2021 2nd Global Conference for Advancement in Technology (GCAT)
Bangalore, India. Oct 1-3, 2021

Alzheimer's Disease Detection from Brain MRI Data using Deep Learning Techniques

Chaihtra DH
Nitte Meenakshi Institute of Technology
Yelahanka Bangalore(India)
chaithradh097@gmail.com

Vijaya Shetty S
Nitte Meenakshi Institute of Technology
Yelahanka Bangalore(India)
vijayashetty.s@nmit.ac.in

2021 2nd Global Conference for Advancement in Technology (GCAT) | 978-1-6654-1836-2/21/$31.00 ©2021 IEEE | DOI: 10.1109/GCAT52182.2021.9587756

***Abstract*— Alzheimer disease(AD) is a neurological disorder. For the AD, there is no specific treatment. Early detection of Alzheimer's disease can help patients receive the correct care. Many studies employ statistical and machine learning techniques to diagnose AD. The human-level performance of Deep Learning algorithms has been effectively shown in different disciplines. In the proposed methodology, the MRI data is used to identify the AD and Deep Learning techniques are used to classify the present disease stage. For the classification and prediction of AD, we have constructed CNN architectures employing transfer learning. DenseNet121, MobileNet, InceptionV3 and Xception neural networks are trained using Kaggel AD dataset. All models in this study are trained on the same dataset in order to analyse their performances. The DenseNet121 architecture gives the highest accuracy of 91% on the test data that detects AD accurately.**

Keywords— Alzheimer's Disease (AD), Deep Learning, CNN, InceptionV3, DenseNet121, MobileNet and Xception

I. Introduction

The form of dementia has a high prevalence in the United States, making it one of the most frequent forms of dementia. After 65 years of age, the prevalence of AD is estimated to be around 5 percent, and it can reach 30 percent in people over 85 years of age in developed countries Alzheimer's disease is estimated to affect 0.64 billion people by 2050. Brain cells are destroyed in Alzheimer's disease, causing patients to lose their capacity to remember things, think clearly, and carry out daily works [1]. First, AD affects the brain regions that control language and memory. AD is caused by both hereditary and environmental factors. An individual will get this condition due to genetic alterations [2]. Rather, it's a disease of the brain and sufferers may display signs of ageing. These include memory loss, trouble finding the perfect words, difficulty executing previously normal tasks, as well as a change in personality and moods. There are no social, economic, racial, ethnic, geographical, or other barriers for dementia. For many types of dementia, there is currently no cure, although there are treatments, advices, and support services available [3].

In AD research, magnetic resonance imaging (MRI) has been widely used as a non-invasive approach to observe brain atrophy changes. In the current clinical practises, there is no conclusive diagnosis of Alzheimer's disease, according to several researchers. A postmortem (PM) study of brain tissue is typically the only way to confirm the existence of AD. Both the patient and the social worker need an accurate early diagnosis of AD [4]. Data analysis and medical imaging have been revolutionised by deep learning [5]. Images in n-dimensions can be analysed using convolutional neural networks (CNNs). Recently, image classification systems have been significantly improved by these networks' ability to recognise high level abstractions. Traumatisms and other medical imaging conditions were classified using it in the years that followed.AD (adverse events).

II. Literature Survey

In this paper the authors mainly focus on the shape of MRI images with AD in this work [5]. The JADNI database provided the data for this investigation. Shape information was obtained using the P-type Fourier descriptor of the lateral ventricle, which excludes the septum lucidum. This resulted in a classification accuracy of 87.5 percent, which was greater than the 81.5 percent accuracy obtained using the conventional method for evaluating changes in brain structure, the ratio of intracranial volume to brain volume. Use of Logistic Regression, Support Vector Machine, Gradient Boosting and Random Forest approaches are included in the proposed methodology [6].

The dataset was compiled from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. According to the definition of accuracy, it is the number of correctly predicted events that have occurred. A different way of classifying labels. They have developed a Deep Neural Network-based approach for identifying Alzheimer's disease [7]. ADNI Dataset (DNN) was used in this project. In order to select the most relevant qualities from the ADNI dataset, researchers used decision trees, random forest feature selection, and deep neural networks. Researchers found that brain MRI can be used to classify patients with Alzheimer's disease (AD) from those who are healthy [8].

