Alzheimer's Detection and Prediction on MRI Scans: A Comparative Study

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***Abstract*—Alzheimer's disease (AD) is one of the most prevalent medical conditions with no effective medical treatment or cure. The issue lies in the fact that it is also a condition which is chronic, with irreversible effects on the brain,like cognitive impairment. The diagnosis of Alzheimer's in elderly people is quite difficult and requires a highly discriminative feature representation for classification due to similar brain patterns and pixel intensities. Although we cannot prevent AD from developing, we can try to detect the stages of development of AD. In this paper, we explore and test the various methodologies used to classify Alzheimer's Disease(AD), Early Mild Cognitive Impairment(EMCI), Late Mild Cognitive Impairment(LMCI), Mild Cognitive Impairment(MCI) and, healthy person(CN) using the Magnetic Resonance Image(MRI)s and Deep Learning techniques. The experiments are performed using ADNI dataset the results are obtained for multiple machine learning and deep learning methods that have been implemented over time. In our proposed work, we take into consideration the different stages of Dementia and Alzheimer's Disease, and use Deep Learning models on the MRI scans for detecting and predicting which stage of Alzheimer's or Dementia a person is suffering from.**

***Index Terms*—Deep Learning, Classification, VGG16, EffNet, 3D-CNN, Alzheimer's Disease, Image Processing, Disease Detection**

I. Introduction

Alzheimer's disease is a progressive neurological disorder that causes the brain to shrink and causes the cells to die. Alzheimer's disease is the most common cause of dementia, which is identified as a continuous decline in thinking, cognitive, behavioural as well as social skills, henceforth causing difficulties in the affected person's daily independent functioning. AD most likely goes unobserved due to the fact that at effects of AD only manifest after a decade or more, which in turn cause late detection of the symptoms as well. Alzheimer's Disease International (ADI), the most referred scientific report for Alzheimer's disease, reports that around more than 70 million people worldwide deal with Dementia, and more than 24 million suffer from Alzheimer's Disease. The predicted numbers for people diagnosed with AD, by the year 2030 is more than 78 million and to more than 100 million people by the end of year 2050 [1]. The 3D imaging as seen in MRI scans for Alzheimer's, makes it easy for physicians to identify and classify anomalies in the brain. These anomalies can be potential markers of Alzheimer's, but not always, since they could also be symptoms of other medical conditions leading to cognitive impairment. Alzheimer's MRI produces 3D imaging of the neural structure, which can show the number of cells present and the size of the cells, which are common identifiers for cancer. It is a widely known fact that the parietal lobe is one of the most affected part of the brain, caused by Alzheimer's. Hence knowing the size of the cells, and the lobes of the brain itself, play a vital role for AD detection. The parietal lobe's size helps indicate to doctors whether the patient is developing the different stages of AD or any other medical condition. Various MRI analytical methods have proved to be of significant benefit in identifying the plausible molecular and signature markers for AD and MCI. These markers, in turn, help improve accuracy fro diagnosis and treatment. Although traditional structural modalities are the recommended methods for MCI and AD detection and diagnosis, the need for further research to overcome methodological limitations of more advanced one is the need of the hour, aiding neuropathological insights to different causes of impairment [33]. Patients are mostly diagnosed with AD during the later stages of Dementia, when they suffer from diverse forms of cognitive decline. Such cases are determined to be too late, hence causing any preventive protocols to slower the imminent cognitive decline to be futile. All forms of treatment, both posological and over-the-counter medication, have proven to be effective in delaying or even reducing cognitive symptoms, the catch being that we need to be able to catch the disease in its early stages [15]. The various stages of the disease progression have been identified. The specific category of catching the disease before it causes further cognitive decline, i.e, catching the disease in it's early stages corresponds to be known as mild cognitive impairment (MCI), whose main characteristic is having minor memory detriment [16](We use the MCI abbreviation,as it is the most frequently used term in the scientific community). It is note-worthy to understand and acknowledge that AD is a progressive medical condition, this implies that patients diagnosed with MCI that will advance on to suffer from AD, those diagnosed with Dementia already have AD, only that cognitive difficulties have not full presented. For this very reason, it is important to differentiate among patients diagnosed with MCI and those who will remain stable ad various other stages of Dementia, for example patients fully diagnosed with AD. In the later stages, i.e when the symptoms of Dementia have already presented, AD is an easier diagnosis imaging methods, as is seen in many studies, like [17], [16]. Although indicators may exist in magnetic resonance image(MRI) or in positron emission tomography(PET), the detection of the stages from MCI to AD is still a challenge. A novel approach to aid the research on tackling this issue, the researchers community now has access to thousands of neuroimaging datasets, in all possible views for example longitudinal, and axial, for the stages of Dementia like MCI, and AD subjects along with other variables (i.e., demographic, genetic, and cognitive measurements, etc.) is the public database Alzheimer Disease Neuroimaging Initiative (ADNI)(http://adni.loni.usc.edu). Many in the machine learning community have used this very dataset classify and detect the two stages of Dementia, AD and MCI [18], [20], [21]. Recently, many emerging works have been able to demonstrate the use of ML algorithms to classify images from AD, MCI, and healthy participants, showing the classification with very high accuracy. The goal of this comparative study is to analyze the existing classification methods based in Deep Learning algorithms applied to neuroimaging data in combination with other variables for predicting the stages even in MCI, and its progression to AD.

