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ALZHEIMER'S DISEASE PREDICTION USING ENHANCED U-NET ARCHITECTURE

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Abstract: Alzheimer's disease (AD) is the most prevalent kind of dementia for which there is now no cure. Correctly classifying AD may facilitate diagnosis and therapy selection. Multiple studies over the last decade have shown that DL algorithms effectively diagnose AD. Based on 3D T1-weighted magnetic resonance imaging, this work presents an E-U-net model for identifying AD (MRI). It has been shown that the Model's performance is boosted when coupled with stringent supervision. Attempts have been attempted to quantify the presence of amyloid-beta in body fluids for clinical diagnosis of Alzheimer's disease. However, these approaches have not been completely successful in predicting cognitive decline in patients. They are not aimed at elucidating the molecular pathogenesis induced by Tau and amyloid-beta proteins in hippocampus neurons of AD patients. This paper proposed Enhanced U-Net architecture for MRI Image segmentation. This study recommends evaluating the segmentation of True and predicted masks by detecting the fluorescence signal inside, which might give valuable insight into the nature of the disease. The experimental results are shown in the input MRI image with corresponding true and predicted masks and training and testing details.
Keywords: prediction disease alzheimers enhanced net

I .INTRODUCTION

Alzheimer's disease (AD) is a neurological condition that results in memory loss and cognitive impairment. Alzheimer's disease is the most common cause of dementia in those over 65, yet there is no effective therapy or prevention. Alzheimer's disease was the sixth largest cause of death in the United States in 2017, according to official death certificates, and the fifth major cause of death among Americans aged 65 and over. Automatic Alzheimer's disease categorization may improve clinicians' capacity to identify high-risk patients, allowing early intervention to prevent or delay disease progression [1]. The most frequent kind of dementia is Alzheimer's disease [2]. Individuals with Alzheimer's disease have insoluble polymeric lesions in their hippocampus and transent orhinal cortex, largely made up of Tau and Amyloid-(A) polypeptides [3]. It is thought that the sickness begins roughly 20 years before the first symptoms, which are often memory and language impairments. Walking and swallowing become more difficult as the condition progresses, eventually leading to death [4]. Alzheimer's disease pathogenesis is characterized by the production of plaques and neuro fibrillary tangles composed of Tau protein [5]. Several fluorescent imaging probes that target plaques and Tau tangles are often utilized in AD research and diagnosis. However, the molecular structures targeted by these probes in the brain, where the sickness occurs, have yet to be thoroughly investigated [6]. In addition to verifying the diagnosis, postmortem brain tissue from AD patients may provide information on the mechanisms that lead to the loss of the hippocampal neuronal population and the aberrant behavior of Tau and A polypeptides [7]. Consequently, neurodegenerative events may be quantified using fluorescence signals against these chemical processes. Through Deep Learning (DL) image segmentation, our research provides a unique approach for giving quantitative information on disease pathology [8].Because of the low intensity of damaged brain cells in MRI images, magnetic resonance (MR) is a good imaging tool for monitoring the morphological and functional neuronal abnormalities associated with Alzheimer's disease [9][10]. Consequently, our study focuses on interpreting MRI data for diagnosing AD [11]. In recent years, DL has improved the performance of various computer vision applications due to its wide feature learning capabilities [12]. Several researchers have used DL to identify and predict patient illnesses. In detecting Alzheimer's disease, the auto encoder model outperforms the Support Vector Machine, logistic regression, and linear discriminate analysis [13]. In recognizing Alzheimer's illness, CNN beat SVM and sparse auto encoder. These findings indicate that DL for computer-assisted AD therapy has shown promising results [14].Existing research has produced some algorithms for diagnosing AD using DL [15-18]. The main barrier is a scarcity of publicly available training data;

