Alzheimer's Disease Detection Using 3D Deep Learning Model

Submitted By

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

INSTITUTE OF TECHNOLOGY

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Alzheimer's Disease Detection Using 3D Deep Learning Model

Major Project

Submitted in partial fulfillment of the requirements

for the degree of

Master of Technology in Computer Science and Engineering

Submitted By

Happy Ramani

(19MCEC04)

Guided By

Dr Swati Jain

NIRMA UNIVERSITY
INSTITUTE OF TECHNOLOGY
NAAC ACCREDITED 'A' GRADE

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

INSTITUTE OF TECHNOLOGY

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May 2021

Certificate

This is to certify that the major project entitled **"Alzheimer's Disease Detection Using 3D Deep Learning Model"** submitted by **Happy Ramani (19MCEC04)**, towards the partial fulfillment of the requirements for the award of degree of Master of Technology in Computer Science and Engineering of Nirma University, Ahmedabad, is the record of work carried out by her under my supervision and guidance. In my opinion, the submitted work has reached a level required for being accepted for examination. The results embodied in this Major Project Part-II, to the best of my knowledge, haven't been submitted to any other university or institution for award of any degree or diploma.

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Statement of Originality

I, **Happy Ramani**, **19MCEC04**, give undertaking that the Major Project entitled **"Alzheimer's Disease Detection Using 3D Deep Learning Model"** submitted by me, towards the partial fulfillment of requirements for the degree of Master of Technology in **Computer Science & Engineering** of Institute of Technology, Nirma University, Ahmedabad, contains no material that has been awarded for any degree or diploma in any university or school in any territory to the best of my knowledge. It is the original work carried out by me and I give assurance that no attempt of plagiarism has been made.It contains no material that is previously published or written, except where reference has been made. I understand that in the event of any similarity found subsequently with any published work or any dissertation work elsewhere; it will result in severe disciplinary action.

Signature of Student

Date: 08 May 2021

Place: Rajkot

Endorsed by

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Abstract

Alzheimer's disease is one of the leading causes of death in the present era of the world. No treatment is available for Alzheimer's disease after it is in a higher stage. Therefore, it is required to detect disease, when it is in the initial stage. The physical symptoms of the disease cannot be noticed by the patient, in an earlier stage, that's why researchers proposed deep learning-based solutions to detect it earlier. In this study, I aimed to present an architecture of convolutional neural network (CNN) model for detecting Alzheimer's disease to handle 2D and 3D data. The proposed 2D model is fast and accurate compared to the AlexNet model. I preprocessed the Alzheimer's Disease Neuroimaging Initiative (ADNI) image dataset of the patient's magnetic resonance images (MRIs). After training and testing of the presented model, I obtained 72.13% accuracy to determine AD vs. NC. The proposed 3D model is more accurate compared to one existing research work. ADNI dataset of T1-weighted images had been used and preprocessed for testing of model. After validating model on that, it gives 96.15% accuracy. Details about the survey of research work and the proposed model architecture are given in this report.

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Chapter 1

Introduction

1.1 General

Alzheimer's disease (AD) is a neuro-degenerative disease and the most common cause of dementia usually seen in elder people i.e. more than 60 years of age. A person suffering from Alzheimer's disease lost their ability to remember things at the level of that, they need a full-time assistant. I have referred a few research papers which diagnose Alzheimer's disease and classify Alzheimer's disease stages. I surveyed technologies that are used by researchers and how they used that technology in their research work.

Based on this survey, I decided to work with MRIs to diagnose Alzheimer's disease using a deep learning approach. Information and facts about Alzheimer's disease is given in followed subsection. The introduction of deep learning technologies that I have used in my research work is given in this section's subsections. With that objective and scope of my work is described. How I had used these techniques in my proposed models - 2D CNN and 3D CNN, results for the same are explained in detail in followed chapters.

1.2 Objective of study

Presently AD is becoming a leading cause for death. Minor changes in the neurons of the brain cannot be noticed by humans and to cure Alzheimer's disease when it is in a higher stage, treatment is not available. Thus, as if Alzheimer's disease is detected in an early stage, it can be prevented by further growth. As CNN is one of the most recent techniques of deep learning used in this research area, I have proposed a CNN model architecture and implemented 2D and 3D CNN model for early detection of AD.

1.3 Scope of Work

In my research work, I studied Alzheimer's disease, the cause of disease, the impact of Alzheimer's disease, and recent research work done in this area. By referring to this survey, I have proposed a model architecture. For the implementation of that, I studied the CNN model and the basic components of that. After implementing a 2D model using the proposed architecture for diagnosing Alzheimer's disease, I compared this model experimental results with the AlexNet model. As AlexNet model is used in majority research work. Presented model use image dataset of MRIs for training and testing purposes. Using 3D images, 3D CNN model had been trained and tested, results of the same has been compared with state-of-art of this research area.