II. RELATED WORK

AD detection is a widely studied, and it involves several issues and challenges. One of the recent trends is using 3D convolutional neural networks(3d-CNN), and implementing new learning methods to these CNN models, like transfer learning, to classify between subjects with Alzheimer's disease and subjects without any disease. A common method was using sparse auto-encoding and 3D-CNN by [38]. A development on this method of this is [38], where an algorithm is built, that detects the condition of a subject affected by cognitive impairment based on a magnetic resonance image (MRI) scan of the brain. [30] proposed an algorithm to predict the AD with a Deep 3D-CNN, which can learn generic features capturing AD markers. The 3D-CNN is built on top of an auto-encoder for CNN, pre-trained for shape differences identification in structural MRI scans of the brain. They also propose CNN fine-tuning for the AD classification task. Another CNN framework proposed the use of a multi-modal MRI analytical method relying on Deep Tissue Injury(DTI) or Functional Magnetic Resonance Imaging (fMRI) data, for the classification of AD, NC(Control Normal), and amnestic mild cognitive impairment (aMCI) patients. Although it achieved quite a high accuracy, they used 2D-CNN stating that 3D-CNN would definitely give a better result [40]. In accordance to the quote "Prevention is better than cure", Alzheimer's Disease progression can also be considered in this way. Although we cannot completely prevent the disease from developing, we can try to take many measure to slow the rate of progression. This where the process of detecting the stages of progression for AD is much required. For this very need, a multi-class, hybrid Deep Learning framework for early diagnosis of AD was proposed by [41]. They used k-Sparse autoencoder (KSA) classification to find degraded brain regions using 150 images of MRI scans as well as Cerebrospinal fluid(CSF) scan and PET images from the ADNI study public dataset. Another approach was by [42] for classification between people with AD, MCI and cognitive normal (CN) with an AUC score of 91.28% and 88.42%, respectively for classification between 2 separate experiments - (i)AD and MCI and, (ii)MCI and CN. All experiments were performed using 50 epochs with a batch size of 8, and the Adam optimizer was adopted with a LearningRateSchedule that uses a piece-wise constant decay schedule. This proposition was focused on how to prepare the data to be fed into the model. Early detection is a crucial goal in the study of Alzheimer's Disease. [9]describes the different techniques that can be used to boost 3D-CNN performance. They achieved around 14% accuracy while using existing models for classification of AD, MCI, and controls in the ADNI dataset, with the AlexNet and ResNet models as baseline 3D CNNs with Instance normalization. They also utilized the method of encoding each age value into a vector and combine the vector with the output of the convolutional layers. The enhancement for early detection for Alzheimer's requires the study of the brain from all angles and notice how AD and progressive stages to AD project in these angles. A 3D-CNN architecture is applied to 4D FMRI images for classifying four AD stages, where they divided MCI as Early MCI(EMCI) and Late MCI(LMCI), hence resulting in the following classification labels - AD, EMCI, LMCI, NC [12]. [10] proposed model using a large dataset of the Open Access Series of Imaging Studies (OASIS) Brain dataset. The proposed model has taken all parts of the human brain that are axial, sagittal, and frontal for Alzheimer's disease detection, and has obtained around 98.35% accuracy with the AlexNet 2012 ImageNet nerual network layers. The model proposal of using genes as indicators was also made, for AD detection, with high yielding accuracy [11]. MRI scans, genetic measures, and clinical evaluation were used as inputs for the APOe4(APOE4 is considered as the strongest risk factor for Alzheimer's disease) model. Compared to pre-trained models such as AlexNet and VGGNet, this model significantly reduced computational complexity, memory requirements, and number of parameters to be used. In addition to this, other CNN structures that deal with 3D MRI for different stages of progression for AD classification are suggested by [13] and [14]. In our work, we focus on having a comparative study on the different Deep Learning methods used to perform classification of AD. We have seen that in most works the most commonly used classes for classification are AD, MCI, and CN. And hence, in our work, we would be focusing on the aforementioned classes as well as additional two more - Early Mild Cognitive Impairment(EMCI), and Late Mild Cognitive Impairment(LMCI), which will be as is and not instead of MCI.

