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Review Article

Evaluation of Early Detection Methods for Alzheimer's Disease

Elyas Irankhah

Department of Biomedical Engineering, International University of Imam Reza (AS), Mashhad, Iran

Email address:
Elyasirankhah@yahoo.com

Abstract: Amnesia, commonly referred to as Alzheimer's, is a type of brain dysfunction that gradually dissipates the patient's mental abilities. Memory disorder usually develops gradually and progresses. At first, memory impairment is limited to recent events and lessons, but old memories are gradually damaged. In this disease, the connection between nerve cells by the formation of neurofibrillary nodes disappeared. Currently, treatment for the disease mainly involves symptomatic treatments, treatment of behavioral disorders and medication use. Although there is no cure for Alzheimer's disease yet, medications can slow the progression of the disease and reduce the severity of memory impairment and behavioral problems. Today, whit the spread of definitive treatment for this disease, in this study, new techniques for the treatment of this disease can be explored by examining the early detection methods of the disease through brain signal processing with classifiers and medical imaging such as MRI and CT Scan. Signal processing has included EEG and ERP brain signals and the use of classifiers such as SVM, LDA and Neural network. In medical image processing, a combination of Neural network and Wavelet is used to expedite the time of diagnosis according to the above method. Given the process under consideration, combining brain signals and medical imaging can provide valuable help in early detection of Alzheimer disease.

Keywords: Alzheimer's Disease, Image and Signal Processing, Classifiers, Neural Network, Wavelet

1. Introduction

The growing population of the elderly has led to an increase in the number of diseases related to them. One of the most common diseases in the elderly is Alzheimer's or dementia. The disorder begins with profound changes in the elderly person's mood, personality and cognitive ability. Most older people develop Alzheimer's, but younger people are also likely to develop the disease. Alzheimer's disease begins with the loss of small items by first eroding the memory of individuals and gradually increasing over the course of 10 to 20 years Age, family history, gender, and Down syndrome are some of the risk factors for Alzheimer's disease. Unfortunately, Alzheimer's disease affects not only one's own life but also that of his family. So, the family has to take care of the Alzheimer's patient. If you leave Alzheimer's patient alone, you may have some irreparable effects. In fact, there is currently no definitive cure for Alzheimer's [1, 3, 4]. The disease generally has three stages.

The first stage is a mild type of Alzheimer's disease and the exact timing of its onset is unclear. The person has not yet noticed his illness but is not interested in his daily activities as before. It is also reluctant to do anything new. The second stage is the midline of Alzheimer's disease, in which the patient becomes weaker than stage one. When he fails to do so he becomes increasingly angry and aggressive, sometimes seeing or hearing things that do not exist at all. In the third stage, the disease is extremely advanced and severe. He doesn't even remember the events that happened just a moment ago. These people do not know their family and friends. People who have reached this stage of Alzheimer's are in dire need of care [7-9, 11]. Considering the fact that the disease is growing rapidly, techniques must be developed in the early detection process. Behavioral symptoms can be of great help in making this early diagnosis. There are now general methods for early detection of Alzheimer' disease in brain signals processing and medical imaging.

2. Method and Materials

2.1. Electroencephalogram (EEG)

Electroencephalogram is a technique for recording cerebral electrical activity that involves receiving signals from surface electrodes, improving signal (usually amplification and noise removal), signal printing and analysis, and is a noninvasive tool for identifying the location and amount of brain activity involved [13]. The range of brain waves recorded at the cranial surface is very weak at about 0-100 MV and at a frequency of about 0-500 Hz. Brain waves can be divided into the following categories according to frequency: 1 - Delta waves: 0.5-5 Hz, 2- Theta waves: 4-8 Hz, 3- Alpha waves: 8-13 Hz, 4- Waves Beta: 30-13 Hz, 5- Gamma waves: more than 30 Hz.

