DELHI TECHNOLOGICAL UNIVERSITY



EE328 - Deep Learning and Artificial Neural Networks

Multiclass Classification (0-9 digits)

INNOVATIVE PROJECT REPORT SUBMITTED TO: Prof. Sudarshan Kumar Babu Valluru

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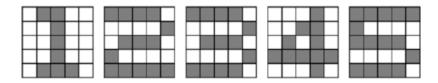
AIM

To perform Analysis of Multiclass Classification problem for image recognition model digits 0-9 for various activation functions using MATLAB.

Introduction

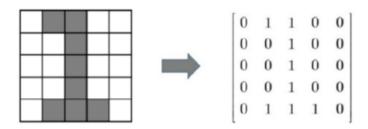
In this project, we've implemented a multiclass classifier network that recognizes digits from the input images.

The input image is considered as a black & white image with a resolution of 5X5 pixels.



For this project, we have created an array of 10 images, each representing a 5X5, 2D, Black & White image of digit from 0 to 9.

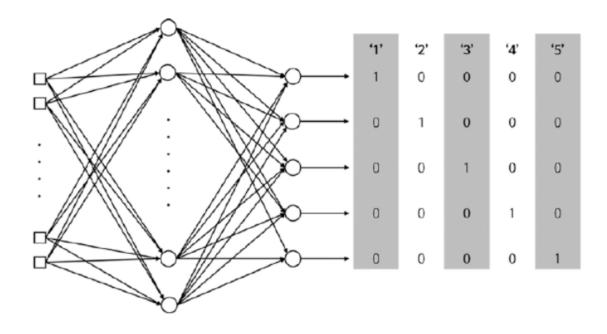
The input data X of the code is a two-dimensional matrix, which encodes the white pixel into a zero and the black pixel into a unity. For example, the image of the number 1 is encoded in the matrix shown



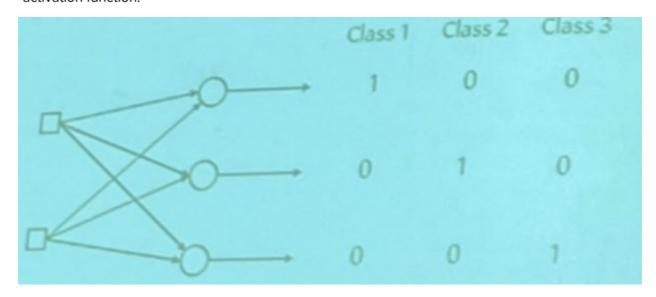
The variable D contains the correct output.

```
D = [
    1 0 0 0 0 0 0 0 0 0 0;
    0 1 0 0 0 0 0 0 0 0;
    0 0 1 0 0 0 0 0 0 0;
    0 0 1 0 0 0 0 0 0;
    0 0 0 1 0 0 0 0 0;
    0 0 0 1 0 0 0 0;
    0 0 0 0 1 0 0 0;
    0 0 0 0 0 1 0 0 0;
    0 0 0 0 0 0 1 0 0;
    0 0 0 0 0 0 1 0;
    0 0 0 0 0 0 0 1 0;
    0 0 0 0 0 0 0 0 1;
};
```

Neural Network Architecture



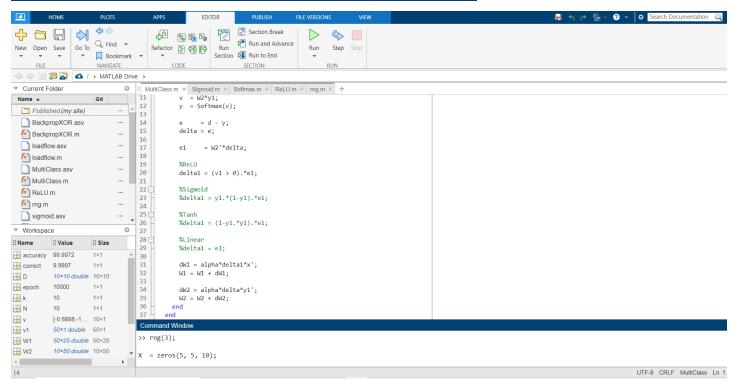
The neural network model contains a single hidden layer, as shown in above figure. As each image is set on a matrix, we set 25 input nodes. In addition, as we have 10 digits to classify(0, 1, ..., 9), the network contains 10 output nodes. The softmax function is used as the activation function of the output node. The hidden layer has 50 nodes and the sigmoid function is used as the activation function.



