

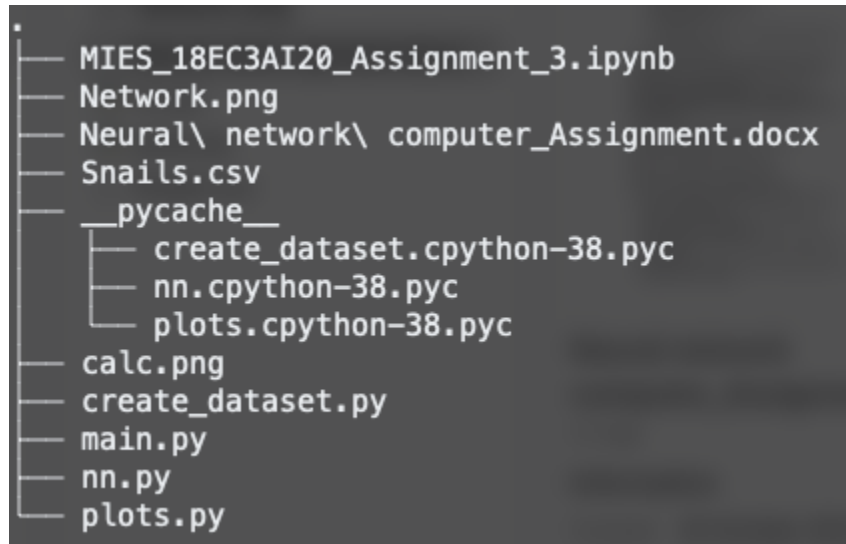
Name - Abhisek Mohanty

Roll - 18EC3AI20

## MIES Coding Assignment README file

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### Details about the folder contents

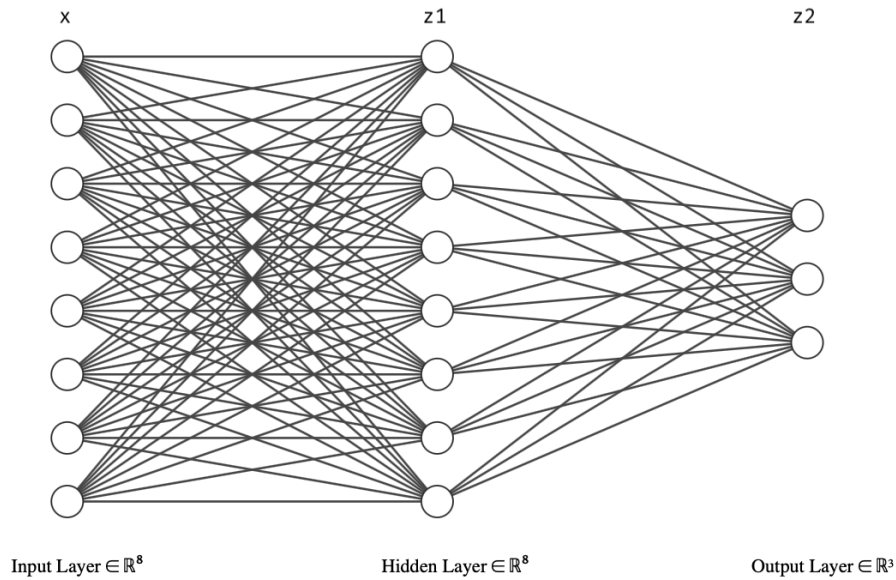


1. **main.py** - The main python file to execute
2. **nn.py** - The file contains the class for Neural network
3. **plots.py** - This contains the functions to do the scatter plots of the dataset
4. **create\_dataset.py** - This contains the function to split the dataset into train and test
5. **MIES\_18EC3AI20\_Assignment\_3.ipynb** - This is python notebook with all outputs
6. **Snails.csv** - The dataset

### Steps to run

1. Open the IPython notebook to get the results.
2. Using terminal -> \$ **python main.py**

## Neural network architecture and the governing equations



### Forward pass

$$a_1 = W_1 x + b_1$$

$$z_1 = \sigma(a_1)$$

$$a_2 = W_2 z_1 + b_2$$

$$z_2 = \sigma(a_2)$$

Thus the predicted output is  $z_2$

### Backpropagation

$Loss(J) = \frac{1}{2}(z_2 - y)^2$ ; where  $y$  is the actual label

$$\frac{\partial J}{\partial z_2} = z_2 - y$$

$$\frac{\partial J}{\partial a_2} = \frac{\partial J}{\partial z_2} \times \frac{\partial z_2}{\partial a_2} = (z_2 - y) \times \sigma(a_2) \times (1 - \sigma(a_2))$$

$$\frac{\partial J}{\partial W_2} = \frac{\partial J}{\partial a_2} \times \frac{\partial a_2}{\partial W_2} = \frac{\partial J}{\partial a_2} \times z_1$$