2.2. ERP

ERPs have a time resolution that allows brain activity to be measured from one millisecond to the next. Many aspects of attention and understanding operate in tens of milliseconds. Since the brain is essentially an electrical device, these electro physical recordings provide a direct benchmark for the process of examining this electrical system. Also, given the nature of the electrical activity and the tissue that produces and releases ERPs, there is no measurable delay between the activity of the brain and the recorded potentials of the skull in this method. However, the biological basis of EEGs and ERPs has been discussed occasionally. However, inability to analyze the activity of individual neurons may be seen as a major drawback in ERP technique [16]. In sum, ERP allows us to observe a series of cognitive operations before transmitting sensory information to the environmental system or even after sending a behavioral response.

3. Classifiers

3.1. Support-Vector Machines (SVM)

A set of points in a n-dimensional space of data is called a supports vector that represents the grouping of categories and sorting of them, and can be changed by moving one of these two items. SVM, or support vector machine, performs the best categorization and separation of data by benchmarking support vectors. Also, in SVM is the basis of machine learning and model building. The purpose of the SVM algorithm is to find the best boundary between the data and take the best possible distance from all categories and not be sensitive to other data points. In fact, in many nonlinear prediction methods, the main purpose is to predict the next point in a time series [18].

3.2. Linear Discriminant Analysis (LDA)

Linear separation methods, similar to non-parametric methods, do not need to know the distribution function $P(x|w_i)$ and by estimating the appropriate form of the separator function and the training data, the parameters of this method are estimated [29, 30]. This method is the basis of many other methods including neural networks, LMS, RLS algorithms and.... Although these methods are not completely optimal, they are easy to use and calculate. In linear separation methods it is assumed to combine the elements of the vector of the property of x with a particular linear weight series expressed by the following relation:

$$g(x) = W^t x + W_0 \qquad (1)$$

In the above relation W is the vector of the weights of this function and W_0 is the bios value. The relation of these separator functions to the Bayes' theorem is also given by the following relation:

$$g(x) = P(x|w_i) \qquad (2)$$

So the classifier first calculates the number of separator function classes and, given the largest of them, specifies the class corresponding to the vector x.

3.3. K-nearest neighbors Algorithm (KNN)

Method K Selects the closest neighbor of a group containing the K record from a set of training records that are closest to the experimental record and based on the class or label's superiority to the test record category. Simply put, this method selects the category with the largest number of records attributable to the selected neighborhood.

3.4. Qualitative Data Analysis (QDA)

In qualitative analysis, the data collected are of the qualitative data type but may also be quantitative experimental data. Then the data should be used in accordance with the logic of qualitative analysis.

4. Shannon Entropy

There are many methods for analyzing the data that are based on the percentage of the frequency of the categories. These methods have their own computational problems that diminish the validity of their results. In qualitative research and content analysis, entropy based on device theory can be used. According to this method, data processing is discussed in content analysis in a new and qualitative way. This method is much stronger and more reliable in content analysis [20, 23].

5. Multilayer Perceptron (MLP)

One of the most basic neural models available is the Multilayer Perceptron (MLP) model that simulates the transient function of the human brain. In this type of neural network, the network behavior of the human brain and its signal propagation have been more commonly considered, and hence are sometimes referred to as Feed Forward Networks [37].

5.1. Radial Basis Function Network (RBF)

Similar to the MLP neural network algorithm, there is

another type of neural network in which processor units are process-focused on a particular location. This focus is modeled through Radial Basis Functions (RBF). In terms of overall structure, RBF neural networks are not much different from MLP networks, and are merely the type of processing that neurons perform on their inputs. However, RBF networks often have a faster learning and preparation process. In fact, because the neurons are focused on a specific functional area, they will be easier to adjust.

5.2. Self-Organizing Map (SOM)

Self-Organizing Map (SOM) is a specific type of neural network that has been thoroughly investigated in terms of functionality, structure and application, with the types of neural networks previously discussed, Is different [42]. The basic idea of self-organizing mapping is inspired by the functional division of the cerebral cortex, and its main application is to solve problems known as 'unsupervised learning'. In fact, the main function of an SOM is to find similarities and clusters among the vast array of data at its disposal. Similar to the work done by the human brain cortex and clustered into similar groups of sensory and motor inputs to the brain.