OBSERVATIONS

MultiClass.m

```
MultiClass.m × Sigmoid.m × Softmax.m × ReLU.m × rng.m × +
      function [W1, W2] = MultiClass(W1, W2, X, D)
 2
         alpha = 0.1;
 3
 4
        N = 10;
 5 😑
        for k = 1:N
 6
          x = reshape(X(:, :, k), 25, 1);
 7
          d = D(k, :)';
 8
 9
          v1 = W1*x;
10
         y1 = ReLU(v1);
11
          v = W2*y1;
          y = Softmax(v);
12
13
14
           e = d - y;
          delta = e;
15
16
           e1 = W2'*delta;
17
18
19
20
           delta1 = (v1 > 0).*e1;
21
22 🗀
           %Sigmoid
23
           delta1 = y1.*(1-y1).*e1;
24
25 E
           %Tanh
26
           delta1 = (1-y1.*y1).*e1;
27
```



Softmax.m

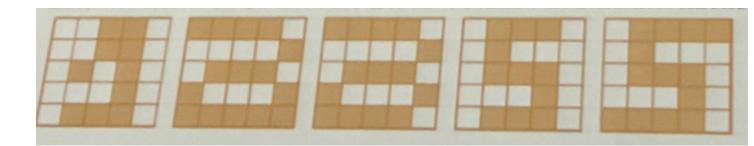
```
Here, in the cross entropy-driven learning rule that uses the softmax activation function, the delta and error are identical.

Even though the back-propagation algorithm applies to the hidden layer: e1 = W2'*delta;

delta1 = y1.*(1-y1).*e1;

The function Softmax, which the function MultiClass calls in, is implemented in the Softmax, m file.
```

TestMultiClass10.m



In order to test the ability of the trained Neural Network to recognize the digits, after training the NN using the correct data, we will give corrupted data as input.

In TestMultiClass10.m file, we have changed the input matrix for each digit, such that a 0 and a 1 have been swapped in the matrix for each digit, thus slightly altering the shape of the figure.

