Neural Networks and Fuzzy Systems

Breast cancer classification using Neural Network

Abstract
Classification is one of the interested areas in the field of Neural Networks. Artificial Neural Networks has been extensively used in pattern recognition, medical diagnosis and there are many other applications of Neural Networks. Breast cancer diagnosis is one of the interesting and important application in Artificial Neural Networks [1]. In this document numerous experiments, on different hypothesis, have been discoursed in order to diagnose breast cancer as malignant or benign.

Background
Breast cancer, is a type of cancer that affects women, mostly. The struggle to fight with breast cancer is an important area in medical. Neural Network can be the powerful tool in robust and reliable recognition of breast cancer [1]. In this document we brought different hypothesis into experiments to check their validity and also discussed the environmental setup to make up an efficient Neural Network to identify breast cancer.

Environment Setup
Wisconsin data set is used in training and testing of Neural Networks. In this data set first column indicates id of each row, next nine columns indicate actual data and the last column is the output against each row. Each column among the nine columns represents a specific property of a cell i-e Clum Thickness, Bare Nuclei, Normal Neucleoli etc. Output column indicates whether it is malignant, means 4 or benign, means 2. We need to separate ids, actual data, which represent properties of a cell and output data from given data set before we train Neural Network. There are some unknown values in the given data set which are replaced by 5 in the following experiments.

Significant key parameters which are used to set architecture in training of Neural Networks are:

- Activation Functions
- Hidden Layers
- Learning Functions
- Mean Square Error
- Epochs

1st Hypothesis
Training of Neural Network on half (50%) of provided data, in which 32.5% of selected data indicates Benign and 17.5% indicates Malignant, would be much more effectual as compare to randomly chosen data from given data set.

Experiments which have been done over the above given hypothesis are explained in **Table 1**. The key parameters which remained constant are:
MSE = 0.01
Epochs = 100

Expr	Hidden Layers	Activation Functions	Output Layer Function	Learning Function	Training Function	Efficiency		Efficiency of Randomly Chosen Data	
						Accuracy %	Time (secs)	Accuracy %	Time (secs)
1	20	{1xtansig}	tansig	learngd	trainr	97.7143	11	73.4286	03
2	{2x20}	{2xtansig}	tansig	learngd	trainr	98	10	70.8571	04
3	{3x20}	{3xtansig}	tansig	learngd	trainr	99.1429	08	74.2857	11
4	{4x20}	{4xtansig}	tansig	learngd	trainr	98.2857	08	74.5714	06
5	{5x20}	{5xtansig}	tansig	learngd	trainr	97.1429	12	74.5714	13
6	{6x20}	{6xtansig}	tansig	learngd	trainr	96.5714	12	75.7143	08
6	{6x20}	{6xtansig}	softmax	learngd	trainr	34.5714	11	0	13
7	{6x20}	{6xtansig}	purelin	learngd	trainr	98.5714	13	74	12
8	20	{1xtansig}	purelin	learngd	trainr	97.4286	7	72.8571	10
9	{2x20}	{2xtansig}	purelin	learngd	trainr	95.4286	6	74.8571	08
10	{3x20}	{3xtansig}	purelin	learngd	trainr	97.1429	11	74	09
11	{3x20}	{2xlogsig}	purelin	learngd	trainr	97.7143	19	69.4286	05
12	{3x20}	{3xlogsig}	logsig	learngd	trainr	34.5714	43	0	11
13	5	{1xtansig}	tansig	learngd	trainr	98	07	74	06
14	10	{1xtansig}	tansig	learngd	trainr	98.5714	05	09	76
15	15	{1xtansig}	tansig	learngd	trainr	98.5714	13	72.8571	07

