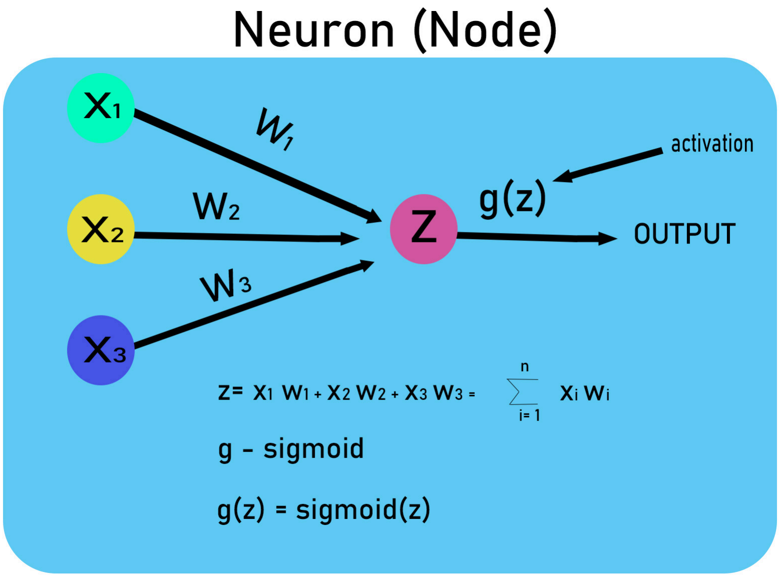
Implementation of neural network from scratch using NumPy

Last Updated : 11 Apr, 2025

Neural networks are a core component of deep learning models, and implementing them from scratch is a great way to understand their inner workings. we will demonstrate how to implement a basic Neural networks algorithm from scratch using the **NumPy** library in Python, focusing on building a three-letter classifier for the characters A, B, and C.



A neural network is a computational model inspired by the way biological neural networks process information. It consists of layers of interconnected nodes, called **neurons**, which transform input data into output. A typical neural network consists of:

- **Input Layer (X_1, X_2, X_3)** : Takes the features of the data as input.
- **Hidden Layers (Z)** : Layers between the input and output that perform transformations based on weights.
- **Output Layer**: Produces the final prediction.

Python Implementation

Step 1 : Creating the Dataset Using NumPy Arrays of 0s and 1s

As the image is a collection of pixel values in matrix, we will create a simple dataset for the letters A, B, and C using binary matrices. These matrices represent pixel values of 5x6 grids for each letter.

```
# Creating data set

# A
a =[0, 0, 1, 1, 0, 0,
   0, 1, 0, 0, 1, 0,
   1, 1, 1, 1, 1, 1,
   1, 0, 0, 0, 0, 1,
   1, 0, 0, 0, 0, 1]
# B
b =[0, 1, 1, 1, 1, 0,
   0, 1, 0, 0, 1, 0,
   0, 1, 1, 1, 1, 0,
   0, 1, 0, 0, 1, 0,
   0, 1, 1, 1, 1, 0]
# C
c =[0, 1, 1, 1, 1, 0,
   0, 1, 0, 0, 0, 0,
   0, 1, 0, 0, 0, 0,
   0, 1, 0, 0, 0, 0,
   0, 1, 1, 1, 1, 0]

# Creating labels
y =[[1, 0, 0],
   [0, 1, 0],
   [0, 0, 1]]
```

