

CNN-based MRI analysis of Alzheimer's disease

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Abstract. The dementia known as Alzheimer's disease (AD) damages the brain. It is very common and almost irreversible in the population, and to date, there is no definitive diagnosis and no effective treatment. Despite the lack of comprehensive treatments, studies have shown that early detection can reduce the severity of the disease and lengthen the patient's life by delaying the development of the illness. Machine learning (ML), often known as deep learning, is a fast-growing science that makes extensive use of convolutional neural networks (CNNs). CNNs can be used for image recognition. One of the important features of AD can be observed by Magnetic resonance imaging (MRI): damage to brain cells and partial atrophy. For the training of CNNs, it is possible to achieve high accuracy in the diagnostic classification of AD. This article reviews the latest related studies, analyses the cases using three common CNN methods, ResNet, VGG-16 and GoogLeNet, and evaluates the use of migration methods. In order to help AD patients, get diagnosed sooner and spend longer in remission, this article assesses the use of multiple ML approaches throughout the diagnostic classification of AD and chooses the most accurate method.

Keywords: CNN, Alzheimer's disease, MRI, VGG, ResNet.

1. Introduction

One of the most prevalent forms of dementia, AD slowly destroys older people's brain cells while disrupting their daily life. Research shows that after age 65, AD doubles every five years and rises exponentially with age. In the US, currently, it is the sixth most prevalent illness, and its incidence is rapidly increasing.

There are three main stages of AD. The first stage is very mild dementia, which is characterized by memory loss, difficulty analyzing or judging things, difficulty accepting new things, and emotional apathy. In the second stage, known as mild dementia, patients experience the impairment of near and distant memory and have the neurological problems, including but not limited to aphasia and loss of consciousness. Patients are largely unable to care for themselves and may be accompanied by the urinary incontinence. Eventually moderate dementia, in addition to severe memory loss, the patient has only a few hours of wakefulness. They usually end up in a coma and most die from the infections and the complications.

Since no one knows what causes Alzheimer's disease, theories include family history, genetics, and medical conditions including hypothyroidism and depression. The majority of identified instances of Alzheimer's disease are ignorant of their condition in the early stages because it is a neurodegenerative ailment that is difficult to accurately identify in clinical practice. Early diagnosis and treatment can prolong patients' lives by stabilizing their disease and more gradually delaying its course, according to studies. Because of this, early diagnosis is crucial.

As AD mostly manifests in the brains of older people, changes can often only be found through scans of the brain. However, Positron emission tomography (PET) is quite pricey and is not frequently utilized in regular medical examinations. Magnetic resonance imaging (MRI) is less expensive and more effective than PET, and it offers a clearer image of the atrophy of some brain areas, like the hippocampus. Therefore, MRI is often used today for related confirmatory diagnosis and treatment today, automated decisions about Alzheimer's disease are often made using machine learning (ML) and deep learning. In deep neural networking, two methods exist, recurrent neural networks (RNN) and CNN, which are used to identify pre-processed MRI. Using pre-processed MRI data, CNN and RNN of deep learning techniques were able to classify AD with an accuracy rate of 96.0 percent.

Mild cognitive impairment (MCI), the initial stage of bereavement of multiple capacities characterized by memory loss, has a conversion prediction accuracy of 84.2 percent.

This article will provide an overview of the most recent advancements and contributions made by DL, particularly CNN, to detecting AD.

2. Methodology

2.1. Data collection

The Alzheimer's Disease Neuroimaging Initiative (ADNI) has made a remarkable contribution to AD and has provided a cool pool of data for social research, most of which is now drawn from the ADNI, which is made up of medical institutions and various universities in Canada and the United States. By examining brain imaging data from individuals with AD, moderate AD, and the elderly, and by formulating various hypotheses in a clinical environment, it seeks to enhance approaches for the diagnosis and treatment of AD.

