MLP Classifier for Dementia Levels

M. M. Patil and A. R. Yardi

***Abstract*—According to world Health Organization (WHO) India's population of those aged over 65, which was 40 million in 1997, is to increase 108 million by 2025 and 240 million by 2050. This means several fold increase in age related problems such as neuro-degeneration, a condition characterized by a progressively declining memory and intellectual functions. In this paper, we propose an Artificial Neural Network based method to evaluate Dementia severity in terms of CDR scale and in turn to classify various Dementia levels. We show that a Multilayer perceptron (MLP) neural network can classify Dementia levels to the accuracy of about 95% , after a process of supervised training.. The study has been performed on dataset of 416 cases, available at the Open Access Series of Imaging Studies (OASIS) database, which is available at http://www.oasis-brains.org.**

***Index Terms*—Neuro-degeneration, dementia, CDR(Clinical Dementia Rating), artificial neural network, MMSE(Minimental Status Examination),multilayer feed forward network, OASIS data set.**

I. Introduction

Neurodegenerative disease (neruo-nerval, degenerative – decline or to worsen) is a condition which affects brain functions. Neurodegenerative disease results from deterioration of neurons which do different functions such as controlling movements, processing sensory information and making decisions [1]. Many times neuronal death begins long before the patient will experience any symptoms. It can be months or years before any effect is felt. Symptoms are noticed after lots of cells have died and certain parts of brain have been weakened to the point that they can no longer function properly [2]-[4]. Here the term early diagnosis is very important since number of neurodegenerative diseases are reversible only when these are diagnosed at early stage. This early diagnosis is very difficult because the symptoms appear after severe damage to the cells;(In case of PD symptoms appear after 80% cells were destroyed) Even patient himself doesn't know that he was suffering from any neurodegenerative disease since it was mistaken as a part of normal aging process. The tragedy with neurodegenerative diseases relies in the fact that the relatives of the patient lose him before his death. What is Dementia? Dementia refers to the loss of memory and other cognitive skills due to changes in the brain caused by disease or trauma. The changes can affect thinking, memory and reasoning, and may occur gradually or quickly. Memory loss alone is not always a sign of dementia, but memory loss along with other forms of cognitive impairment is an indicator that dementia may be occurring. Cognitive functions that might be affected by dementia include: decision making/judgment, memory, spatial orientation, thinking/reasoning, verbal communication, neglect of personal safety, hygiene, and nutrition, coordination or balance.

Problems in correct diagnosis: An estimate tells around 24 million people worldwide suffer from dementia—and the numbers are growing. To make matters worse, many people don't understand the difference between Alzheimer's and other forms of dementia, causing many cases to go undiagnosed and untreated. As Alzheimer's Dementia is irreversible but others are reversible on timely diagnosis.[5] Neural networks have proven their capabilities in many domains including medical applications. Neural networks with their abilities to learn by examples make them very flexible and powerful in the field of medical diagnosis. Neural networks show that experience of an expert is not always enough for correct diagnosis of a disease. Nowadays, an expertise of a physician combined with the power of neural network can detect the diseases at their early stages. Artificial Neural Network (ANN) has been used in a number of different ways in medicine and medically related fields [6 – 10]. The principle advantages of artificial neural networks are that they are able to generalize, adapting to signal distortion and noise without loss of robustness. They are trained by example and do not require precise description of patterns to be classified or criteria for classification [11 – 13]. In this paper, we present MLP classifier for various Dementia levels. The dataset used is Open Access Series of Imaging Studies (OASIS) database, which is available at http://www.oasis-brains.org.

II. Method

OASIS Dataset consists of a cross-sectional collection of 416 subjects covering the adult life span aged 18 to 96 including individuals with early-stage Alzheimer's disease (AD). For each subject, 3 or 4 individual T1-weighted MRI scans obtained within a single imaging session are included. The subjects are all right-handed and include both men and women. Subjects have been diagnosed for mild dementia, dementia and severe dementia. Attributes Included in the Data Set are-

1) Age :Age at time of image acquisition (years)
2) The authors of the accepted manuscripts will be given a copyright form and the form should accompany your final submission. Sex :Sex (male or female)
3) Education : Years of education
4) Socioeconomic status : Assessed by the Hollingshead Index of Social Position and

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classified into categories from 1 (highest status) to 5 (lowest status) (Hollingshead, 1957)

5) MMSE score : Ranges from 0 (worst) to 30 (best) (Folstein, Folstein, & McHugh,1975)
6) CDR scale : 0 = No Dementia, 0.5= very mild AD, 1= mild AD, 2= moderate AD (Morris, 1993)
7) Atlas scaling factor: Computed scaling factor (unitless) that transforms native-space brain and skull to the atlas target (i.e., the determinant of the transform matrix) (Buckner et al., 2004)
8) eTIV : Estimated total intracranial volume (cm3) (Buckner et al., 2004)
9) nWBV : Expressed as the percent of all voxels in the atlas-masked image that are labeled as gray or white matter by the automated tissue segmentation process (Fotenos et al., 2005)

The data are available at http://www.oasis-brains.org.