Nine CPCs produced the best accuracy (77%) on average at four time points, while non diagnostic CPCs were used as features to achieve the highest accuracy (95%). The work [9] explains how to acquire 2D characteristics from MRI and how they can be applied to a machine learning system for classifying images. A CNN softmax classification score based on scratch-trained CNNs is not an outstanding result, but it demonstrates that this method could be superior. In order to improve accuracy, sensitivity, and specificity of the created feature, it is well-manipulated and polished. Medical imaging data has been revolutionised by deep learning, which provides remarkable insight into non-linear variables. In paper [10], By predicting neuropsychological test results based on the MRI, researchers hope to acquire a deeper understanding of the course of Alzheimer's disease (AD). MRI data is decomposed using a deep convolutional auto encoder.

There are various sectors in which deep learning algorithms have already sparked change, as reviewed by Aly Al-Amyn Valliani et al. [11]. There have been comprehensive reviews in the fields of deep learning in neurology, medical image segmentation, functional connectivity and classification of brain disorders, as well as risk prognosis. In this study, recurrent neural networks are used [12]. (RNNs). ADNI stands for Alzheimer's Disease Neuroimaging (ADNI Database). Before it can be utilised to construct an early prediction model for AD dementia, an autoencoder must be trained to acquire compact representations and encode the temporal dynamics of longitudinal data for each individual patient. The learned representations are integrated with baseline data in order to construct a model with time-to-event analysis.

A machine learning strategy for diagnosing Alzheimer's disease is given in [13]. ADNI data have been used in this paper. Logistic Regression(LR), Decision Trees(DT), and Support Vector Machines(SVM)). Classifiers using logistic regression were more accurate than those using DT and SVM. In the ADNI dataset, logit regression is the best classifier for AD prediction. Diagnosing Alzheimer's Disease Using Enhanced Inception(V3) Network, developed by Zhenyu Cui et al [14]. A brain magnetic resonance image dataset is used to test the efficiency of the Inception(V3) network. Inception (V3recognition)'s accuracy can be improved with the addition of three new blocks, which can be utilised to diagnose the problem. the Inception(V3) network that was proposed finally attained an accuracy of 85.7% after a series of comparisons and changes.

In this research, [15] the main focus is on the use of deep learning techniques and tools to clinical decision making. An overview of several healthcare areas was presented, as well as the key disease kinds that have been studied using Deep Learning. As a result of this study, using deep learning and predictive analysis, a framework for monitoring healthcare data is proposed. To verify empirical data and highlight the benefits of the model, it is possible to use the model in practical situations.

In this research paper they focus on the Deep transfer learning for detecting AD [16]. Their main aim is to verify the combined use of dynamic feature and shape to allow a support system to increase performance to diagnose AD. The handwriting samples are converted to RGB channels for dynamic information and finally they use DNN to extract features automatically.

In paper [17]. they give review of AD classification. After reviewing many research progress by utilizing machine learning technologies and neuropshysiological data they have pointed, at the beginning, the data of the AD must have expanded by reviewing of a certain topic and next more specific features are to be selected automatically using machine learning, and finally, DNN architectures used to predict AD.

By using CNN and DNN a Volumetric feature of MRI is used to diagnose AD [18]. In this paper they use a method based on features extracted of right, left hippocampal of MRI data. They proposed a model using DNN and CNN model. The left, right hippocampal used automatically using an ensemble of 2 stage CNN. In Paper [19] the authors are trying to verify CNN behaviour that moves 2D to 3D architectures. This paper aims to give the output of variety CNN architectures implemented on MRI or PET clarifications task to predict AD. In this paper they use Hirerchical extraction feature to detect AD [20]. The authors proposed the voxel novel for hierarchical feature extraction (VHFE) for the early AD diagnosis.

III. DATASET DESCRIPTION

From the Kaggel website, the AD dataset has been extracted. Classification of the dataset into four categories:

1. Mild Dementia
2. Moderate Dementia
3. Non Dementia
4. Very Mild Dementia

The link of the dataset is: https://www.kaggle.com/tourist55/alzheimers-dataset-4-class-of-images/kernels Dataset is available in Kaggle. It consists of total 2565 images that is classified into four classes.