III. Deep Learning and MRI Classification

Deep learning(DL) methods are increasingly used to improve clinical practice, and make more efficient smart systems. We will not go into great detail on the different DL architectures, but we will simply draw an outline on the models we would be using for out study, and how the models in Deep Learning are being implemented for medical imaging and MRI classification. A critical step in locating and categorising dangerous diseases is the categorization of MRI brain tumour images. The descriptiveness and discriminativeness of the extracted features have been identified as complementary qualities that are essential for strong classification performance in the extensive research that has been done to identify brain tumours based on medical images. Machine learning is essential in classification because of its variety of approaches and suitability for a particular issue. The segmentation and classification of reconstructed magnitude pictures have traditionally been the main goals of deep learning in MRI. It has only recently, but impressively, entered the lower levels of MRI measurement methods [23]. Convolutional neural networks(CNN) can be used to increase productivity in radiology settings; for instance, [24] showed how chemical elements dosage like gadolinium Gadolinium MRI(which is used for contrast enhancement) can be reduced without causing any reduction in image quality. Deep learning can also be applied in PET scan - MRI scan correction [25], in the information extraction from medical images [26], just to name a few more. In the field of Magnetic Resonance Imaging (MRI) classification and detection, deep learning has seen applications at each level of end-to-end workflows and solutions. From acquisition to image retrieval, from segmentation to disease classification and prediction. The entire image acquisition to disease prediction pipeline is broken down into two parts [23](i) Signal processing chain which includes including image restoration and, (ii) DL algorithms and models for image segmentation, disease detection and so on. Our work focuses on the second part, the disease detection and classification, primarily focusing on the stages of progression of AD.

A. Classification of Diseases using Deep Learning

Deep learning owns its leading position in computer vision owing to neural networks outperforming other methods on image processing and analysis baselines. Deep learning techniques have become the de-facto standard a huge number of computer vision problems, in various industry fields. While looking at the healthcare field, healthcare providers generate and store hulking amounts of data with extremely valuable information, far superseding the rate of analysis and processing done by "traditional" methods. The medical imaging problem is of utmost interest in the deep learning application, being chiefly triggered by CNNs [28]. Today's deep learning methods all but exclusively implemented in TensorFlow, a Google Research framework, Keras, the deep learning library originally built by Francois Chollet and has been henceforth incorporated in TensorFlow, and Pytorch, the Facebook Research framework. In our study we used 3D-CNN, EffNet, and VGG for classification of the different stages of AD. We also increase the size, and the labels used in our dataset. It is explained further in the next sections.

B. Evaluation Criteria

In this context, we evaluate and assess these methods for suitability in an MRI classification purpose, and then choose the model which performs the best. We do this using the entire Alzheimer's Disease Neuroimaging Initiative(ADNI) dataset, based on the below mentioned goals :

1) Best performance with least training : We look for a model which can reach a good F1-score with least amout of data and epochs.
2) Type and Size of training data : Although we can easily obtain annotated MRI scans from healthcare providers, it need not always be the case, as it depends on the healthcare provider's facilities. Hence it is important to have models that can scale up and produce high results even with low amounts of data.
3) Deployment : As most hospitals with Hospital Information Systems already have sizable hardware, models that do not impose additional significant hardware requirements, but instead add GPU are desirable. As many Deep Learning models, and especially image classification task use a standard dataset, fine-tuning will need to be done on custom corpuses.

The above mentioned criteria are used to evaluate the following : Convolutional Neural Networks(CNN) [33], EfficientNet(EffNet) [34], Very Deep Convolutional Networks for Large-Scale Image Recognition(VGG) [35].

