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A Comparative Study of the CNN Model for AD Diagnosis

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Abstract

Alzheimer's disease is one type of dementia, the symptoms can be treated by detecting the disease at its early stages. Recently, many computer-aided diagnosis using magnetic resonance image(MRI) have shown a good results in the classification of AD. Taken these MRI images and feed to Free surfer software to extra the features. In consideration, using T1-weighted images and classifying using the convolution neural network (CNN) model are proposed. In this paper, taking the subjects from ADNI of subcortical and cortical features of 190 subjects. Consider the study to reduce the complexity of the model by using the single layer in the Res-Net, VGG, and Alex Net. Multi-class classification is used to classify four different stages, CN, EMCI, LMCI, AD. The following experiment shows for respective classification Res-Net, VGG, and Alex Net with the best accuracy with VGG at 96%, Res-Net, GoogLeNet and Alex Net at 91%, 93% and 89% respectively.

Keywords : Alzheimer's disease | Free surfer | Convolution Neural Network | MRI

II. INTRODUCTION

Over 10 million people are expected to be affected by 2050 as per World Alzheimer's report[1]. Alzheimer's Disease is one type of dementia which mainly seen in elderly people. Death is inevitable in AD, and its been sixth disease which causes most people deaths around the world [2,3]. Destruction of neurons causes the change in the brain with few years of symptoms leads to AD. Dementia is not a single illness but damage to the brain shrinking, and additional areas and lobes will be affected. Symptoms are memory loss, gradual loss of speech, impulsive behavior, abnormalities in mood and sleep[4]. AD patient's diagnosis includes a collection of neurological, laboratory and neuroimaging examination. Recently by using the speech/voice of the patients along with laboratory results [5-7]AD is identified.[voice/speech paper]. Much research is going on but there is no cure, yet the only way is slow the processes of aging of the disease. Therefore it's necessary to detect Alzheimer's at the early stage. They are 4 stages in the process of the disease healthy brain CN, EMCI, LMCI, and AD[8,9]. The uncurable stage/severe conditions of the disease is considered as Alzheimer's disease(AD). Mild Cognitive Impairment (MCI) is the stage where the symptoms can be observed. Symptoms shown during this stage are a decrease in the ability to learn, inability to daily

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tasks/slow down[10]. Mild cognitive impairment has started showing in different ranges known as early MCI and late MCI. In the present years, machine learning has improved in the field of health/medicinal. Health care has large-scale data to be processed, by using ML algorithms[11,12] its shows success in the detection and prediction of different diseases including Alzheimer' s disease. In recent years, convolutional neural networks have given better results in the medical field.

In the present paper, sMRI is intended to perform AD classification, the MRI influence the cumulative loss and results in the compression of the neuropil showing the volume of the cortical and sub-cortical thickness of the brain image[13-15].

We have studied the CNN model for the classification of Alzheimer' s disease. Normalization is performed of the feature to improve the performance and stability in the training of the model. Normalization helps the model dataset to have a common scale without the different range of values. Three different network models are used for diagnosis Res-Net, VGG, GoogLeNet, and Alex Net with one convolutional layer. All these are selected to achieve better accuracy with simple algorithm structure in medical images.

III. METHODOLOGY

2.1 sMRI Dataset

For diagnosis, the Alzheimer' s disease, Alzheimer' s disease neuroimaging initiative database(http://adni.loni.usc.edu/) has been taken. ADNI project created in 2003, made a public-private partnership to examine AD at the early stage. ADNI Consist of a different combination of data like MRI, PET, and other biomarker images with neuro-physical assessment. ADNI data used in this performing this paper is found in ADNI serve data.

2.2 Subjects

In our study, we have accessed the data from ADNI. The dataset consists of 4 groups: AD, EMCI, LMCI, and CN. A total of 190 subjects: 46 AD subjects, 54 EMCI subjects, 51 LMCI subjects, and 49 CN subjects have been taken from the ADNI website as shown in Table 1.