Some researchers have used transfer learning to overcome the AD diagnosis problem. Before being utilized to diagnose Alzheimer's disease, the models will be trained on many datasets. Some persons, for example, have been diagnosed with Alzheimer's, moderate cognitive impairment, or a neuro cognitive illness due to transfer learning through trained CNN. Using cross-modal transfer learning [19].Categorized patients as NC, AD, or MCI. A variety of neural network topologies have also been employed to classify AD. A simple neural network was fitted using an inception-based neural network model and an embedding dense block to identify AD phases [20].Previous research has shown that models of neural networks that transmit information from the shallow to the deep levels are more effective [20]. It may be because mixing shallow and deep characteristics increases data usage, enhancing model performance. This resulted in the developing of a U-net-based neural network model for the AD diagnostic problem. Within the recommended U-net topology, encoders and decoders are symmetrical. It uses skip connections to integrate high-level semantics with low-level fine-grained surface representation, allowing it to categorize more source images. Furthermore, some studies imply that rigorous supervision may improve the efficacy of a model's categorization. Therefore, intensive supervision is included in the suggested paradigm [16-20]. The rest of this paper is organized as follows. In Section 2, several writers discuss various AD segmentation diagnostic methodologies. Section 3 depicts the E-U Net Model. Section 4 describes the investigation's findings. Section 5 finishes with a discussion of the findings and future directions.

II. BACKGROUND STUDY

Anandh, K. et al. [1] It is difficult to discern between normal and AD patients with abnormal ventricles due to the overlap in ventricular shape, size, and volume measurement. Tukey'sbi weight anisotropic diffusion filtering was employed as a segmentation edge indicator in this study's modified distance regularized level set technique. According to the findings, Tukey'sbi weight anisotropic diffusion filtering may act as a substantial edge operator, increasing the edges of ventricles. Ventricles were segmented, and geometric features were extracted and statistically analyzed. It was shown that distinct features might visually distinguish the clinical pathology of individuals with AD. Therefore, this study seems to have therapeutic value.

Biju, K. et al. [3] This study presents a software method for identifying brain anomalies, namely AD. Existing technology requires a physician to manually diagnose a patient's Magnetic Resonance Imaging (MRI). He must examine the prior clinical history to confirm the condition. A brain MRI consists of around 120 slices. Diagnosing each slice demands a significant deal of care and time. This approach was also susceptible to human mistakes. This paper describes a system that automates physician-performed MRI image analysis. MRI data sets were used to assess white matter volume, grey matter volume, cortical area, cavity area, and brain density between healthy and Alzheimer's patients. According to the findings, those with brain disorders had a higher volume ratio of grey matter to white matter. The ratio was typically 1.1 for a normal individuals between the ages of 20 and 45, 1.3 for those between 50 and 80, and 1.5 for those older than 60. If the determined ratio does not match the usual ratio, the patient was identified as having a brain abnormality.

Kumar, P. et al. [7] The PSO algorithm is used to improving the PIDC algorithm's behavior while segmenting the brains of Alzheimer's patients to examine the phases of the disease. The PSO-based Patch Image Differential Clustering (PIDC) approach outperforms Fuzzy C Means and K-Means for brain subject segmentation. It was discovered that Particle Swarm Optimization (PSO) using the PIDC algorithm produced better segmentation results than clustering strategies based on different cluster initialization. The volumetric analysis of each split area contributes to predicting the different phases of AD.

Liu, M. et al. [11] this study presents a novel classification framework for concurrently learning hippocampus segmentation and illness categorization using a deep convolutional neural network and various models (CNNs). Initially, a multi-task deep CNN model was developed to discover hippocampus segmentation and illness classification parameters simultaneously. A new 3D DenseNet was built based on the segmented hippocampus area to learn the unique visual properties for illness diagnosis. Finally, CNN and DenseNet learned features were integrated with illness stage classification. In addition to providing the illness situation, the suggested framework may also provide the hippocampus segmentation result. For MR image processing, tissue segmentation and non-linear registration were not necessary. The experimental findings from the AD Neuroimaging Initiative (ADNI) database reveal that this author-suggested method for diagnosing AD and MCI has shown excellent performance.

Marghalani, B. F., & Arif, M. [12] Computer vision (CV) and image processing may be used to diagnose brain disorders. Machine learning may help detect brain tumors and Alzheimer's disease in MRI scan images, allowing for a high-resolution investigation of the brain's numerous tissues. The bag of features Model and the support vector machine classifier are useful in classifying MRIs of Alzheimer's disease, normal brains, and brain tumors into three categories in this study.