C. Methodology

1) Dataset: : The dataset we use is ADNI, which is an open source dataset for Alzheimer's Disease data collection, in both csv(comma separated values) as well as MRI scans in DICOM and NIFTI formats. The dataset that used consisted of 83K DICOM and NIFTI files combined. These medical images, after pre-processing, were classified into the below mentioned classes :

1) CN : Control Normal. This refers to the MRI scans taken of candidates with no clinical diagnosis of suffering from Dementia or Alzheimer's Disease.
2) AD: Alzheimer's Disease. These are the MRI scans of candidates clinically diagnosed with Alzheimer's

3) MCI : Mild Cognitive Impairment. These are of those who either reported memory loss themselves, or were clinically diagnosed with the same.
4) EMCI : Early Mild Cognitive Impairment. This refers to those candidates present in the early stages of Cognitive Impairment.
5) LMCI : Late Mild Cognitive Impairment. These scans refers to those in the later stages of Cognitive Impairment.

Although, many of researchers have worked on the classification of AD, we have noticed that the maximum number of classes they would use would be only 3 - AD, CN, MCI(Combination of both EMCI and LMCI). We chose to keep EMCI and LMCI as separate classes because we aims at predicting each stage of AD and in turn provide better insights and comforts to someone living with AD.

2) Experimental Setup: : All experiments were run using Tensorflow platform. We initially ran the DICOM and NIFTI files as they are on a simple CNN model, which proved to us that we needed to do a simple clean up on the data. We used a small sample of 150 DICOM files for this dry run. For the pre-processing we initially converted all the DICOM and NIFTI Files to spliced, JPEG files. We also ensured that the quality was not lost during the conversion. Each JPEG image underwent maxpooling and was reshaped, and re-labelled as well. The configurations used are as follows :

1) *3D-CNN* : A simple network of DenseNet layers make up the 3D-CNN model. A ReLU activation function was used, with a standardized learning rate of 0.0001 and epochs of 100(min).
2) *EffNet* : We used Softmax activation with Imagenet weights. This model was built on Dense Layers of CNN as well as AlexNet layers. Here also we ran the experiments for the standard 100 epochs with 0.0001 learning rate.
3) *VGG* : Here we used a Sequential model with Dense as well as Flatten layers. We also used ReLU activation function with Auto-tuning, and hence running the model for a standard 100 epoch with learning rate of 0.0001, the standard for all the experiments.
4) Convergence occurs when no improvement happens. Thus this convergence section was added onto all the models, hence aiding in save both time and memory.
5) *Training / Test Split*: We used an 80%, 10%, and 10% ratio to split the dataset into training, validation, and test sets, respectively.

IV. Results

For the entire training data, one run were done for each configuration, presented in Table I. As mentioned before, the run was conducted for 100 epochs and the best result was chosen. The best Micro-F1 value attained within 10 epochs is shown in Column 2. Column 3 shows the the best reached Micro-F1 score. We observe the following:

TABLE I
Model Performance

Exp. No.	Architecture	F1-Micro at 10 epochs	Best F1-Micro
1.	3D-CNN	93.55	95.43
2.	VGG	96.39	97.16
3.	EffNet	97.22	97.22

1) While the traditional base model of traditional CNN does catch up to the 3D-CNN model, the 3D-DNN model proved to be more efficient in comparison, by reaching convergence at around 50 epochs to provide an overall performance of 95.43%.
2) while comparing the model of traditional CNN with 3D-CNN, we noticed that it took much longer, around the 70 epochs for the traditional model to reach a convergence with 93% as the best F1-score.
3) The VGG model does outperform the 3D-CNN model, but only by a maximum of 2%. We also noticed that the VGG model reached convergence only much later at around the 55 epochs. We herein inferred that both VGG and 3D-CNN are undeniably part of the fore-runners for MRI classification, in our experiment.
4) The EffNet model outperformed both VGG and 3D-CNN, by achieving convergence at around 40 epochs with its best F1-score at 97.22%.
5) Although the EffNet model and VGG model F1-scores are negligibly different, the convergence epochs show that EffNet can perform better much faster.

A. Limitations

1) *CN*, and *AD* sections facilitate relatively straight-forward classification while *EMCI*, *LMCI*, and *MCI* present a challenge.

   An image that was identified to be *LMCI* was misclassified as *MCI* although it occurred in the *MCI* labelled class. It was noted that without more bio-indicators, such misclassifications could occur in *LMCI*, *EMCI* and *MCI*.
2) The performance of VGG and EffNet are comparable. However, training VGG is quite memory-intensive compared to EffNet, which makes the latter attractive from a deploy-ability standpoint. This leads us to the inference that additional fine-tuning in VGG will consume more memory, while maybe not providing any better results than when we fine-tune EffNet.
3) Based on the discussions so far, creating a curated data-set of about 3000 samples, by identification of the misclassified samples and curating them will help push the accuracy higher.

