Alzheimer's Disease Detection using Deep Learning

By:

S Arvind (BT18CSE004)
Tarun Saxena (BT18CSE050)
Praneetha Yekkaluru (BT18CSE051)

Supervisor:

Dr. Nishat A. Ansari
Assistant Professor
Indian Institute of Information Technology, Nagpur

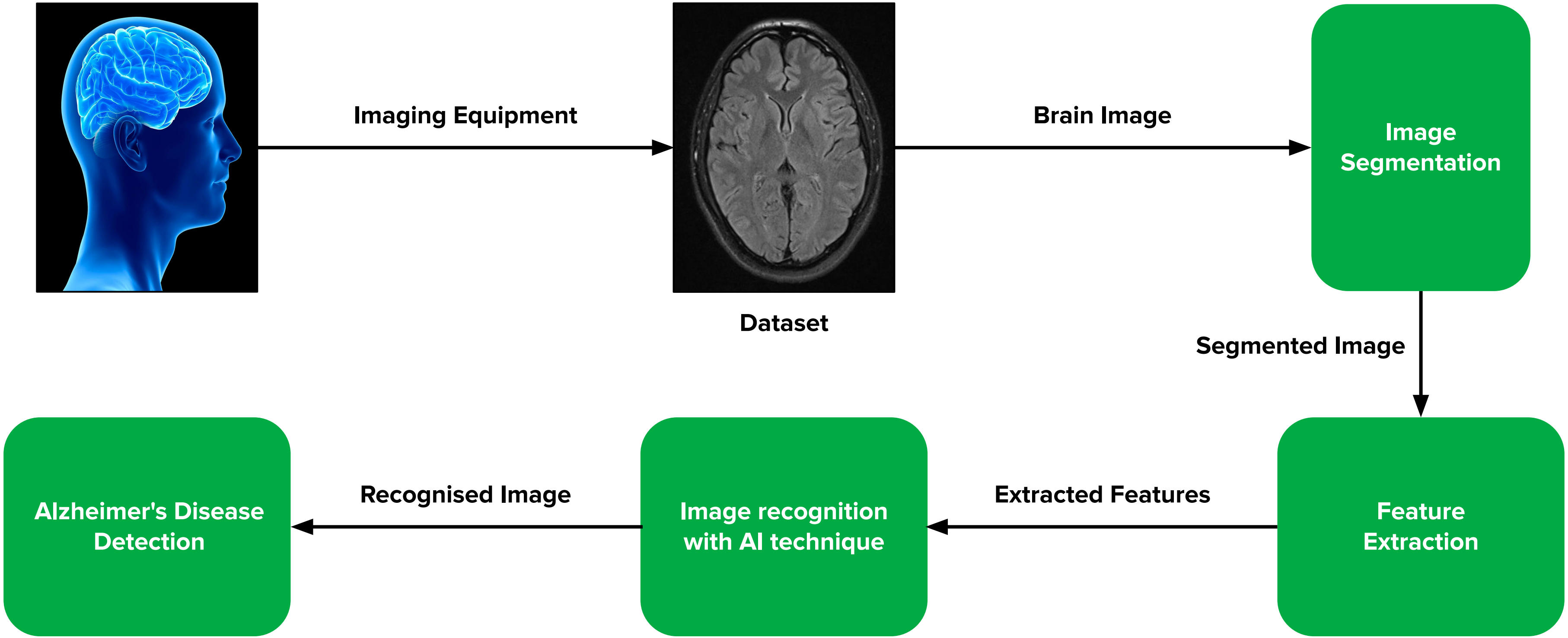
INDEX

INTRODUCTION

Alzheimer's disease (AD) is a prominent cause of death in developed countries. Although significant findings have been reported utilizing computer-aided algorithms in research, no practically applicable diagnostic approach is available. Deep models have grown in popularity in recent years, particularly when dealing with images. Deep learning has gained significant attention in AD detection research since 2017. Deep models have been shown to be more accurate than typical machine learning techniques in detecting Alzheimer's disease which give promising results with successful implementation in clinical settings that necessitate a mix of high accuracy, fast processing time, and generalizability to varied populations. Although deep learning has shown promising results in diagnosing Alzheimer’s disease, there are significant constraints, particularly in terms of dataset availability and training process.

