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Review Article

A proposed network of an effective deep belief for the recognition of Alzheimer

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Abstract:

Alzheimer(A.Z) is a gradually advancing condition that leads to the degeneration of brain cells. rendering an individual unable of independent functioning. During the initial stages of AZ development, an individual may forget prior talks or the occurrence of an incident. Subsequently, there may be a substantial decline in memory, rendering the individual unable of doing daily tasks . Therefore, this study aims to differentiate between patients with AZ and those in the normal control (NC) group by employing magnetic resonance imaging (MRI). Four phases were used in our study: collected (420)subjects as dataset , preprocessing with a 2D Gaussian filter, and feature extraction by using deep neural networks , while last step is classification . Machine learning algorithms are used to determine if the subject are demented or not . In this study , applied Random Forest and Naive Bayesian methods as classifier . For analysis purpose , (WEKA.) tool is utilized .The experimental results show that accuracy was 83 %with Random forest while 79% with Naive Bayesian

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1. Introduction

Alzheimer(A.Z) affects over 5% of the population in Europe, with as many cases as 11.08 per 1000 people annually [1]. The origin of this type of neurodegenerative disease, . Current diagnosis methods primarily rely on a comprehensive neuropsychological exam, such as the Mini-Mental State Exam (MMSE), which may introduce confusing variables into the diagnosis process [2]. The prodromal stages of AZ in mild cognitive impairment (MCI) are occasionally mistaken for cognitive decline associated with aging or other medical conditions.

The Alzheimer's Disease Neuroimaging Initiative (ADNI), the Open Access Series of Imaging Studies (OASIS), and the Dominantly Inherited Alzheimer Network (DIAN) are three longitudinal studies which follow up the individuals with mild cognitive impairment (MCI) to AZ. These studies include biological markers, cognitive evaluations, and magnetic resonance imaging (MRI). These initiatives have significantly increased the applicability of computational analytical methods. These days, it's rather usual to find processing pipelines that combine feature extraction with spatial and intensity normalization, like FreeSurfer or Statistical Parametric Mapping (SPM) [10]. Differential diagnostic studies are increasingly depending on structural and functional aspects [3], [4]. Moreover, the progress of machine learning (ML) methods has made it possible to provide complete systems using automated feature extraction, selection, and classification techniques [6]. However, a small number of these studies [7] are dedicated to elucidating the interaction between test results, biomarkers, and structural alterations in the brain—a critical phase of diagnosis validation. The transforming framework provided by deep learning (DL) has significantly improved biomedical image processing, as evidenced by the numerous techniques that employ dense networks, residual networks, two- and three-dimensional convolutional neural networks, and other approaches. Autoencoders (AEs) [15] and [1] are highly intriguing techniques due to their ability to self-supervised model the manifold of a dataset. This skill has been successfully implemented in the fields of psychiatry [12], breast cancer [8], and A.Z [1]. By combining convolutional layers—which are perfect for image processing since they can directly extract data-driven features from three-dimensional arrays—convolutional autoencoders (CAEs) enhance this design. This study implies that the arrangement of an MRI image collecting determines the direction of AZ evolution. Using a CAE model, we wish to forecast clinical and neuropsychological scores, track individual development from cognitive impairment to dementia, and generate a dataset [1]. Self-supervised decomposition of the original data reveals a manifold structure that is connected to other data types, including biological markers (ApoE, Tau protein), neuropsychological assessments, and the conventional classifications of A.Z, mild cognitive impairment (MCI), and healthy controls (CTLs).

2. Related works

Using transfer learning on MRI scans, Ebrahimi-Ghahnavieh et al. (2019) [16] successfully identified AZ. This work used a range of pre-trained CNNs and datasets including single- and multi-view modalities. We first used CNN to extract vectors from the MRI scans. We next loaded the vectors into an image categorization recurrent neural network (RNN). The RNN had various difficulties including disappearing or extending gradients and insufficient processing speed for image categorization.