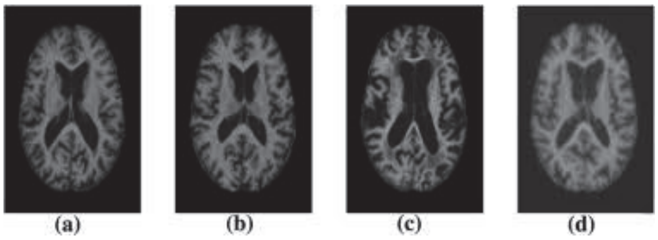


Fig. 1. Shows the Brain MRI Images of AD Stages (a) Non Dementia (b) very mild Dementia (c) Mild Dementia (d) Moderate Dementia

IV. PROPOSED SYSTEM

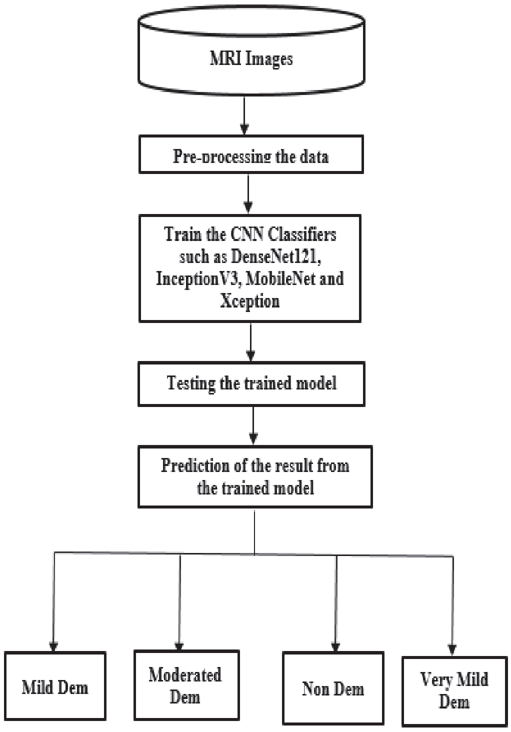


Fig. 2. Flow diagram of the proposed system

In the proposed system, deep neural network models are trained on Imagenet and then transferred to Imagenet. The data are employed because they are easy to incorporate, the models will perform well quickly, and there are a variety of use cases, including transfer learning, prediction, and feature extractions.

Fig. 2 depicts the flowchart for the approach utilised in this investigation. In the next phase, the images are scaled as colour image channels, which is the first step in the preprocessing process (224,224,3). Then Deep Neural Networks such as DenseNet121, MobileNet, Xception, and Inception-V3 are trained on the given input. The model is subsequently tested, and the trained model is then used to forecast AD. By adding layers of fully connected, dropout and dense layers to existing neural network models, this study aims to optimise the performance, training accuracy and prediction capability of the trained models. When fine tuning, two completely linked and three dropout layers are added to the mix along with 3 denser layers. An output layer with a softmax classifier is implemented to classify the images into 4 classes. So, there is no need to train the network from scratch.

V. RESULT AND ANALYSIS

In this research, 80% data was used for training and 20% for testing during cross-validation. The experiment was conducted using transfer learning with fine-tuning, Relu was used to fine-tune the CNN architectures. Transfer Learning and Fine-tuning generated the greatest results for DenseNet121. Fig .3 indicates the result of DenseNet121 with, without transfer learning and fine-tune, Fig.4 gives the result of InceptonV3 with, without transfer learning and fine-tune. Fig.5. gives result of MobileNet with, without Transfer Learning and Fine-tuning, Fig.6. shows result of Xception with and without Transfer Learning and Fine-tune. The Table 1, Table 2 and Table 3 contains the result before and after Transfer Learning with Fine-tune, the findings are presented in the following tables. Fig.6 gives Confusion matrix(CM) from different CNN architectures. (a) gives the CM for DenseNet121, (b)shows the CM of Inception V3. (c) gives the CM of MobileNet, (d) shows the CM of Xception,

TABLE I. VLIDATION AND TRAINING ACCURACY OF DIFFERENT CNN'S ARCHITECTURE WITHOUT TRANSFER LEARNING.

CNN Architecture	Training Accuracy	Validation Accuracy
DenseNet121 without Transfer Learning	90%	69%
InceptionV3 without Transfer Learning	83%	79%
MobileNet without Transfer Learning	52%	51%
Xception without Transfer Learning	72%	58%

TABLE II. VLIDATION AND TRAINING ACCURACY OF DIFFERENT CNN'S ARCHITECTURE WITH TRANSFER LEARNING.