$$\frac{\partial J}{\partial b_2} = \frac{\partial J}{\partial a_2} \times \frac{\partial a_2}{\partial b_2} = \frac{\partial J}{\partial a_2} \times 1$$

$$\frac{\partial J}{\partial z_1} = \frac{\partial J}{\partial a_2} \times W_2$$

$$\frac{\partial J}{\partial a_1} = \frac{\partial J}{\partial z_1} \times \frac{\partial z_1}{\partial a_1} = \frac{\partial J}{\partial z_1} \times \sigma(a_1) \times (1 - \sigma(a_1))$$

$$\frac{\partial J}{\partial W_1} = \frac{\partial J}{\partial a_1} \times \frac{\partial a_1}{\partial W_1} = \frac{\partial J}{\partial a_1} \times x$$

$$\frac{\partial J}{\partial b_1} = \frac{\partial J}{\partial a_1} \times \frac{\partial a_1}{\partial b_1} = \frac{\partial J}{\partial a_1} \times 1$$

## Details about the code

### 1. nn.py -> class Dense\_Layer()

- **\_\_init\_\_**: This function takes the inputs and initialises the weights and biases, **weights\_layer1** and **bias\_layer1** are the weights and biases for hidden layer and are of dimension 8x8 and 1x8 respectively and **weights\_layer2** and **bias\_layer2** are the weights and biases for final/output layer and are of dimension 8 x 3 and 1 x 3 respectively.
- **sigmoid(self,input)** : return the sigmoid value of input
- **sigmoid\_derivative(self,input)** : returns the derivative of the sigmoid for the input.
- **forward(self,input)** : Calculates the outputs for each layer, **output\_layer1** and **activated\_output\_layer1** are the output and activated sigmoid output of hidden layer(dimension:Batch\_sizex8). **output\_layer2** and **activated\_output\_layer2** are the output and activated sigmoid output of the output layer(dimension:Batch\_sizex3).
- **calc\_loss(self,predicted\_label,actual\_label)** : computes the MSE loss after feed forward pass and returns the normalized loss
- **backward(self,input,y\_pred,y\_actual)** : This calculates the partial derivatives of the Loss (J) with respect to **activated\_output\_layer2**, **output\_layer2**, **weights\_layer2** and **bias\_layer2** for the output layer and **activated\_output\_layer1**, **output\_layer1**, **weights\_layer1** and **bias\_layer1** for the hidden layer
- **update\_parameters(self,dW1,db1,dW2,db2)** : It updates the weights and the biases of both the layers using the partial derivatives that we have passed
- **train(self,input,y\_actual)** : This trains the model by first calling **self.forward**, the **self.calc\_loss** to find the loss, the **self.backward** to find the derivatives of Loss(J) wrt model parameters and **self.update\_parameters** to backpropagate and update the parameters.
- **predict(self,input)** : Predicts the output label for an input
- **calc\_accuracy(self,input,y\_actual)** : It calculates the accuracy by first passing the batch through **self.forward** and then predicting the labels.

## 2. create\_dataset.py

- **split\_dataset(df, ratio)** : It takes the dataframe df and the ratio with which we want to divide the training data. It splits the dataset into train and test, and also stores the labels in Y\_train and Y\_test. Finally returns **train, Y\_train, test, Y\_test**

## 3. plots.py

- **scatter\_plot(df, gender\_label, column1, column2)** : It takes the dataframe df as input and also the gender\_label which is df['sex'] column. Then it also takes two features in column1 and column2 respectively. Finally plots the scatter plot for the two features
- **scatter\_plot\_normalized (df, gender\_label, column1, column2)** : It takes the dataframe df as input and also the gender\_label which is df['sex'] column. It then normalizes the dataframe df after converting it to a numpy array. Then it also takes two features in column1 and column2 respectively. Finally plots the scatter plot for the two features