V. Conclusion

This paper shows that various CNN models do provide an efficient solution to the task of MRI multi-class classification. It is inferred and reflected that around even a small sample of 500 medical image files would be a sufficient starting point for a well performing model. The comparison of models shows that they can achieve comparable accuracy and can be used independently. EffNet outperforms marginally. Future work will look into validation with diverse MRI images of the brain, and integration into an intelligent predictive interface for effective generation of clinical diagnosis, and assuaging physician burn-out. This paper builds on the same principle as the previous papers referred here, easily identifying the causes of concern, as well as focusing on a wider range of sections to be identified. Another focus will be on looking at how various conditions like brain tumour or trauma of any sort, which affect the brain, could learn to Alzheimer's Disease and how we can reduce the speed of progression using early warning predictions, based on similar principles.

REFERENCES

[1] Helaly, Hadeer A., Mahmoud Badawy, and Amira Y. Haikal. "Deep learning approach for early detection of Alzheimer's disease." Cognitive computation (2021): 1-17.

[2] G. Eason, B. Noble, and I. N. Sneddon, "On certain integrals of Lipschitz-Hankel type involving products of Bessel functions," Phil. Trans. Roy. Soc. London, vol. A247, pp. 529–551, April 1955.

[3] J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[4] I. S. Jacobs and C. P. Bean, "Fine particles, thin films and exchange anisotropy," in Magnetism, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271–350.

[5] K. Elissa, "Title of paper if known," unpublished.

[6] R. Nicole, "Title of paper with only first word capitalized," J. Name Stand. Abbrev., in press.

[7] Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, "Electron spectroscopy studies on magneto-optical media and plastic substrate interface," IEEE Transl. J. Magn. Japan, vol. 2, pp. 740–741, August 1987 [Digests 9th Annual Conf. Magnetics Japan, p. 301, 1982].

[8] M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

[9] Liu, Sheng, et al. "On the design of convolutional neural networks for automatic detection of Alzheimer's disease." Machine Learning for Health Workshop. PMLR, 2020.

[10] Kumar, L. Sathish, et al. "AlexNet approach for early stage Alzheimer's disease detection from MRI brain images." Materials Today: Proceedings 51 (2022): 58-65.

[11] Spasov, Simeon E., et al. "A multi-modal convolutional neural network framework for the prediction of Alzheimer's disease." 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2018.

[12] Parmar, Harshit, et al. "Spatiotemporal feature extraction and classification of Alzheimer's disease using deep learning 3D-CNN for fMRI data." Journal of Medical Imaging 7.5 (2020): 056001-056001.

[13] Basaia, Silvia, et al. "Automated classification of Alzheimer's disease and mild cognitive impairment using a single MRI and deep neural networks." NeuroImage: Clinical 21 (2019): 101645.

[14] Pan, Dan, et al. "Early detection of Alzheimer's disease using magnetic resonance imaging: a novel approach combining convolutional neural networks and ensemble learning." Frontiers in neuroscience 14 (2020): 259.

[15] Robinson, Louise, Eugene Tang, and John-Paul Taylor. "Dementia: timely diagnosis and early intervention." Bmj 350 (2015).

[16] Mittal, Vijay A., and Elaine F. Walker. "Dyskinesias, tics, and psychosis: Issues for the next Diagnostic and Statistical Manuel of Mental Disorders." Psychiatry research 189.1 (2011): 158.

[17] Hinrichs, Chris, et al. "Predictive markers for AD in a multi-modality framework: an analysis of MCI progression in the ADNI population." Neuroimage 55.2 (2011): 574-589.

[18] Suk, Heung-Il, and Dinggang Shen. "Deep learning-based feature representation for AD/MCI classification." Medical Image Computing and Computer-Assisted Intervention–MICCAI 2013: 16th International Conference, Nagoya, Japan, September 22-26, 2013, Proceedings, Part II 16. Springer Berlin Heidelberg.

[19] Chandra, Avinash, et al. "Magnetic resonance imaging in Alzheimer's disease and mild cognitive impairment." Journal of neurology 266 (2019): 1293-1302.