Platero, C., & Tobar, M. C. [15] The author offers a novel hippocampal segmentation technique based on categorizing normalized hippocampus volume and surface roughness to discriminate between AD and MCI patients and normal-aging people. The author developed a unique approach for automatic hippocampus segmentation using T1-MRI based on a training sample of 134 ADNI-HarP patients. This approach combines patch-based labeling with a non-rigid registration atlas-warping methodology based on multiple-atlas segmentation. The authors suggest utilizing a modified U-Net architecture to segregate fluoro chrome immune fluorescence channels in brain images with three channels.

Shen, Q. et al. [18] This study shows that entirely automated atlas-based segmentation using a template-based method may be used to more accurately estimate regional volumes for certain subject groups, such as the elderly and those suffering from degenerative diseases. A key drawback of our study is the lack of a direct comparison between automated segmentation using multiple atlases and templates and manual segmentation on all subjects with no cognitive impairment (NCI), amnestic mild cognitive impairment (aMCI), and Alzheimer's disease (AD). Nonetheless, this study demonstrates that simple, template-based MRI volumetry may improve research and clinical applications by modifying anatomical atlases and spatial coordinate templates to account for the subject's age and sickness.

III. MATERIALS AND METHODS

This section deals with AD segmentation with Enhanced U Net architecture.

3.1 Dataset:

The MRI image dataset has collected from the Kaggle.com website.

3.2 Base U-net

The U-net network, as previously indicated, may be divided into two sections: The first segment is the contracting route, which is typical of CNN. There are two 3x3 convolutions, a ReLU activation unit, and a max-pooling layer in each contracting route block. This arrangement is repeated many times. The lengthy path of u-net, which uses 2x2 up-convolutions to up-sample the feature map at each level, is its distinguishing characteristic. The shorter path's feature map is then trimmed and added to the up-sampled feature map. Following that, there are two 3x3 convolutions with ReLU activation. Finally, a 1x1 convolution is done to compress the feature map to the required number of channels and construct the segmented picture. Cropping is required because pixels at the image's boundaries contain the least amount of contextual information. As a result, a U-shaped network forms. Furthermore, it disseminates contextual information across the network, allowing it to differentiate between items in a context-based zone and those in a larger overlapping zone.

3.3 Enhanced U-Net Architecture

The proposed architecture is based on the U-Net, which has grown in popularity in medical picture segmentation due to its ability to provide excellent results with a small number of annotated images.

