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An Implementation of Effective CNN Model for AD Detection

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Abstract

This paper focuses on detecting Alzheimer’s Disease (AD). The most usual form of dementia is Alzheimer's disease, which causes permanent cause memory cell damage. Alzheimer's disease, a neurodegenerative disease, increases slowly over time. For this matter, early detection of Alzheimer's disease is important. The purpose of this work is using Magnetic Resonance Imaging (MRI) to diagnose AD. A Convolution Neural Network (CNN) model, Reset, and VGG the pre−trained learning models are used. Performing analysis and validation of layers affects the effectiveness of the model. T1−weighted MRI images are taken for preprocessing from ADNI. The Dataset images are taken from the Alzheimer's Disease Neuroimaging Initiative (ADNI). 3D MRI scans into 2D image slices shows the optimization method in the training process while achieving 96% and 94% accuracy in VGG 16 and ResNet 18 respectively. This study aims to classify AD from brain 3D MRI images and obtain better results.

Keywords: Alzheimer's disease (AD)| Magnetic Resonance Imaging (MRI)| Convolution Neural Network (CNN)

I. INTRODUCTION

In the 1900s, Alzheimer’s Disease (AD)[1] was first defined by Alois Alzheimer. AD is a brain disease that elderly people mainly cause. Destruction of neurons causes changes in the brain, the symptoms of Dementia are memory loss, [2] inability to recognize the world around us frightening experiences, and incapable to do daily activities. A memory stores the entire history of our lives and plays an important role in our character and identity. Over[3] 10 million by 2050 are expected to have dementia according to the World Alzheimer’s report. Dementia is divided into many types; Alzheimer’s disease is one of them. Alzheimer's Disease (AD) causes memory loss over some time from weeks to months which makes detection of AD in the early stage necessary. Despite much research head and going yet, there is no cure for AD, slowly down the symptoms.

Alzheimer’s disease is classified into 4 stages Alzheimer's Disease (AD), Early Mild Cognitive Impairment (EMCI), and Late Mild Cognitive Impairment (LMCI), Cognitively Normal (CN). A healthy brain maintains an intricate neural network, facilitating robust cognitive and memory functions. Effective neuron communication through synapses ensures information retrieval, memory retention,

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and seamless daily task execution while upholding structural integrity and the absence of abnormal protein accumulations. In contrast, Alzheimer's disease profoundly disrupts brain health. Structural anomalies, marked by amyloid plaques and tau tangles, lead to neuronal damage and impaired neural communication. This significantly impairs cognitive functions, causing a progressive decline in memory, reasoning, and higher-order processes. Alzheimer's disease is characterized by the gradual degeneration of brain tissue, ultimately resulting in severe cognitive impairment and dependence on caregivers.

The Early Stage of Alzheimer's Disease represents a critical transition [4], [5], featuring more prominent disease manifestations. Individuals in this stage commonly experience mild memory deficits, confusion, and challenges with previously routine activities. Notably, they maintain a substantial degree of functional independence and can generally handle daily living tasks. Conversely, Late-Stage Alzheimer's Disease marks the advanced and severe phase of the condition. At this stage, affected individuals experience a profound loss of communication abilities and require constant assistance for their daily care[6]. They may also lose fundamental functions, such as swallowing and mobility, becoming highly dependent on caregivers for comprehensive support in all aspects of daily life.

For analysis, image analysis of magnetic resonance imaging (MRI) is important. MRI produces an image of contrast in tissue and in MRI T1-weighted images are taken to perform the study as these images generate common structural analytical annotation of tissue, In these t1-weighted images both Repetition Time (TR) and Time of Echo (TE)[7] are short. We also consider taking 2D but 3D images in this study to explore the different angles and views of each subject's brain. 3D images are sliced and used in this study.

Recently, Convolutional Neural Networks (CNN) have been widely used for classification, analysis, and prediction in various fields. A neural network, a fully connected layer[8], is used in AD classification. Traditional methods[9] often use multiple modalities, requiring time and feature selection. This study uses MRI images of only one modality of T1-weighted and tests and compares activation functions to ensure the model learns even from the negative values. This study develops the neural network for improving AD classification using binary tasks. Our contribution is to introduce a novel method of classification using convolutions for AD detection with higher accuracy than other models. Furthermore, the study can be utilized for the identification of AD stage of AD is classified, AD, EMCI, and LMCI. We compared the results of ResNet[10] [11], [12] and VGG[13], [14] with different layer structures. We also compared the results with other models in machine learning methods on the same data.