1.4 Information & facts about Alzheimer's Disease

Alzheimer's Association Report - "2019 Alzheimer's disease facts and figures" [1] describe facts related to the impact of Alzheimer's disease, cost required to care an Alzheimer's patient, and overall impact of Alzheimer's disease on society. Between 2000 and 2017, deaths resulting from heart disease, prostate cancer, and stroke are decreased while recorded deaths caused by AD is increased by 145%. Every year a large time is spent for caring Alzheimer's patients and other dementia patients. Though the number of death caused by Alzheimer's disease is increasing every year. Leading causes of death globally from 2000 to 2019 has been shown in Fig. 1.1 [2], which has been referred from WHO Global Health Estimates.

Detection of Alzheimer's disease in the early stage is required but symptoms of the disease arise after 20 years or more than that, as minor changes in the brain are unnoticeable by the affected person. Some serious changes in the brain are experienced such as memory loss or language problems only after a long time.

As the disease proceeds, neurons in the brain are destroyed. Neurons in the brain are connected by synapses for information flow. Signals are travel from one neuron to another neuron in the brain. At that time, the growth of the protein fragment beta-amyloid plaques outside neurons and the growth of an abnormal form of the protein tau tangles inside neurons are two of particular brain changes associated with Alzheimer's disease. Beta-amyloid plaques are the reason for neuron death by preventing neuron-

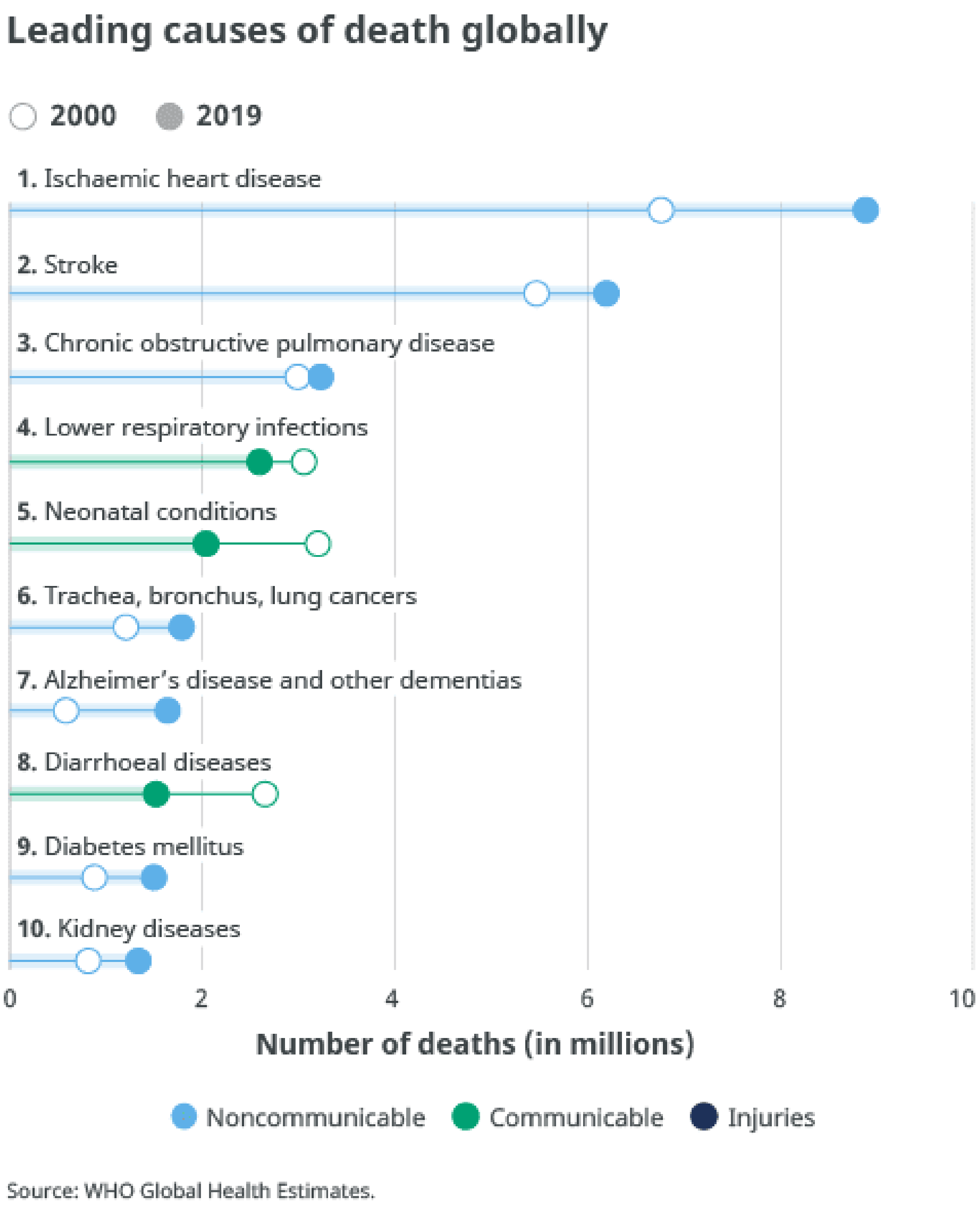

Figure 1.1: Leading causes of death [2]

to-neuron communication. Tau tangles block the transportation of nutrients and other molecules inside the neurons. It's all about causes of AD and related facts.

