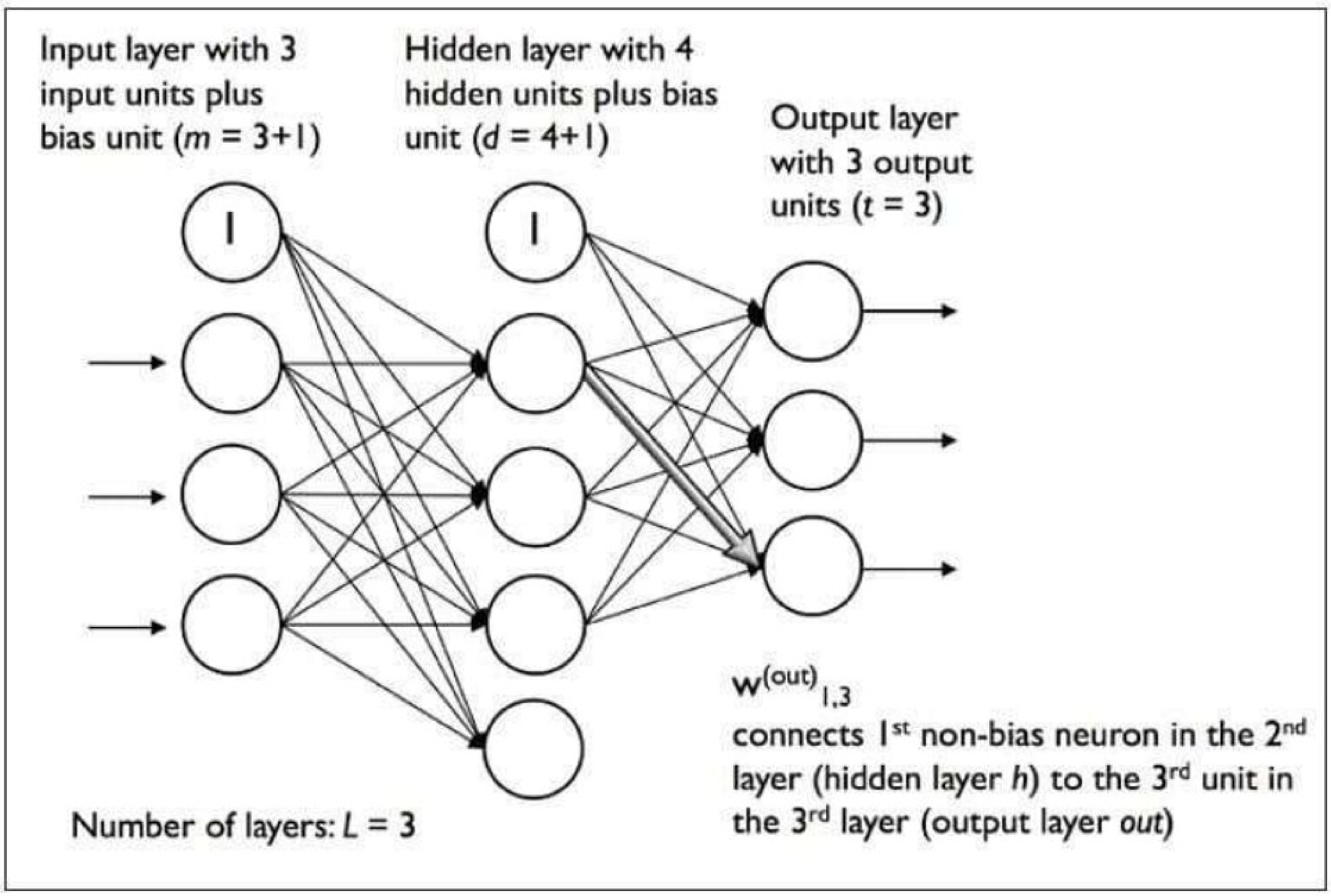
Experiment No. 2
Implement Multilayer Perceptron algorithm to simulate XOR gate
Date of Performance:
Date of Submission:

Aim: Implement Multilayer Perceptron algorithm to simulate XOR gate.

Objective: Ability to perform experiments on different architectures of multilayer perceptrons.

Theory:

a multilayer artificial neuron network is an integral part of deep learning. And this lesson will help you with an overview of multilayer ANN along with overfitting and underfitting.



A fully connected multi-layer neural network is called a Multilayer Perceptron (MLP).

At has 3 layers including one hidden layer. If it has more than 1 hidden layer, it is called a deep ANN. An MLP is a typical example of a feedforward artificial neural network. In this figure, the ith activation unit in the lth layer is denoted as ai(l).

The number of layers and the number of neurons are referred to as hyperparameters of a neural network, and these need tuning. Cross-validation techniques must be used to find ideal values for these.

The weight adjustment training is done via backpropagation. Deeper neural networks are better at processing data. However, deeper layers can lead to vanishing gradient problems. Special algorithms are required to solve this issue.

A multilayer perceptron (MLP) is a feed forward artificial neural network that generates a set of outputs from a set of inputs. An MLP is characterized by several layers of input nodes connected as a directed graph between the input nodes connected as a directed graph between the input and output layers. MLP uses backpropagation for training the network. MLP is a deep learning method.

Code: -

```
import numpy as np

def unitStep(v):

        if v >= 0:

                return 1

        else:

                return 0

def perceptronModel(x, w, b):

        v = np.dot(w, x) + b

        y = unitStep(v)

        return y

def NOT_logicFunction(x):

        wNOT = -1
```

```
    bNOT = 0.5
    return perceptronModel(x, wNOT, bNOT)
def AND_logicFunction(x):
    w = np.array([1, 1])
    bAND = -1.5
    return perceptronModel(x, w, bAND)
def OR_logicFunction(x):
    w = np.array([1, 1])
    bOR = -0.5
    return perceptronModel(x, w, bOR)
def XOR_logicFunction(x):
    y1 = AND_logicFunction(x)
    y2 = OR_logicFunction(x)
    y3 = NOT_logicFunction(y1)
    final_x = np.array([y2, y3])
    finalOutput = AND_logicFunction(final_x)
    return finalOutput
test1 = np.array([0, 1])
test2 = np.array([1, 1])
test3 = np.array([0, 0])
test4 = np.array([1, 0])
print("XOR({}, {}) = {}".format(0, 1, XOR_logicFunction(test1)))
print("XOR({}, {}) = {}".format(1, 1, XOR_logicFunction(test2)))
print("XOR({}, {}) = {}".format(0, 0, XOR_logicFunction(test3)))
print("XOR({}, {}) = {}".format(1, 0, XOR_logicFunction(test4)))
```

Output: -

```
PS C:\Users\admin> & C:/Users/admin/AppData/Local/Microsoft/WindowsApps/python3.11.exe c:/Users/admin/Documents/Priyanshu_ai/xor.py
XOR(0, 1) = 1
XOR(1, 1) = 0
XOR(0, 0) = 0
XOR(1, 0) = 1
PS C:\Users\admin>
```

Conclusion:

Implementing a multilayer perceptron to simulate the XOR gate demonstrates the power of neural networks in solving non-linear problems, highlighting the importance of activation functions and backpropagation for successful learning. This basic example lays the groundwork for understanding more complex tasks and applications of artificial neural networks.