16	{2x5}	{2xtansig}	Tansig	learngd	trainr	98.2857	10	74.8571	09
17	{3x5}	{3xtansig}	tansig	learngd	trainr	98.2857	10	75.7143	05
18	{3x10}	{3xtansig}	tansig	learngd	trainr	97.1429	09	74.8571	11
19	{1x15, 2x10}	{3xtansig}	tansig	learngd	trainr	97.7143	09	74.2857	06
20	{3x20}	{3xtansig}	softmax	learngd	trainr	34.5714	23	0	06
21	{3x20}	{3xtansig}	purelin	learngd	trainr	97.4286	15	68.8571	07
22	{3x0}	{3xtansig}	tansig	learngdm	trainr	96	08	75.4286	09
23	{3x20}	{3xtansig}	purelin	learngdm	trainr	97.4286	11	74	06
24	{3x20}	{3xtansig}	tansig	learngdm	traingdx	97.1429	00	73.4286	0
25	{3x15}	{3xtansig}	tansig	learngd	trainr	98	10	74.2857	09
26	{1x20, 1x15, 1x10}	{3xtansig}	tansig	learngd	trainr	98.5714	10	75.1429	08
27	{1x20, 2x15}	{3xtansig}	tansig	learngd	trainr	98	07	74.2857	10

Table 1

Analysis: - We can see a great difference in the performance of Neural Networks if we compare accuracy of experiments being done under given hypothesis and under randomly chosen data. Nearly all of the experiments gave more than 96% of correctness. The appropriate environmental setup for training of Neural Network, for above given hypothesis, has been conversed below.

i. Hidden Layers: - According to the accuracy rate of above experiments it has been observed that the number of hidden layers may vary between 1 to 3 and the size of hidden layers can be set between 5 to 20. More than 3 hidden layers would be of no use because we see that the performance decreases, a little bit or stays constant, as we set number of hidden layers more than 3.

ii. Activation Functions: - **logsig** and **tansig** activation functions have been used for hidden layers in above experiments and **tansig**, **purelin** and **softmax** have been used for output layer. The finest activation function for hidden layer remained **tansig** while for output layer

purelin and **tansig** functions gave a much better performance than **softmax**. Therefore, we could use **tansig** or **purelin** as activation functions for output layer.

iii. Learning and Training Functions: - Recommended learning and training functions are **learngd** and **trainr**. **learngdm** and **traingdx** also gave similar performance to **learngd** and **trainr**.

Results: - It has been perceived from above examination between hypothesis and trials that the supposed hypothesis is right.

2nd Hypothesis

Performance of Neural Network rises as we increase number of hidden layers but after a perimeter performance reduces and if we frequently increase hidden layers performance surges again. This rise and fall in the performance of neural network would persist if we stay increasing hidden layers.

To test this hypothesis training of Neural Network is done according to the first hypothesis. The key parameters which remained constant are:

MSE = 0.01
Epochs = 100
Training Function = learngd
Training Function = trainr
Output Layer Functions = tansig t, purelin p

Expr	**Hidden Layers**	**Activation Functions**	**Efficiency**	
			Accuracy %	Time (secs)
1	20	{1xtansig}	t=96.8571 p=98.5714	t=07 p=19
2	{2x20}	{2xtansig}	t=98.5714 p=97.7143	t=05 p=04
3	{3x20}	{3xtansig}	t=97.4286 p=97.4268	t=11 p=08
4	{4x20}	{4xtansig}	t=98.5714 p=96.8571	t=14 p=06
5	{5x20}	{5xtansig}	t=98.2857 p=98	t=11 p=10
6	{6x20}	{6xtansig}	t=97.1429 p=97.1429	t=08 p=24
7	{7x20}	{7xtansig}	t=97.4286 p=96.8571	t=12 p=12
8	{8x20}	{8xtansig}	t=98 p=97.7143	t=18 p=17

9	{9x20}	{9xtansig}	t=98.2857 p=97.4286	t=10 p=10
10	{10x20}	{10xtansig}	t=97.1429 p=98.2857	t=26 p=16
11	{1x5}	{1xtansig}	t= 97.7143 p= 98.2857	t=04 p=16
12	{2x5}	{2xtansig}	t=94.5714 p=97.7143	t=13 p=37
13	{3x5}	{3xtansig}	t=97.4286 p=98.5714	t=29 p=30
14	{4x5}	{4xtansig}	t=98.2857 p=97.4286	t=12 p=15
15	{5x5}	{5xtansig}	t=97.1429 p=97.1429	t=16 p=23
16	{1x10, 4x5}	{5xtansig}	t=97.4286 p=98.2857	t=19 p=33
17	{1x20, 1x10 3x5}	{5xtansig}	t=96.5714 p=98.8571	t=35 p=30