1.5 Used Technologies

1.5.1 Convolutional Neural Network (CNN)

"Convolutional Neural Network (CNN) is a well-known deep learning architecture inspired by the natural visual perception mechanism of the living creatures." [3] From the invention of the first framework of CNN to present, there is a large development has done on CNN. Some benchmark models of CNN are also developed by researchers such as LeNet, AlexNet, IncenptionNet, VGGNet, ResNet, GoogleNet, etc. Fundamental components of CNN are convolutional layer, pooling layer, activation function, loss function, regularization, and optimization.

There is a wide category of applications for CNN. For instance, image classification, text recognition, object detection, natural language processing, etc. This was an overview of CNN. And the reason for being this much popular is that CNN automatically extracts important features without any human intervention therefore CNN is having better learning capacity compared to other predecessors.

1.5.2 Convolution Layers

The convolution layer is an essential component of the CNN framework, which performs the feature extraction by using an aggregation of non-linear and linear operations. By making proper use of convolutional layers in model architecture, the representation ability of input can be improved in the application.

Convolutional layers are having learnable parameters such as filters or kernels. Each filter is convolved over the entire input volume and calculate the dot product between input and values of the filter in the forward pass. The output of this process is the activation map of that filter. By doing this process, as per the given parameters, the network learns a specific type of feature.

1.5.3 Pooling Layers

A pooling layer implements a downsampling procedure, which decreases the in-plane dimensionality of the feature maps to introduce a translation invariance to small shifts and reduce the number of succeeding learnable parameters [4]. Pooling layers do not have any learnable parameters, while parameters like filter size, padding, and stride are hyperparameters of the pooling layer.

The pooling layer divides the input image into to group of non-overlapping portions and that each sub-portion gives the output as per requirement like maximum value or minimum value etc. Based on that, pooling layers are having three most used variations: Max pooling, min pooling, and average pooling.

1.5.4 Fully Connected Layers

The output of the last convolutional layer or pooling layer is converted into a one-dimensional array of a vector, which means the last layer is flattened. This flattened layer is connected to dense layers, which are called fully connected layers as each input is connected to all output using learnable weight.

Activation functions and the number of nodes can be defined as parameters in the fully connected layers. After extracting features from the input using the convolutional layer and down-sampling them using the pooling layer, the output of that layers is mapped by a combination of fully connected layers to the final output of the network. The last layer from a set of fully connected layers is having a similar number of nodes as the number of classes.

Chapter 2

Literature Survey

2.1 General

Across the past several years, many techniques are developed to diagnose Alzheimer's disease and classify its stages. Because of the inadequate dataset, most of the research work is done on publicly available Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset and Open Access Series of Imaging Studies (OASIS) dataset. This research work can be categorized into proposed techniques based on convolutional neural networks, mechanisms based on transfer learning, models based on graph neural network, methodologies which uses explainable AI and other methodologies. Details of various approaches have been explained in below section.

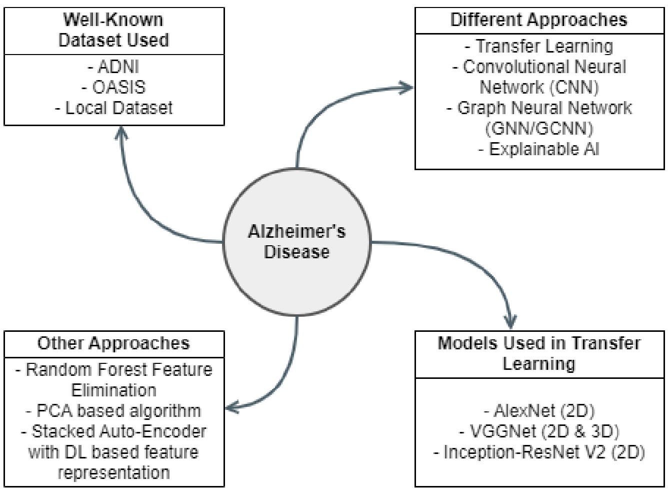

Figure 2.1: Literature Survey Taxonomy

2.2 Based on 2D - Convolutional Neural Network

Paper Title	**Year**	**Dataset**	**Method Used**	**Result**
A novel deep learning based multi-class classification method for alzheimer's disease detection using brain MRI data	2017	OASIS T1-weighted MRI	Data augmentation with deep CNN model	73.75% for classification of AD
Convolutional neural networks-based MRI image analysis for the alzheimer's disease prediction from mild cognitive impairment	2018	ADNI 1.5T MRI	Skull-stripping and histogram normalization	79.9% for MCI-to-AD conversion
Classification of SMRI for alzheimer's disease diagnosis with cnn: Single siamese networks with 2d+ approach and fusion on adni	2017	ADNI 1.5T T1-weighted MRI	2D+ Fusion approach along with the CNN model	91.41% - AD vs NC 69.53% - AD vs MCI 65.62% - NC vs MCI
Brain MRI analysis for alzheimer's disease diagnosis using an ensemble system of deep convolutional neural networks	2018	OASIS T1-weighted MRI	Data augmentation with deep CNN model	93.18% for AD vs CN