Table 1. Subject Report

Group	No. of Subjects	Age Range
AD	46	75.65 ± 7.9
EMCI	54	72.80±6
LMCI	51	74.5 ± 3.6
CN	49	78.34 ± 8.6

The dataset has four different categories:

(1) AD with 46 subjects: Age ranging from 75.65 ± 7.9.

(2) EMCI with 54 subjects: Age ranging from 72.80±6.

(3) LMCI with 51 subjects: Age ranging from 74.5 ± 3.6.

(4) CN with 49 subjects: Age ranging from 78.34 ± 8.6.

We have almost equal number of subjects in all the groups to make the model more unbiased. The data set has been split into 70% training and 30% testing for evaluation.

2.3 Feature Extraction:

After the data is collected, we extract

the features from those T1-weighted images in the next step. For the current study, we have used Free Surfer using the full pipeline to compute comprise 31 regions from each hemisphere. In the study we have used from both hemispheres, 62 features of each subject. These 31 regions are shown in Table 2.

Table 2. Regions extracted from each hemisphere using free surfer software

Regions
1. caudal anterior cingulate cortex
2. caudal middle frontal gyrus
3. cuneus cortex
4. entorhinal cortex
5. fusiform gyrus
6. inferior parietal cortex
7. inferior temporal gyrus
8. isthmus cingulate cortex
9. lateral occipital cortex
10. lateral orbital frontal cortex
11. lingual gyrus
12. medial orbital frontal cortex
13. middle temporal gyrus
14. Para hippocampal gyrus
15. paracentral lobule
16. pars opercularis
17. pars orbitalis
18. pars triangularis
19. pericalcarine cortex
20. postcentral gyrus
21. posterior cingulate cortex
22. precentral gyrus
23. precuneus cortex
24. rostral anterior cingulate cortex
25. rostral middle frontal gyrus
26. superior frontal gyrus
27. superior parietal cortex
28. superior temporal gyrus
29. supramarginal gyrus
30. transverse temporal cortex
31. temporal pole

And [4], [16], [17]each of the anatomical fields is calculated for each region included (vertices, surface area, gray matter, average thickness, thickness standard, integrated rectified mean curvature, integrated rectified Gaussian curvature, folding index, intrinsic curvature index). A total of 558 features have been used during this study taken for each subject/patient.

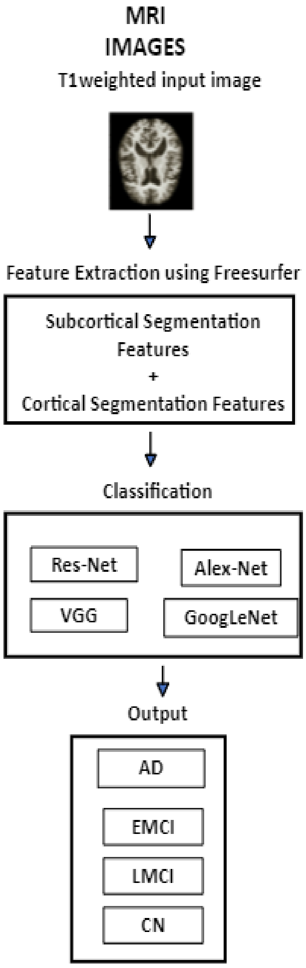

Fig 1. Block diagram of the diagnosis process.

2.4 Proposed Model

In the proposed work, we have evaluated and compared four different models, Res-Net, VGG, GoogLeNet, and Alex Net for the classification of Alzheimer's disease. For identifying the disease, accurate models are desired appropriate measures should be applied for an earlier stage.

The flow followed is shown in Figure 1. Magnetic resonance imaging (MRI) are having both subcortical segmented features and cortical segmentation features that have been used in the proposed model. The data taken from ADNI are preprocessed images by ADNI-approved protocol.

The obtained features are used for classification. Before sending these extracted features, the normalization step is done which make the model have better accuracy. The normalization step helped to overcome the problem the clear out the abnormality of the data. The classification is done by four methods: Residual network, Visual geometry group, Going deeper with convolution, and Alex Net with a single convolutional layer.