This study aims to understand the model ResNet and VGG requires fewer resources but performs better than previous methods. By comparing the

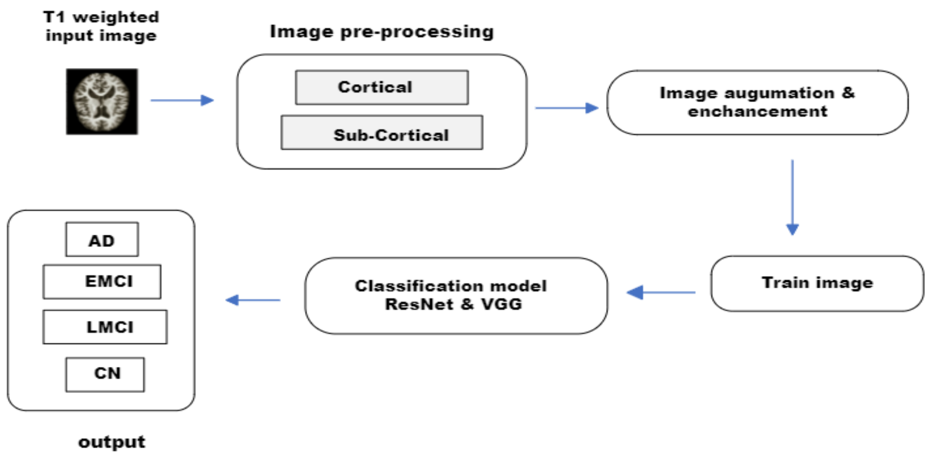

Fig 1. Block diagram of the diagnosis process

accuracy, sensitivity, and specificity.

II. MATERIAL AND METHOD

2.1 sMRI Dataset

In our study, we accessed data available on the Alzheimer's Disease Neuroimaging Initiative (ADNI). ADNI helps researchers collect, validate, and utilize data, including MRI and PET images, genetics, cognitive tests, and blood biomarkers as predictors of the disease. Through this imaging modalities can measure the progression or early detection of AD. For diagnosis, the Alzheimer's disease, ADNI database (http://adni.loni.usc.edu/) has taken.

2.2 Subjects

Experiment data is taken from the ADNI website, which has thousands of subjects with different age structures. It is authorized by the Institutional Review Board (IRB). We have taken about 1390 images. The dataset consists of 4 groups: AD, LMCI, EMCI, and CN. Total of 1390 subjects: 173 AD subjects (72 females, 101 males; mean age =78.562), 285 LMCI subjects (126 females, 159 males; mean age =73.621), 488 EMCI subjects (206 females, 282 males; mean age =73.343), and 454 CN subjects (261 females, 193 males; mean age =78.091) as shown in Table 1.

In this study, we have an equal number of female and male subjects in total. The dataset is split into two, 70:30 ratio for the training and testing of the model. The model validation accuracy is trained and finally used to predict the test data

Table 1. Subject Report

Class		CN	EMCI	LMCI	AD
Nos. of subject		454	488	285	173
Female		261	206	126	72
Male		193	282	159	101
Age		78	73	73	78

2.3 Methodology

In this study, we have collected data from the ADNI and extracted the features from 3D images by slicing. These t1-weighted images are taken to the next stage. We have taken about 1390 images from patients. For the experiment, ResNet and VGG are used as a classifier by comparing different layer dimensions in this model structure. Every layer of this ResNet and VGG is composed of serval blocks making better results in the different studies but to understand this we have done this experiment in medical image MRI. Brain images are one of the most complicated to study and train the images. These models have different ResNet and VGG layers consisting of multiple blocks, increasing operations within blocks while maintaining total layer dimensions. Each of these architectures consists of a convolution layer, a pooling layer, and a fully connected layer.

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Figure 2. ResNet 18 Variants

ResNet:

Deep neural networks face challenges in vanishing gradients, which slow down gradient descent. Microsoft introduced the deep residual network to address this issue, using a skip connection shortcut to facilitate easy information flow between layers. This approach bypasses the standard Convolution Neural Network flow and allows the network to fit residual mapping instead of learning from the underlying mapping. ResNet 18 architecture improves with sequential layer, linear (512,512), ReLU activation function, dropout, linear (512,2), Log SoftMax, and Negative log−likelihood loss function for the logarithm of probabilities. Increase complexity by increasing residual block layers. Variants have varied with ResNet 18, ResNet 34, ResNet 50, ResNet 101, ResNet 152.[15] can be seen in Figure 2.