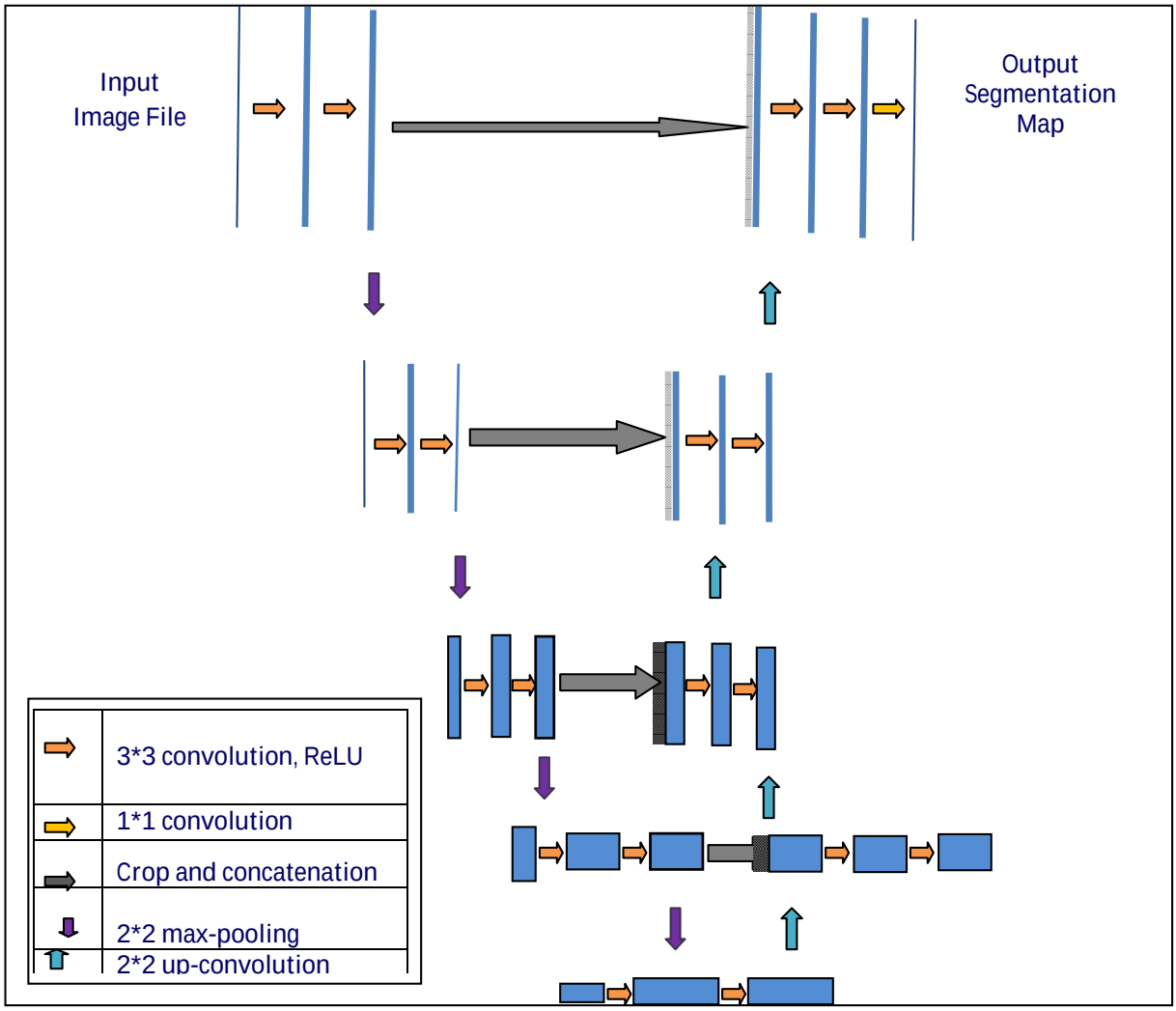

Figure 1: Enhanced U-Net Architecture

The original U-Net comprises an encoder path (on the left) and a decoder path (on the right), with skip links connecting them at each network level to transport the feature map from the end to the decoder. The U-characteristics Nets are suited for our analysis, which seeks to differentiate between the several affected locations. Figure 1demonstrates the Enhanced U-Net structure. The arrows represent the various processes, the blue boxes represent feature maps at each layer, and the grey boxes represent chopped features along the contracting route.
The following equation describes the network's energy function:

$$E = \sum w(x) \log (p_{k(x)}(x)), \quad \text{---------- (1)}$$

Where pk represents the SoftMax function applied pixel-by-pixel to the final feature map.

$$p_k(x) = \frac{e^{a_k(x)}}{\sum_{k'=1}^{k} e^{a_k(x)'}} \quad \text{---------- (2)}$$

And ak (x) represents channel k activation.

3.4 Manual Segmentation of Affected Regions

Using the Label box web program, two biomedical professionals manually segmented the training photos. To accommodate for all possible color channel combinations, four labels were created for each image: red and green (RG), red and blue (RB), green and blue (GB), and red, green, and blue (RGB) (RGB). A region must be part of a significant clump of fluorescence (as evaluated by experts) and have significant intensity in all associated channels to be included in the segmentation. Both experts must concur for the final segmentation to be approved. They achieved a final segmentation by mutual consultation if they couldn't agree. The manual measurements were stored as binary segmentation masks in JPEG format. The binary segmentation masks were converted to NumPy arrays to access the information in each label and then processed using the Python computer language.

IV RESULTS AND DISCUSSION

The Proposed Model has been implemented using a python programming language. Figure 2 to 4 illustrates the proposed model output for MRI Image with predicted output.