Next slide shows the basic process for Alzheimer’s Disease Detection.

INTRODUCTION



LITERATURE REVIEW

1. Alzheimer's Disease Diagnostics by Adaptation of 3D Convolutional Network

Ehsan Hosseini-Asl, Robert Keynto, Ayman El-Baz

Objective: This paper proposed predicting Alzheimer's disease (AD) using a deep 3D convolutional neural network (3D-CNN) that can learn generic features capturing AD biomarkers and adapt to diverse domain datasets.

Methodology: This study presents a novel deep 3D convolutional neural network (3DCNN) shown in Figure 1. for unsupervised generic and transferable feature extraction based on a 3D extension of convolutional autoencoder (3D-CAE) . The proposed AD diagnostic framework extracts generic features related to the AD biomarkers, such as the ***ventricular size***, ***hippocampus shape***, *and* ***cortical thickness*** of a brain MRI with a source-domain-trained 3D-CAE and performs task-specific classification with a target-domain-adaptable 3D-CNN. The implementation of the 3D-CNN uses the ***ReLU*** activation functions at each inner layer and the fully connected upper layers with a ***softmax*** top-most output layer, predicting the probability of belonging an input brain sMRI to the **AD, MCI, or NC group**. Because of this adaption of previously learned generic characteristics, the proposed classifier is referred to as a **3D Adaptable CNN (3D-ACNN)**.

***AD - Alzheimer's Disease *NC - Normal Control *MCI - Mild Cognitive Impairment**

LITERATURE REVIEW

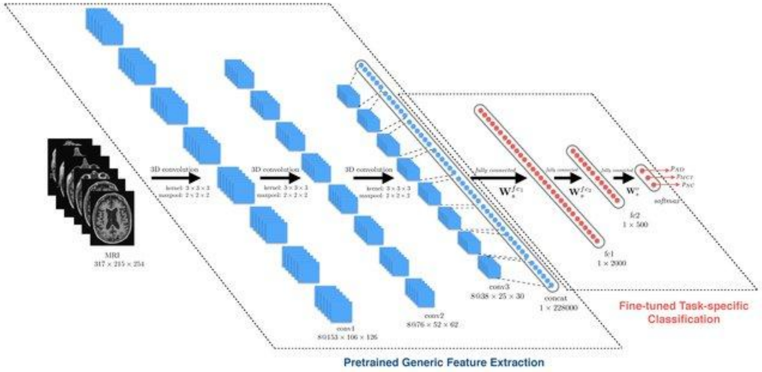


Fig. 1. Proposed 3D adaptable CNN

Results: For five classification tasks (AD vs. NC, AD+MCI vs. NC, AD vs. MCI, MCI vs NC, AD vs. MCI vs. NC), the classification performance of the proposed 3D-ACNN is examined using the Alzheimer's Disease Neuroimaging Initiative (ADNI) database as the target domain. The proposed 3D-ACNN classifier's performance in terms of accuracy was examined and came out to be with an average of **87.56%** for task-specific classification.

LITERATURE REVIEW

2. A Novel Deep Learning-Based Multi-class Classification Method for Alzheimer’s Disease Detection Using Brain MRI Data

Jyoti Islam and Yanqing Zhang

Objective: This paper presents a unique deep learning model for multi-class Alzheimer's disease detection and classification utilizing Brain MRI data, and demonstrates it on the Open Access Series of Imaging Studies (OASIS) database.

