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Transfer Learning Approaches for Alzheimer disease Classification: A Review

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ABSTRACT

Alzheimer's disease is a kind of dementia that causes cell death in the brain. Consistent cell death in the brain causes a gradual loss of cognitive abilities. We are only scratching the surface of a therapy for this illness. Whatever the case, its early results have the potential to help in stopping the spread of illness. An automated localization and classification framework that can identify and organize the individual with Alzheimer's disease should be constructed for use in the early diagnosis of the illness utilizing MRI of the brain (MRI). These systems need not only to be able to identify Alzheimer's patients, but also to differentiate between the four phases of Alzheimer's. The paper aims to Future research on Alzheimer's stage prediction will be guided by a discussion of various Machine Learning and Deep Learning methodologies and their advantages. The advantages and disadvantages of deep learning, as well as other machine learning methods, are reviewed so that the best option may be selected.
Keywords : Alzheimer's disease, Convolution network, Alex-net, Recurrent Neural Network, Resnet, VGG-net.

I. INTRODUCTION

By far, Alzheimer's disease is the most prevalent kind of dementia. Alzheimer's disease is a neurodegenerative disorder characterised by progressive brain shrinkage and cell death. Of the estimated 50 million persons with dementia globally, 60–70% are thought to have Alzheimer's disease. The illness is named after the German doctor who discovered it, Alois Alzheimer. In 1906, he documented "Auguste Symptoms. "'s Memory loss, abnormal behaviour, and a diminished brain volume were some of the symptoms. In a medical journal article published in 1910, Dr. Alzheimer's colleague, psychiatrist Emil Kraepelin, first used the term "Alzheimer's disease." High levels of beta-amyloid and tau, two proteins found in the brain, are a strong indicator of Alzheimer's disease. In 1984, scientists discovered beta-amyloid. In Alzheimer's disease patients, tau tangles were first identified two years later. The two proteins may inflict harm on brain cells (neurons) [1,4,6].

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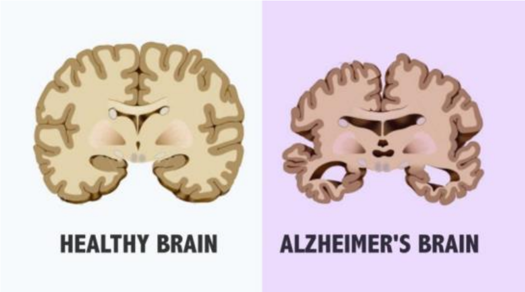

Figure 1. Alzheimer Brain

Alzheimer's disease destroys brain cells and disrupts their ability to communicate with one another. The five stages of Alzheimer's disease are as follows: (1) preclinical Alzheimer's disease, (2) mild cognitive impairment due to Alzheimer's disease, (3) mild dementia due to Alzheimer's disease, (4) moderate dementia due to Alzheimer's disease, (5) severe dementia due to Alzheimer's disease [8,9].

II. LITERATURE STUDY

Sr. No	Name of paper	Year	Journal	Methods	Advantages
1.	Transfer Learning Assisted Classification and Detection of Alzheimer's Disease Stages Using 3D MRI Scans [1]	2019	Sensors	AlexNet, ImageNet, contrast stretching, K-Mean clustering	It is giving overall accuracies of 89.6% and 92.8% for binary and multi-class problems, respectively
2.	Auto-Detection of Alzheimer's Disease Using Deep Convolutional Neural Networks [2]	2018	14th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD	Convolutional Neural Network SVM	Using DCNN for diagnosing the disease of AD to achieve high level of accuracy.
3.	Transfer Learning for Alzheimer's Disease Detection on MRI Images [3]	2019	The 2019 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT)	Deep learning, CNN, RNN	recurrent neural networks can improve the accuracy of CNNs in general.
4.	Transfer Learning With Intelligent Training Data Selection for	2019	SPECIAL SECTION ON DEEP LEARNING FOR	CNN	They validate their hypothesis with detailed experiments