Table 2

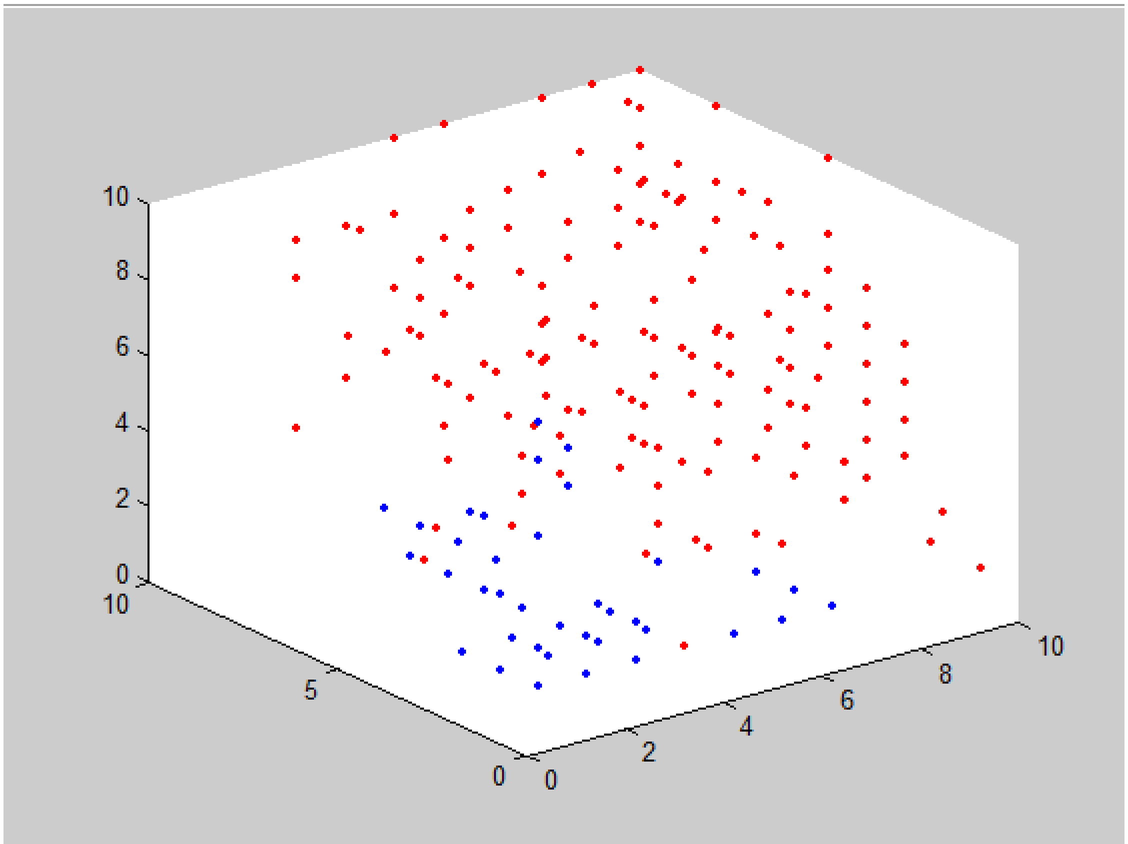
Analysis: - We have experienced from above experiments that accuracy remains more than 95% in, almost all experiments. Increasing number of hidden layers did not affect accuracy. Our Neural Network gave almost same accuracy with single hidden layer and with five neurons as with ten hidden layers with twenty neurons. This verifies that the hypothesis that we made does not match with actual results because there is no fluctuation in the accuracy rate against different experiments. So, the above hypothesis could be well stated as follows.

Evolved Hypothesis: - Performance of Neural Network is not affected with continual increase of hidden layers. Therefore, increasing number of hidden layers, after a maximum, would be of no use.

3rd Hypothesis

Performance of Neural Network increases if we train Neural Network on fewer-dimensional data instead of higher- dimensional data.