Methodology: The model utilized in this study is based on the **Inception-V4 network.** The network receives an MRI image as input and extracts feature representations layer by layer from the first stem layer to the last drop-out layer. The input MRI picture is categorized into one of four output classes based on this feature representation. The last softmax layer is redesigned to identify and classify Alzheimer's illness. The softmax layer has four output classes: **nondemented**, **very mild**, **mild**, and **moderate** Alzheimer's disease. The proposed framework is illustrated in Figure 3.

LITERATURE REVIEW

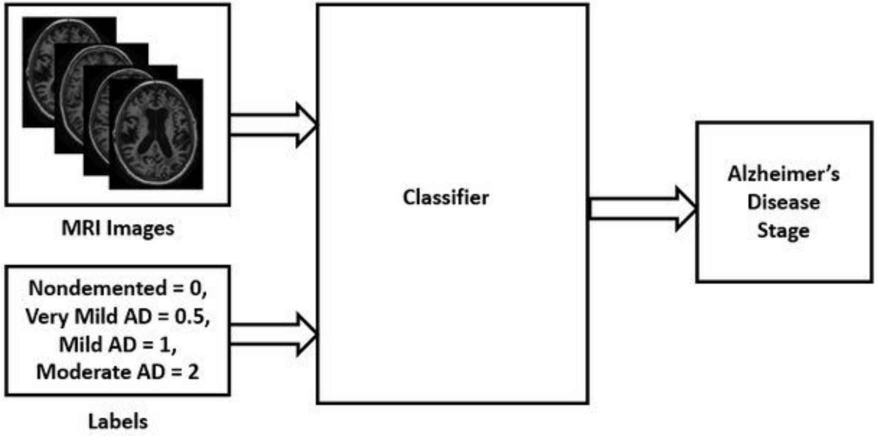


Fig. 2. Diagram of a generic Alzheimer's disease detection and classification framework.

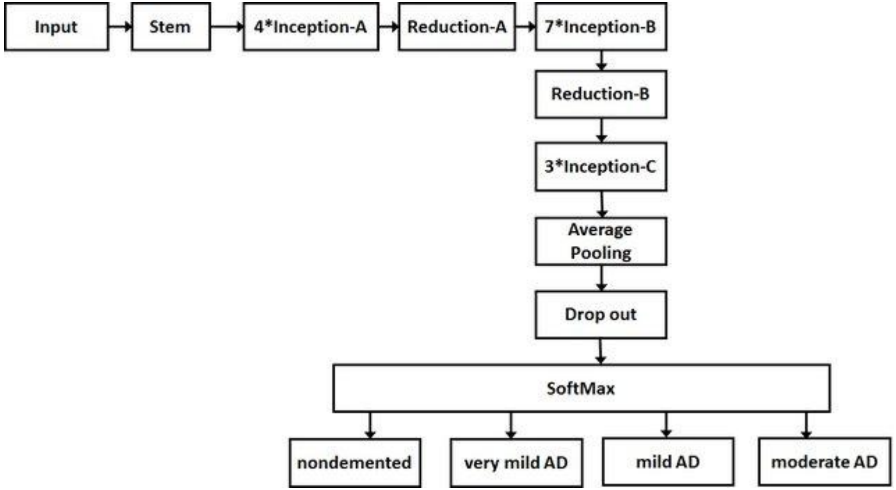


Fig. 3. Block diagram of proposed Alzheimer's disease detection and classification framework.

Results: The proposed approach has a **73.75%** accuracy. The suggested model for Alzheimer's disease detection and classification is substantially faster and requires less time to train and test on the OASIS dataset.

LITERATURE REVIEW

3. Residual and Convolutional Neural Networks for 3D Brain MRI Classification

Sergey Korolev, Amir Safiullin, Mikhail Belyaev, Yulia Dodonovay

Objective: This paper shows the residual and plain 3D convolutional neural network architectures using namely **VoxCNN** and **ResNet** as well as the performance of the proposed approach for classification of **Alzheimer's disease** (AD) versus **mild cognitive impairment** (MCI) and **normal cohort** (NC) on ADNI dataset.