	Prediction of Alzheimer's Disease [4]		COMPUTER-AIDED MEDICAL DIAGNOSIS		on the benchmark ADNI dataset, obtain 95.19% accuracy results.
5.	Binary Classification of Alzheimer's Disease Using MRI Imaging Modality and Deep Learning [5]	2019	Journal of Digital Imaging	ANN, 2D-CNN	They work for custom CNN model built with separable convolutional layers and compared its performance on three datasets.
6.	Detection of Alzheimer's Disease with Shape Analysis of MRI Images [6]	2018	10th International conference on soft computing and intelligent systems	Fourier Descriptor	The results revealed classification accuracy of 87.5%.
7.	A deep feature-based real-time system for Alzheimer disease stage detection [7]	2020	Multimedia Tools and Applications-Springer	AlexNet	They use efficient transfer learning architecture ALexnet to extract deep features which are further used for AD stage classification
8.	Automatic classification of cognitively normal, mild cognitive impairment and Alzheimer's disease using structural MRI analysis [8]	2020	Informatics in Medicine Unlocked-Elsevier	Linear SVM	MRI based classification with neuropathological AD using ML algorithms such as RF and SVM classifiers with 77% accuracy
9.	Early Diagnosis of Alzheimer's Disease Based on Resting-State Brain Networks and Deep Learning [9]	2019	IEEE/ACM Transaction on Computational Biology and Bioinformatics	Deep neural network	DNN classify high dimensionally multimedia data and could help to predict and prevent AD.

10.	Effective Use of Data Science Toward Early Prediction of Alzheimer's Disease [10]	2018	IEEE 20th International Conference on High Performance Computing and Communications	ML techniques- PCA, ICA	The use of Machine Learning to assist in the diagnosis and prediction process of Alzheimer's disease will help to learn more about the disease and its behaviour.

III. METHODS AND MATERIAL

A. AlexNet [1,3,11]

A large perceptron (RNN) may be able to achieve high excellent on a highly difficult dataset by using solely supervised learning methodologies, according to the findings of the AlexNet study. In the year after the debut of AlexNet, a competition was launched that has continued to this day.

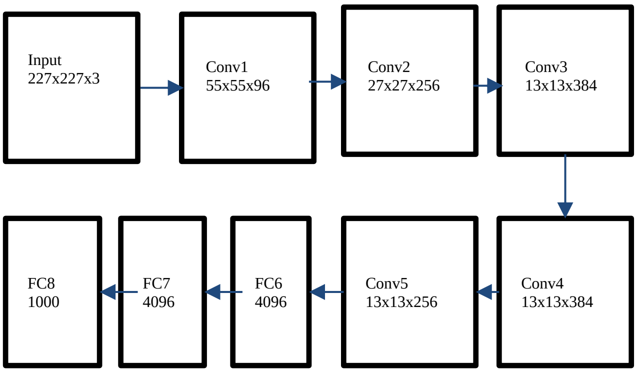

Figure 4. AlexNet Model Layers

The Convolutional Neural Network is used to categories all contributions to the ImageNet database. CNN is a pioneer in biomedical research, ushering in a new age with AlexNet, which was created in collaboration with the National Institutes of Health and launched in 2004. Because a variety of deep learning are readily available, the mounting of AlexNet is rather basic.

B. Resnet [2,4]

ResNet-50 is a convolutional neural network that is 50 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [1]. It is a construction piece that was destroyed but which still contains a bridged connector (formerly known as a legacy connection) that permits data to flow through it without being altered in any way despite the destruction. The data signal x is converted into an output signal F by the activation curve layer. It is composed of two types: layer 1 and layer 2, which are interconnected (x). The transfer seems to be comparable to those of a connection that has been skipped in this instance. The residual unit in this specific design demonstrates how it control signal x varies from those of the thanks to advances F, which is a result of the construction process itself (x). In accordance with the findings of this study, if the infrastructure has also fruitfully recreated the linear mapping that is assembled on a given spot, the improvements may be effective to minimize muscular endurance in the unavailable slabs on varying scales to essentially zero, but also guarantee that the output passes across the disconnect with next to no damage.

The ResNet architecture follows two basic design rules. First, the number of filters in each layer is the same depending on the size of the output feature map. Second, if the feature map's size is halved, it has double the number of filters to maintain the time complexity of each layer. ResNet-50 has an architecture based on the model depicted above, but with one important difference. The 50-layer ResNet uses a bottleneck design for the building block. A bottleneck residual block uses 1×1 convolutions, known as a “bottleneck”, which reduces the number of parameters and matrix multiplications. This enables much faster training of each layer. It uses a stack of three layers rather than two layers.