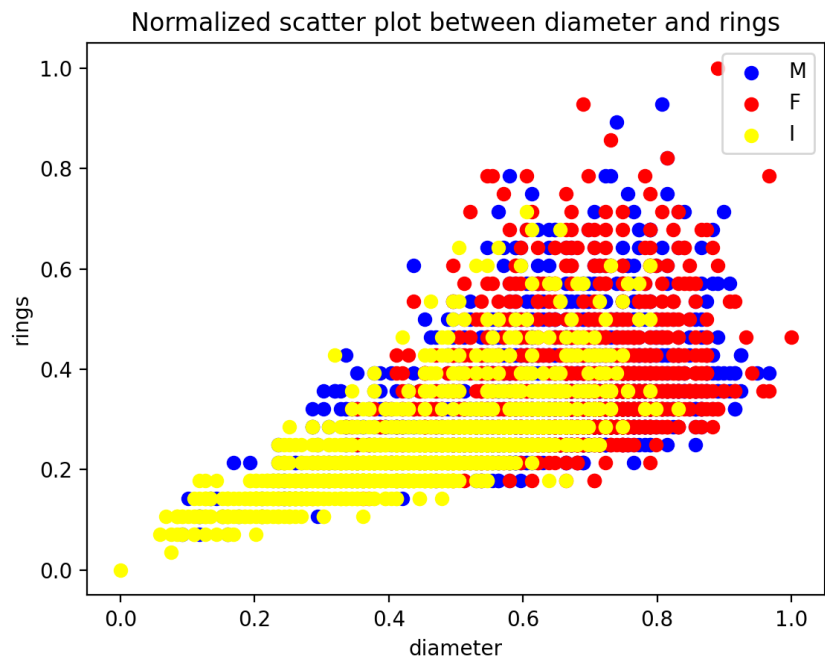
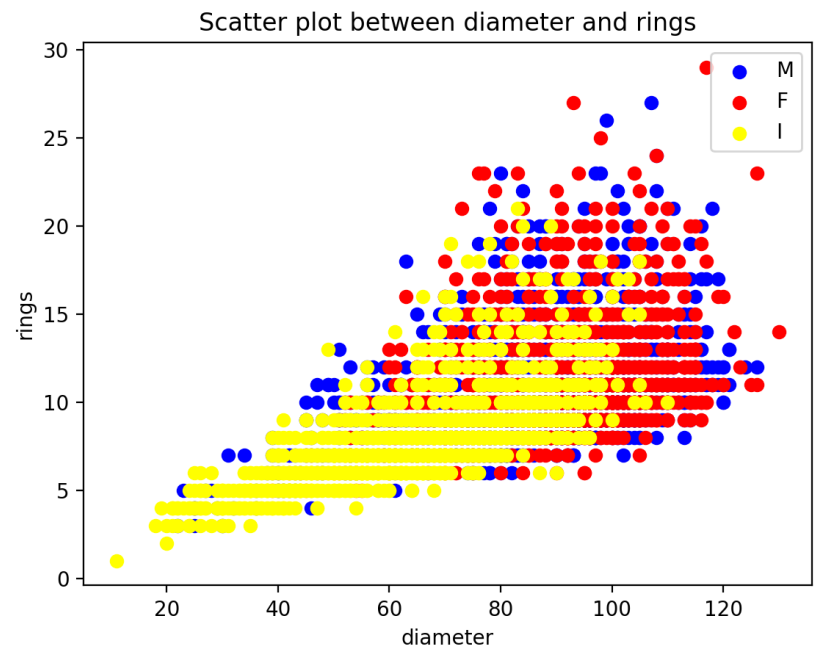
## 4. main.py

