TEST Engineering & Management

March - April 2020
ISSN: 0193-4120 Page No. 9992 - 9996

Various parametric classifications of Alzheimer's disease using EEG Signals

J. Shafiq Mansoor[1], G. Premananthan[2]
[1]Asst Prof,Dept of ECE ,Karpagam Academy of Higher Education,India
[2]Asst Prof,Dept of EEE, Karpagam College of Engineering, India.
shafiqmansoor.j@kahedu.edu.in

Article Info
Volume 83
Page Number: 9992 - 9996
Publication Issue:
March - April 2020

Article History
***Article Received**: 24 July 2019*
***Revised**: 12 September 2019*
***Accepted**: 15 February 2020*
***Publication**: 11 April 2020*

Abstract: Alzheimer's disease (AD) also known as Dementia. It is a most vulnerable disease in our human brain which can be detected with the help of EEG signals. Further, this paper represents the review of AD and EEG signals, it consists of totally 161 subjects of which 79 subjects with AD and 82 subjects with cognitive normal.Besides, two parametric functions are compared for further results. Based on the experimental analysis, it can be measured that AR pole tracking with 15th order using FBNN reported the highest classification accuracy of 97.5 per cent with specificity 94%, sensitivity 97% and F measure 91% when compared to FFNN algorithm.

Keywords: *Alzheimer's disease, EEG Signals*

I. INTRODUCTION

One of the complex diseases in our human body is Alzheimer's Disease (AD). It is otherwise known as dementia (or)memory loss which occurs at the age of 65. It has ability to change the thinking and behavior of the patients also it reducesthe people's day to day activities. In current progress these diseases are diagnosed through Electroencephalogram (EEG) Signals. The electric current is produced by human brain within few microvolts and the continuous brain activities are observed between 20 – 40 minutes which leads to generate the EEG signal. Further, it consists of four typesi.e). alpha, beta, theta and delta waves. These waves help to identify diseases such as insomnia and epilepsy [1].

In recent years, the testing of neuro imaging data has supported many researches for early detection and accurate analysis of an Alzheimer's disease. It is diagnosed using MRI which taken by MRI scanner and produce images in the form of scanner tissue, but it is time consumption process. Hence, several software programs are available for an automatic classification of grey matter. Following, the detection of gray matter possible which is highly viewed in the study of MRI data based on fractal measurement [2, 3], independent component analysis [4]and advanced local binary pattern of brain [5]. Thus the early detection of MRI data is highly possible in AD [6]. Further, this paper contributes various parametric functions and compares the results based on good prediction algorithms.

II. DATA COLLECTION

In this study, data set was acquired through auditory oddball paradigm to analyze the Alzheimer disease. The dataset used in this

March - April 2020
ISSN: 0193-4120 Page No. 9992 - 9996

research work consist of totally 161 subjects of which 79 subjects EEG signals with AD and 82 subjects EEG signals with cognitive normal. Three different types of auditory signals were stimulated with 1 K Hz and 2 K Hz. Duration of the presentation of the stimuli is 30 minutes. 16 channel EEG is used to acquire the signal along with 256 Hz of sampling frequency. The evoked potential response signals were averaged and classified with AD and Cognitive normal.

III. PARAMETRIC CLASSIFICATION

Feed forward Neural Network (FNN)

In multilayer neural networks, the information processing takes place only in the fed forward path, through the input layer, output layer and hidden layer. A MFNN is said to be static neural network model because it is characterized by non-linear equations that are memory less. In general, a single neuron computes the weighted input values and obtains output values through a non-linear activation function with a threshold. The Feed-forward neural networks (FNN) are widely used for pattern classification, due to probability distribution (or) classify the distant regions. It is mainly used for accurate classification of input data into various classes were these are obtained by pretrained model. Generally, the FNN architecture consists of multilayer neural network for specific application as shown in the fig. 1.