CNN Architecture	Training Accuracy	Validation Accuracy
DenseNet121 with Transfer Learning	97%	96%
InceptionV3 with Transfer Learning	98%	95%
MobileNet with Transfer Learning	97%	95%
Xception with Transfer Learning	98%	94%

TABLE III. VLIDATION AND TRAINING ACCURACY OF DIFFERENT CNN'S ARCHITECTURES WITHTRANSFER LEARNING FINE TUNE.

CNN Architecture	Training Accuracy	Validation Accuracy
DenseNet121 Transfer Learning Fine-tune	99%	97%
InceptionV3 Transfer Learning Fine-tune	99%	96%
MobileNet Transfer Learning Fine-tune	99%	97%
Xception Transfer Learning Fine-tune	99%	95%

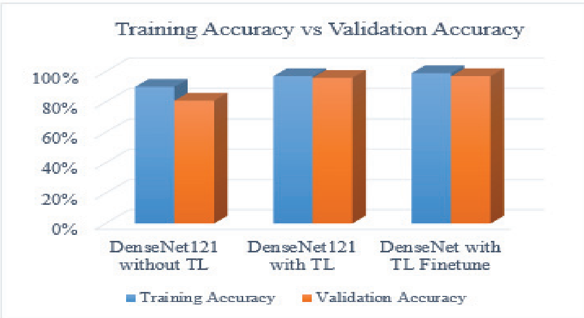


Fig. 3. DenseNet121 Results.

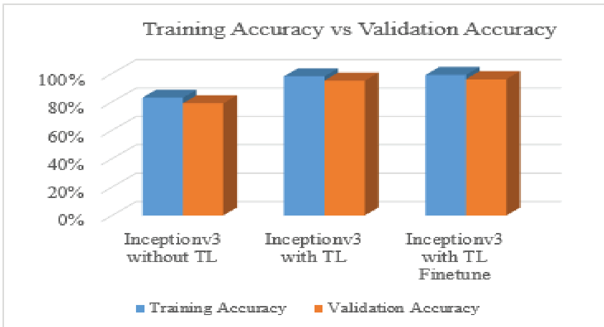


Fig. 4. InceptionV3 results

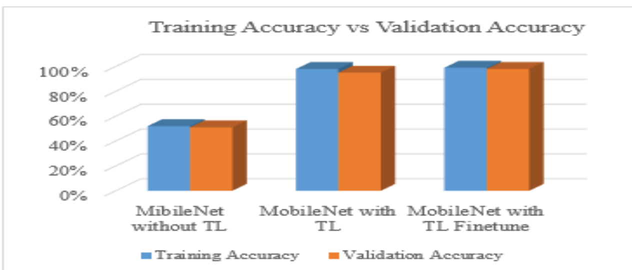


Fig. 5. Mobilenet Results

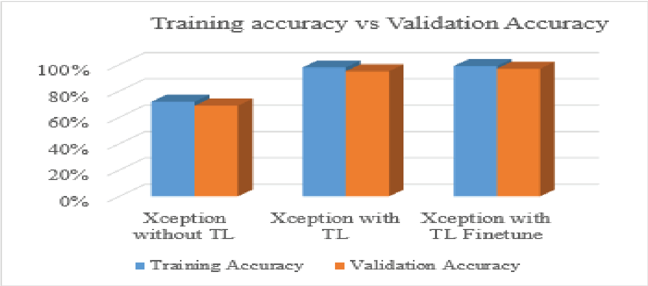
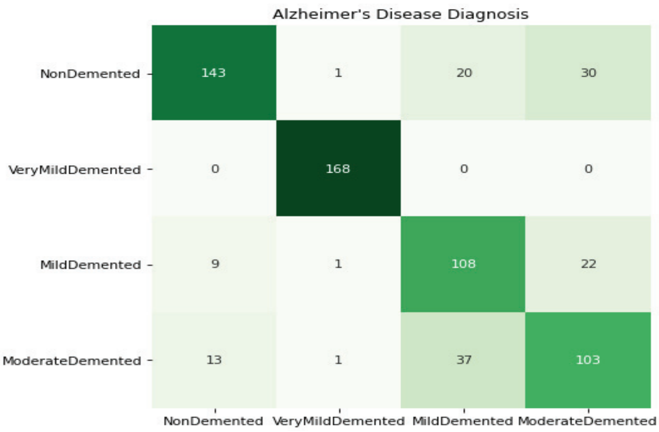
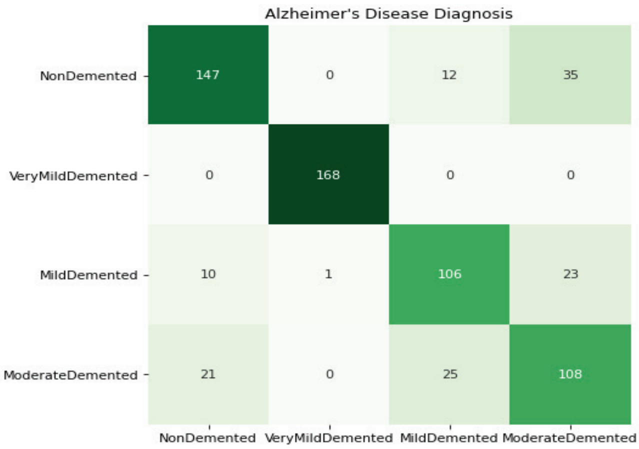