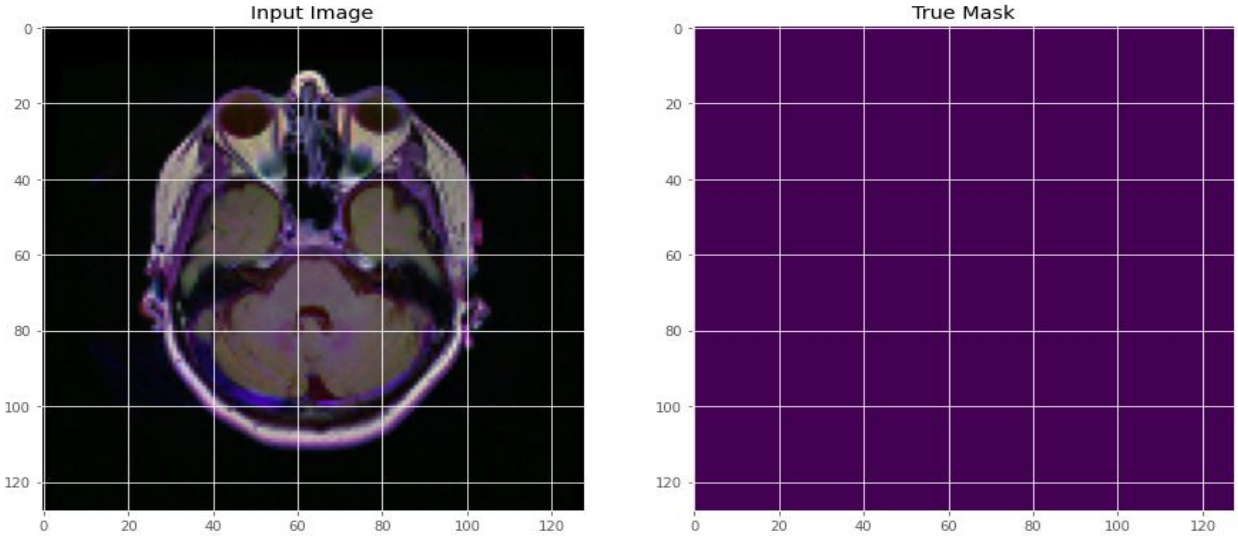

Figure 2: MRI image and True mask Result

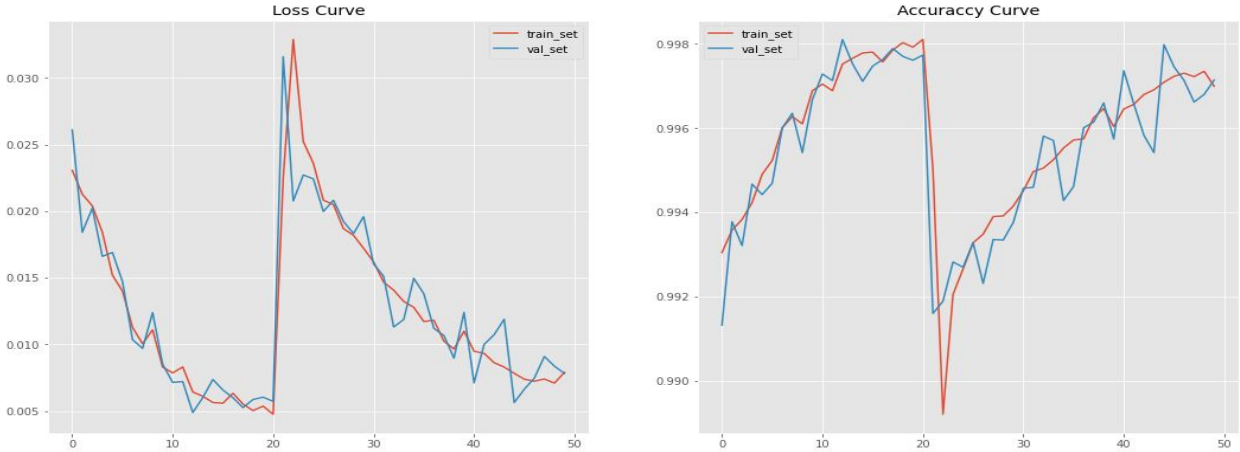

Figure 3: Training and Testing Accuracy and loss percentage.