Description: - We know that every attribute (Symptoms of a Cell) is mapped to real number in the domain of 1-10. If an attribute is closer to 1 it indicates benign and if it is nearer to 10 it indicates malignant [2]. If we take a look at the given data we perceive that in the most of the cases if the values of first three columns are greater than or equal to 5 it is malignant and if the values of last three columns are less than 5 it is benign. For training purpose we separate the first three columns for malignant and last three columns for benign. In three dimension data complexity can be seen in the following figure. Red dots indicate Malignant and blue dots indicates Benign.



Data Complexity of Benign and Malignant

All of the environmental setup for training of Neural Network remains same as of above experiments; data dimension changes. . The key parameters which remained constant are:

MSE = 0.01
Epochs = 100
Training Function = learngd
Training Function = trainr
Output Layer Functions = tansig t, purelin p

Expr	Hidden Layers	Activation Functions	Efficiency	
			Accuracy %	Time (secs)
1	{1x5}	{1xtansig}	t=98.5714 p=98.5714	t=28 p=29
2	{2x5}	{2xtansig}	t=98.5714 p=98.8571	t=35 p=25

3	{3x5}	{3xtansig}	t=99.1429 p=98.5714	t=70 p=44
4	{1x10, 2x5}	{3xtansig}	t=98 p=98	t=26 p=50
5	{2x10, 1x5}	{3xtansig}	t=98.5714 p=97.7143	t=22 p=18
6	{3x10}	{3xtansig}	t=99.4286 p=98.8571	t=31 p=11
10	{1x20, 2x10}	{3xtansig}	t=99.4286 p=99.4286	t=14 p=31
11	{2x20, 1x10}	{3xtansig}	t=98.2857 p=99.4286	t=13 p=06
12	{3x20}	{3xtansig}	t=98.8571 p=98.8571	t=08 p=24

Table 3

Analysis: - It has been observed from above experiments that if we bring data down to fewer dimensions we get more good accuracy as compared to higher dimensional data because all the experiments done above gave more than 98% of accuracy which is a more good precision as compared to experiments done in the first hypothesis, on 9 dimensional data and some of the experiments gave almost 100% accuracy.

Results: - It has been detected from above investigation between hypothesis and experiments that the supposed hypothesis is correct.

4^{th} Hypothesis

With higher number of hidden layers Neural Network takes less time to be trained as compared to the time with less number of hidden layers.

The key parameters which remained constant in the experiments of the above given hypothesis are:

MSE = 0.01
Epochs = 100
Training Function = learngd
Training Function = trainr
Output Layer Functions = tansig t, purelin p

Expr	Hidden Layers	Activation Functions	Training Time (secs)
1	{1x5}	{1xtansig}	t=21 p=19

2	{2x5}	{2xtansig}	t=24 p=20
3	{3x5}	{3xtansig}	t=12 p=11
4	{4x5}	{4xtansig}	t=18 p=15
5	{5x5}	{5xtansig}	t=24 p=12
6	{1x10}	{1xtansig}	t=10 p=23
7	{2x10}	{2xtansig}	t=19 p=9
8	{3x10}	{3xtansig}	t=18 p=17
9	{1x20, 2x10}	{3xtansig}	t=13 p=22
10	{2x20, 1x10}	{3xtansig}	t=14 p=17
11	{3x20}	{3xtansig}	t=18 p=21

Table 4

Analysis: - The above stated hypothesis is incorrect because sometimes Neural Network takes more time in training on higher number of hidden layers and sometimes it takes less time in training with lesser number of hidden layers. So, time is not affected by number of hidden layers and its size. The given hypothesis could be stated as:

Evolved Hypothesis: - Time taken by Neural Network during training is independent of number and size of hidden layers.

Bibliography

(1). Tike Thein, H. T. and Mo Tun, K. M. (2015) ‘An Approach for Breast Cancer Diagnosis Classification Using Neural Network’, Advanced Computing: An International Journal, 6(1), pp. 1–11. doi: 10.5121/acij.2015.6101.

(2). Wolberg, W. H. and Mangasarian, O. L. (1990) ‘Multisurface method of pattern separation for medical diagnosis applied to breast cytology.’, Proceedings of the National Academy of Sciences of the United States of America, 87(23), pp. 9193–6. doi: 10.1073/pnas.87.23.9193.