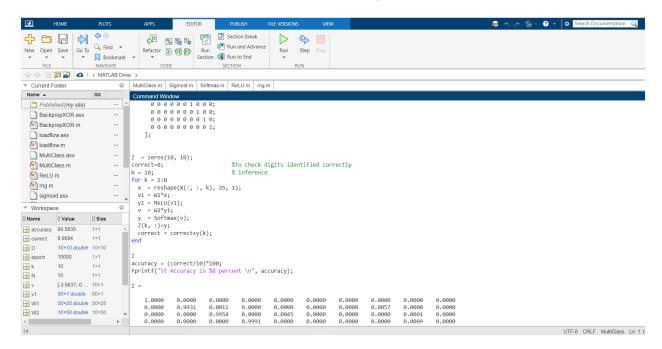
```
MultiClass.m Sigmoid.m Softmax.m ReLU.m rng.m
Command Window
>> rng(3);
X = zeros(5, 5, 10);
X(:, :, 1) = [01100;
            00100;
            00100;
            00100;
            0 1 1 1 0
X(:, :, 2) = [111110;
            00001;
            0 1 1 1 0;
            10000;
            1 1 1 1 1
           ];
X(:, :, 3) = [11110;
            00001;
            0 1 1 1 0;
            00001;
            1 1 1 1 0
           ];
X(:, :, 4) = [ 0 0 0 1 0;
            0 0 1 1 0;
            0 1 0 1 0;
            1 1 1 1 1;
             00010
MultiClass.m Sigmoid.m Softmax.m ReLU.m rng.m
Command Window
            1 1 1 1 1;
            00010
           ];
X(:, :, 5) = [11111;
            10000;
            1 1 1 1 0;
            00001;
            1 1 1 1 0
           ];
X(:, :, 6) = [11111;
            10000;
            1 1 1 1 1;
            10001;
            1 1 1 1 1
           ];
X(:, :, 7) = [11111;
            00010;
            00100;
            0 1 0 0 0;
            10000
X(:, :, 8) = [01110;
            10001;
            0 1 1 1 0;
            10001;
```

```
MultiClass.m Sigmoid.m Softmax.m ReLU.m rng.m
Command Window
           10001;
           01110
         ];
X(:, :, 9) = [ 0 1 1 1 0;
          10010;
           0 1 1 1 0;
           00010;
          00010
X(:, :, 10) = [0010];
                     %For Zero
           0 1 0 1 0;
           10001;
           0 1 0 1 0;
           00100
         ];
D = [ 1 0 0 0 0 0 0 0 0 0;
    0100000000;
    0010000000;
    0001000000;
    0000100000;
    0000010000;
    0000001000;
    0000000100;
    0000000010;
    0000000001;
   ];
```

```
MultiClass.m Sigmoid.m Softmax.m ReLU.m
                                  rng.m
Command Window
W1 = 2*rand(50, 25) - 1;
W2 = 2*rand(10, 50) - 1;
for epoch = 1:10000
                         % train
 [W1 W2] = MultiClass(W1, W2, X, D);
X(:, :, 1) = [ 0 0 1 1 0;
             00100;
             0 0 1 0 0;
             00100;
             0 1 1 1 0
           ];
X(:, :, 2) = [01110;
             00001;
             0 1 1 1 1;
             10000;
             1 1 1 1 1
           ];
X(:, :, 3) = [111110;
             00010;
             0 1 1 1 0;
             00001;
             1 1 1 1 0
           ];
X(:, :, 4) = [00010;
          00110
```

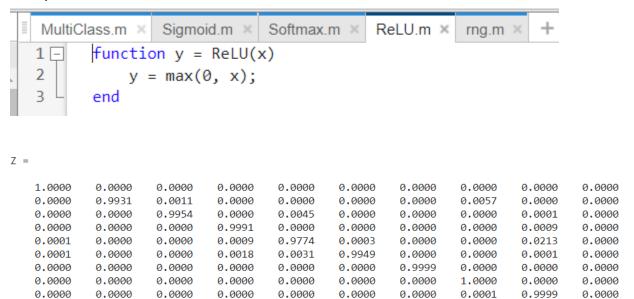
```
MultiClass.m Sigmoid.m Softmax.m R
Command Window
X(:, :, 4) = [00010;
             0 0 1 1 0;
             0 1 0 1 0;
            0 1 1 1 1;
             00011
           ];
X(:, :, 5) = [11111;
            10000;
            1 1 1 1 0;
            00010;
            1 1 1 1 0
           ];
X(:, :, 6) = [11111];
           10000;
            1 1 1 1 1;
            01001;
            1 1 1 1 1
X(:,:,7) = [01111;
            00010;
             00100;
            0 1 1 0 0;
            10000
           ];
X(:, :, 8) = [ 0 1 1 1 0;
             10001:
```

```
MultiClass.m Sigmoid.m Softmax.m ReLU.m rng
           1 0 0 0 1;
           0 1 1 1 0;
           10001;
           0 1 1 1 0
X(:, :, 9) = [ 0 1 1 1 0;
           10010;
           1 1 1 1 0;
           00010;
           00000
X(:, :, 10) = [00100;
                      %For Zero
            0 1 0 1 0;
            10010;
            0 1 0 1 0;
            00100
         ];
D = [ 1 0 0 0 0 0 0 0 0 0;
    01000000000;
    0010000000;
    0001000000;
    0000100000;
    0000010000;
    0000001000;
    0000000100;
    0000000010;
    0000000001:
```