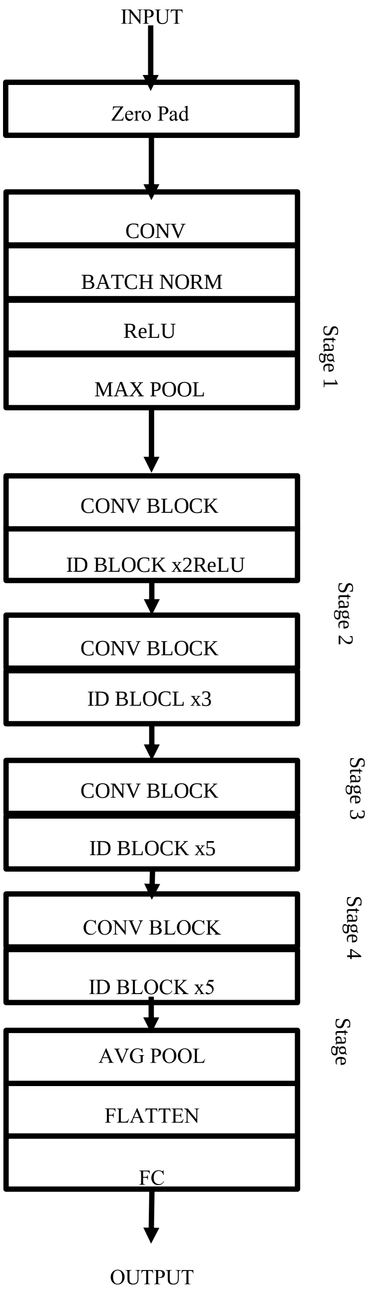

Figure 2. ResNet Model Layers

All hidden layers are equipped with the rectification (ReLU) non-linearity. It is also noted that none of the networks (except for one) contain Local Response Normalisation (LRN), such normalization does not improve the performance on the ILSVRC dataset but leads to increased memory consumption and computation time.

C. **VggNet [3,8]**

The input to cov1 layer is of fixed size 224 x 224 RGB image. The image is passed through a stack of convolutional (conv.) layers, where the filters were used with a very small receptive field: 3×3 (which is the smallest size to capture the notion of left/right, up/down, centre). In one of the configurations, it also utilizes 1×1 convolution filters, which can be seen as a linear transformation of the input channels (followed by non-linearity). The convolution stride is fixed to 1 pixel; the spatial padding of conv. layer input is such that the spatial resolution is preserved after convolution, i.e., the padding is 1-pixel for 3×3 conv. layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. layers (not all the conv. layers are followed by max-pooling). Max-pooling is performed over a 2×2-pixel window, with stride 2. Three Fully Connected (FC) layers follow a stack of convolutional layers (which has a different depth in different architectures): the first two have 4096 channels each, the third performs 1000-way ILSVRC classification and thus contains 1000 channels (one for each class). The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks.

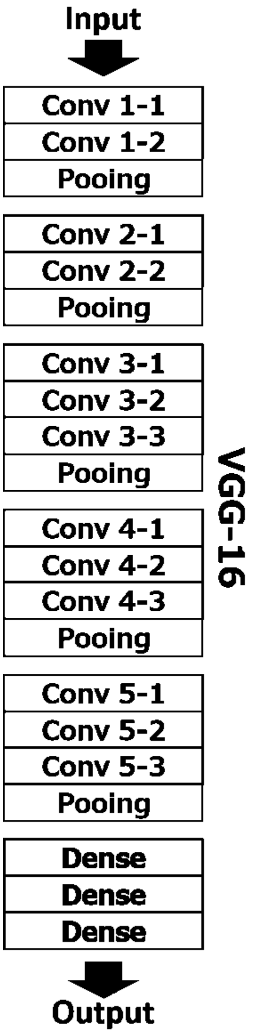

Figure 4. Vgg-16 Model Layers

IV. Comparative Analysis

TABLE I

COMPARATIVE ANALYSIS

Method	Advantage	Disadvantages
CNN [1,2,4]	Increased efficiency. It is simple to categories. Deals with a large amount of data Handles a wide range of data	Takes more time to train Complex
RNN [3]	Every piece of knowledge accumulated through time. It is only effective in time series prediction since it has the ability to recall past inputs.	It is quite tough to train an RNN. When utilizing tanh or relu as an activation function, it won't be able to handle very lengthy sequences.
AlexNet [1,3,11]	This led to faster training of models. It also worked well for the time with color images. It does not limit the output unlike other activation functions. Improve model training speed since not all perceptron's are active.	This model has a relatively shallow depth compared to the other models discussed in this post, and as a result, it fails to learn features from picture sets.
ResNet [2,4]	Allows you to bypass connections. To increase efficiency and accuracy, batch normalization is used.	Complex to Implement

VggNet [3,8]	VGG introduces a model that has been pre-trained. As the depth of the model is increased, the accuracy improves. The non-linearity, which is always positive, increases as the number of layers with smaller kernels increases.	The model produced using VggNet has a problem with disappearing gradients. The ResNet is slower.