Lian et al. (2020) developed a fully hierarchical CNN model to identify AZ early by detecting discriminative local regions and segments in MRI images. Additionally, Bi et al. (2020)employed a layered CNN model to diagnose AZ. The proposed CNN models significantly improved AZ recognition on the AZNI datasets;

however, their temporal complexity was relatively high. In their GAN model for AZ identification application,
Hu et al. (2020) also investigated class

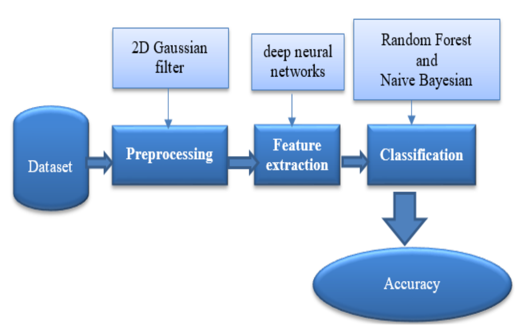
imbalance issues. The GAN model required a significant amount of computational resources and time for training in the context of image classification. In order to identify A.Z in structural MRI (sMRI) images and Mild Cognitive Impairment (MCI), Zhu et al. (2021) created a Dual Attention Multi Instance Deep Learning (DA-MIDL) model. Three primary processes were engaged in the development of the DA-MIDL model: the integration of multiple spatial attention blocks within the Patch-Net model produces discriminative vectors; pooling runs are employed to equilibrate each (sMRI) patch; and a global attention-aware classification model is implemented to facilitate classification decision-making. The results suggest that the DA-MIDL model was able to achieve improved classification performance by accurately identifying the impacted areas. In comparison to their performance, conventional methods were enhanced by generalizability and classification accuracy. Nevertheless, the primary concerns of the DA-MIDL model were overfitting and limited interpretability. Rani In order to enhance the contrast of MRI images and eradicate the skull area, Kaka and Prasad (2022) [19] implemented adaptive histogram equalization and region growth strategies. Vectors were recovered using a local directional pattern and Gabor features, following the fuzzy c-means technique to segment the relevant areas. To perform feature selection and classification, they integrated correlation/ensemble-based feature selection technique with a multi-class SVM (MSVM)

classifier. The MSVM classifier was found to be insufficient when the target classes overlapped in larger datasets.
An efficient ensemble learning strategy for exact(A.Z)identification with a CNN model was presented by Kang et al. (2021) [20]. The proposed system was divided into two phases: the first phase employed a majority vote to predict maladies, while the second phase employed ResNet50 and VGG-16 models to generate an ensemble learning classifier. Task adaption transfer and domain transfer are two transfer learning techniques we used to address the biological categorization difficulties. The results show that, despite its great temporal complexity, the proposed ensemble learning system exceeded the individual classifiers in classification performance.
Liu et al. (2021) [21] developed a successful CNN-based AZ classification algorithm. We first split the brain scans into several areas, then classified similar portions from each region using the K-means clustering method. Finally, features from the aggregated areas were extracted using the DenseNet model in order to classify images. The DenseNet model's very aggressive parameter control led to overfitting problems.

3. System Design for the Detection of Alzheimer

The quality of images fluctuates based on the patient and the equipment used, resulting in intricate identification challenges for AZ patients with X-ray images. Figure 1 illustrates the proposed work.

Figure 1: proposed work



3.1 Collection of data

The data.set used in this work was taken from the ADNI database, which can be foundat“adni.loni.usc.edu”[24].In 2002, the ADNI was established as a public-private collaboration. Under the direction of ”VAM” Medical Center and University main investigator [.Michael Wn. Weiner, MLD of San ;Francisco- California. The collection can be accessed in http://www.nature.com/nm/journal/v13/n11/suppinfo/nm1653_S1.html

3.2 Pre-processing

Preprocessing is an essential step to enhance the accuracy of classification systems. We eliminated the noise from the medical images during the preprocessing phase. In this instance, we utilized a 2D Gaussian filter on the X-ray images. The noise level affecting picture sensitivity has influenced these photographs. Equation 1 mathematically delineates a Gaussian two-dimensional filter.

$$Gu(xi , yi) = \frac{1}{\sqrt{2\pi\delta}} \exp\left(-(x^2 + y^2)/2\delta^2\right) \ldots\ldots\ldots\ldots(1)$$

The filter's kernel size is denoted by (δ^2), (-1<= xi_i , yi_i<=1) refer to variance. When the said filter is applied, the ratio from signal to noise is improved [10]. Figure 2 illustrates the application of a Gaussian filter to remove noise from the X-ray image in AZ. The initial image, possessing an SNR value of 6, is the first image. The second image has a filtered SNR value of 10.