5.3. Learning Vector Quantization (LVQ)

This particular type of neural network is a generalization of the idea of SOM neural networks to solve supervised learning problems. On the other hand, the LVQ (or Learning Vector Quantization) neural network can be interpreted as saying that the MLP neural network learns what to do with a different approach. The main application of this type of neural network is to solve classification problems, which cover a wide range of applications of smart systems.

5.4. Hopfield Neural Network

This kind of neural network is more like a dynamic system, having two or more stable equilibrium points. The system eventually converges to one of its equilibrium points, starting with each initial condition. Convergence to any point of equilibrium is a diagnosis made by the neural network and can actually be used as an approach to solving classification problems. The system is one of the oldest types of neural networks, with a recursive structure and built-in feedback loops.

6. Images of MRI or CT Scan

Today, diagnostics of Alzheimer's disease is through medical imaging tests such as CT scans, MRI, and brain MRI. Using an MRI scanner, it is possible to take pictures of almost all body tissues. The tissue that has the fewest hydrogen atoms (such as bones) is darkened in the image, while the tissues with high hydrogen atoms (such as fat tissue) are brighter. As the pulse time of radio waves changes, it is possible to obtain information about different tissues. An MRI scan is also able to provide clear images of parts of the body surrounded by

bone tissue, so the above technique is also useful for investigating Alzheimer's disease. CT scans can view the tissues inside the body and examine their shape. With this information we can know about possible diseases. The CT scan also provides virtual slices of the human body, the cross section of which is visible.

7. Segmentation

Segmentation in image implies separating the image into zones, so that the pixels in each area share a specific property (which can belong to an object). The most basic feature in segmenting a single-color image is the brightness of the image and in segmenting a color image its color components. Image and texture edges are also useful features for segmentation [44].

8. Wavelet

Wavelet are tools that have many applications in various branches of engineering science, especially artificial intelligence, machine learning, time series prediction and pattern recognition. The wavelet theory is, in fact, a generalization of Fourier transforms and series and compensates for the weaknesses of Fourier analysis in local performance and short-term behavior modeling. Generally, batch wavelets are mathematical functions that are used to break down a signal consistently into its frequency components whose resolution is equal to its scale. Wavelets are transposed and scaled samples of a function with finite length and oscillation, which are extremely Mira.

8.1. Continuous Wavelet Transform

One of the spectral decomposition methods for unstable signal analysis is to obtain better temporal and frequency resolution of the signal. Among the spectral analysis methods is STFT (Short time Fourier Transform). In this method, the time-frequency resolution is limited by the choice of fixed window length. Instead, the continuous wavelet transform method does not need to select the window length and the time-frequency results are not constant in the time-frequency domain. CWT uses wavelet expansion to produce a time-scale map. It then converts to CWT time-scale map TFCWT (Time-Frequency Continuous Wavelet Transform) to achieve good temporal resolution at high frequencies and good frequency resolution at low frequency.

8.2. Discrete Wavelet Transform

In functional analysis, discrete wavelet transform is the wavelets transform whose wavelet functions are sampled.

8.3. Fast Wavelet Conversion

Rapid Wavelet Conversion is a mathematical algorithm for finding the signal wavelet transform. For this purpose, the signal image is calculated on each of the wavelet functions at different times and scales. In other words, the product of the

internal multiplication of the signal f (t) with each of the wavelets $\emptyset$ is calculated as follows:

$$s_n^{(J)} := 2^J \langle f(t), \emptyset(2^J t - n) \rangle \quad (3)$$

So, the signal image over space V_j equals:

$$P_J[f](x) := \sum_{n \in Z} s_n^{(J)} \emptyset(2^J x - n) \quad (4)$$

8.4. Wavelet Packet Decomposition

A wavelet transform is a signal passing through more filters relative to a discrete wavelet transform. In the discrete wavelet transform, the approximation coefficient passes through the low-pass and high-pass filters at each step, but in the wavelet's packets both the approximate and partial coefficients pass through the filter.