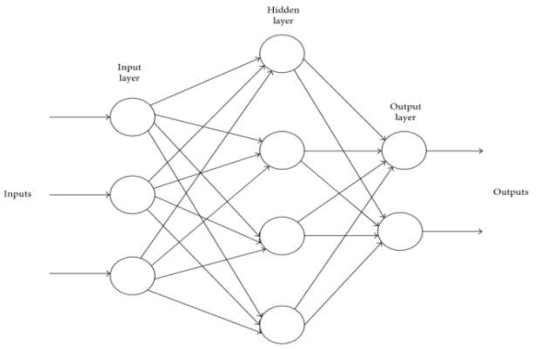

Fig. 2 Diagram of Feed forward Neural Network (FNN)[30]

The major property of FNN are assigned in three ways i) Network topology, ii) the training and iii) activation function of neuron. The network might have more layers of neurons and its architecture supported for a feed-forward network. Similarly, linear neurons are selected for the output layer. Finally, the configuration represents the input neurons, hidden layer, and it indicates the brain underAD.

Feedback Neural Network (FBNN)

The feedback neural network consists of arbitrary functions of neurons which have feedback interactions among different layers, but it is suitable for simple set of neurons. It consists of many feedback connections between the neurons. It is a dynamic network even at evolve in either continuous or discrete time. In general, the fig.1 shows the basic structure of a single-layer feedback network (or) Hopfield network. The loops are introduced in the network to guide their signals from one direction to another direction. Further, this network gives an impression in the input of earlier derived algorithms, and then FBNN will change repeatedly till it attains the state of equilibrium point. When the input of the network is changed then a new equilibrium will be farmed. The FBNN architecture also known as interactive or recurrent neural network RNN's, which often used to determine the feedback connectionswithin a single layer. After, the network allowed the feedback loops that are used in content based addressable memories.

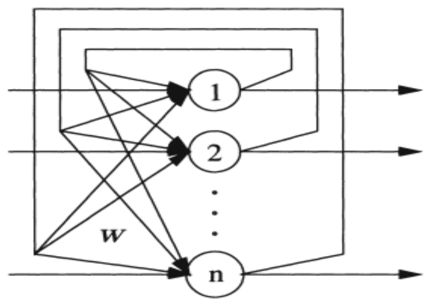

Fig. 2Diagram of Feed Back Neural Network (FBNN) [30]

Table 1: Comparison results of FFNN and FBNN

Parametric Function	Parametric Feature	Accuracy (%)	Sensitivity (%)	Specificity (%)	F measure (%)
FFNN	AR Pole Tracking with 10^{th} order	88	90	88	85
	AR Pole Tracking with 15^{th} order	96.5	96	93	90
	AR Pole Tracking with 20^{th} order	95	93	94	93.5
FBNN	AR Pole Tracking with 10^{th} order	91	93	91	88
	AR Pole Tracking with 15^{th} order	97.5	97	94	91
	AR Pole Tracking with 20^{th} order	95	93	95	94

IV. RESULT AND DISCUSSION

In order to develop a neural network, the training samples are selected randomly from the total samples then the neural networks are trained. 60% of dataset has been used for training the neural network and the remaining 40% of dataset has been used to test the performances of the neural network.

From the Table 1, it can be observed that AR pole tracking with 15^{th} order using FBNN gives highest accuracy of 97.5 per cent and the AR pole tracking with 15^{th} order using FFNN reported the lowest classification accuracy of 95per cent than FBNN.

V. CONCLUSION

Alzheimer's disease (AD) is otherwise known as Dementia which is most vulnerable disease in our human brain. It detected with the help of EEG signals that consists of totally 161 subjects of which 79 subjects EEG signals with AD and 82 subjects EEG signals with cognitive normal. From the results, it can be measured that AR pole tracking with 15^{th} order using FBNN reported the highest classification accuracy of 97.5 per cent with specificity 94%, sensitivity 97% and F measure 91% when compared to FFNN algorithm.

REFERENCES

[1]. Biju K Sa, Alfa S Sa , KavyaLala, 'Alzheimer's Detection Based on Segmentation of MRI Image', 7th International Conference on Advances in Computing & Communications, Vol. 22-24, 2017.