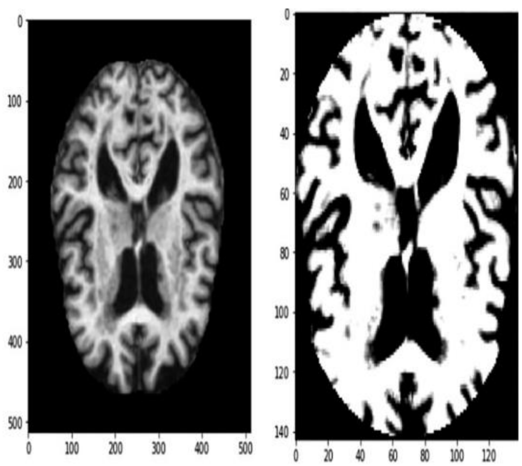


Figure. 2: de-noising utilizing a 2^{nd} Gaussian filter (image 1 is the original one, while image 2 is the filtered one)

3.3 Feature Extraction

Among the several deep learning techniques accessible are recurrent neural networks, deep belief networks, convolutional neural networks, deep conventional extreme machine learning. Each form of network is characterized by unique mathematical operations and statistical properties. In this phase, we implemented deep belief networks. In general, deep learning employs numerous layers of feature detection units.

To extract more complex features, we remove basic attributes from lower levels and incorporate them into higher levels. This deep belief network idea consists in both hidden and visible levels. This network seeks to identify the most intricate aspect capable of exposing buried information inside the data and higher-order correlations. In the left side of figure 3, figure vi, the vector of visible strata is given by (i=1, 2, 3, 4,...). Still, hi (i=1, 2, 3, 4,... marks the vector of the hidden layer). Moreover, the right-hand side of the figure [15] consists of both an exposed and a hidden layer. [16] [Also The number of hidden units in the next network corresponds with the number of visible units in the previous one. During the training phase of a deep belief network model—which consists of successive learning of the networks—the features obtained from one deep belief network act as input for the next one.

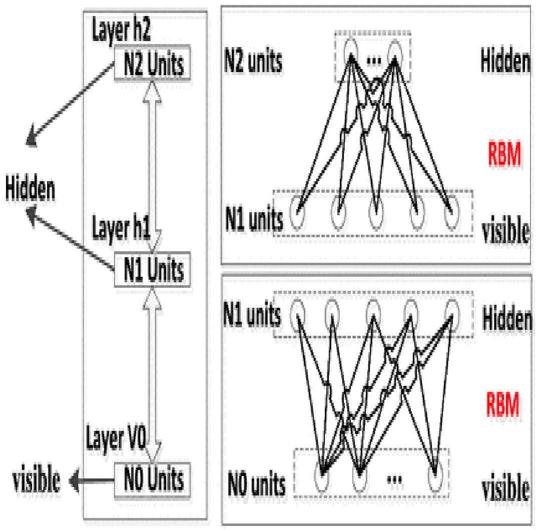


Figure. 3: A network of deep belief

3.4. C-SLBP-based network of deep belief

Implementing a deep belief network on accurately sized images presents a significant challenge. The high dimensionality of pixie-level AZ images substantially increases the computational difficulty of the training algorithm. To solve problems in medical imaging, particularly with regard to images of AZ, Heikkila [17] presented the C-SLBP method. Heikkila [17] initially presented the Center Symmetric-Local Binary Pattern (C-S LBP). < Studies imply that a consistent feature descriptor for textures is the local binary pattern (LBP). Feature description. The center-symmetric principle, referred to as "C-SLBP", encodes image alterations from four distinct orientations. An equation can be employed to define the features of C-SLBP (2).

$$\text{C-SLBPR,N,T}\ (X,Y)=\sum_{i=0}^{(\frac{N}{2})} S\left(n_i - n_{i+\frac{N}{2}}\right)2^i \qquad \text{...................}(2)$$