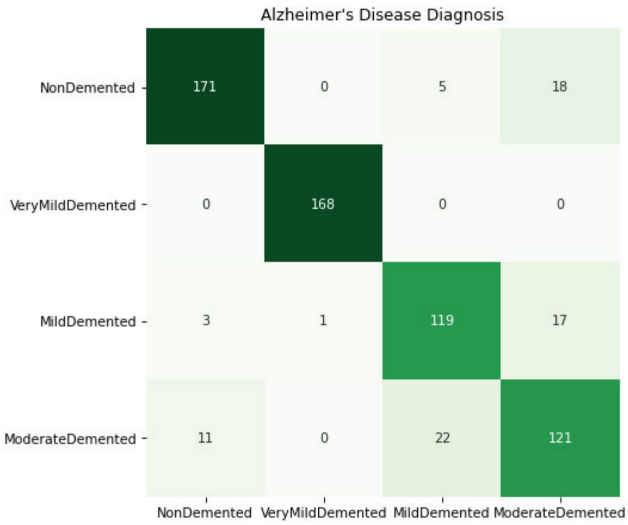
Fig. 6. Xception Results



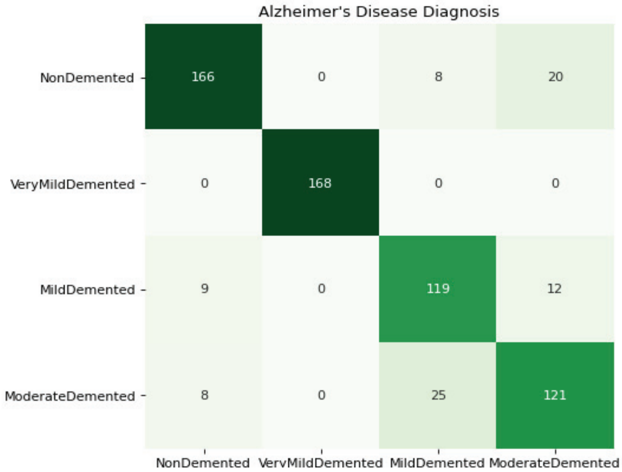
(a)



(b)



(c)



(d)

Fig. 7. shows the Confusion Matrix of (a) DenseNet121, (b) Inception V3, (c) MobileNet, (d) Xception on Test

VI. CONCLUSION

AD is a neurological brain illness that is incurable and untreatable. It is possible to prevent brain tissue damage by detecting this condition early. According to the proposed methodology, AD is classified into four classes: non-demented, mildly demented, very mildly demented, and moderately demented individuals. DenseNet121 architecture provide 99% of training accuracy and 97% of validation accuracy based on deployments and results analysis. The Densenet121 gives the highest accuracy of 91% on test data, that detects AD accurately.

VII. FUTURE WORK

AD datasets such as ADNI, OASIS and other neurological disorders diagnosis can be evaluated and the future, you'll need to construct your own network for predicting AD.

REFERENCES

[1] Jyoti Islam and Yanqing Zhang, "Early Diagnosis of Alzheimer's Disease: A Neuroimaging Study with Deep Learning Architectures", IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, 2018 IEEE DOI 10.1109/CVPRW.2018.00247.