**In the main function we are doing the following things**

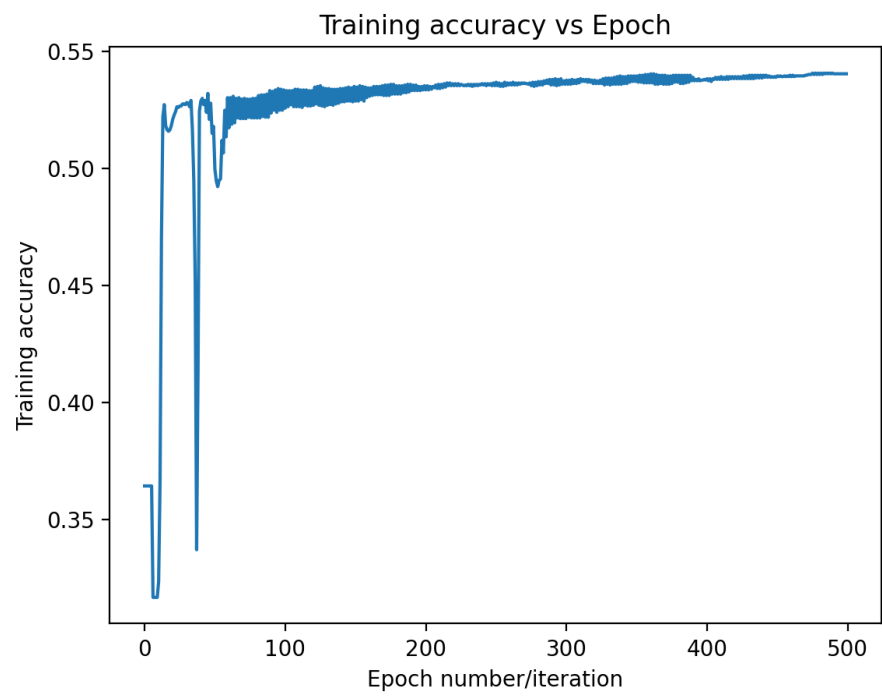
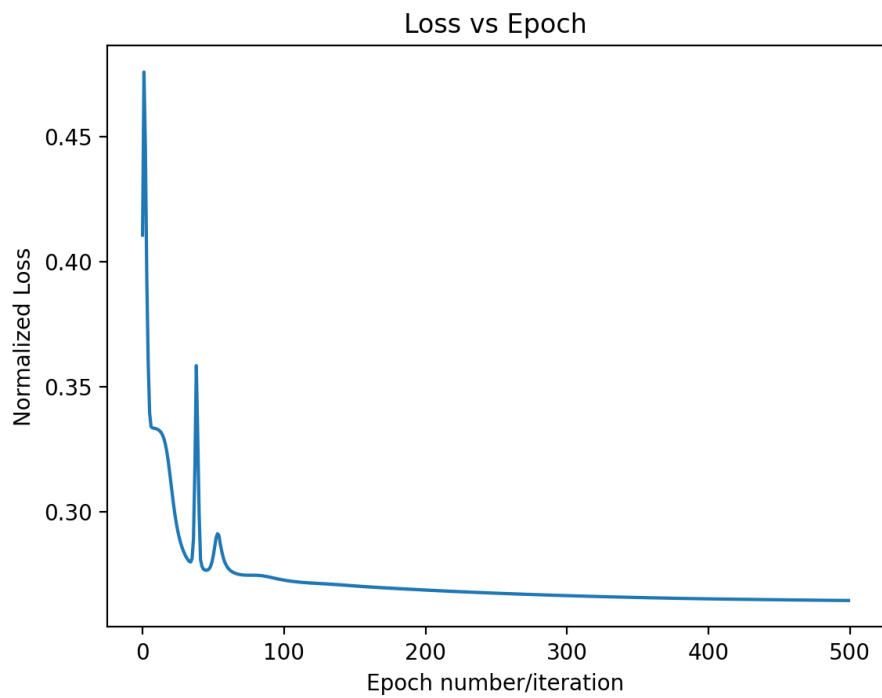
1. Reading the dataset and storing it in a variable df
2. Plotting the scatter plots wrt any two features as per choice
3. We define our model in the variable 'neural\_net'
4. Divide the dataset into train and test with labels Y\_train and Y-test respectively
5. Train the model for 500 epochs, and after every epoch we calculate and store the loss, training accuracy and the testing accuracy respectively
6. Then we print the final training and test accuracies
7. Then we plot the model statistics and analyse the plots

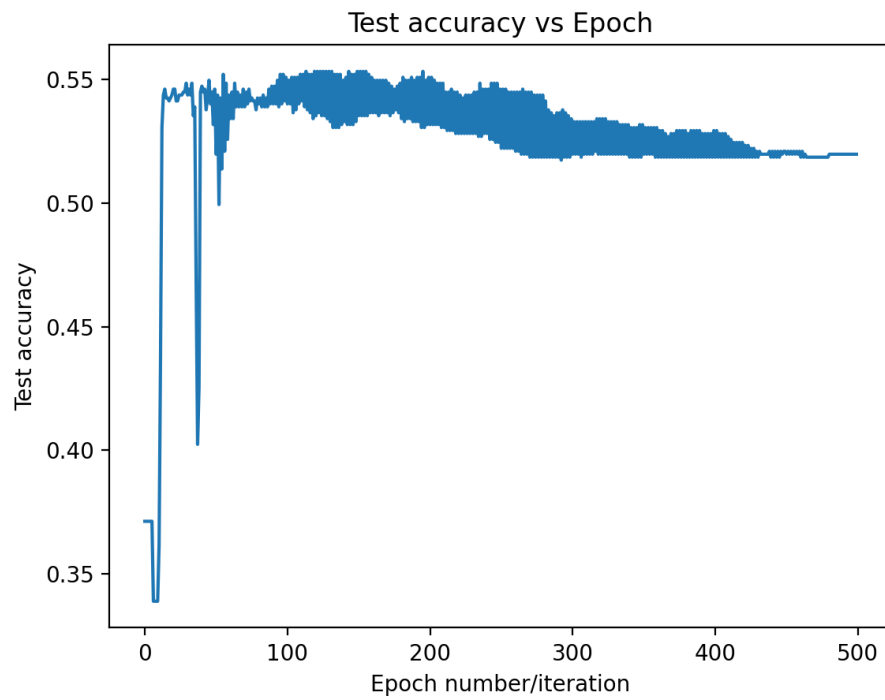
Scatter plots

Scatter plot for features 'diameter' and 'rings' for both normalized and non-normalized dataset



## Model statistics and results





```
→ MIES 3 git:(main) x python main.py  
Training accuracy = 0.5403949730700179  
Test accuracy = 0.5197604790419161
```