This is made to reduce the computation time and reduce the complexity of the model. Alex-net is used because of reduce overlapping and reduction of error. It contains convolution, max-pooling, and fully connected layers. As we study in the revisors study VGG outperforms the task outside the images and is built as deep CNN and used for prediction of images with a large scale of data. The Res-Net is used to support hundreds and thousands of convolutional layers and has significantly enhanced the performance of neural networks. It helps to maintain a low error rate with much deeper in the network. It will help to solve the vanishing gradient problem effectively during the backpropagation. It learns residual functions from its inputs. Skip connections map identities in Residual Networks, and layers add their outputs. GoogLeNet is used for its advantage of loss combination of the intermediate and final loss and reduction of the computation. This google net is based on inception and used multiple filter sizes.

IV. EXPERIMENT RESULT & DISCUSSION

3.1 Performance and Evaluation Parameters

In the present study we have used the multi-class classification to evaluate the model performance by using the Res Net, VGG, GoogLeNet, and Alex Net classifiers.

Table 3. Multiclass confusion matrix

Prediction 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}
CN	F_{HA}	F_{HL}	F_{HE}	TP

Each of these classifiers is responsible for the prediction of the result class accurately. To determine we have used the parameters for the number of correct output form n the matrix by true positive(TP), true negative(TN), false positive(FP), and false negative(FN). To understand this by using the Table 3.

Other parameters which are used to predict are accuracy, precision, and recall from the equation (1), (2), and (3).

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall}= \frac{TP}{TP+FN} \quad (3)$$

Evaluation and accuracy are the parameters of the multi-class classifier with the help of a confusion matrix.

Accuracy can vary depending on the dataset so by adding on precision and recall can be predicted accurately.

3.2 Experiment Result

Table 4. Results of classification

Classification	Acc%	Rec%	Pre%
CNN-VGG	96%	98%	89%
CNN-Alex Net	89%	86%	92%
CNN-GoogLeNet	93%	99%	87%
CNN-ResNet	91%	95%	86%

Acc% = Accuracy percentage, Rec% = Recall percentage, and Pre% = precision percentage.

The experiment used the Python environment. All the techniques have performed well with 96%, 89%, 93% and 91% accuracy for VGG, Alex net, GoogLeNet, and Res net respectively. Though the accuracy may not be accurate because of the unstable distribution of class. In addition, precision and recall are also calculated as shown in Table 4.

3.3 Discussion

Many research approaches have been used by researchers for the classification of AD by using deep learning methods. Jing Sun et al.[18] have proposed the Alex-net model for the classification of scene images. The convolutional neural network model is used to classify the images of the different room structures via Alex Net. Taranjit Kaur et al.[19]

Classification based on VGG for the brain images. Has been used the pre-trained model of VGG and obtained the labels. This model used the T2 weighted images of the brain MRI. Sachin kumar et al.[20] have studied residual networks with a different number of layers for the classification of tomato disease. Shruti Pallawi et al.[21] have proposed the evolution and comparison of different networks having used the deep layers and overcoming the problem of overfitting the data To solve this, multiple filters at the sample level of different sizes made the mode1. wider instead of deeper. The method for preprocessing the sMRI data[22,23]. Various splitting methods are taken for the classification and obtained the significant effect of AD.

V. CONCLUSION

We presented the comparison of the different models of CNN with a single convolutional layer to classify Alzheimer's disease. Subjects are taken from the ADNI website and taken the T1-weighted images which later used sMRI are sent to pre-processed stage using free surfer software to extract the features and used obtained features for classification. In the current study classification is done by using four different classifiers VGG, Alex Net, GoogLeNet, ResNet. VGG shows the better results with 96% and GoogLeNet with 93%, ResNet with 91% and Alex-Net with 89%. We compared the results with other factors recall and precision during the experiment. In the study, we understand the accuracy also depends on the type of data used. In the future, we will continue to propose models for classification based on the different datasets, and other modalities of medical imaging data will also be considered.

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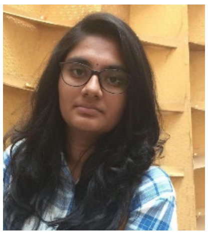

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