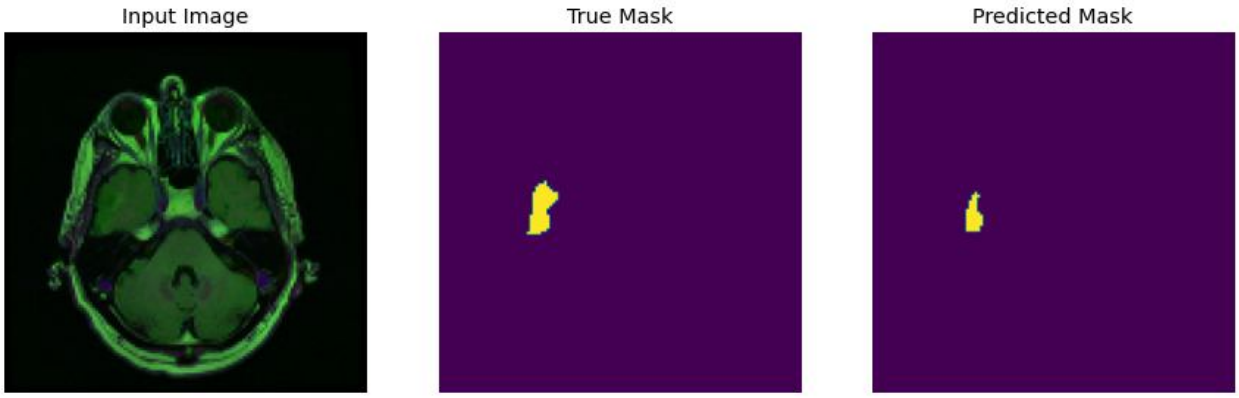

Figure 4: Input Image and Predicted Output.

Figure 2 shows the input MRI image and True Mask values. Up to 50 epochs are trained with E-U-Net architecture and displayed with accuracy, and the loss curve is displayed in figure 3. The MRI input predicted output image and true mask images are displayed in figure 4.

V. CONCLUSION

This research article proposed AD Segmentation using E-U-Net architecture for early AD prediction. This paper proposed for Enhanced U-Net to increase the layers. We demonstrated that these metrics could distinguish between persons with and without Alzheimer's disease. Overall, our first findings indicate that the branching structure is crucial in distinguishing AD from a normal brain. This is mirrored in the description provided by complicated FDs, particularly for vessels with branching points. Other features, such as branching structure, are discriminative (density and tortuosity) for improved MRI image segmentation based on the 3D UNET Model.

REFERENCES

1. Anandh, K. R., Sujatha, C. M., &Ramakrishnan, S. (2014). Segmentation of ventricles in Alzheimer MR images using Tukey's biweight edge indicator and level set method. 2014 40th Annual Northeast Bioengineering Conference (NEBEC). https://doi:10.1109/nebec.2014.6972712
2. Anitha, R., Prakash, &Jyothi, S. (2016). A segmentation technique to detect the Alzheimer's disease using image processing. 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT). https://doi:10.1109/iceeot.2016.7755424
3. Biju, K. S., Alfa, S. S., Lal, K., Antony, A., &Akhil, M. K. (2017). Alzheimer's Detection Based on Segmentation of MRI Image. Procedia Computer Science, 115, 474–481. https://doi:10.1016/j.procs.2017.09.088
4. Carmo, D., Silva, B., Yasuda, C., Rittner, L., &Lotufo, R. (2021). Hippocampus segmentation on epilepsy and Alzheimer's disease studies with multiple convolutional neural networks. Heliyon, 7(2), e06226. https://doi:10.1016/j.heliyon.2021.e06226
5. Dadar, M., Pascoal, T. A., Manitsirikul, S., Misquitta, K., Fonov, V. S., Tartaglia, M. C., ... Collins, D. L. (2017). Validation of a Regression Technique for Segmentation of White Matter Hyperintensities in Alzheimer's Disease. IEEE Transactions on Medical Imaging, 36(8), 1758–1768. https://doi:10.1109/tmi.2017.2693978
6. Khagi, B., Lee, C. G., & Kwon, G.-R. (2018). Alzheimer's disease Classification from Brain MRI based on transfer learning from CNN. 2018 11th Biomedical Engineering International Conference (BMEiCON). https://doi:10.1109/bmeicon.2018.8609974
7. kumar, P. R., Arunprasath, T., Rajasekaran, M. P., &Vishnuvarathanan, G. (2019). MR Brain image segmentation for the volumetric measurement of tissues to differentiate Alzheimer's disease using hybrid algorithm. 2019 IEEE International Conference on Clean Energy and Energy Efficient Electronics Circuit for Sustainable Development (INCCES). https://doi:10.1109/incces47820.2019.9167723
8. Landeau, B., & Baron, J.-C. (2001). Voxel-based atrophy correction of functional brain images in Alzheimer's disease (AD) using probabilistic MRI segmentation. NeuroImage, 13(6), 181. https://doi:10.1016/s1053-8119(01)91524-1
9. Lazli, L., Boukadoum, M., &Ait Mohamed, O. (2018). Computer-Aided Diagnosis System for Alzheimer's Disease Using Fuzzy-Possibilistic Tissue Segmentation and SVM Classification. 2018 IEEE Life Sciences Conference (LSC). https://doi:10.1109/lsc.2018.8572122
10. Leandrou, S., Petroudi, S., Kyriacou, P. A., Reyes-Aldasoro, C. C., &Pattichis, C. S. (2018). Quantitative MRI Brain Studies in Mild Cognitive Impairment and Alzheimer's Disease: A Methodological Review. IEEE Reviews in Biomedical Engineering, 11, 97–111. doi:10.1109/rbme.2018.2796598
11. Liu, M., Li, F., Yan, H., Wang, K., Ma, Y., Shen, L., & Xu, M. (2020). A multi-model deep convolutional neural network for automatic hippocampus segmentation and classification in Alzheimer's disease. NeuroImage, 208, 116459. https://doi:10.1016/j.neuroimage.2019.116459