9. Combining Wavelet and Neural Network

There are generally two ways to combine these two issues. Initially, the signal is broken down into several levels by discrete wavelet transform and its ability to analyze the signal at different resolutions. Then, using the standard deviation of the Wavelet coefficients of each level for each perturbation, a feature vector is extracted which is the basis of the signal classification by the neural network. The second method uses the Wavelet at the heart of the MLP neural network. As explained above, a neural network consists of several neurons, each neuron having a conversion function at its output. In this way the neuron conversion function undergoes change. In other words, we write one of the wavelets as a function and place them at the output of each neuron of the neural network. The neural network therefore receives inputs and produces outputs based on its weights and bias and passes a conversion function at the output end.

10. Conclusion

Extracting features from the brain signal contains very useful and important information that helps us to diagnose brain-related diseases. But since medical images such as MRI, CT Scan and other medical images can also help physicians in the process of diagnosis and improvement of these disease, extracting features from both methods and combining them together can help us in these kinds of diseases help to definitive treatment. According to the successful methods reviewed, brain signals processing alone can detect the disease at the appropriate time. But since medical images come with the help of physicians, they can give physicians better and more accurate results in addition to brain signals processing. Since there is no definitive and effective method for early diagnosis of Alzheimer's disease, considering the above methods, combining brain signals with medical images can be an effective way to diagnosis this disease.

References

[1] Pedro Miguel Rodrigues, Joã Paulo Teixeira, Carolina Garrett, Dílio Alves and Diamantino Freitas, Conference on Enterprise. Alzheimer's Early Prediction with Electroencephalogram. Information Systems / International Conference on Project MANagement / Conference on Health and Social Care Information Systems and Technologies, CENTERIS / Proj MAN / HCist 2016, October 5-7, 2016.

[2] Ballard C, Gauthier S, Corbett A, Brayne C, Aarsland D, Jones E. Alzheimer's disease. The Lancet 2011; 377: 1019-1031.

[3] Rodrigues P., Teixeira J. P. Alzheimer's Disease Recognition with Artificial Neural Networks, In Information Systems and Technologies for Enhancing Health and Social Care, by R. Martinho, R. Rijo, M. Cruz-Cunha and J. Varajão (Eds.), IGI Global 2013, 102-118, 2013.

[4] Rodrigues P, Teixeira J. Artificial neural networks in the discrimination of alzheimer's disease. Communications in Computer and Information Science 2011; 221: 272-281.

[5] Rodrigues, P. M., Freitas, D. R. and Teixeira, J. P. Alzheimer's electroencephalogram event scalp localization", IEEE 9th International Workshop on Multidimensional (nD) Systems (nDS); Vila Real, 2015, 1-4.

[6] Akrofi, K., Pal, R., Baker, R. C., Nutter, B. S. and Schiffer, R. W. Classification of Alzheimer's disease and mild cognitive impairment by pattern recognition of EEG power and coherence, Acoustics Speech and Signal Processing (ICASSP), 2010 IEEE International Conference on, Dallas, 2010, 606-609.

[7] O Pogarell, S J Teipel, G Juckel, L Gootjes, T Mo¨ller, K Bu¨rger, G Leinsinger, H-J Mo¨ller, U Hegerl, H Hampel. EEG coherence reflects regional corpus callosum area in Alzheimer's disease. J Neurol Neurosurg Psychiatry 2005; 76: 109–111. doi: 10.1136/jnnp.2004.036566.