N is the number of the pixels on a circle with a radius of R. In [18], [19], the gray values of the center symmetric area pixels are represented by (ni) and (n i+(N/2)). If S(x) = 1... X > T, otherwise. We establish the threshold for T to modify the image's intensity, hence improving its resilience in uniform areas. Furthermore, it determines that C-SLBP exhibits greater resilience to noise interference and possesses fewer dimensions than traditional LBP. It possesses lower computational complexity. We employ C-SLBP for feature extraction to retain significant information from images and mitigate the impact of noise, including posture variation. Figure 4 demonstrates the initial extraction of local features from the input image via C-SLBP. In the second stage, the deep belief network utilizes the extracted features as input for the visible layers, substituting the original AZ images. The third stage entails training the Deep Belief Network from the lowest to the highest layers [22, 23, 24]. The network, its parameters, and the output of the initial layer are intended to be trained using this method. This data is used as the input for the ensuing layer, and so forth. In order to obtain the optimal network configuration, the backpropagation approach refines the parameters of the trained deep belief network. In total, the ultimate deep belief network technique consists of three layers and twenty iterations for each layer.

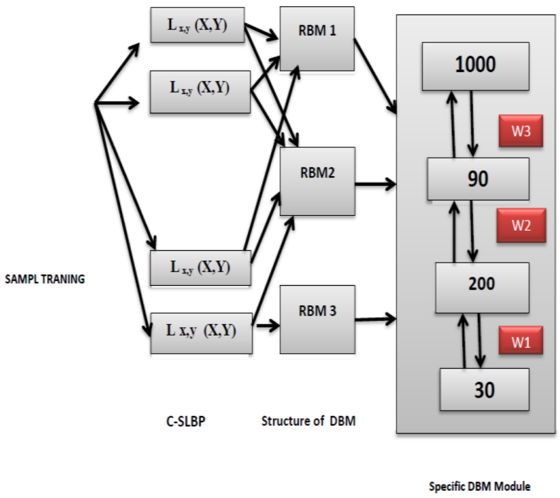


Figure. 4: A C-SLBP-based network of deep belief

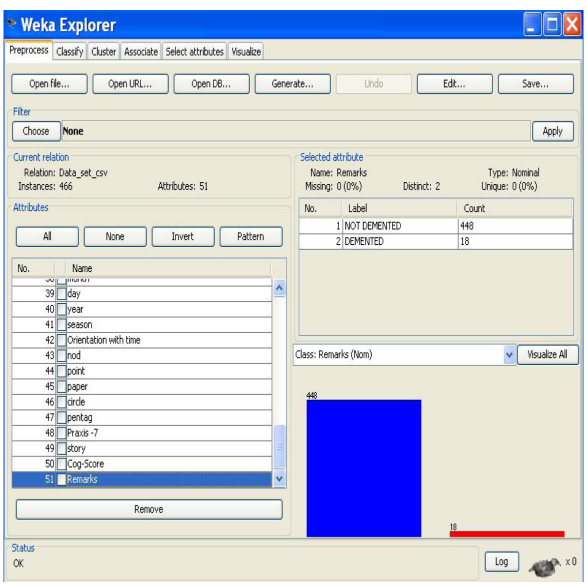


Figure 5: CSV. file loaded to Weka .explorer.[12]

4.Model Evaluation and Discussion

During this research, we utilized WEKA includes two(2) learning performance evaluations[5].

1-Training- Set : In this instance, the classifier merely divides the data_.set into test and training sets.

2- Cross _.Validation: When using n fold cross validation, WEKA creates (T) models, after that determines the (average) of those (T) models , and shows the outcomes , while The models that remain are removed.

Analyzing the model with Explorer Figure 5: illustrates how the {CSV. file } is loaded into the WEKA. There are (46)attributes also (420) instances in the data set. Additionally, there are (391) negative(N-) instances while (29) positive(P+) instances.

This paper examines the effects of AZ on the brain. X-ray scans of AZ were included among the medical images employed, as stated in

http://www.nature.com/nm/journal/v13/n11/suppinfo/nm1653_S1.html

The information-data used in this research was. in the form of datasheet . While, [*ARFF] is WEKA's native data storage format. [11] Spreadsheet data will be transformed into CSV format. The CSV file is then changed to an ARFF file [12].