[2]. Y. Kaewaramsri,S A. Alfarozi, 'Fractal dimension for classifying 3D brain MRI using improved triangle box counting method', Information Technology and Electrical Engineering (ICITEE), pp. 1-6, 2016.

March - April 2020
ISSN: 0193-4120 Page No. 9992 - 9996

[3]. S. Lahmiri, M. Boukadoum, 'Automatic detection of Alzheimer disease in brain magnetic resonance images using fractal features', 6th International Conference on Neural Engineering (NER), pp. 1505-1508, 2013.

[4]. W. Yang, H. Xia, B. Xia, 'ICA-based feature extraction and automatic classification of AD-related MRI data', 6th International Conference Natural Computation (ICNC), Vol. 3, pp. 1261-1265, 2010.

[5]. D. Sarwinda, A. Bustamam, 'Detection of Alzheimer's disease using advanced local binary pattern from hippocampus and whole brain of MR images', International Joint Conference Neural Networks (IJCNN), pp. 5051-5056, 2016.

[6]. K P. Gunawardena, R N. Rajapakse, N D. Kodikara, I U. Mudalige, 'Moving from detection to pre-detection of Alzheimer's Disease from MRI data', 6thInternational Conference on Advances in ICT for Emerging Regions (ICTer), pp. 324-324, 2016.

[7]. Pierrick Coupe, P Manjon, J.V Lanuza, 'Lifespan Changes of the Human Brain in Alzheimer's Disease', Scientific Reports, Vol. 9, pp. 3998, 2019.

[8]. Planche V, Coupe P, Helmer C, 'Evolution of brain atrophy subtypes during aging predicts long-term cognitive decline and future Alzheimer's clinical syndrome', Neurobiological Aging, Vol. 79, pp. 22-29, 2019.

[9]. KilianHett, 'Graph of Brain Structures Grading for Early Detection of Alzheimer's Disease', International Conference on Medical Image Computing and Computer-Assisted Intervention, pp 429-436, 2018.

[10]. Jorge Samper, Gonzal, 'Reproducible evaluation of classification methods in Alzheimer's disease: Framework and application to MRI and PET data', Elsevier, Vol. 183, pp. 504-521, 2018.

[11]. Palmer K, Bäckman L, Winblad B, Fratiglioni L, 'Detection of Alzheimer's disease and dementia in the preclinical phase: population based cohort study', Biomedical Journal, 2003.

[12]. Jose Vicente Manjón, Enrique Lanuza, Gwenaelle Catheline, 'Timeline Of Brain Alterations In Alzheimer's Disease Across The Entire Lifespan, Alzheimer's Disease Neuroimaging Initiative, 2017.

[13]. Coupe P, Fonov VS, Bernard C, 'Detection of Alzheimer's disease signature in MR images seven years before conversion to dementia: Toward an early individual prognosis', Epub, Vol. 13, pp. 4758-4770, 2015.

[14]. De Vos F, Schouten TM, Hafkemeijer A, Dopper EG, 'Combining multiple anatomical MRI measures improves Alzheimer's disease classification', 2016.

[15]. KilianHett, Vinh-Thong Ta, GwenaelleCatheline, 'Multimodal Hippocampal Subfield Grading For Alzheimer's Disease Classification', Scientific Reports volume 9, pp. 13845, 2019.

[16]. Amoroso N, Rocca M,Bellotti R, Fanizzi A, 'Alzheimer's disease diagnosis based on the Hippocampal Unified Multi-Atlas Network (HUMAN) algorithm', Biomedical Engineering Online, 2018.

[17]. Nikhil Bhagwat ,Joseph D. Viviano,Aristotle N. Voineskos,M. MallarChakravarty, 'Modeling and prediction of clinical symptom trajectories in Alzheimer's disease using longitudinal data', 2018.

[18]. Weiha O Zhang, 'Identification of Alzheimer's Disease and Mild Cognitive Impairment Using Networks Constructed Based on Multiple Morphological Brain Features', Cognitive Neuroscience and Neuroimaging, Vol. 3, Issue 10, pp. 887-889, 2018.