V. CONCLUSION

Alzheimer's Disease Stages diagnosis or categorization necessitates an understanding of the disease's distinct characteristics. However, spotting distinctive patterns in features is sometimes difficult, especially when the data is huge. We can't utilise typical approaches to discover patterns or develop mathematical models since data obtained from the environment is frequently non-linear. Machine learning-based methods, on the other hand, do not work for massive data, and they take longer and provide less accuracy than deep learning approaches.

So, in the future, if deep learning is the most recent technology that is aiming to tackle this problem. Deep learning's layers may be changed, and when combined with Max Polling, fully connected and soft max layers perform better for Alzheimer's Disease Stages categorization.

VI.REFERENCES

[1] M. Maqsood et al., "Transfer learning assisted classification and detection of alzheimer's disease stages using 3D MRI scans," Sensors (Switzerland), vol. 19, no. 11, 2019, doi: 10.3390/s19112645.

[2] L. Yue et al., "Auto-detection of alzheimer's disease using deep convolutional neural networks," ICNC-FSKD 2018 - 14th Int. Conf. Nat. Comput. Fuzzy Syst. Knowl. Discov., pp. 228–234, 2018, doi: 10.1109/FSKD.2018.8687207.

[3] A. Ebrahimi-Ghahnavieh, S. Luo, and R. Chiong, "Transfer learning for Alzheimer's disease detection on MRI images," Proc. - 2019 IEEE Int. Conf. Ind. 4.0, Artif. Intell. Commun. Technol. IAICT 2019, pp. 133–138, 2019, doi: 10.1109/ICIAICT.2019.8784845.

[4] I. R. R. Silva, G. S. L. Silva, R. G. De Souza, W. P. Dos Santos, and R. A. A. De Fagundes, "Model Based on Deep Feature Extraction for Diagnosis of Alzheimer's Disease," Proc. Int. Jt. Conf. Neural Networks, vol. 2019-July, no. July, pp. 1–7, 2019, doi: 10.1109/IJCNN.2019.8852138.

[5] N. M. Khan, N. Abraham, and M. Hon, "Transfer Learning with Intelligent Training Data Selection for Prediction of Alzheimer's Disease," IEEE Access, vol. 7, pp. 72726–72735, 2019, doi: 10.1109/ACCESS.2019.2920448.

[6] A. Bin Tufail, Y. K. Ma, and Q. N. Zhang, "Binary Classification of Alzheimer's Disease Using sMRI Imaging Modality and Deep Learning," J. Digit. Imaging, 2020, doi: 10.1007/s10278-019-00265-5.

[7] H. Fuse, K. Oishi, N. Maikusa, and T. Fukami, "Detection of alzheimer's disease with shape analysis of MRI images," Proc. - 2018 Jt. 10th Int. Conf. Soft Comput. Intell. Syst. 19th Int. Symp. Adv. Intell. Syst. SCIS-ISIS 2018, pp. 1031–1034, 2018, doi: 10.1109/SCIS-ISIS.2018.00171.

[8] H. Nawaz, M. Maqsood, S. Afzal, F. Aadil, I. Mehmood, and S. Rho, "A deep feature-based real-time system for Alzheimer disease stage

detection," Multimed. Tools Appl., 2020, doi: 10.1007/s11042-020-09087-y.

[9] V. P. S. Rallabandi, K. Tulpule, and M. Gattu, "Automatic classification of cognitively normal, mild cognitive impairment and Alzheimer's disease using structural MRI analysis," Informatics Med. Unlocked, vol. 18, 2020, doi: 10.1016/j.imu.2020.100305.

[10] I. Beheshti and H. Demirel, "Feature-ranking-based Alzheimer's disease classification from structural MRI," Magn. Reson. Imaging, vol. 34, no. 3, pp. 252–263, 2016, doi: 10.1016/j.mri.2015.11.009.

[11] T. Altaf, S. M. Anwar, N. Gul, M. Majid, and M. N. Majeed, "2017 Multi-class Alzheimer Disease Classification using Hybrid Features.pdf," 2017 Futur. Technol. Conf., no. November, pp. 264–267, 2017.

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