Methodology: In this paper, two different 3D convolutional network architectures for brain MRI classification are proposed, which are the modifications of a **plain** and **residual convolutional neural network**. First, these networks can generalize local features into a meta-representation of an object for image recognition or classification. Second, modern advancements in deep learning for image classification such as **batch normalization** techniques and residual network architectures relieve the issues of having small training datasets, while providing a powerful framework for automatic feature generation. As a result, these models can be applied to 3D MRI images without intermediate handcrafted feature extraction.

LITERATURE REVIEW

Results: The network learns to accurately classify Alzheimer's Disease subjects from Normal Cohort, however struggles to separate them from intermediate classes of Late and Early Mild Cognitive Impairment. Both networks show similar results within a standard deviation as shown in table below.

	VoxCNN		ResNet	
	AUC	Acc.	AUC	Acc.
AD vs NC	$.88 \pm .08$	$.79 \pm .08$	$.87 \pm .07$	$.80 \pm .07$
AD vs EMCI	$.66 \pm .11$	$.64 \pm .07$	$.67 \pm .13$	$.63 \pm .09$
AD vs LMCI	$.61 \pm .12$	$.62 \pm .08$	$.62 \pm .15$	$.59 \pm .11$
LMCI vs NC	$.67 \pm .13$	$.63 \pm .10$	$.65 \pm .11$	$.61 \pm .10$
LMCI vs EMCI	$.47 \pm .09$	$.56 \pm .11$	$.52 \pm .11$	$.52 \pm .09$
EMCI vs NC	$.57 \pm .12$	$.54 \pm .09$	$.58 \pm .09$	$.56 \pm .07$

Fig. 4. Result comparison between VoxCNN and ResNet

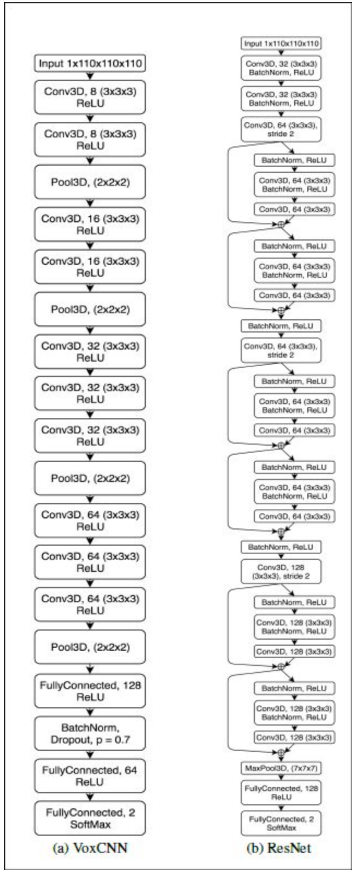


Fig. 5. VoxCNN and ResNet

LITERATURE REVIEW

4. Early Diagnosis of Alzheimer's Disease with Deep Learning

Siqi Liu, Sidong Liu, Weidong Cai, Sonia Pujol, Ron Kikinis, Dagan Feng

Objective: In this study, a deep learning architecture is designed which contains **stacked auto-encoders** and a **softmax** output layer, to overcome the bottleneck and aid the diagnosis of **AD** and its prodromal stage, **Mild Cognitive Impairment** (MCI).

Methodology: The learning structure can be demonstrated by two primary components:

- The auto-encoders obtain deep representations of the original input. The **sparse auto-encoder** is an encoding structure, which consists of **a neural network with multiple hidden layers**. Neurons of the input layer represent the original input vector. Each hidden layer can be seen as a higher-level representation of the previous layer. The hidden layers of sparse auto-encoder were trained one at a time and stack them to form a complete neural network by removing the temporary output layer.