Steps in data analysis:

1) Clean data – blank cells filled by interpolation.
2) Field in dataset Male/Female made numeric using M=1, F=0.
3) Similarly field hand, Right Hand R=1 else R=0.
4) Column CDR mentioned in the dataset is utilized for giving output during training phase. Applied filter to column CDR to separate cases with CDR = 0,0.5,1 since it provides the basis for our classification as in Table. I

TABLE I. CDR MEANING

CDR	Patient status
0	Nondemented
0.5	Mild Dementia
>=1	Severe dementia

Data analysis is done using MS Excel.

Multilayer perceptron backpropagation neural network is implemented using C language .The classifier employed in this paper is a three-layer backpropagation neural network. The backpropagation neural network optimizes the net for correct responses to the training input data set. More than one hidden layer may be beneficial for some applications, but one hidden layer is sufficient if enough hidden neurons are used .The output from the each hidden neuron is calculated using the sigmoid function [14],

$$S_1 = 1 / (1 + e^{-\lambda x})$$

where λ=1, and $x = \Sigma_i w_{ih} k_i$, where w_{ih} is the weight assigned between input and hidden layer, and k is the input value. The output from the output layer is calculated using the sigmoid function,

$$S_2 = 1 / (1 + e^{-\lambda x})$$

where λ=1, and $x = \Sigma_i W_{ho} S_1$, where W_{ho_o} is the weight assigned between hidden and output layer, and S_i is the output value from hidden neurons. S_2 is subtracted from the desired output. Using this error $(d)^2$ value, the weight change is calculated as:

$$\text{delta} = d \times S_2 \times (1 - S_2)$$

And the weights assigned between input and hidden layer and hidden and output layer are updated as:

$$W_{ho_o} = W_{ho} + (n \times \text{delta} \times S_1)$$

$$W_{ih} = W_{ih} + (n \times \text{delta} \times k)$$

where n is the learning rate, k is the input values. Again calculate the output from hidden and output neurons. Then check the error (d) value, and update the weights. This procedure is repeated till the target output is equal to the desired output. Training is carried out for 90% cases in dataset and weights are saved to weight file.

During training period we utilized: 8 number of input nodes, experiments done to decide hidden layer nodes choosing 6 nodes , 12 nodes and finally 16 hidden nodes were used, 3 number of output nodes and varying learning rate. The three output neurons correspond to three Dementia levels(CDR= 0,0.5,>=1).The training error continues to decrease as the number of epoch's increases. Repeated experiments were performed to determine the size of the hidden layer and training sample. As shown in fig.1 our final ANN consists of 16 hidden units, which provide compromise between, mapping error and the computational time.

Weights were initialized to random values and network was run until Minimum Gradient is obtained. After training is complete test inputs, comprising samples of all three Dementia levels are presented to check the classification performance of the trained network.

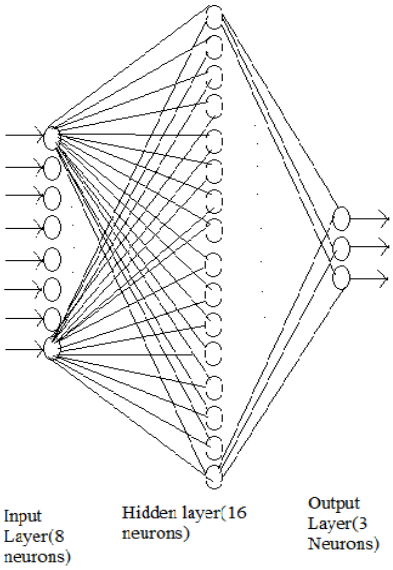

Fig. 1. MLP architecture used

III. RESULTS

TABLE II: TEST OUTPUTS

Sr	Input case with CDR	Desired Output (DO)			Actual Output (AO)		
		DO 1	*DO 2*	*DO 3*	*AO1*	*AO2*	*AO3*
1	0	0	0	1	0.000000	0.005826	0.999996
2	0	0	0	1	0.000130	0.063736	0.901791
3	0	0	0	1	0.000000	0.261744	0.918912
4	0.5	0	1	0	0.000000	0.881298	0.173567
5	0.5	0	1	0	0.000000	0.997826	0.000352
6	0.5	0	1	0	0.000000	0.968157	0.011723
7	0.5	0	1	0	0.000000	0.628426	0.334749
8	1	1	0	0	0.795199	0.287693	0.366883
9	1	1	0	0	0.699240	0.338530	0.001013
10	1	1	0	0	0.942181	0.194007	0.002962

Test cases comprising all three types of Dementia are applied to the trained network again and again, and it was found that every time it classifies them correctly. And overall accuracy provided is above 95%. A few representative test inputs and outputs are presented over here as in Tab.II.