Table 2.1: 2D CNN based literature summary

2.3 Based on 2D - Transfer Learning

Paper Title	Year	Dataset	Method Used	Result
Transfer learning assisted classification and detection of alzheimer's disease stages using 3d MRI scans	2019	OASIS	Image segmentation and AlexNet	92.8% for classifying ADstages
Analysis of brain sub regions using optimization techniques and deep learning method in alzheimer disease	2019	Local 1.5T 2D T2 weighted MRI	Segmentation of brain regions and AlexNet	95% for AD vs CN
Intelligent alzheimer's detector using deep learning	2018	ADNI T1-weighted MRI	Inception-ResNet V2 deep architecture	98.41% for AD vs CN
A data augmentation-based framework to handle class imbalance problem for alzheimer's stage detection	2019	OASIS	Data augmentation and AlexNet	98.41% for AD vs CN
Transfer learning with intelligent training data selection for prediction of alzheimer's disease	2019	ADNI	Pretrained weights of the VGG model	99.36% for AD vs NC 95.91% for three-class classification

Table 2.2: 2D Transfer Learning based literature summary

2.4 Based on 2D - Conventional Approaches

Paper Title	Year	Dataset	Method Used	Result
Automated classification of alzheimer's disease using deep neural network (dnn) by random forest feature elimination	2018	ADNI clinical data	Random forest feature elimination method and neural network	67% for AD vs CN
Classification of alzheimer's disease stages: An approach using pca-based algorithm	2019	ADNI Functional MRI(fMRI) dataset	Principal Component Analysis (PCA) based algorithm	95% for classifying AD stages
Deep learning-based feature representation for AD/MCI classification	2018	ADNI	DL-based feature representation along with stacked auto-encoder	95.9% for AD vs CN 85% for MCI vs CN 75.8% for MCI-C vs CN

Table 2.3: 2D Conventional Approaches based literature summary

2.5 Based on 3D - Convolutional Neural Network

Paper Title	Year	Dataset	Method Used	Result
A Novel Deep Learning Approach with a 3D Convolutional Ladder Network for Differential Diagnosis of Idiopathic Normal Pressure Hydrocephalus and Alzheimer's Disease	2020	Local T1-weighted	Residual extraction approach - CNN	90% accuracy
Automated MRI-Based Deep Learning Model for Detection of Alzheimer's Disease Process	2020	ADNI - 3T T1-weighted	3D-CNN-SVM	95.74±2.31% aacuracy
A deep learning model for early prediction of Alzheimer's disease dementia based on hippocampal magnetic resonance imaging data	2019	ADNI T1 weighted 1.5T & 3T	CNN	90% accuracy
3D-Deep Learning Based Automatic Diagnosis of Alzheimer's Disease with Joint MMSE Prediction Using Resting-State fMRI	2019	Local research center data	CNN	85.27% accuracy
Alzheimer's Disease stage identification using deep learning models	2020	35 subjects - local data	CNN	90.91% accuracy

Table 2.4: 3D CNN based literature summary

2.6 Based on 3D - Transfer Learning

Paper Title	Year	Dataset	Method Used	Result
3D Convolutional Neural Networks for Diagnosis of Alzheimer's Disease via structural MRI	2020	ADNI and OASIS dataset T1 weighted MRI	3D CNN model inspired by VGG-16	73.4% - ADNI 69.9% - OASIS
Deep Convolution Neural Network Based System for Early Diagnosis of Alzheimer's Disease	2020	ADNI fMRI and PET	VGG 16	99.95% - fMRI 73.46% - PET
Deep residual learning for neuroimaging: An application to predict progression to Alzheimer's disease	2020	ADNI	Modified form of deep residual neural networks (ResNet)	89.3% AD vs CN
A multi-model deep convolutional neural network for automatic hippocampus segmentation and classification in Alzheimer's disease	2019	ADNI T1 - weighted structural MRI	ResNet and DenseNet with segmentation	88.9% AD vs CN
Deep Learning Framework for Alzheimer's Disease Diagnosis via 3D-CNN and FSBi-LSTM	2019	MRI data and18-Fluoro-DeoxyGlucose PET data	LSTM network framework instead of the FC layer in 3D-CNN	94.82% AD vs CN

Table 2.5: 3D Transfer Learning based literature summary

2.7 Based on 3D - Graph Convolutional Neural Network

Paper Title	Year	Dataset	Method Used	Result
Anatomical Landmarks and DAG Network Learning for Alzheimer's Disease Diagnosis	2020	ADNI	Landmarks and DAG network feature learning (LDNFL) based classification framework	91.57% Accuracy
Classification of Mild Cognitive Impairment Based on a Combined High-Order Network and Graph Convolutional Network	2020	ADNI	Combined high-order network and GCN for MCI classification	82.7% EMCI vs NC 88.7% LMCI vs NC
Attention-Guided Deep Graph Neural Network for Longitudinal Alzheimer's Disease Analysis	2020	ADNI	Attention Guided Deep Graph Neural (AGDGN) network	93.67% Accuracy
Cortical graph neural network for AD and MCI diagnosis and transfer learning across populations	2019	ADNI	Cortical graph neural network	85.8% CN vs. AD
Graph convolutional neural networks For AAlzheimer's Disease Classification	2019	ADNI	GCNN	89% using GCNN 65% using SVM