While, Use deep belief network as feature selection. Gaussian filter to select attributes is best 1first, figure 6 refer to the result of Weka explorer when using (RF-Random Forest) and Naive Bayesian

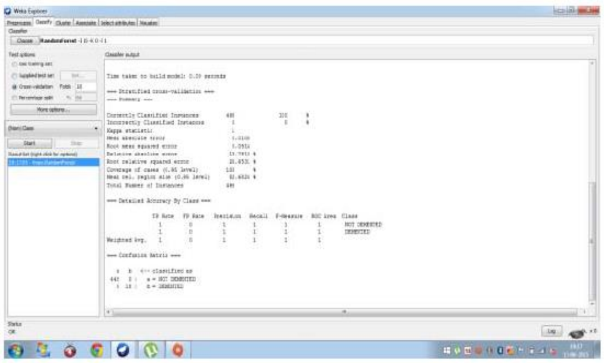


Figure 6: Random Forest and Naive Bayesian with Weka

Two groups made out of the experimental data set: 30% for testing and 70% for training. Table 1 shows the results of the suggested approach tested and trained upon. Among several criteria, our suggested system method assesses false negative rate, false positive rate, and precision. Consult equations 3, 4, and 5 to assess system performance. By means of a deep belief network with C-SLBP, the proposed system achieves 78% accuracy in detecting AZ presence in the brain, together with lowered false positive and false negative rates, when compared with past research indicated by [20]. The degree of precision attained in [20] was less than that suggested approach. Previous studies also used a partition approach or tested without first eliminating noise from the image or usage.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{..........(3)}$$

Where :TP, TN:, FP, and FN : refer to the number of True Positive case , True Negative case , False Positive case , and False Negative cases respectively.

Precession is the proportion of documents returned that are actually related to the inquiry.

Recall refer to the amount of documents that were actually retrieved that are pertinent to the query.

$$\boldsymbol{Precision} = \frac{|\{relavant\} \cap \{retrieved\}|}{\{retrieved\}} \qquad (4)$$

$$Recall = \frac{|\{relavant\} \cap \{retrieved\}|}{\{retrieved\}} \qquad (5)$$

Table . 1: The effectiveness of the system presented in this study in testing and training

method	Accuracy	Recall	Precession	F-Measure
Random Forest	83%	1	1	1
Naive Bayesian	79%	0.96	0.95	0.95

5. Concluding Remarks

This research provides a way for identifying AZ using a deep learning model that will help physicians in their diagnostic processes. To accomplish this, we used X-ray images from medical institutions to show a deep belief network architecture for differentiating individuals with and without AZ. In this study these medical image have been converted in to spread sheet. Upon comparison , the proposed method yielded favorable outcomes. The accuracy was 83%. With random forest while 79%with Naive Bayesian. The findings of our study can aid medical professionals or the institution in making more informed decisions.

Acknowledgement

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References

[1] shaymaa Adnan and Abdel-Badeeh M. Salem ," A efficient deep belief network for Detection of Corona Virus Disease COVID-19" *Fusion: Practice and Applications, Vol. 02, No. 01, PP. 05-13, 2020*

[2] H. Niu, I. A´ lvarez A´ lvarez, F. Guille´n-Grima, and I. Aguinaga-Ontoso, "Prevalencia e incidencia de la enfermedad de Alzheimer en europa: metaan´alisis," *Neurologia*, vol. 32, no. 8, 2017, Art. no. 523532.

[3] S. Z. Klekociuk, J. J. Summers, J. C. Vickers, and M. J. Summers, "Reducing false positive diagnoses in mild cognitive impairment: The importance of comprehensive neuropsychological assessment," *Eur. J. Neurol.*, vol. 21, no. 10, Jun. 2014, Art. no. 1330e83.

[4] G. H. Weissberger, J. V. Strong, K. B. Stefanidis, M. J. Summers, M. W. Bondi, and N. H. Stricker, "Diagnostic accuracy of memory measures in Alzheimer's dementia and mild cognitive impairment: A systematic review and meta-analysis," *Neuropsychol. Rev.*, vol. 27, pp. 354–388, Sep. 2017.

[5] G. B. Frisoni *et al.*, "Strategic roadmap for an early diagnosis of Alzheimer's disease based on biomarkers," *Lancet Neurol.*, vol. 16, no. 8, 2017, Art. no. 661676.

[6] B. Dubois *et al.*, "Advancing research diagnostic criteria for Alzheimer's disease: The IWG-2 criteria," *Lancet Neurol.*, vol. 13, no. 6, pp. 614–629, 2014.