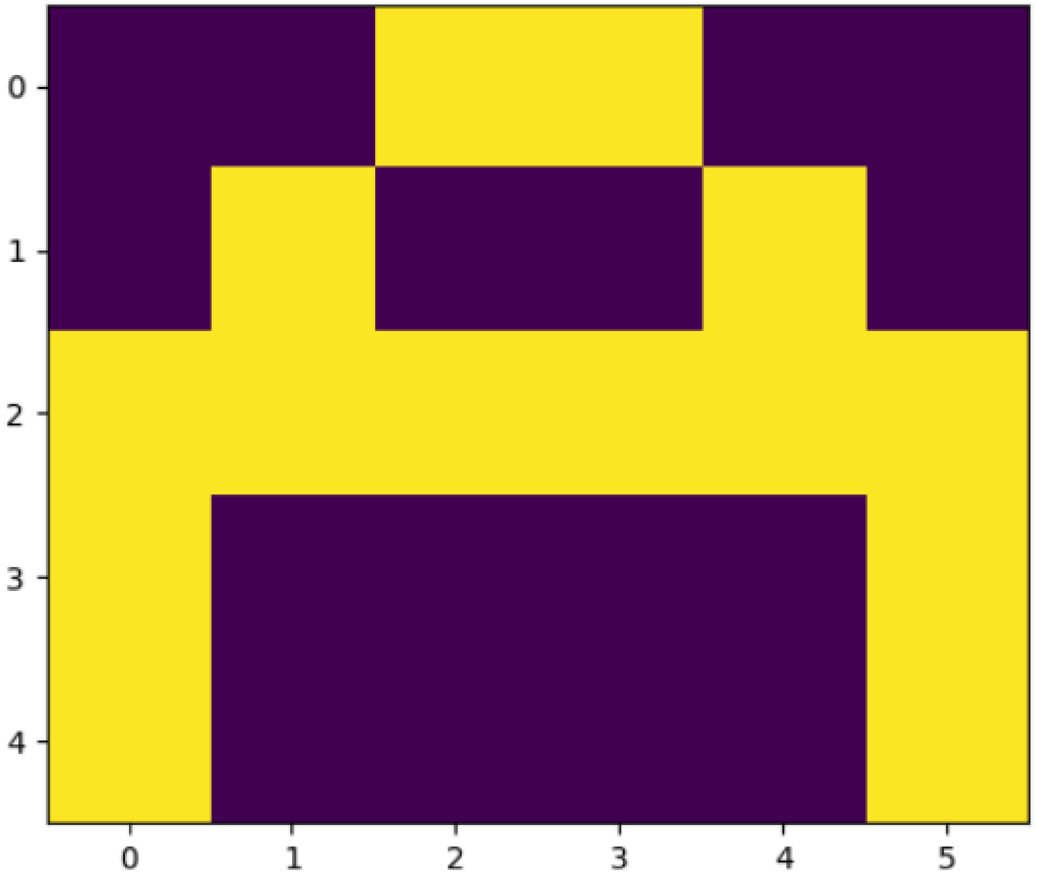
Step 2 : Visualizing the Dataset

To visualize the datasets, we can use **Matplotlib** to plot the images for each letter. This will give us a clear understanding of what the data looks like before feeding it into the neural network.

```
import numpy as np
import matplotlib.pyplot as plt

# visualizing the data, plotting A.
plt.imshow(np.array(a).reshape(5, 6))
plt.show()
```

Output



Visualizing the Data

Step 3 : As the data set is in the form of list we will convert it into numpy array.

We convert the lists of pixel values and the corresponding labels into **NumPy arrays** to work with them efficiently in the neural network.

```
# converting data and labels into numpy array
x =[np.array(a).reshape(1, 30), np.array(b).reshape(1, 30),
                                np.array(c).reshape(1, 30)]

y = np.array(y)
# Printing data and labels
```

```
print(x, "\n\n", y)
```

Output

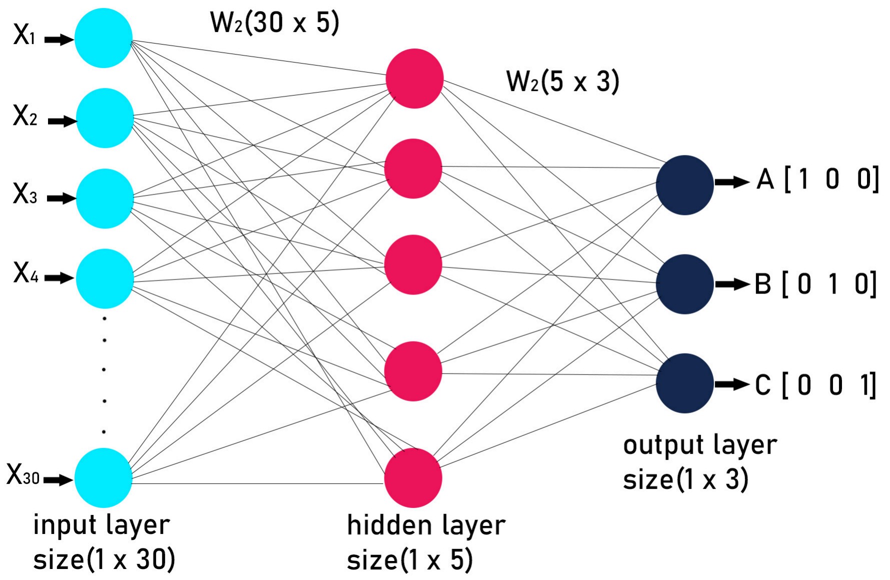
```
[array([[0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1,
1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1]]),
 array([[0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0,
0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0]]),
 array([[0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0]])]

[[1 0 0]
[0 1 0]
[0 0 1]]
```

Step 4: Defining the Architecture of the Neural Network

Our neural network will have the following structure:

- **Input Layer**: 1 layer with 30 nodes (representing the 5x6 grid).
- **Hidden Layer**: 1 layer with 5 nodes.
- **Output Layer**: 1 layer with 3 nodes (representing the letters A, B, and C).