2.2. ResNet

The literature cites two popular techniques—intensity normalization and registration—mentioned by Ebrahimi et al. in 2020 as alternatives to the ResNet-18 method used by Maqsood et al. [1] for image pre-processing. In contrast to the first way, which maps the MRI-scannable space to a predetermined standard range, the second method defines the MRI-scannable space in terms of a reference anatomical space. Unlike 3D CNNs, which train using the whole pre-processed MRI, 2D CNNs train by removing 2D image segments from each plane of the 3D MZRI scans and discarding the beginning and end uninformative images. Using 2D RGB images (red, green, and blue), three neighboring apprentices are superimposed to provide 16, 19, and 24 images in the axial, sagittal planes, and coronal [1]. By using bilinear interpolation, the resulting scaled images were matched to Figure 1.

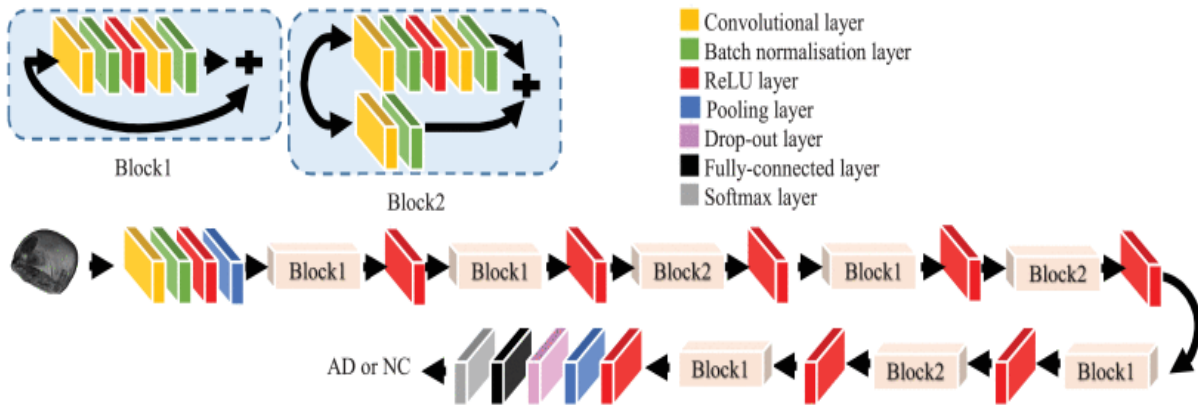


Figure 1. ResNet-18 Model [2].

2D convolutional neural networks were used in the past to analyze Alzheimer's disease, but it was found that 2D was not sufficient to analyze MRI images. For image processing, Maqsood et al. proposed migratory learning utilizing 3D level convolutional neural networks [1]. MRI images were separated into two categories in the original work [2]. A cognitive normal (CN) test and an Alzheimer's disease test each have different results (AD). In contrast to ResNet-18 proposed by He et al. in 2016 where 18 represents the depth, Ebrahimi et al. optimized the model and introduced the concept of migratory learning [3]. Table 1 shows the ResNet-18 model implemented in the study by Ebrahimi et al.

Table 1. The implemented Resnet-18 model [2].

Network	Depth	#Connection	#Layers	#Conv layers	#FCs	#Parameters (MM)	Size (MB)	Image Dimensions
2D	18	78	71	20	1	11.7	44	224*224*3
3D						34	46	224*224*224
Adjusted 3D								112*112*112

It is essential to train CNN models with optimization solvers such stochastic gradient descent, root mean square propagation (SGDM) and adaptive moment estimation. The backpropagation learning method and Taguchi analysis are used in the article to optimize five parameters: learning rate, exit factor, L2 regularization factor, small batch size, and degree of data augmentation [4].

The classification accuracy with or without migration learning of 2D/3D ResNet-18 is displayed in Table 2. Both migration learning and ab initio training were used for the 2D/3D methods. Unlike the 2D model where there is no significant difference after adding different views, migration learning makes a very significant difference in the 3D model by reducing the training time by a factor of three.