[7] A. Ortiz, J. Munilla, J. M. Gorriz, and J. Ramirez, "Ensembles of deep learning architectures for the early diagnosis of the Alzheimers disease," *Int. J. Neural Syst.*, vol. 26, no. 7, 2016, Art. no. 1650025.

[8] A. Payan and G. Montana, "Predicting Alzheimer's disease: A neuroimaging study with 3D convolutional neural networks," 2015, *arXiv:1502. 02506*.

[9] F. J. Martinez-Murcia, J. M. G´orriz, J. Ramirez, and A. Ortiz, "Convolutional neural networks for neuroimaging in Parkinson's disease: Is preprocessing needed?" *Int. J. Neural Syst.*, vol. 2018, Art. no. 1850035.

[10] G. Litjens *et al.*, "A survey on deep learning in medical image analysis," *Med. Image Anal.*, vol. 42, pp. 60–88, 2017.

[11] R. D. Hjelm, V. D. Calhoun, R. Salakhutdinov, E. A. Allen, T. Adali, and S. M. Plis, "Restricted boltzmann machines for neuroimaging: an application in identifying intrinsic networks," NeuroImage, vol. 96, pp. 245–260, 2014.

[12] Shaymaa Adnan Abdulrahman, Wael Khalifa, Mohamed Roushdy, Abdel-Badeeh M. Salem" Comparative Study for 8 Computational Intelligence Algorithms for Human Identification" Journal, Computer Science Review Vol 36 2020 https://doi.org/10.1016/j.cosrev.2020.100237

[15] 9- Shaymaa Adnan Abdulrahman and , Bilal Alhayani ," A comprehensive survey on the biometric systems based on physiological and behavioural characteristics" Materials Today: Proceedings https://doi.org/10.1016/j.matpr.2021.07.005

[16] Ebrahimi-Ghahnavieh, A., Luo, S., and Chiong, R. (2019). "Transfer learning for Alzheimer's disease detection on MRI images," in 2019 IEEE international conference on industry 4.0, artificial intelligence, and communications technology (IAICT) (Bali, Indonesia: IEEE), 133–138.

[17] Lian, C., Liu, M., Zhang, J., and Shen, D. (2020). Hierarchical fully convolutional network for joint atrophy localization and Alzheimer's disease diagnosis using structural MRI. IEEE Trans. Pattern Analysis Mach. Intell. 42 (4), 880–893. doi:10. 1109/TPAMI.2018.2889096

[18] Zhu, W., Sun, L., Huang, J., Han, L., and Zhang, D. (2021). Dual attention multiinstance deep learning for Alzheimer's disease diagnosis with structural MRI. IEEE Trans. Med. Imaging 40 (9), 2354–2366. doi:10.1109/TMI.2021.3077079

[19] Rani Kaka, J., and Prasad, K. S. (2022). Alzheimer's disease detection using correlation based ensemble feature selection and multi support vector machine. Int. J. Comput. Digital Syst. 12 (1), 9–20. doi:10.12785/ijcds/120102

[20] Kang,W., Lin, L., Zhang, B., Shen, X., Wu, S., and Alzheimer's Disease Neuroimaging Initiative (2021). Multi-model and multi-slice ensemble learning architecture based on 2D convolutional neural networks for Alzheimer's disease diagnosis. Comput. Biol. Med. 136, 104678. doi:10.1016/j.compbiomed.2021.104678

[21] Liu, J., Li,M., Luo, Y., Yang, S., Li,W., and Bi, Y. (2021). Alzheimer's disease detection using depthwise separable convolutional neural networks. Comput. Methods Programs Biomed. 203, 106032. doi:10.1016/j.cmpb.2021.106032

[22] Zahraa A. Jaaz , etal "A dynamic task scheduling model for mobile cloud computing" 2022 9th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI2022) - 6-7 October 2022

[23] Shaymaa Adnan Abdulrahman, etal ,"Intrusion Detection in Wireless Body Area Network using Attentive with Graphical Bidirectional Long-Short Term Memory" Intrusion Detection in Wireless Body Area Network using Attentive with Graphical Bidirectional https://doi.org/10.3991/ijoe.v19i06.37593

[24] Ray S, Britschgi M, Herbert C, et al, Classification and prediction of clinical Alzheimer's diagnosis based on plasma signaling proteins, Nature medicine,13(11): 1359-1362 (2019)