Step 5: Defining the Neural Network Functions

Here, we will define the key components of the neural network:

- **Activation Function**: We'll use the **sigmoid** activation function.
- **Feedforward Process**: Computes the output by passing the input through the layers.
- **Backpropagation**: Updates weights to minimize the loss.
- **Loss Function**: We’ll use **Mean Squared Error (MSE)** to compute the loss.

```
# activation function
def sigmoid(x):
    return(1/(1 + np.exp(-x)))

# Creating the Feed forward neural network
def f_forward(x, w1, w2):
    # hidden
    z1 = x.dot(w1)     # input from layer 1
    a1 = sigmoid(z1)  # out put of layer 2
    z2 = a1.dot(w2)   # input of out layer
    a2 = sigmoid(z2)  # output of out layer
    return(a2)

# initializing the weights randomly
def generate_wt(x, y):
    li =[]
    for i in range(x * y):
        li.append(np.random.randn())
    return(np.array(li).reshape(x, y))

# for loss we will be using mean square error(MSE)
def loss(out, Y):
    s =(np.square(out-Y))
    s = np.sum(s)/len(y)
    return(s)

# Back propagation of error
def back_prop(x, y, w1, w2, alpha):

    # hidden layer
    z1 = x.dot(w1)
    a1 = sigmoid(z1)
    z2 = a1.dot(w2)
    a2 = sigmoid(z2)
    # error in output layer
    d2 =(a2-y)
    d1 = np.multiply((w2.dot((d2.transpose()))).transpose(),
                                (np.multiply(a1, 1-a1)))
    # Gradient for w1 and w2
    w1_adj = x.transpose().dot(d1)
    w2_adj = a1.transpose().dot(d2)

    # Updating parameters
    w1 = w1-(alpha*(w1_adj))
    w2 = w2-(alpha*(w2_adj))

    return(w1, w2)
```

Step 6: Initializing Weights

We initialize the weights for both the hidden layer and the output layer randomly.

```
w1 = generate_wt(30, 5)
w2 = generate_wt(5, 3)

print(w1, "\n\n", w2)
```

Output

```
[[ 0.75696605 -0.15959223 -1.43034587  0.17885107 -0.75859483]
 [-0.22870119  1.05882236 -0.15880572  0.11692122  0.58621482]
 [ 0.13926738  0.72963505  0.36050426  0.79866465 -0.17471235]
 [ 1.00708386  0.68803291  0.14110839 -0.7162728   0.69990794]
 [-0.90437131  0.63977434 -0.43317212  0.67134205 -0.9316605 ]
 [ 0.15860963 -1.17967773 -0.70747245  0.22870289  0.00940404]
 [ 1.40511247 -1.29543461  1.41613069 -0.97964787 -2.86220777]
 [ 0.66293564 -1.94013093 -0.78189238  1.44904122 -1.81131482]
 [ 0.4441061  -0.18751726 -2.58252033  0.23076863  0.12182448]
 [-0.60061323  0.39855851 -0.55612255  2.0201934   0.70525187]
 [-1.82925367  1.32004437  0.03226202 -0.79073523 -0.20750692]
 [-0.25756077 -1.37543232 -0.71369897 -0.13556156 -0.34918718]
 [ 0.26048374  2.49871398  1.01139237 -1.73242425 -0.67235417]
 [ 0.30351062 -0.45425039 -0.84046541 -0.60435352 -0.06281934]
 [ 0.43562048  0.66297676  1.76386981 -1.11794675  2.2012095 ]
 [-1.11051533  0.3462945   0.19136933  0.19717914 -1.78323674]
 [ 1.1219638  -0.04282422 -0.0142484  -0.73210071 -0.58364205]
 [-1.24046375  0.23368434  0.62323707 -1.66265946 -0.87481714]
 [ 0.19484897  0.12629217 -1.01575241 -0.47028007 -0.58278292]
 [ 0.16703418 -0.50993283 -0.90036661  2.33584006  0.96395524]
 [-0.72714199  0.39000914 -1.3215123   0.92744032 -1.44239943]
 [-2.30234278 -0.52677889 -0.09759073 -0.63982215 -0.51416013]
 [ 1.25338899 -0.58950956 -0.86009159 -0.7752274   2.24655146]
 [ 0.07553743 -1.2292084   0.46184872 -0.56390328  0.15901276]
 [-0.52090565 -2.42754589 -0.78354152 -0.44405857  1.16228247]
 [-1.21805132 -0.40358444 -0.65942185  0.76753095 -0.19664978]
 [-1.5866041   1.17100962 -1.50840821 -0.61750557  1.56003127]
 [ 1.33045269 -0.85811272  1.88869376  0.79491455 -0.96199293]
 [-2.34456987  0.1005953  -0.99376025 -0.94402235 -0.3078695 ]
 [ 0.93611909  0.58522915 -0.15553566 -1.03352997 -2.7210093 ]]

 [[-0.50650286 -0.41168428 -0.7107231 ]
 [ 1.86861492 -0.36446849  0.97721539]
 [-0.12792125  0.69578056 -0.6639736 ]
 [ 0.58190462 -0.98941614  0.40932723]
 [ 0.89758789 -0.49250365 -0.05023684]]
```