Table 2.6: 3D Graph CNN based literature summary

2.8 Based on 3D - Explainable AI

Paper Title	Year	Dataset	Method Used	Result
Understanding Alzheimer disease's structural connectivity through explainable AI	2020	ADNI	E2E layer followed by an E2N layer and two fully-connected (FC) layers	78% AD vs CN
Explainable CNN- Attention Networks (C-Attention Network) For Automated Detection Of Alzheimer's Disease	2020	DementiaBank dataset	Unified C-Attention Network	92.2% AD vs CN

Table 2.7: 3D Explainable AI based literature summary

Chapter 3

Details of 2D model

In this chapter details regarding 2D model is described such as which dataset is used, which preprocessing techniques had been applied, implementation of model and results.

3.1 Dataset and Data Preprocessing

3.1.1 Dataset Representation

To diagnose Alzheimer's disease, I used the Alzheimer's Disease Neuroimaging Initiative (ADNI) collaborative dataset from their LONI Image Data Archive (IDA) [5, 6]. From there, I selected 715 Magnetic Resonance Images (MRIs). There is an Axial view of PD/T2 weighted - FSE/TSE MRIs in NiFTI format. These images are split into 160 Alzheimer's Disease (AD), 343 Mild Cognitive Impairment (MCI), and 212 Normal Aging / Cognitively Normal (CN). MCI is one of the different stages of Alzheimer's disease, subjects of MCI and AD subjects are merged in one class vs. CN subjects to diagnose Alzheimer's disease. Hence 503 subjects are of AD and 212 of CN.

	Subject	Age [Range]	Gender [M/F]
AD+MCI	503 (160 + 343)	[55,91]	296/207
CN	212	[60,90]	107/105

Table 3.1: Dataset Representation

Table 3.1 contains information about the dataset used such as age range and gender about all subjects.

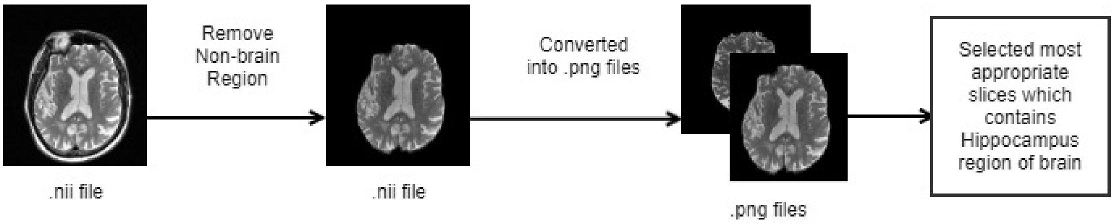

Figure 3.1: Preprocessing steps of proposed system

3.1.2 Data Preprocessing

To remove non-brain regions from the MRIs FSL-BET is used [7, 8]. After that these 3D .nii extension files are converted into 2D .png extension files using nii2png python package [9]. In this work, a 2D slice from each subject is selected which is having the Hippocampus region. These 2D slices are scaled into 227x227. These preprocessing steps are done in Ubuntu – 16.04 LTS Operating System.Preprocessing steps of proposed system are illustrated in Fig. 3.1.

3.2 Proposed CNN Model

The proposed model is implemented using Tensorflow and Keras on Google Colab. Training and test datasets are split in a ratio of 77% and 23% respectively. Accordingly, training dataset consist of 550 subjects of 387 for AD and 163 for CN, test dataset consist of 165 subjects of 116 for AD and 49 for CN.

In the proposed CNN model there is the use of convolutional layers, pooling layers, and fully convolutional layers as shown in Fig. 4.1. The proposed CNN architecture consists of three convolutional layers and each layer is followed by a max-pooling layer. After the first and last batch of the convolution layer and pooling layer there is a dropout of 0.1 rate. After the second batch of these layers, Batch Normalization is applied for 0.2 epsilon, 0.99 momentum, 0.99 renorm-momentum, -1 axis, and scale parameter with False value. Batch normalization mechanism useful to accelerate the training in deep networks [10].

Information regarding the number of filters, the size of the kernel, and the activation function of each layer is illustrated in architecture Fig. Fig. 4.1 of the proposed network. At last four fully connected convolutional layers are used with sigmoid and ReLU