Table 2. 2D/3D ResNet-18 Accuracy [2].

Model ResNet-18 (R18)			Accuracy
Training from scratch	2D	R18 Axial	81.25
		R18 Sagittal	84.38
		R18 Coronal	87.50
		R18 Multi-view	84.38
	3D	R18	68.75
		Adjusted R18	87.5
Training Learning	2D	R18 Axial	87.5
		R18 Sagittal	81.25
		R18 Coronal	81.25
		R18 Multi-view	84.38
	3D	R18	96.88
		Adjusted R18	93.75

Table 3 shows the different optimization algorithms and the corresponding performance metrics. The first is accuracy, which refers to the percentage of individuals that are classified among all tested individuals. Second, specificity represents the ratio of healthy individuals that are classified among all individuals evaluated. Additionally, sensitivity is the measure of how many people with AD are identified among all test samples. The outcomes of this example demonstrate that the learning migration strategy produced by transferring 3D in 2D considerably increases the diagnostic accuracy of 3D ResNet-18.

Table 3. Results of each optimization algorithm's optimal combination of variables for classification [2].

Parameter	RMSProp	Optimization algorithm SGDM	ADAM
Mini-batch size	10	10	10
Learning Rate	0.00005	0.005	0.0001
Data augmentation	0	15	15
L2 Regularization	0	0	0.05
Drop-out	0	0	0.4
Specificity %	100	93.75	87.5
Sensitivity %	87.5	100	100
Accuracy %	93.75	96.88	93.75

2.3. VGG & VIN

The VGG network structure was developed by the Visual Geometry Group at the University of Oxford. Because VGG-16 has fewer layers and is simpler to construct, it was chosen for the study instead of VGG-19. Figure 2 displays the VIN developed for this work and impacted by VGG-16. According to Figure 2, VIN includes three FCLs and four CBs [5]. VIN and VGG-16 share some characteristics, including the use of small (3 3) convolution kernels and a small (2 2) max-pooling kernel. Although they are placed at the end of the deep network [6], the fully connected layers also have some variations. As an illustration, the output of the former input, $176 \times 176 \times 1$, is two neurons, whereas the output of the latter input, $224 \times 224 \times 3$, is 1000 neurons, which corresponds to 1000 categories that need to be classified [5].