Step 7: Training the Model

Now that we've defined the structure, functions, and initialized the weights, we can train the model using the **train** function. This function will update the weights through backpropagation for a specified number of epochs.

```
def train(x, Y, w1, w2, alpha = 0.01, epoch = 10):
    acc =[]
    losss =[]
    for j in range(epoch):
        l =[]
        for i in range(len(x)):
            out = f_forward(x[i], w1, w2)
            l.append((loss(out, Y[i])))
            w1, w2 = back_prop(x[i], y[i], w1, w2, alpha)
        print("epochs:", j + 1, "======== acc:", (1-
(sum(l)/len(x)))*100)
        acc.append((1-(sum(l)/len(x)))*100)
        losss.append(sum(l)/len(x))
    return(acc, losss, w1, w2)

acc, losss, w1, w2 = train(x, y, w1, w2, 0.1, 100)
```

Step 8: Plotting Accuracy and Loss

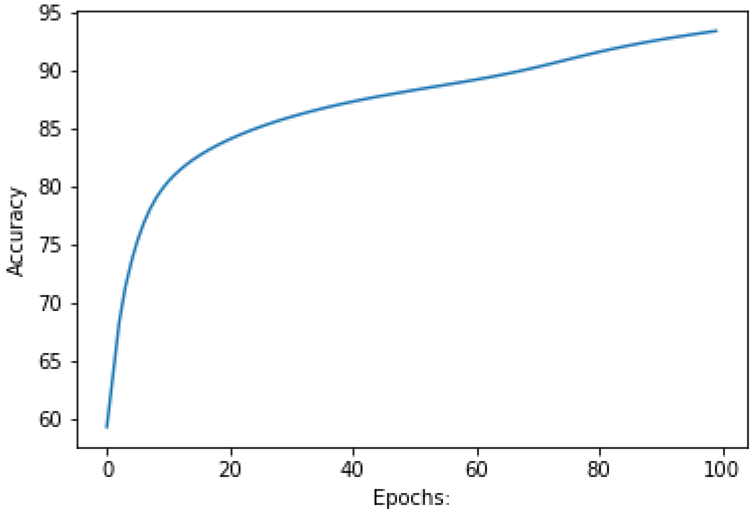
After training, we can visualize the **accuracy** and **loss** over the epochs to understand the model's learning process.

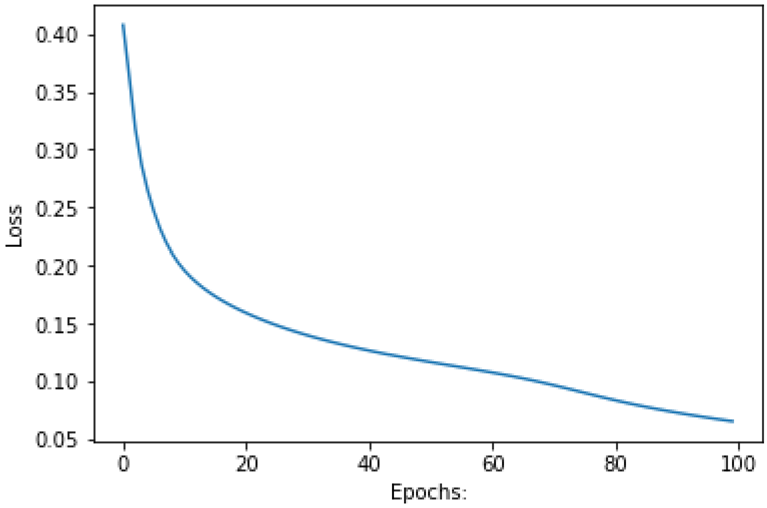
```
import matplotlib.pyplot as plt1

# plotting accuracy
plt1.plot(acc)
plt1.ylabel('Accuracy')
plt1.xlabel("Epochs:")
plt1.show()

# plotting Loss
plt1.plot(losss)
plt1.ylabel('Loss')
plt1.xlabel("Epochs:")
plt1.show()
```