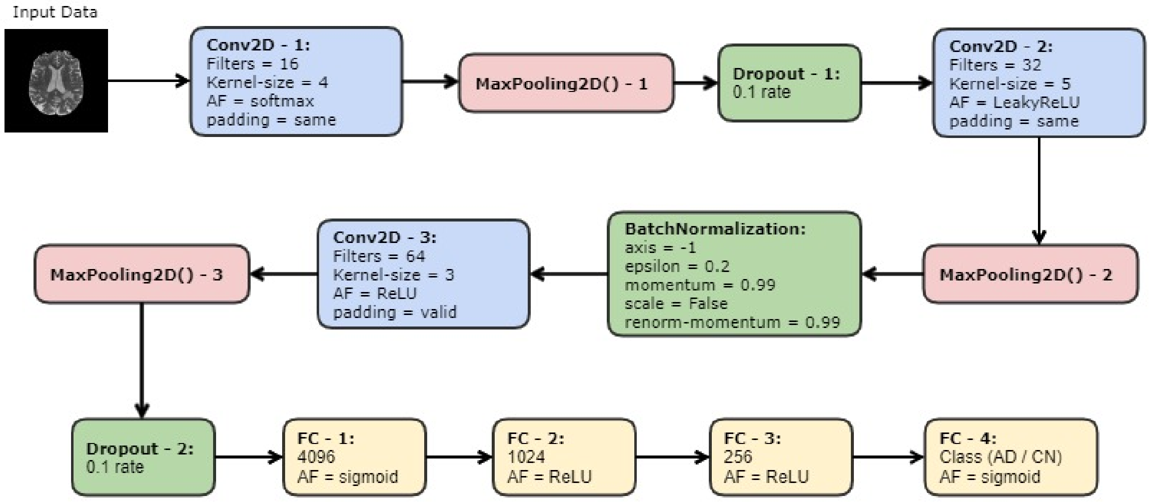

Figure 3.2: CNN Model Architecture

activation functions.

3.3 Results

The proposed model is executed on the Keras framework in python. The parameters for the training phase were: Loss was binary_crossentropy, the optimizer was stochastic gradient descent (sgd), epochs were 9, Batch-size was 128, steps per epoch was 1, and other parameters were same as their default values. The results of the model were 64.48% average training accuracy and 72.13% average testing accuracy. Fig. 3.3 exhibits the accuracy and loss for training and testing/validation phase of presented CNN model.

I compared this result with the same input on the well-known AlexNet model. In AlexNet model parameters for the training phase were: Adam optimizer with 0.001 Learning rate, binary_crossentropy, steps per epoch was 1, epochs were 9, and other parameters were set as their default values. Results for the AlexNet model were 63.88% average training accuracy and 70.83% average testing accuracy. Fig. 3.4 exhibits the accuracy and loss for training and testing/validation phase of presented AlexNet model.

AlexNet model is having more depth and hence it requires more time for the training process. In a comparison of that, the presented CNN model is taking less time for the training phase as it is having less layers. By that, the CNN model is more time-efficient than the AlexNet model.

Comparison of proposed CNN model and AlexNet is given in Table 4.1 , for the parameters, such as average testing accuracy, average testing loss, and time taken by

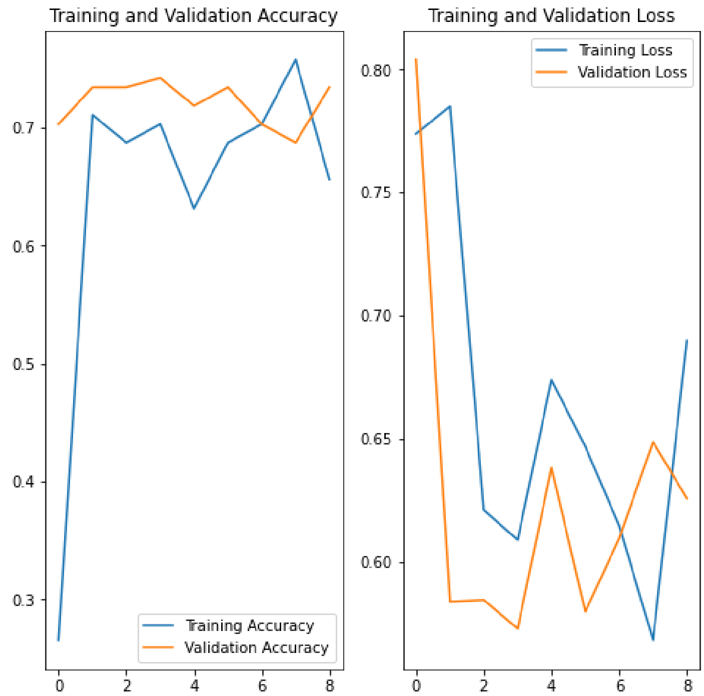

Figure 3.3: Accuracy and loss for CNN model

Table 3.2: Comparison of Proposed Model and AlexNet

	Proposed CNN Model	AlexNet Model
Accuracy	71.13%	69.53%
Loss	0.6 – 0.7%	4.5 – 5.2%
Time taken (per epoch)	t	2t

models. AlexNet model has more depth, and hence it requires more time for the training process. In a comparison of that, the presented CNN model is taking less time for the training phase as it has fewer layers. By that, the CNN model is more time-efficient and less complex in structure, than the AlexNet model. Additionally, as per the state-of-art data augmentation is used for enlarging dataset, for avoiding overfitting in deep models. But when there is a model with less depth, data augmentation can lead to overfitting instead of reducing it. Therefore, focusing on time and space trade-off, we avoided to use data augmentation and more deep model.