LITERATURE REVIEW

- For AD classification, a **softmax output layer** is added on the top of the trained auto-encoder stack. The softmax layer uses a different activation function, which has nonlinearity, different from the one applied in the auto-encoders stack. Four output neurons at the softmax layer can be interpreted as the **probabilities** of diagnosing an example as **NC, ncMCI, cMCI, or AD**.

Results: The deep learning method produced a better overall **accuracy (87.76%)** in the binary classification of AD. In addition to the classification accuracy, higher **sensitivity values (74.29%)** were observed. A performance gain has been obtained as compared to SVMs.

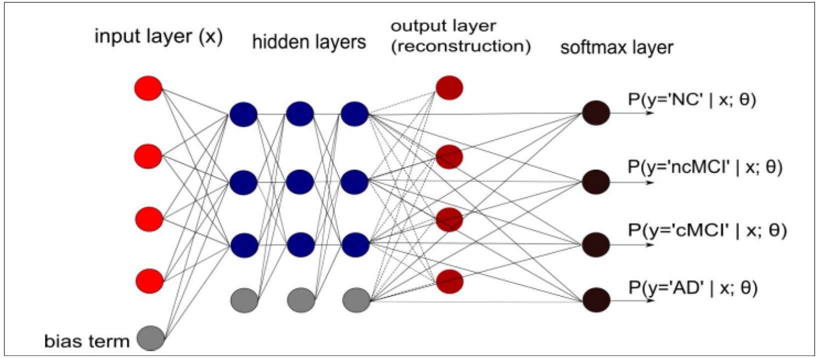


Fig. 6. Deep learning architecture used in this study

LITERATURE REVIEW

5. Detection of Alzheimer's Disease (AD) in MRI Images using Deep Learning

Amnaya Pradhan , Jerin Gige , M. Eliazer

Objective: This paper proposes a model that takes brain MRI sample images as input and gives output, using the VGG19 and DenseNet169 architectures, whether the person has mild, moderate or severe Alzheimers disease.

Methodology: This research compares two state-of-the-art deep learning models' detection accuracy in detecting Alzheimer's disease in an MRI image. The Keras module of tensor flow, an open- source library for implementing deep learning models, is used to implement VGG19. Using the Image Data Generator function, the ata was augmented and loaded into the model. The training consisted of a batch size of 128, with 50 epochs with early stopping. Similarly, the Keras module is used to implement the Densenet Model, and the data is loaded into the densenet model via the Image Data Both models are trained on 3048 MRI images consisting of four classes, and both models are tested on a total of 2067 MRI images. All the work was done on Google colab.Generator function. The densenet model is trained using a batch of 128 images each.

LITERATURE REVIEW

Results: The Densenet169 Model provided an accuracy of about 87% in the train data and about 80% in the test data.

VGG19 Model provided an accuracy of 82.6% on training dataset and 86.7% on test dataset.