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
Input (224 × 224 RGB image)					
Conv3-64	Conv3-64 **LNR**	Conv3-64 **Conv3-64**	Conv3-64 Conv3-64	Conv3-64 Conv3-64	Conv3-64 Conv3-64
maxpool					
Conv3-128	Conv3-128	Conv3-128 **Conv3-128**	Conv3-128 Conv3-128	Conv3-128 Conv3-128	Conv3-128 Conv3-128
maxpool					
Conv3-256 Conv3-256	Conv3-256 Conv3-256	Conv3-256 Conv3-256	Conv3-256 Conv3-256 **Conv1-256**	Conv3-256 Conv3-256 **Conv3-256**	Conv3-256 Conv3-256 Conv3-256 **Conv3-256**
maxpool					
Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512 **Conv1-512**	Conv3-512 Conv3-512 **Conv3-512**	Conv3-512 Conv3-512 Conv3-512 **Conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
Soft-max					

Figure 3. VGG 16 Variants

VGG:

A convolutional neural network (CNN) is an artificial neural network with input, output, and hidden layers. Its depth was increased using small convolution filters, resulting in trainable parameters. VGG 16 consists of 16 weight layers, including 13 convolutional layers, 5 max−pooling layers, and 3 dense layers. It uses input tensors with 3 RGB channels and focuses on convolution layers with 3*3 filters and 2*2 filters.

The architecture is consistent in arrangement, with 64 filters in Conv−1, 128 filters in Conv−2, 256 filters in Conv−3, and 512 filters in Conv−4 and 5 along with the Fully Connected layer and soft−max layer. VGG19 had three more convolutional layers than VGG16 and three less convolutional layers than VGG13 and VGG 11 three less convolutional than VGG13.

Variants have varied with VGG 11, VGG 13, VGG 16, and VGG 19 as shown in Figure 3 above [16].

3.1 Performance and evaluation parameters

Table 2. Multiclass confusion matrix

	Prediction classification				
Actual classification	classes	AD	LMCI	EMCI	HC
	AD	**TP**	F_{AL}	F_{AE}	F_{AH}
	LMCI	F_{LA}	**TP**	F_{LE}	F_{LH}
	EMCI	F_{EA}	F_{EL}	**TP**	F_{EH}
	HC	F_{HA}	F_{HL}	F_{HE}	**TP**

In the present study, multi-class classification [17] evaluates model performance using ResNet and VGG with different weight dimensions shown in table 2. Classifiers accurately predict classes using parameters like true positive (TP), true negative (TN), false positive (FP), and false negative (FN) and other parameters that are used to predict accuracy, precision, and recall from the equation (1, 2, 3).

We can see the understanding of the calculation mathematically. True negative and true positive indicates the correctly identified controls; False positive and false negative represents the incorrectly identified controls.

Evaluation and accuracy are the parameters in multi-class classifiers that compute the confusion matrix.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{precision} = \frac{TP}{TP+FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

However, accuracy may not be accurate because of the unstable class distribution. So, adding on Precision (4), Recall (5), and F1-score. Sensitivity for predicting group accuracy (3) and Recall for the absence of the group's accuracy whereas the F1-score is the harmonic mean of precision and recall. Multi-class classifier evaluates accuracy using a confusion matrix, adjusting accuracy based on dataset, specificity, and recall. Recall can also be called as sensitivity.

3.2 Classification results and Conclusion.

The current study is done in using a python environment. In the current work, a multi-class classification is used. Images taken from ADNI are MRI brain images T1-weighted images are used for image pre-processed, augmentation, and enhancement. ResNet and VGG models are then used as classifiers with different weight dimensions to understand. This experiment compares the different layers of ResNet and VGG with the same environment using medical images. The understanding of this study was number of layers are different for every experiment and training.

In the study, we used ResNet 18, ResNet 34, ResNet 50, ResNet 101, and ResNet 151 in the Residual network, and In VGG used VGG 16, VGG13, and VGG 19. Through the experiment results and by comparing other results with other factors accuracy, sensitivity, and specificity. In this work, we understand the accuracy also depends on the type of data used, the weight dimension of the classifier, and other parameters of medical images considered.

Table 3. Classification Result

Classifier	ACC %	SEN	SPEC
ResNet 18	94 %	99 %	90 %
ResNet 34	89 %	94 %	82 %
ResNet 50	92 %	98 %	89 %
ResNet 101	91 %	95 %	84 %
ResNet 152	92 %	97 %	86 %
VGG 16	96 %	100 %	92 %
VGG 19	88 %	94 %	80 %
VGG 11	87%	94%	81%
VGG 13	90 %	97 %	88 %

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