790b1564768b4be91b6","version_major":2,"version_minor":0}

Epoch 35/60, Loss: 1.5096614342380836, Accuracy: 95.94666666666667%

{"model_id":"0cb8f05cc7fe4ee2ad3fa50127352d22","version_major":2,"version_minor":0}

Epoch 36/60, Loss: 1.5088636110370286, Accuracy: 95.99%

{"model_id":"398f687077a648789cbadeefab84c3ce","version_major":2,"version_minor":0}

Epoch 37/60, Loss: 1.5081666611242985, Accuracy: 96.07666666666667%

{"model_id":"474d9b7af94f4cd4b775f6a43a65844d","version_major":2,"version_minor":0}

Epoch 38/60, Loss: 1.5074257141150138, Accuracy: 96.16833333333334%

{"model_id":"2fc777e2c7584b71881eb01ff02ea100","version_major":2,"version_minor":0}

Epoch 39/60, Loss: 1.506759120185594, Accuracy: 96.195%

{"model_id":"8a23562de29a45dc80f60246a20c138d","version_major":2,"version_minor":0}

Epoch 40/60, Loss: 1.5060676064468237, Accuracy: 96.27166666666666%

{"model_id":"49f1dd61df594a339735f29babd5eadb","version_major":2,"version_minor":0}

Epoch 41/60, Loss: 1.5054368605360318, Accuracy: 96.30166666666666%

{"model_id":"a4316f041ec8495a851b5c6312470ee0","version_major":2,"version_minor":0}

Epoch 42/60, Loss: 1.5047721217795846, Accuracy: 96.41333333333333%

{"model_id":"7eee5001ad3d4db1914783b060010af6","version_major":2,"version_minor":0}

Epoch 43/60, Loss: 1.5040893065180756, Accuracy: 96.45%

{"model_id":"5a2d8de91b874a319b99e529322efad3","version_major":2,"version_minor":0}

Epoch 44/60, Loss: 1.503465499854894, Accuracy: 96.515%

{"model_id":"a7bfb0ddd3be4dd9834bb2ed708f62c5","version_major":2,"version_minor":0}

Epoch 45/60, Loss: 1.50292389024283, Accuracy: 96.54666666666667%

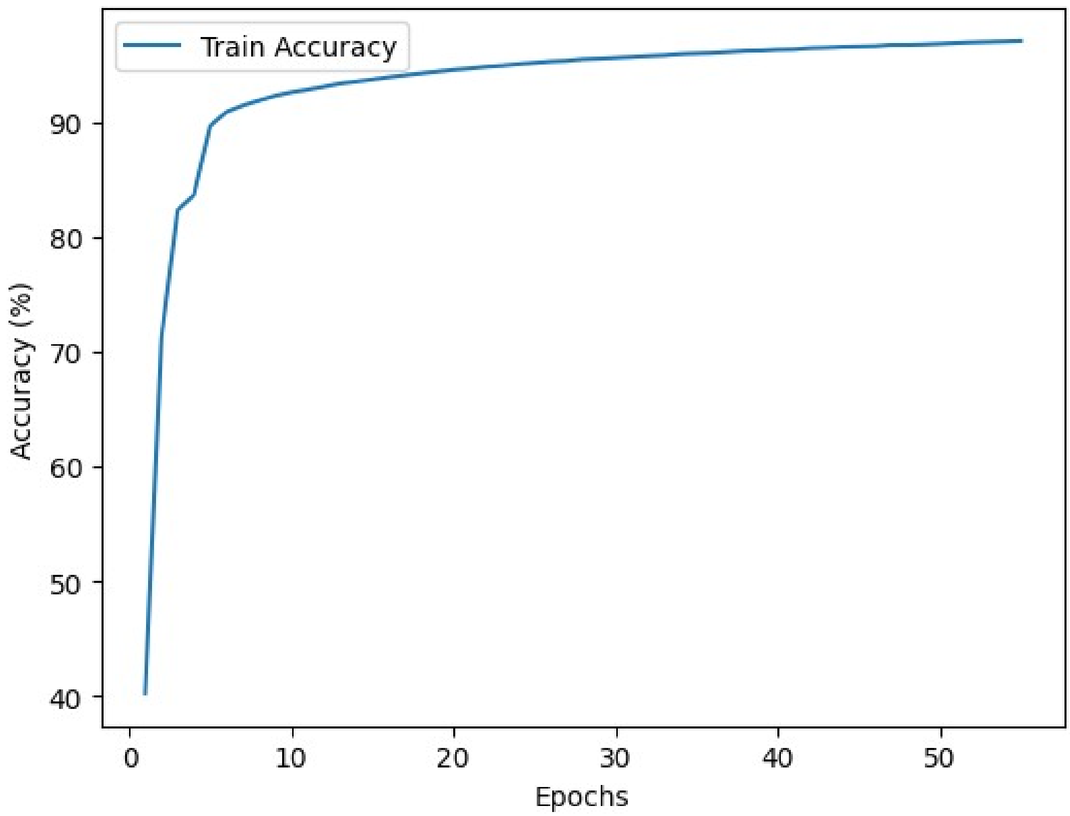
{"model_id":"88386035763c435088767f2115d9c46c","version_major":2,"version_minor":0}

Epoch 46/60, Loss: 1.502423764311749, Accuracy: 96.57833333333333%

{"model_id":"5d4c468390fb4667bf0a8eefb2d13f1f","version_major":2,"version_minor":0}

Epoch 47/60, Loss: 1.50179328860868, Accuracy: 96.68833333333333%

```
{"model_id":"d8d5d7cb5fad442fac70555cf73ba949","version_major":2,"version_minor":0}

Epoch 48/60, Loss: 1.5012381536373194, Accuracy: 96.69166666666666%

{"model_id":"72c7d2bcac0e4ef9b36e8c58a84faddd","version_major":2,"version_minor":0}

Epoch 49/60, Loss: 1.5007242580542817, Accuracy: 96.72666666666667%

{"model_id":"b438fdae53f746579ed0b0ef58506d6a","version_major":2,"version_minor":0}

Epoch 50/60, Loss: 1.5002722668762944, Accuracy: 96.79%

{"model_id":"3be4a78868c142ab9583f4d201758592","version_major":2,"version_minor":0}

Epoch 51/60, Loss: 1.499660228876676, Accuracy: 96.86%

{"model_id":"61bf01b106064a809472bdede1bc96b1","version_major":2,"version_minor":0}

Epoch 52/60, Loss: 1.49906821815288, Accuracy: 96.91666666666667%

{"model_id":"371e7bcac5c64dd48c6d117f346c8b08","version_major":2,"version_minor":0}

Epoch 53/60, Loss: 1.498663577941305, Accuracy: 96.955%

{"model_id":"6777b196ccd24555bc34c2997305ec04","version_major":2,"version_minor":0}

Epoch 54/60, Loss: 1.4981930539227915, Accuracy: 96.99666666666667%

{"model_id":"f26051a3a2ac49a1b4ad30bd8efd2c4e","version_major":2,"version_minor":0}

Epoch 55/60, Loss: 1.497764365684583, Accuracy: 97.04666666666667%
Target accuracy of 97% reached. Stopping training.
Test Accuracy: 96.32%
```


Train Accuracy
90
80
70
60
50
40
Accuracy (%)
0
10
20
30
40
50
Epochs