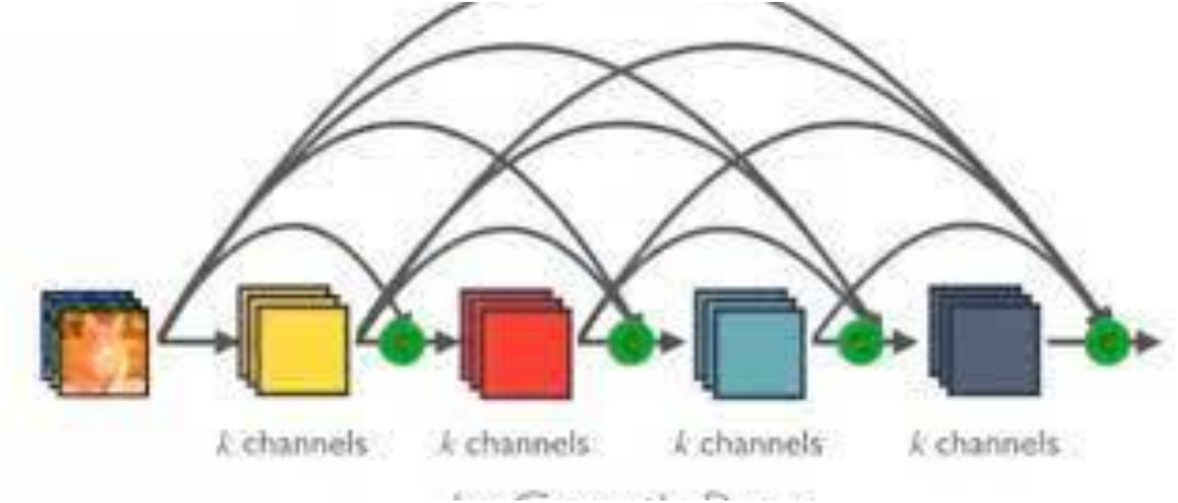


Fig. 7. Densenet architecture with 4 dense blocks

Fig. 8. VGG19

LITERATURE REVIEW

6. Early Diagnosis of Alzheimer's Disease Using Deep Learning

Huanhuan Ji, Wei Qi Yan, Zhenbing Liu, Reinhard Klette

Objective: This paper mainly focuses on the early diagnosis of AD based on convolutional neural networks (ConvNets) by using magnetic resonance imaging (MRI). Image slices of gray matter and white matter from MRI have been used as the inputs for classification.

Methodology:

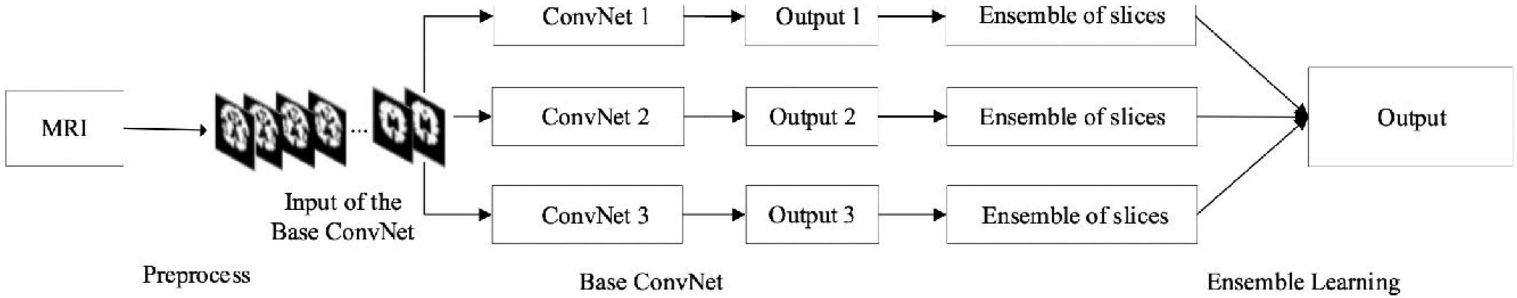


Fig. 9. Proposed Model

LITERATURE REVIEW

Results: This method was mainly validated for early diagnosis of AD (i.e., AD vs. MCI, and MCI vs. NC). The classification was evaluated by using four measures: Classification accuracy (ACC), specificity (SPE), sensitivity (SEN), and the area under receiver operating.