[20] Li, Feng, et al. "A robust deep model for improved classification of AD/MCI patients." IEEE journal of biomedical and health informatics 19.5 (2015): 1610-1616.

[21] Mirzaei, Golrokh, and Hojjat Adeli. "Machine learning techniques for diagnosis of alzheimer disease, mild cognitive disorder, and other types of dementia." Biomedical Signal Processing and Control 72 (2022): 103293.

[22] Jack Jr, Clifford R., et al. "The Alzheimer's disease neuroimaging initiative (ADNI): MRI methods." Journal of Magnetic Resonance Imaging: An Official Journal of the International Society for Magnetic Resonance in Medicine 27.4 (2008): 685-691.

[23] Lundervold, Alexander Selvikvåg, and Arvid Lundervold. "An overview of deep learning in medical imaging focusing on MRI." Zeitschrift für Medizinische Physik 29.2 (2019): 102-127.

[24] Gong, Enhao, et al. "Deep learning enables reduced gadolinium dose for contrast-enhanced brain MRI." Journal of magnetic resonance imaging 48.2 (2018): 330-340.

[25] Liu, Fang, et al. "Deep learning MR imaging–based attenuation correction for PET/MR imaging." Radiology 286.2 (2018): 676-684.

[26] Oakden-Rayner, Luke, et al. "Precision radiology: predicting longevity using feature engineering and deep learning methods in a radiomics framework." Scientific reports 7.1 (2017): 1648.

[27] Lundervold, Alexander Selvikvåg, and Arvid Lundervold. "An overview of deep learning in medical imaging focusing on MRI." Zeitschrift für Medizinische Physik 29.2 (2019): 102-127.

[28] LeCun, Yann, et al. "Gradient-based learning applied to document recognition." Proceedings of the IEEE 86.11 (1998): 2278-2324.

[29] Diao, Zhaoshuo, et al. "EFNet: evidence fusion network for tumor segmentation from PET-CT volumes." Physics in Medicine & Biology 66.20 (2021): 205005.

[30] Sarraf, Saman, and Ghassem Tofighi. "Classification of Alzheimer's disease structural MRI data by deep learning convolutional neural networks." arXiv preprint arXiv:1607.06583 (2016).

[31] Majib, Mohammad Shahjahan, et al. "Vgg-scnet: A vgg net-based deep learning framework for brain tumor detection on mri images." IEEE Access 9 (2021): 116942-116952.

[32] Bhanothu, Yakub, Anandhanarayanan Kamalakannan, and Govindaraj Rajamanickam. "Detection and classification of brain tumor in MRI images using deep convolutional network." 2020 6th international conference on advanced computing and communication systems (ICACCS). IEEE, 2020.

[33] O'Shea, Keiron, and Ryan Nash. "An introduction to convolutional neural networks." arXiv preprint arXiv:1511.08458 (2015).

[34] Tan, Mingxing, and Quoc Le. "Efficientnet: Rethinking model scaling for convolutional neural networks." International conference on machine learning. PMLR, 2019.

[35] Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." arXiv preprint arXiv:1409.1556 (2014).

[36] Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 9.8 (1997): 1735-1780.

[37] Graves, Alex, and Alex Graves. "Long short-term memory." Supervised sequence labelling with recurrent neural networks (2012): 37-45.

[38] Payan, Adrien, and Giovanni Montana. "Predicting Alzheimer's disease: a neuroimaging study with 3D convolutional neural networks." arXiv preprint arXiv:1502.02506 (2015).

[39] Hosseini-Asl, Ehsan, Robert Keynton, and Ayman El-Baz. "Alzheimer's disease diagnostics by adaptation of 3D convolutional network." 2016 IEEE international conference on image processing (ICIP). IEEE, 2016.

[40] Wang, Yan, et al. "A novel multimodal MRI analysis for Alzheimer's disease based on convolutional neural network." 2018 40th annual international conference of the IEEE engineering in Medicine and biology society (EMBC). IEEE, 2018.

[41] Bhatkoti, Pushkar, and Manoranjan Paul. "Early diagnosis of Alzheimer's disease: A multi-class deep learning framework with modified k-sparse autoencoder classification." 2016 international conference on image and vision computing New Zealand (IVCNZ). IEEE, 2016.

[42] Gamal, Aya, Mustafa Elattar, and Sahar Selim. "Automatic Early Diagnosis of Alzheimer's Disease Using 3D Deep Ensemble Approach." IEEE Access 10 (2022): 115974-115987.