[2] J.Neelaveni and M.S.Geetha Devasana, "Alzheimer Disease prediction using Machine learning algorithm", International Conference on Advanced Computing & Communication Systems (ICACCS), 2020.

[3] H. M. Tarek Ullah et al, "Alzheimer's Disease and Dementia Detection from 3D Brain MRI Data Using Deep Convolutional Neural Networks", 3rd International Conference for Convergence in Technology, IEEE 2018.

[4] Emimal Jabason et al, "Classification of Alzheimer's Disease from MRI Data Using an Ensemble of Hybrid Deep Convolutional Neural Networks", IEEE 2019.

[5] Hiroki Fuse et al, "Detection of Alzheimer's Disease with Shape Analysis of MRI Images", IEEE 2019, DOI 10.1109/SCIS-ISIS.2018.00171

[6] Priyanka Lodha et al, "Diagnosis of Alzheimer's Disease using Machine Learning", Fourth International conference on Computer Communication Control and Automation (ICCUBEA) IEEE 2018.

[7] Dilek Manzak et al, "Automated Classification of Alzheimer's Disease using Deep Neural Network (DNN) by Random Forest Feature Elimination", The 14th International Conference on Computer Science & Education (ICCSE 2019) August 19-21, 2019. Toronto, Canada, IEEE 2019.

[8] Kota Oishi et al, "Classification of Patients with Alzheimer's Disease and Healthy Subjects from MRI Brain Images Using the Existence Probability of Tissue Types", IEEE 2018, DOI 10.1109/SCIS-ISIS.2018.00172.

[9] Bijen Khagi et al, "Alzheimer's disease Classification from Brain MRI based on transfer learning from CNN", The 2018 Biomedical Engineering International Conference (BMEiCON-2018), IEEE 2018.

[10] F. J. Mart´ınez-Murcia et al, "A Deep Decomposition of MRI to Explore Neurodegeneration in Alzheimer's Disease", IEEE 2018.

[11] Aly Al-Amyn Vallian et al, "Deep Learning and Neurology: A Systematic Review", Neurol Ther (2019) 8:351–365 https://doi.org/10.1007/s40120-019-00153-8.

[12] Hongming L, and Yong Fan, "Early Prediction of Alzheimer's Disease Dementia Based On Baseline Hippocampal MRI and 1-Year Follow-Up Cognitive Measures Using Deep Recurrent Neural Networks", IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019) Venice, Italy, April 8-11, 2019.

[13] Muhammad Hammad Memon et al, "EARLY STAGE ALZHEIMER'S DISEASE DIAGNOSIS METHOD", IEEE, 2019.

[14] Zhenyu Cui et al, "Alzheimer's Disease Diagnosis Using Enhanced Inception Network Based on Brain Magnetic Resonance Image", IEEE International Conference on Bioinformatics and Biomedicine (BIBM) 2019.

[15] Anandhavalli Muniasamy et al, "Deep Learning for Predictive Analytics in Healthcare", Springer Nature Switzerland AG 2020 A. E. Hassanien et al. (Eds.): AMLTA 2019, AISC 921, pp. 32–42, 2020.

[16] Gang Lyu, "A Review of Alzheimer's Disease Classification Using Neuropsychological Data and Machine Learning", International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI 2018).

[17] Nicole Dalia Cilia, Claudio De Stefano et al, "Deep Transfer Learning for Alzheimer's disease detection", 25th International Conference on Pattern Recognition (ICPR) Milan, Italy, Jan 10-15, 2021.

[18] Abol Basher, Byeong C. KIM et al, "Volumetric Feature-Based Alzheimer's Disease Diagnosis from MRI Data Using a Convolutional Neural Network and a Deep Neural Network", National Research Foundation of Korea (NRF) NRF-2019R1A4A1029769, February 25, 2021.

[19] Bijen Khagi and Goo-Rak Kwon, "3D CNN Design for the Classification of Alzheimer's Disease Using Brain MRI and PET", National Research Foundation of Korea, NRF-2019R1A4A1029769 and Grant NRF-2019R1F1A1060166, 2020.

[20] Lulu Yue, Xiaoliang Gong et al, "Hierarchical Feature Extraction for Early Alzheimer's Disease Diagnosis", Special Section on Data-Enabled Intelligence for Digital Health, July 30, 2019.