[19]. KilianHett, 'Graph of Brain Structures Grading for Early Detection of Alzheimer's Disease', International Conference on Medical Image Computing and Computer-Assisted Intervention, pp 429-436, 2018.

March - April 2020
ISSN: 0193-4120 Page No. 9992 - 9996

[20]. Vasavada MM, Wang J, Eslinger PJ, Gill DJ, Sun X, Karunanayaka P, Yang QX, ‘Olfactory cortex degeneration in Alzheimer's disease and mild cognitive impairment’, Vol. 45, pp. 947-58, 2015.

[21]. Saiz-Sanchez D, Flores-Cuadrado A, ‘Interneurons in the human olfactory system in Alzheimer's disease’, 2015.

[22]. Quarmley M, Moberg PJ, Mechanic-Hamilton D, ‘Odor Identification Screening Improves Diagnostic Classification in Incipient Alzheimer's Disease’, Vol. 55, pp. 1497-1507, 2017.

[23]. Diana LorenaGiraldo Franco, ‘Morphometric Data Fusion for Early Detection of Alzheimer's Disease’, 2015.

[24]. AnjaSoldan, ‘Relationship of medial temporal lobe atrophy, APOE genotype, and cognitive reserve in preclinical Alzheimer's disease’, BIOCARD Research Team, pp. 2826-41, 2015.

[25]. Kinnunen KM, Cash DM, Poole T, Frost C, Benzinger TLS, ‘Presymptomatic atrophy in autosomal dominant Alzheimer's disease: A serial magnetic resonance imaging study, pp. 43-53, 2017.

[26]. KilianHett,Vinh-Thong Ta, Jose V. Manjon, ‘Adaptive fusion of texture-based grading: Application to Alzheimer's disease detection’, International workshop on patch based technique in medical imaging, 2017.

[27]. Kamalraj S, Rejith K N and Prasanna Venkatesan G K D, ‘Frequency domain analysis for the classification of Parkinson’s disease patients’, IOP Conference Series: Materials Science and Engineering, 2019.

[28]. Rejith K N, KamalrajSubramaniam, ‘Classification of Emotional States in Parkinson’s disease Patients using Machine Learning Algorithms’, Biomedical and pharmacology journal, 2018.

[29]. Rejith KN, Kamalraj Subramaniam, ‘Analysis of Emotional States in Parkinson's Disease using Entropy, Energy-Entropy and Teager Energy-Entropy Features’, Indian Journal of Public Health Research & Development, 2018.

[30]. https://www.hindawi.com/journals/jhe/2017/9060124/fig4/

[31]. Kumar, R. S., Ali, M. A., Osman, H., Ismail, R., Choon, T. S., Yoon, Y. K., ...&Manogaran, E. (2011). Synthesis and discovery of novel hexacyclic cage compounds as inhibitors of acetylcholinesterase. Bioorganic & medicinal chemistry letters, 21(13), 3997-4000.

[32]. Ali, M. A., Ismail, R., Choon, T. S., Yoon, Y. K., Wei, A. C., Pandian, S., ...&Manogaran, E. (2010). Substituted spiro [2.3′] oxindolespiro [3.2 ″]-5, 6-dimethoxy-indane-1 ″-one-pyrrolidine analogue as inhibitors of acetylcholinesterase. Bioorganic & medicinal chemistry letters, 20(23), 7064-7066.

[33]. Revathi, P., &Hemalatha, M. (2012, December). Classification of cotton leaf spot diseases using image processing edge detection techniques. In 2012 International Conference on Emerging Trends in Science, Engineering and Technology (INCOSET) (pp. 169-173). IEEE.

[34]. Revathi, P., &Hemalatha, M. (2012, July). Advance computing enrichment evaluation of cotton leaf spot disease detection using Image Edge detection. In 2012 Third International Conference on Computing, Communication and Networking Technologies (ICCCNT'12) (pp. 1-5). IEEE.

[35]. Paulraj, M. P., Subramaniam, K., Yaccob, S. B., Adom, A. H. B., &Hema, C. R. (2015). Auditory evoked potential response and hearing loss: a review. The open biomedical engineering journal, 9, 17.