Output





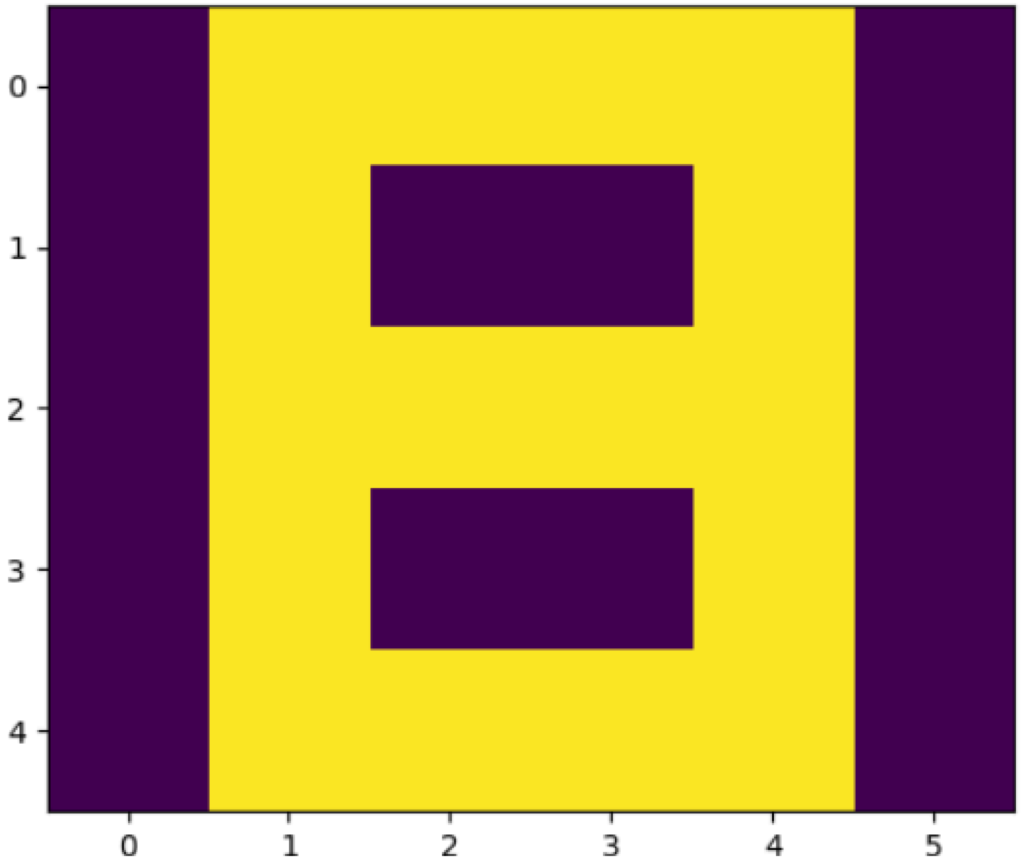
Step 9: Making Predictions

We use the trained weights to predict the letter class for a new input. The class with the highest output value is chosen as the predicted class.

```
def predict(x, w1, w2):
    Out = f_forward(x, w1, w2)
    maxm = 0
    k = 0
    for i in range(len(Out[0])):
        if(maxm<Out[0][i]):
            maxm = Out[0][i]
            k = i
    if(k == 0):
        print("Image is of letter A.")
    elif(k == 1):
        print("Image is of letter B.")
    else:
        print("Image is of letter C.")
    plt.imshow(x.reshape(5, 6))
    plt.show()
# Example: Predicting for letter 'B'
predict(x[1], w1, w2)
```

Output

```
Image is of letter B.
```



Predicted Image

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