12. Marghalani, B. F., & Arif, M. (2019). Automatic Classification of Brain Tumor and Alzheimer's Disease in MRI. Procedia Computer Science, 163, 78–84. https://doi:10.1016/j.procs.2019.12.089
13. Mattsson, N., Insel, P. S., Donohue, M., Jögi, J., Ossenkoppele, R., Olsson, T., ... Hansson, O. (2019). Predicting diagnosis and cognition with 18F-AV-1451 tau PET and structural MRI in Alzheimer's disease. Alzheimer's & Dementia. https://doi:10.1016/j.jalz.2018.12.001
14. Nestor, S. M., Gibson, E., Gao, F.-Q., Kiss, A., & Black, S. E. (2013). A direct morphometric comparison of five labeling protocols for multi-atlas driven automatic segmentation of the hippocampus in Alzheimer's disease. NeuroImage, 66, 50–70. https://doi:10.1016/j.neuroimage.2012.10.081
15. Platero, C., & Tobar, M. C. (2016). A fast approach for hippocampal segmentation from T1-MRI for predicting progression in Alzheimer's disease from elderly controls. Journal of Neuroscience Methods, 270, 61–75. https://doi:10.1016/j.jneumeth.2016.06.013
16. Shaikh, T. A., & Ali, R. (2019). Automated atrophy assessment for Alzheimer's disease diagnosis from brain MRI images. Magnetic Resonance Imaging. https://doi:10.1016/j.mri.2019.06.019
17. Shanthi, K. J., Ravish, D. K., &Sasikumar, M. (2013). Image segmentation an early detection to Alzheimer's disease. 2013 Annual IEEE India Conference (INDICON). https://doi:10.1109/indcon.2013.6726006
18. Shen, Q., Zhao, W., Loewenstein, D. A., Potter, E., Greig, M. T., Raj, A., ...Duara, R. (2012). Comparing new templates and atlas-based segmentations in the volumetric analysis of brain magnetic resonance images for diagnosing Alzheimer's disease. Alzheimer's & Dementia, 8(5), 399–406. https://doi:10.1016/j.jalz.2011.07.002
19. Thurfjell, L., Lötjönen, J., Wolz, R., Koikkalainen, J., Julkunen, V., Waldemar, G., ...Rueckert, D. (2011). Automatic segmentation of hippocampus in Alzheimer's disease. Alzheimer's & Dementia, 7(4), S226. https://doi:10.1016/j.jalz.2011.05.634
20. Won, W., Lim, H. K., Hahn, C., & Lee, C. U. (2012). Automated segmentation of hippocampal subfields in drug-naive patients with Alzheimer's disease. Alzheimer's & Dementia, 8(4), P534. https://doi:10.1016/j.jalz.2012.05.1435