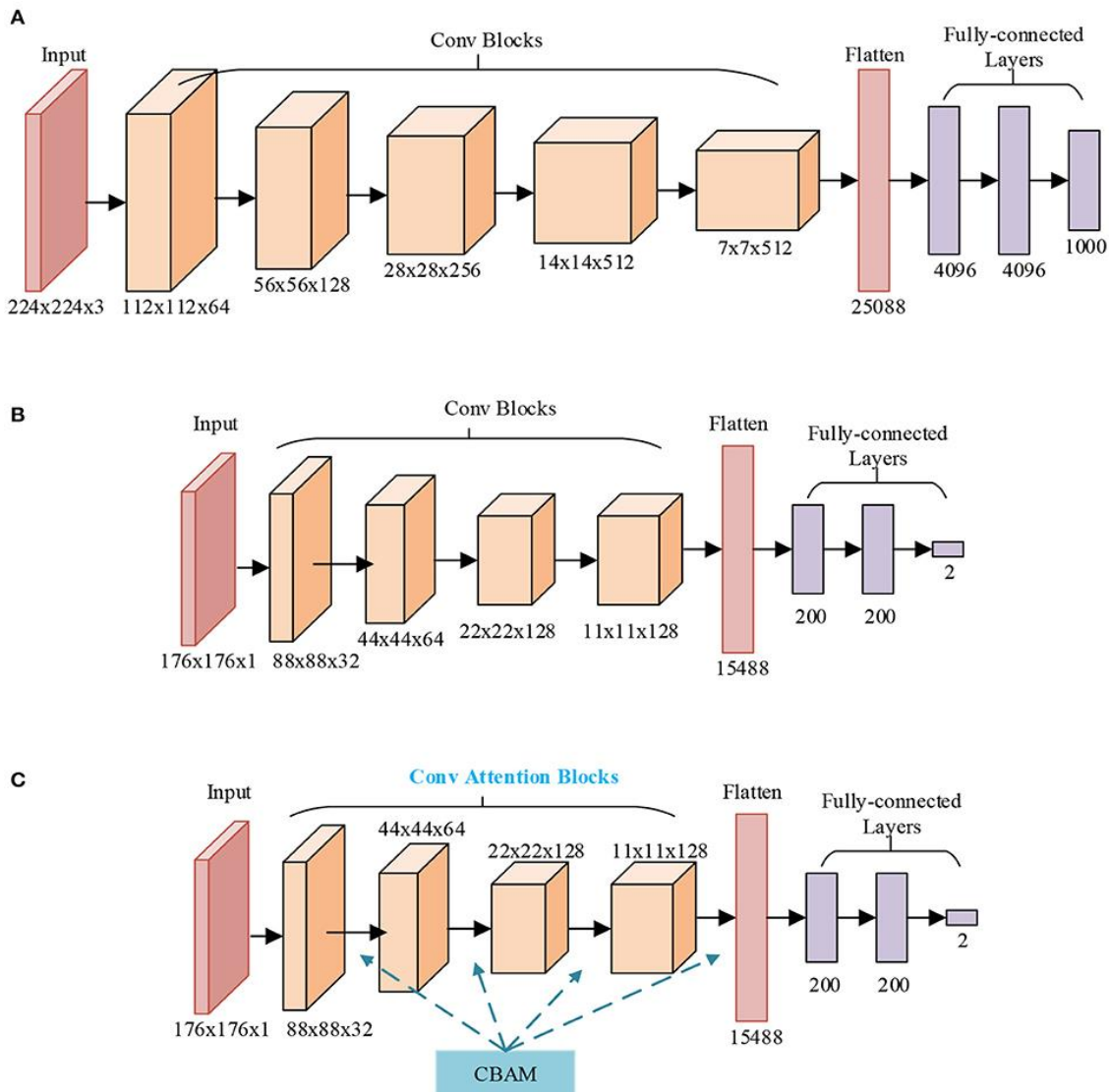


Figure 2. VGG-16 & VIN & ADVIAN Structure [5].

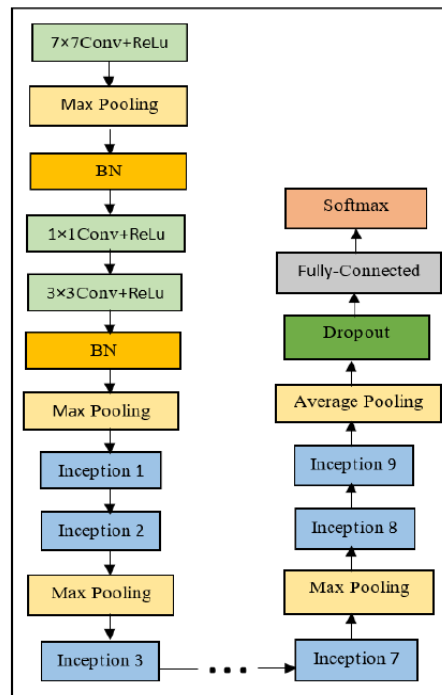
According to the article, Arora et al. offers suggestions for automatically segmenting skin lesions based on attentional flavors [7]. The network's performance may be enhanced by attracting attention. According to the article, Arora et al. offers suggestions for attentional flavors-based automatic skin lesion segmentation. Among them, Wang et al. were motivated to employ the AD VGG-Inspired Attention Network (ADVIAN) for convolutional neural networks and suggested 18-way data improvement to prevent overfitting because of insufficient data [5]. The results of 10 ADVIAN runs are displayed in Table 4 along with the representative accuracy and sensitivity. Results for this article's sensitivity, specificity, and accuracy are 97.65 ± 1.36 , 97.86 ± 1.55 , and 97.76 ± 1.13 , respectively.