[8] Francesco Carlo Morabito, Senior Member, IEEE, Domenico Labate, Alessia Bramanti, Fabio La Foresta, Member, IEEE, Giuseppe Morabito, Isabella Palamara, and Harold H. Szu, Fellow, IEEE. Enhanced Compressibility of EEG Signal in Alzheimer's Disease Patients. IEEE SENSORS JOURNAL, VOL. 13, NO. 9, SEPTEMBER 2013.

[9] A. J. Casson, D. C. Yates, S. J. Smith, J. S. Duncan, and E. RodriguezVillegas, "Wearable electroencephalography," IEEE Eng. Med. Biol. Mag., vol. 29, no. 3, pp. 44–56, May–Jun. 2010.

[10] D. Labate, I. Palamara, G. Occhiuto, G. Morabito, F. La Foresta, and F. C. Morabito, "Complexity analysis of Alzheimer's disease EEG data through multiscale permutation entropy," in Proc. 7th Int. Workshop Biosignal Interpretat., 2012, pp. 185–188.

[11] J. Dauwels, K. Srinivasan, M. R. Reddy, T. Musha, F.-B. Vialatte, C. Latchoumane, J. Jeong, and A. Cichocki, "Slowing and loss of complexity in Alzheimer's EEG: Two sides of the same coin?" Int. J. Alzheimer's Disease, vol. 2011, no. 539621, Feb. 2011.

[12] Ruofan Wang, Jiang Wang, Haitao Yu, Xile Wei, Chen Yang, Bin Deng. Power spectral density and coherence analysis of Alzheimer's EEG. Cogn Neurodyn (2015) 9: 291–304 DOI 10.1007/s11571-014-9325-x.

[13] Dauwels J, Srinivasan K, Reddy MR, Cichocki A (2013) Nearlossless multichannel EEG compression based on matrix and tensor decompositions. IEEE J Biomed Health Inform 17 (3): 708–714.

[14] Gallego-Jutgla ` E, Elgendi M, Vialatte F, Sole ´-Casals J, Cichocki A, Latchoumane C, Jeong J, Dauwels J (2012) Diagnosis of Alzheimer's disease from EEG by means of synchrony measures in optimized frequency bands. Conf Proc IEEE Eng Med Biol Soc 2012: 4266–4270.

[15] Han CX, Wang J, Yi GS, Che YQ (2013) Investigation of EEG abnormalities in the early stage of Parkinson's disease. Cogn Neurodyn 7 (4): 351–359.

[16] Haleh Aghajani et al. "Diagnosis of early Alzheimer's disease based on EEG source localization and a standardized realistic head model". In: IEEEjournalofbiomedicalandhealthinformatics17.6 (2013), pp. 1039– 1045.

[17] Kaj Blennow Colin L. Masters Randall Bateman. "Primer Alzheimer's diseasel". In: NatureReviewsDiseasePrimers1. 15056 (2015).

[18] Justin Dauwels, Francois Vialatte, and Andrzej Cichocki" Diagnosis of Alzheimer's disease from EEG signals: where are westanding?" In: CurrentAlzheimerResearch7.6 (2010), pp. 487–505.

[19] Gareth James et al. "Support vector machines". In: An Introduction to StatisticalLearning. Springer, 2013, pp. 337–372.

[20] Aunsia Khan and Muhammad Usman. "Early diagnosis of Alzheimer's disease using machine learning techniques: A review paper". In: Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K), 20157thInternationalJointConferenceon. Vol. 1. IEEE. 2015, pp. 380–387.

[21] Morabito FC, Campolo M, Labate D, Morabito G, Bonanno L, et al: A longitudinal EEG study of Alzheimer's disease progression based on a complex network approach. Int J Neural Syst 2015; 25: 1550005.

[22] M. Prince, R. Bryce, E. Albanese, A. Wimo, W. Ribeiro, and C. P. Ferri, "The global prevalence of dementia: a systematic review and metaanalysis." Alzheimers Dement, vol. 9, no. 1, pp. 63–75. e2, 2013.