Here in this table first three cases belong to class 1(CDR=0), represented as neuron1 output =0, neuron2 output=0, neuron3 output =1. Next four cases belong to class 2(CDR=0.5), represented as neuron1 output =0, neuron2 ouput=1, neuron3 output =0. Last three cases belong to class 3(CDR>=1), represented as neuron1 output =1, neuron2 ouput=0, neuron3 output =0.The train in which actual output follows desired output is represented in graphical form as in fig.2. Here X-axis represents input case number and Y-axis represents the neuron output for that particular input case. First graph shows the result for neuron1, second for neuron2 and third for neuron3. Blue colour represents desired output and red colour represents actual output. It can be easily figured out from the result Tab.II and graphs of fig.2 that in all 10 test cases network is generating correct outputs. These findings could be observed in fig.2.

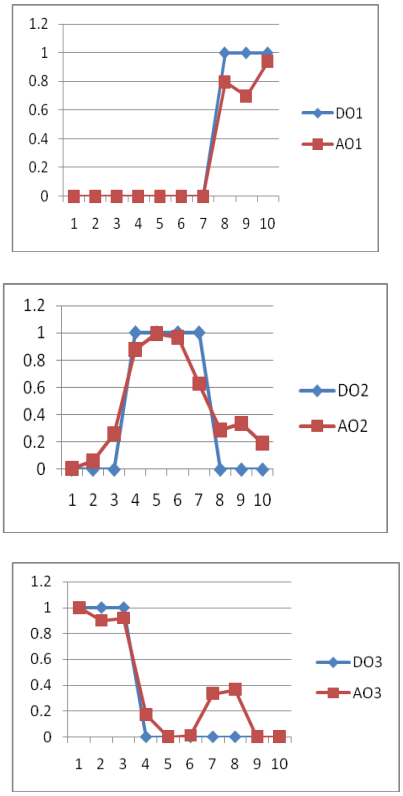

Fig. 2. Neuron Outputs (DO1,AO1-desired and actual output from neuron1, DO2,AO2-desired and actual output from neuron2, DO3,AO3-desired and actual output from neuron3).

IV. Conclusion and Discussion

In the present article, MLP classifier for various Dementia levels has been developed to the accuracy of about 95% and can be used further for diagnosis of Dementia level of a patient. Further it is planned to use of momentum term in weight change for faster convergence of network.

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References

[1] R. J. Vidmar. On the use of atmospheric plasmas as electromagnetic reflectors. *IEEE Trans. Plasma Sci.* vol. 21. no. 3. pp. 876-880. (August 1992). [Online]. Available: http://www.halcyon.com/pub/journals/21ps03-vidmar

[2] A. Krishnakumar et al. March 2003, "Understanding Dementias," *Frontline*, vol. 20, issue 6.

[3] Multi-infarct dementia From Wikipedia, the free encyclopedia MID, wikipedia, free encyclopedia.

[4] *Mechanism of Ageing: A Review*

[5] MID, *wikipedia, free encyclopedia*.

[6] Alzheimers Disease. [Online]. Available: http://www.helpguide.org/elder/alzheimers_disease_symptoms_stages.htm

[7] G. Zahlmann, S. Wilson, and E. Micheli-Tzanakou, "A Knowledge Based Neural Network Classifier For Visual Evoked Potentials," in *Proceedings of the Annual International Conference of the IEEE* , pp.1345 –1346, 1991.

[8] R. Iezzi and Jr. E. Micheli-Tzanakou, "2-D spatial frequencydependence of VEPs: A neural network analysis," *Bioengineering Conference, Proceedings of the 1993 IEEE Nineteenth Annual Northeast*, pp. 111 – 112, 1993

[9] E. Micheli-Tzanakou, "Biomedical applications of parallel processing and artificial neural networks," *Biomedical Engineering Days*, pp. 10 –17, 1992.

[10] R. Sivakumar and G. Ravindran, "Using Feed Forward Neural Network to monitor mental state from changes in EEG spectral components," *Journal Of Biomedical Technology* , vol. 4, 2001.

[11] R. Sivakumar and G. Ravindran, "Using Feed Forward Neural Network to discriminate abnormal subjects using the Visual Evoked Potential Spectral Components," in *Proc. of Sixth International Conference on Cognitive and Neural Systems, xi*, 2002.

[12] E. Casi, A. Ceravola, R. Cionini, A. Sperduti, A. Starita, and S. Viti, "Diabetic retina analyzer," in *Proceedings of the 18th Annual International Conference of the IEEE* , vol. 3, pp. 1128 –1129, 1996 .

[13] E. Micheli-Tzanakou, "Applications of neural networks in biomedical engineering," in *Proceedings of the 1990 IEEE* , pp. 7 –12, 1990.

[14] J. A. Sgro, R. G. Emerson, and P. C. Stanton, "Automated evoked potential analysis using backpropagation networks," *Neural Networks Proceedings*, vol. 1, pp. 123 –127,1998

[15] B. Rao M. Valluru and T. Books, "C++ Neural Networks and Fuzzy Logic," IDG Books Worldwide, Inc., 1995.

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