Table 4. Ten runs of ADVIAN and classification results [5].

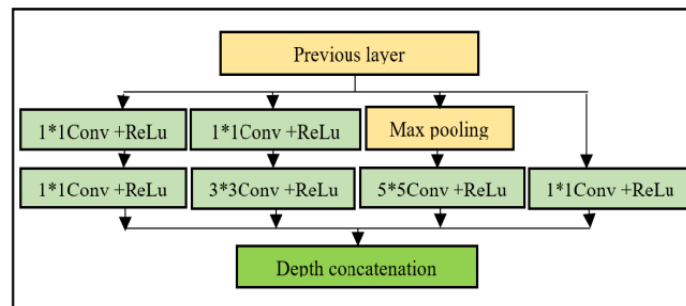
Run	Sensitivity %	Specificity %	Accuracy %
1	100.00	97.96	98.98
2	97.96	96.94	97.45
3	97.96	95.92	96.94
4	97.96	100.00	98.98
5	95.92	98.98	97.45
6	97.96	95.92	96.94
7	97.96	98.98	98.47
8	95.92	96.94	96.43
9	95.92	96.94	96.43
10	98.98	100.00	99.49
MSD	97.65 ± 1.36	97.86 ± 1.55	97.76 ± 1.13

2.4. GoogLeNet

GoogLeNet, launched by the Google team in 2015, was the winner in ILSVRC-2014. Figure 3 (a) shows the GoogLeNet structure with 22 layers in the CNN model, and (b) shows the nine initial template layers [8]. All convolutions use the rectified linear unit (ReLU), as illustrated in Figure a, as their activation function. The origination layers' intricate structure is displayed in b.



(a)



(b)

Figure 3. (a) GoogLeNet structure with 22 (b) the nine initial template layers [8].

Unlike the traditional CNN structure, GoogLeNet not only takes care of the computational budget but also deals with depth and width. Erhan et al. mentioned that the error disappears with backpropagation due to its convolutional machine with 60 layers and a depth of 22, while the lower layers are not optimized [9]. Although increasing the depth may produce the better results, it may also lead to overfitting of the results. To address this point, two auxiliary classifiers were used to optimize the parameters of the lower layer. Due to its excellent performance, G-MS2F was used as a development model for GoogLeNet to study multi-stage features. At the same time, GoogLeNet can learn 12 times fewer parameters compared to other structures. Table 5 presents the result of GoogLeNet, which has an accuracy of 98.88% [10].

Table 5. GoogLeNet and classification results [10].

Model	Class	SPE %	SEN %	ACC %
GoogLeNet	AD	99.2	97.6	98.88
	MCI	99.6	98.6	
	NC	98.6	97.6	

3. Conclusion

Testing for Alzheimer's disease is still far from trustworthy and effective, and its causes are still poorly understood. Early detection is crucial for patients because of the disease's severe and irreversible nature. Through early diagnosis, patients can purchase time to remission and chances for improvement. Deep learning and machine learning, two modern innovations, are employed often in daily life. Convolutional neural networks have a significant positive impact on AD discovery. This article summarizes new research comparing three popular convolutional neural network techniques for MRI analysis. The essay examines how ResNet, VGG-16, and GoogLeNet work while demonstrating how migratory learning may significantly increase the effectiveness of image processing. The examples' findings demonstrate that the GoogLeNet technique performs well in terms of sensitivity and specificity, with accuracy that is much greater than that of VGG and ResNet (98.88 vs. 97.76 ± 1.13). GoogLeNet classification of MRI images of AD patients and healthy participants is thus one of the techniques deserving of praise. Although no model is entirely accurate, the advancement of deep learning should not be understated because a more accurate identification of AD will undoubtedly be possible in the future.

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