[23] F. Falahati, E. Westman, and A. Simmons, "Multivariate Data Analysis and Machine Learning in Alzheimer's Disease with a Focus on Structural Magnetic Resonance Imaging." J Alzheimer Disease, vol. 41, no. 3, pp. 685–708, 2014.

[24] M. Liu, D. Zhang, "Inherent Structure Based Multi-view Learning with Multi-template Feature Representation for Alzheimer's Disease Diagnosis", IEEE Transactions on Biomedical Engineering, vol. 63, pp. 1473-1482, 2015.

[25] A. L. Spedding, G. Di Fatta, J. D. Saddy t, and ADNI, "An LDA and Probability-based Classifier for the Diagnosis of Alzheimer's Disease from Structural MRI" BIBM, IEEE International Conference on, pp. 1404-1411, 2015.

[26] G. Lizarraga, M. Cabrerizo, "A Web Platform for Data Acquisition and Analysis for Alzheimer's Disease", SoutheastCon, pp. 1-5, 2016.

[27] J. C. Daza, A. Rueda, "Classification of Alzheimer's Disease in MRI using Visual Saliency Information", IEEE 11th Colombian Computing Conference (CCC), pp. 1-7, 2016.

[28] T. Li, W. Zhang, "Classification of brain disease from magnetic resonance images based on multi-level brain partitions", Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 5933-5936, 2016.

[29] H. T. Gorji, J. Haddadnia "A novel method for early diagnosis of Alzheimer's Disease based on pseudo Zernike moment from structural MRI", Neuroscience, pp. 361-31, 2015.

[30] A. Demirhan, T. M. Nir, "Feature selection improves the accuracy of classifying Alzheimer's disease using diffusion tensor images", IEEE 12th International Symposium on Biomedical Imaging (ISBI), pp. 126130, 2015.

[31] H. Matsuda. MRI morphometry in Alzheimer's disease. Ageing research reviews. 2016; 30: 17-24.

[32] Biju K S, Alfa S S, Kavya Lal, Alvia Antony, Akhil M Kurup. Alzheimer's Detection Based on Segmentation of MRI Image. 7th International Conference on Advances in Computing & Communications, ICACC-2017, 22-24 August 2017, Cochin, India.

[33] Elisa Canu, Federica Agosta, Gorana Mandi-Stojmenovica,, Tanja Stojković, Elka Stefanova, Alberto Inuggi, Francesca Imperiale, Massimiliano Copetti, Vladimir S. Kostic, Massimo Filippi. Multiparametric MRI to distinguish early onset Alzheimer's disease and behavioral variant of frontotemporal dementia. Neuro Image: Clinical 15 (2017) 428–438.

[34] Johnson, K. A., Fox, N. C., Sperling, R. A., Klunk, W. E., 2012. Brain imaging in Alzheimer disease. Cold Spring Harb. Perspect. Med. 2.

[35] Liu, F., Zhou, L., Shen, C., Yin, J., 2014. Multiple kernel learning in the primal for multimodal alzheimer's disease classification. IEEE J. Biomed. Health Inform. 18.

[36] Ritter, K., Schumacher, J., Weygandt, M., Buchert, R., Allefeld, C., Haynes, J.-D., 2015. Multimodal prediction of conversion to Alzheimer's disease based on incomplete biomarkers. Alzheimer's Dement. Diagn. Assess. Dis. Monit. 1, 206–215.

[37] Xia, Y., Lu, S., Wen, L., Eberl, S., Fulham, M., Feng, D. D., 2014. Automated identification of dementia using FDG-PET imaging. Biomed. Res. Int. 2014.

[38] Ahmed, M. U.; Mandic, D. P. Multivariate multiscale entropy. IEEE Signal Process. Lett. 2012, 19, 91–95.

[39] Morabito, G.; Bramanti, A.; Labate, D.; La Foresta, F.; Morabito, F. C. Early detection of Alzheimer's onset with permutation entropy analysis of EEG. Nat. Intell. 2011, 1, 30–32.