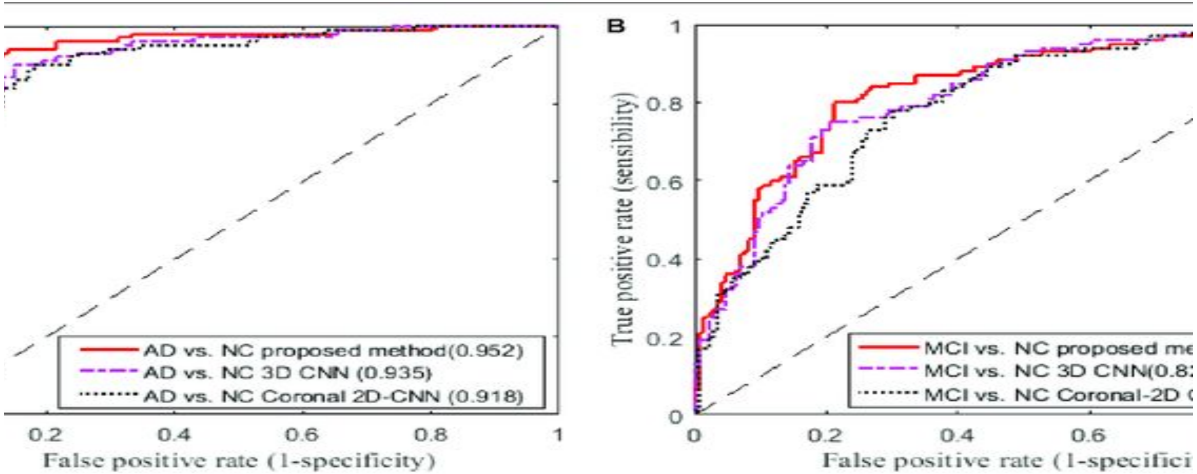


Fig. 10. ROC curves for the classification of AD vs NC and MCI vs NC

SUMMARY

Title	Publication Year	Name of Journal / Conference	Technique Used	Results	Dataset	Scope of Improvement
Alzheimer's Disease Diagnostics by Adaptation of 3D Convolutional Network	2016	IEEE International Conference on Image Processing	3D Adaptable CNN	Average of **87.56%** for each task-specific classification.	ADNI Dataset	- Could be implemented on higher number of subject samples for better accuracy.
A Novel Deep Learning-Based Multi-class Classification Method for Alzheimer's Disease Detection Using Brain MRI Data	2017	International Conference on Brain Informatics	Inception V4	The proposed method has an accuracy of **73.75%**.	Open Access Series of Imaging Studies (OASIS) dataset	- Achieve higher accuracy. - Transfer learning approach could be applied to check if the results could be improved.

SUMMARY

Title	Publication Year	Name of Journal / Conference	Technique Used	Results	Dataset	Scope of Improvement
Residual and Convolutional Neural Networks for 3D Brain MRI Classification	2017	IEEE International Symposium on Biomedical Imaging 2017	VoxCNN ResNet	Both methods provided accuracy of about **80%** for **AD vs NC** and reducing values for other classifications.	ADNI Dataset	- Oversampling on ADNI dataset. - Reducing the dependency on high-end compute elements.
Early Diagnosis of Alzheimer's Disease with Deep Learning	2014	IEEE International Symposium on Biomedical Imaging 2014	Sparse Auto-encoders with Softmax Layer	Accuracy of **87.76%** for **AD vs NC** and **76.9%** for **MCI vs NC**.	ADNI Dataset	- Image preprocessing can be reduced for better use in real life situations.

SUMMARY

Title	Publication Year	Name of Journal / Conference	Technique Used	Results	Dataset	Scope of Improvement
Detection of Alzheimer's Disease (AD) in MRI Images using Deep Learning	2021	IJERT	VGG19 DenseNet169	The proposed model had an accuracy of about **82.6%**	Kaggle	- Image preprocessing can be reduced for better use in real life situations.
Early Diagnosis of Alzheimer's Disease Using Deep Learning	2019	ICCV	CNN	The proposed model had an accuracy of about **80.6%**	ADNI dataset	- Increasing dataset size. - Achieve better metrics.

REFERENCE LINKS

1. https://arxiv.org/abs/1607.00455
2. https://link.springer.com/chapter/10.1007/978-3-319-70772-3_20
3. https://arxiv.org/abs/1701.06643
4. https://ieeexplore.ieee.org/document/6868045
5. https://www.ijert.org/detection-of-alzheimers-disease-ad-in-mri-images-using-deep-learning
6. https://dl.acm.org/doi/abs/10.1145/3341016.3341024

THANK YOU