# **MLP Implementation on Iris Dataset**

#### 1. Case Explanation

In our previous assignments, we implemented an SLP model of feedforward artificial neural network. That is, a neural network that consists of an input layer and an output layer. Though the implementation is simpler, an SLP typically fails in reaching certain accuracy standards. In this case a multiple layer of classification is necessary to gain a more accurate prediction. By principle, each layer added in a feed-forward multi-layer perceptron adds a new level of non-linearity that is not possible in a single layer.

For this assignment, we will be implementing a Multi-Layer Perceptron on the Iris dataset. Inside this dataset, there are 4 input layers that will be used (sepal/petal width and length). There will be only one additional hidden layer that will be put in between the Input layer and the Output layer, as illustrated by *Figure 1*.

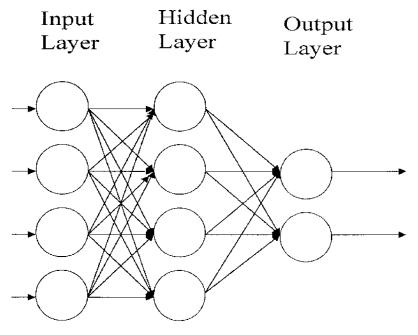


Figure 1.

## 2. Implementation

In writing the code, the language that was used in this assignment was Python (version 3.7.1). It was written in the Sublime text editor and was tested in the cmd.

https://github.com/andkwv/MPL\_Iris

### 3. Experiment & Result

#### Running the code:

The model will be trained and validated by using the split method. Out of the 150 tuples in the dataset, 30 will be set aside randomly for validation. The rest, 120, will be used for training the model. This time, our model will go through 200 epochs of training.

Figure 2.

#### 4. Result:

As expected, this model was able to converge at much better accuracy compared to the Single-Layer implementation. The model was able to predict the category of Iris with almost perfect accuracy (96 %). This value happens in both the training data and the validation data.

However, though the accuracy is satisfactory, there are inconsistencies in performance. For example, one instance of running may see that the model converges on a 60-70% accuracy (*Figure 5.*), while others show convergence at different rates. We can conclude that this is caused by the varying number of initialization values. Because of unrestricted random values of 0 until 1, the performance of the model will vary greatly.

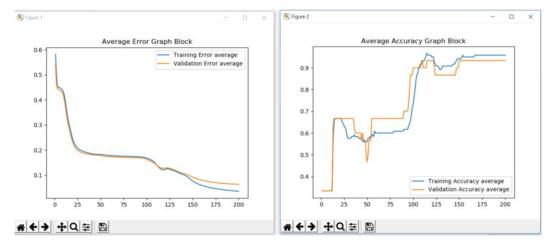


Figure 3.

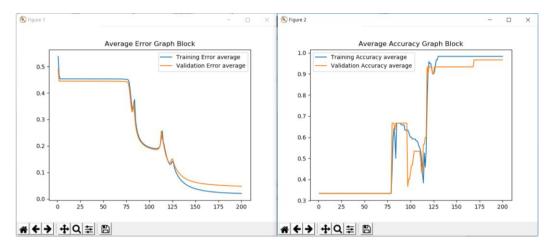


Figure 4.

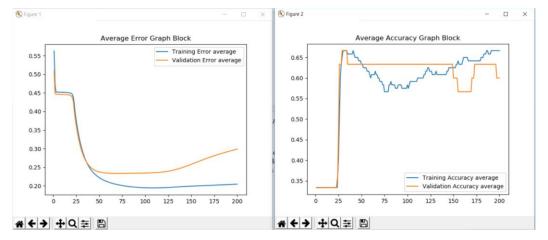


Figure 5

# 5. Conclusion

Through our results, we can conclude that the performance of the MLP model can predict with better accuracy compared to single layer type of model. However, the random initial values will greatly affect the performance of the model. There comes a need to restrict the initial random values for the input.