Moreover, as per the literature survey done for research in AD, most of the study is done using T1-weighted MRIs or dataset used which is publicly not available. While T1 weighted MRIs have their benefits, T2 weighted MRIs can identify the difference between normal and abnormal more easily, because it can recognize abnormal lesions of fluid, and demonstrate CSF better [11]. And, beta-amyloid plaques and tau tangles are

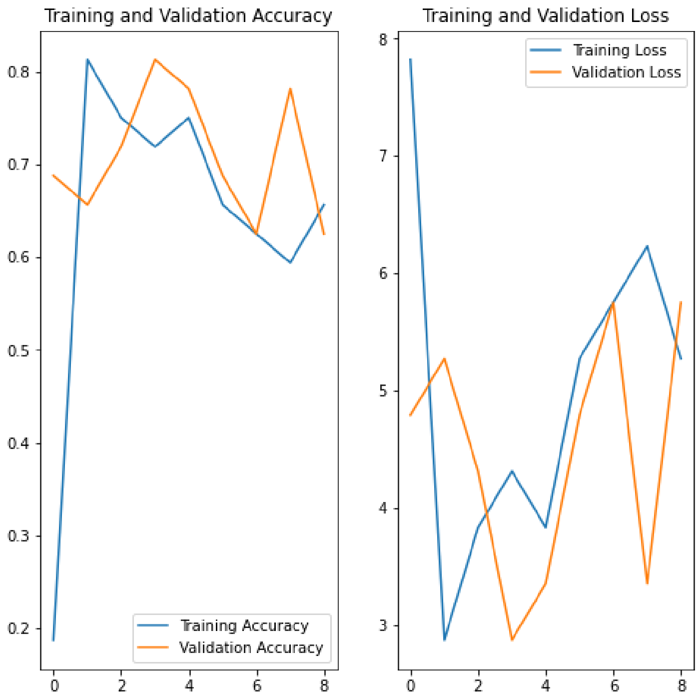

Figure 3.4: Accuracy and loss for AlexNet model

CSF biomarkers of AD [12]. Only after the comparison of different modalities of MRIs of the same subject, any modality can be said as beneficial for particular research. Hence, we presented a model which uses different modality of input set than other research studies.

Chapter 4

Details of 3D model

In this chapter details regarding 3D model is described such as data collection, data preprocessing and proposed model implementation in following sections.

4.1 Dataset and Data Preprocessing

4.1.1 Dataset Collection

Data used in the preparation of this research work were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu). The ADNI was launched in 2003 as a public-private partnership, led by Principal Investigator Michael W. Weiner, MD. The primary goal of ADNI has been to test whether serial magnetic resonance imaging (MRI), positron emission tomography (PET), other biological markers, and clinical and neuro-psychological assessment can be combined to measure the progression of mild cognitive impairment (MCI) and early Alzheimer's disease (AD). [5, 6] To detect AD, 174 MRIs have been selected. There is an Axial view of T1 weighted MRIs in NiFTI format. These images are split into 26 Alzheimer's Disease (AD), 47 Mild Cognitive Impairment (MCI), and 101 Normal Aging/ Cognitively Normal (CN). As MCI is one of the different stages of AD, subjects of MCI and AD subjects are merged in one class vs CN subjects to diagnose AD. Hence 73 subjects are of AD and 101 of CN. .nii format has been used in model execution.

Table 4.1 contains information about the dataset used, such as age range and gender about all subjects.

	Subject	Age [Range]
AD+MCI	73 (26 + 47)	[55,95]
CN	101	[65,90]

Table 4.1: Dataset Representation - 3D

4.1.2 Data Preprocessing

There are some basic data preprocessing methods, which need to be followed when working with brain MRIs such as removal of non-brain regions. Non-brain regions were removed from .nii files of ADNI using FSL-BET tool which is supported on Linux Operating System only [7, 8]. After removing unnecessary brain regions, skull-extraction/skull-stripping have been done to normalize the brain tissues. At the end, inputs have been resized to 192x192x140.

4.2 Proposed model implementation

Architecture of the model is followed same for 3D model also. Model consist of convolutional layer, pooling layer, dropout, batch-normalization and fully connected layers. Model architecture is shown in Fig. 4.2