1) ReLU

0.0000



0.0000

0.0000

0.0002

0.0001

Accuracy is 9.958355e+01 percent

0.0000

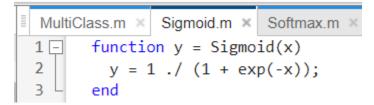
0.0000

0.0001

0.0009

0.9986

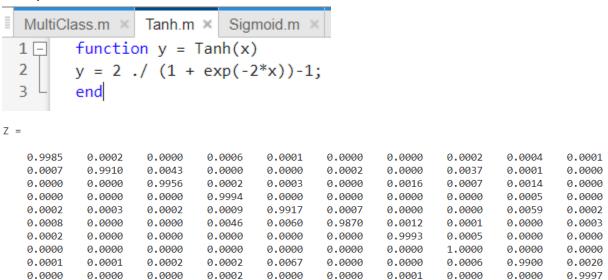
2) Sigmoid



```
Z =
    0.9989
              0.0003
                         0.0001
                                    0.0001
                                               0.0000
                                                         0.0000
                                                                    0.0001
                                                                               0.0002
                                                                                          0.0002
                                                                                                    0.0002
    0.0014
              0.9833
                         0.0013
                                    0.0000
                                               0.0000
                                                         0.0020
                                                                    0.0001
                                                                               0.0117
                                                                                          0.0000
                                                                                                    0.0001
    0.0000
              0.0001
                         0.9964
                                    0.0005
                                                         0.0000
                                                                    0.0011
                                                                                          0.0003
                                                                                                    0.0000
                                               0.0015
                                                                               0.0001
    0.0000
              0.0000
                         0.0000
                                    0.9995
                                               0.0000
                                                         0.0000
                                                                    0.0000
                                                                               0.0000
                                                                                          0.0004
                                                                                                    0.0001
    0.0002
               0.0002
                         0.0000
                                    0.0001
                                               0.9886
                                                         0.0005
                                                                    0.0000
                                                                               0.0000
                                                                                          0.0103
                                                                                                    0.0001
    0.0001
              0.0001
                         0.0000
                                    0.0004
                                               0.0059
                                                         0.9918
                                                                    0.0015
                                                                               0.0001
                                                                                          0.0000
                                                                                                    0.0000
    0.0005
              0.0000
                         0.0000
                                    0.0000
                                               0.0000
                                                         0.0000
                                                                    0.9994
                                                                               0.0000
                                                                                          0.0000
                                                                                                    0.0000
    0.0000
              0.0000
                         0.0001
                                    0.0000
                                                         0.0000
                                                                    0.0000
                                                                               0.9998
                                                                                          0.0000
                                                                                                    0.0000
                                               0.0000
    0.0000
              0.0000
                         0.0000
                                    0.0001
                                               0.0010
                                                         0.0000
                                                                    0.0000
                                                                               0.0003
                                                                                          0.9980
                                                                                                    0.0005
    0.0000
               0.0000
                         0.0000
                                    0.0002
                                               0.0000
                                                         0.0000
                                                                    0.0000
                                                                               0.0000
                                                                                          0.0002
                                                                                                    0.9995
```

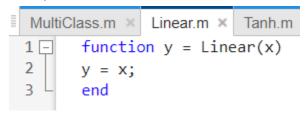
Accuracy is 9.955231e+01 percent

3) tanh



Accuracy is 9.952102e+01 percent

4) Linear



Ζ	=

1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.9987	0.0000	0.0000	0.0000	0.0013	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

Accuracy is 9.998687e+01 percent

RESULTS AND CONCLUSION

The Accuracy for various activation functions in this case was found to be:

S.No.	FUNCTION	ACCURACY
1.	ReLU	99.58355%
2.	Sigmoid	99.55231%
3.	Tanh	99.52102%
4.	Linear	99.98687%

In this case, the Linear Activation Function is found to be the most accurate. However, it may not always be the most accurate activation function in all cases since accuracy will vary from case to case depending upon the training data and other factors.

Since, for all Activation functions, the accuracy is above 99.5%. Hence, the experiment has been conducted successfully.

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