[40] Mizuno, T.; Takahashi, T.; Cho, R. Y.; Kikuchi, M.; Murata, T.; Takahashi, K. Assessment of EEG dynamical complexity in Alzheimer's Disease using multiscale entropy. Clin. Neurophysiol. 2010, 27, 1091–1106.

[41] Hu, M.; Liang, H. Adaptive multiscale entropy analysis of multivariate neural data. IEEE Trans. Biomed. Eng. 2012, 59, 12–15.

[42] Dauwels, J.; Vialatte, F.; Cichocki, A. Diagnosis of Alzheimer's Diseases from EEG Signals: Where Are We Standing? Curr. Alzheimer Res. 2010, 7, 487–505.

[43]   Yang, A. C.; Wang, S. J.; Lai, K. L.; Tsai, C. F.; Yang, C. H.; Hwang, J. P.; Lo, M. T.; Huang, N. E.; Peng, C. K.; Fuh, J. L. CognitiveandneuropsychiatriccorrelatesofEEGdynamiccomple xityinpatientswithAlzheimer's   disease.   Prog. Neuro-Psychopharmacol. Biol. Psychiatry 2013, 47, 52–61.

[44]   Mcbride, J. C.; Zhao, X.; Munro, N. B.; Smith, C. D.; Jicha, G. A.; Hively, L. S.; Broster, L. S.; Schmitt, F. A.; Kryscio, R. J.; Jiang, Y. Spectral and Complexity Analysis of Scalp EEG Characteristics for Mild Cognitive Impairmentand Early Alzheimer's Disease. Comput. Methods Programs Biomed. 2014, 114, 153–163.

[45]   Garn, H.; Waser, M.; Deistler, M.; Benke, T.; Dal-Bianco, P.; Ransmayr, G.; Schmidt, H.; Sanin, G.; Santer, P.; Caravias, G.; et al. Electroencephalographic Complexity Markers Explain Neuropsychological Test Scores in Alzheimer's Disease. In Proceedings of the 2014 IEEE-EMBS International Conference on Biomedical and Health Informatics, Valencia, Spain, 1–4 June 2014.

[46]   Garn, H.; Waser, M.; Deistler, M.; Benke, T.; Dal-Bianco, P.; Ransmayr, G.; Schmidt, H.; Sanin, G.; Santer, P.; Caravias, G.; et al. Quantitative EEG markers relate to Alzheimer's diseases severity in the Prospective Dementia Registry Austria (PRODEM). Clin. Neurophysiol. 2015, 126, 505–513.

[47]   Wu, S. D.; Wu, C. W.; Lee, K. Y.; Lin, S. G. Modified multiscale entropy for short-term time series analysis. Phys. A Stat. Methods Appl. 2013, 392, 5865–5873.

[48]   Kork, F.; Gentsch, A; Holthues, J.; Hellweg, R; Jankowski, V.; Tepel, M.; Zidek, W.; Jankowski, J. Abiomarker for severity of Alzheimer's disease: H-NMR resonances in cerebrospinal fluid correlate with performance in mini-mental-state-exam. Biomarkers 2012, 17, 36–42.

[49]   N. N. Kulkarni & V. K. Bairagi. Extracting Salient Features for EEG-based Diagnosis of Alzheimer's Disease Using Support Vector Machine Classifier. ISSN: 0377-2063 (Print) 0974-780X (Online) Journal homepage. IETE JOURNAL OF RESEARCH, 2016.

[50]   N. Kulkarni and V. Bairagi, "Diagnosis of Alzheimer disease using EEG signals," Int. J. Eng. Res. Technol. (IJERT), Vol. 3, no. 4, pp. 1835–8, Apr. 2014.

[51]   S. Du, D. Huang, and H. Wang, "An adaptive support vector machine – based workpiece surface classification system using high definition metrology," IEEE Trans. Instrument. Meas., Vol. 64, no. 10, pp. 2590–604, 2015.