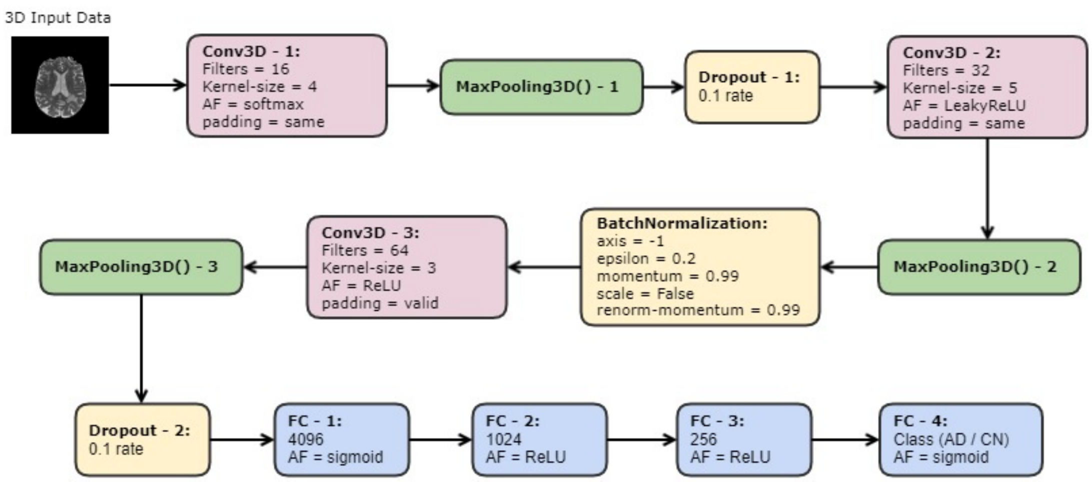

Figure 4.1: CNN Model Architecture

Model is implemented using Keras and Tensorflow. Optimal solution have been find by tuning the hyperparameters of model such as activation function, kernel size, etc.

Model training have been done using Nvidia GPU with capacity of 125 GB RAM, and using Ubuntu Operating System.

4.3 Results

3D MRI dataset of 174 subjects which has preprocessed as explained in previous section, had been given as input to model. Training and validation datasets are divided in 85% and 15% respectively. Training set consist of 148 subjects and validation set consist of 26 subjects. Model summary is generated using Google colab and shown in Fig. 4.2

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv3d (Conv3D)              (None, 192, 192, 104, 64) 1792
_________________________________________________________________
max_pooling3d (MaxPooling3D) (None, 96, 96, 52, 64)    0
_________________________________________________________________
dropout (Dropout)            (None, 96, 96, 52, 64)    0
_________________________________________________________________
conv3d_1 (Conv3D)            (None, 96, 96, 52, 32)    55328
_________________________________________________________________
max_pooling3d_1 (MaxPooling3 (None, 48, 48, 26, 32)    0
_________________________________________________________________
batch_normalization (BatchNo (None, 48, 48, 26, 32)    96
_________________________________________________________________
conv3d_2 (Conv3D)            (None, 46, 46, 24, 64)    55360
_________________________________________________________________
max_pooling3d_2 (MaxPooling3 (None, 23, 23, 12, 64)    0
_________________________________________________________________
dropout_1 (Dropout)          (None, 23, 23, 12, 64)    0
_________________________________________________________________
flatten (Flatten)            (None, 406272)            0
_________________________________________________________________
dense (Dense)                (None, 4096)              1664094208
_________________________________________________________________
dense_1 (Dense)              (None, 1024)              4195328
_________________________________________________________________
dense_2 (Dense)              (None, 256)               262400
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 257
=================================================================
Total params: 1,668,664,769
Trainable params: 1,668,664,705
Non-trainable params: 64
_________________________________________________________________
```

Figure 4.2: 3D - CNN Model Summary

The proposed model is executed on the Keras framework in python. The parameters for the training phase were: Loss was binary_crossentropy, the optimizer was stochastic gradient descent (sgd), epochs were 2, Batch-size was 128, steps per epoch was 1, and other parameters were same as their default values. Model training and testing time is approx 4 hours. The results of the model is 96.15% accuracy and 0.80 f1-score. Results have been compared to R. Irie et al. [13]. Table 4.2 shows the comparison of research work done to the exiting research work. Additionally, proposed model is having less complex structure with more accuracy which needs less computational power compare to more complex structure. Model is trained and validated on large dataset compare to R. Irie et al.[13] research work.

Table 4.2: Comparison of Proposed Model and Existing work

	Proposed CNN Model	**R. Irie et al. [13]**
Dataset size	174 Subjects	69 Subjects
Accuracy	96.15%	90%

Chapter 5

Future Work

Following are the work that could be done in future for more optimized solution:

- Proposed model is beating the state-of-art in the research work done on AD based on accuracy in 3D-CNN models. Which can be optimized for other measurements such as AUC, F1-score, etc.

- 3D model had used T1-weighted MRIs as other research work of AD, model can be tested and optimized for variation of datasets.

Other than this, in today's world, Alzheimer's disease is one of the leading causes of death. For that more efficient in terms of time and space, deep, and the accurate network is required for early diagnosis of Alzheimer's disease. Clinical assessment data can be used along with image data for better results. After getting satisfactory results in that pathological and genetic data can also be used collaboratively. As this area of research is in the initial stage there are many ways open for researchers to contribute to this research area.

Chapter 6

Conclusion

As an output of this research work, I have proposed an architecture of CNN model. This model can be used for the early diagnosis of Alzheimer's disease. While most of the existing research work for AD diagnosis is done using AlexNet, the 2D CNN model of proposed architecture is time-efficient compared to AlexNet. The model is trained and tested on the ADNI dataset, which is used by the majority of researchers in this research area. In the future, the proposed model can be improved to increase accuracy and make use of the large dataset. Though, the presented model is giving 72.13% accuracy when for a similar dataset as an input, AlexNet was giving less accuracy than this. 3D version of proposed architecture is validated on T1 weighted 3D MRIs of ADNI dataset, which is giving 96.15% accuracy. This model can be improvised to cover up other measurements such as recall, precision, f1-score, etc. Though, the proposed model is giving more accuracy then compared research work.

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