Single Deep CNN Features to Detect Neurodegenerative Diseases: Alzheimer, Parkinson and Dementia

by

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Abstract

Despite extensive research and ongoing clinical trials, there is currently no cure for neurodegenerative diseases (ND) including Alzheimer's disease (AD), Parkinson's disease (PD) and Dementia disease(DD). Over the past ten years, advances in deep learning techniques, high-speed computing infrastructure development, and greater knowledge of deep learning algorithms have created new opportunities for advanced analysis of neuroimaging data. The data from neuroimaging can now be used by neuroscientists to diagnose neurodegenerative diseases. Deep learning has achieved significant performance improvements over traditional machine learning. Modern neuroimaging has been defined by the development of magnetic resonance imaging (MRI) techniques. Besides, the amount of data generated by neuroimaging is both huge and complex. This work proposes a new model by stacking the Deep Convolutional Neural Network. Our method consists of convolution layers. By using this model, we can detect three neurodegenerative diseases: Alzheimer, Parkinson and Dementia. For the three diseases, we used three different MRI data sets. We used a preprocessed dataset that we obtained from the Kaggle platform for Alzheimer's disease. For Parkinson's disease, we used the dataset from the Parkinson Progression Marker Initiative (PPMI), and for dementia, we used the dataset from the Open Access Series of Imaging Studies (OASIS). We have to preprocess the datasets for Parkinson and dementia disease. From the three collected datasets, we made six different datasets. As a model, we used a pre-trained ResNet50 model with a transfer learning technique that provides the best accuracy of 99.03% and an AUC Score of 94.

Declaration

We do hereby declare that the work presented in this capstone project entitled ***"Single Deep CNN Features to Detect Neurodegenerative Diseases: Alzheimer, Parkinson and Dementia"*** *is the result of our own work, carried out in the Department of Computer Science and Engineering, Bangladesh University of Business and Technology under the supervision of Mr. M M Fazle Rabbi. We further declare that the capstone project has been compiled and written by us. No part of this capstone project has been submitted elsewhere for the requirements of any degree, award or diploma, or any other purposes except for publications. The materials that are obtained from other sources are duly acknowledged in this capstone project.*

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Certification

This is to certify that we are students of B.Sc. in CSE, have completed the capstone project titled **“Single Deep CNN Features to Detect Neurodegenerative Diseases: Alzheimer, Parkinson and Dementia"** satisfactorily in partial for the requirement of the Bachelor of Science in the Department of Computer Science and Engineering, Bangladesh University of Business and Technology in the year 2022.

_____

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Dedication

Dedicated to our parents and family members for their support, love and inspirations.

Approval

We do hereby acknowledge that the works presented in this capstone project entitled **"Single Deep CNN Features to Detect Neurodegenerative Diseases: Alzheimer, Parkinson and Dementia"** result from the original work carried out by Mohammad Sabbir Ahmed, Syeda Nowshin Ibnat, Rakibul Ahasan, Nusrat Jahan Anka and Sk. Abu Hanif respective ID No: 17183103004, 17183103020, 17183103022, 17183103008 and 17183103043 Department of CSE, Bangladesh University of Business and Technology (BUBT) under the supervision of Mr. M M Fazle Rabbi, Assistant Professor, Department of Computer Science and Engineering (CSE), BUBT. We further declare that no part of this work has been submitted elsewhere for the requirements of any degree, award or diploma, or any other purposes except for publications.

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List of Abbreviations

DL Deep Learning

CNN Convolutional Neural Network

DCNN Deep Convolutional Neural Network

MRI Magnetic Resonance Imaging

ND Neurodegenerative Disease

AD Alzheimer’s Disease

PD Parkinson’s Disease

DD Dementia Disease

OASIS Open Access Series of Imaging Studies

PPMI Parkinson's Progression Markers Initiative

AUC Area Under the Curve

ROC Receiver Operating Characteristic

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Chapter 1

Introduction

1.1 Introduction

Millions of people throughout the world suffer from neurodegenerative diseases. Alzheimer's disease, Parkinson's disease, and dementia are the most common NDs. By 2022, there may be 6.2 million cases of Alzheimer's disease in the US, according to an estimate from the Alzheimer's Disease Association. Neurodegenerative diseases represent a major threat to human health. These age-dependent disorders are becoming increasingly prevalent, in part because the elderly population has increased in recent years (Heemels, 2016) [1].

Symptoms of the neurodegenerative disease include the death or malfunction of central nervous system cells. The majority of neurodegenerative diseases are incurable and often worsen with time. They could be inherited or brought on by a tumor or stroke. People who consume significant amounts of alcohol or are exposed to specific viruses or toxins may potentially develop neurodegenerative diseases. Neurodegenerative disease is an umbrella term for a range of conditions that primarily affect the neurons in the human brain. Neurodegenerative diseases occur when nerve cells in the brain or peripheral nervous system lose function over time and ultimately die. Alzheimer's disease, Parkinson's disease, and dementia are examples of neurodegenerative diseases. Alzheimer’s disease (AD), is a chronic neurodegenerative disease causing the death of nerve cells and tissue loss throughout the brain [10].

Deep-learning algorithms have notable advantages rather than machine learning methods. Many recent research studies that have used brain MRI scans and convolutional neural networks (CNN) achieved promising results [11]. Deep learning

methods have gained more popularity recently in medical image analysis [14], this work proposes a deep convolutional neural network (DCNN) that can detect three neurodegenerative diseases using magnetic resonance imaging (MRI) samples.

Parkinson's disease (PD) is a non-curable progressive neurological disorder, which affects the motor system of the human brain [21]. According to Parkinson's Foundation, more than 10 million people worldwide are living with PD. The incidence of Parkinson's disease increases with age, but an estimated four percent of people with PD are diagnosed before age 50. Men are 1.5 times more likely to have Parkinson's disease than women.

Dementia disease is a neurological disorder that is characterized by a decline in memory, language, problem-solving, and other cognitive skills [31]. According to World Health Organization-WHO, around 55 million people have dementia worldwide with over 60% living in low and middle-income countries. As the proportion of older people in the population is increasing in nearly every country, this number is expected to rise to 78 million in 2030 and 139 million in 2050.

In our work, we used a pre-built DL model to detect three neurodegenerative diseases with this single model. Founding the suitable MRI dataset was the most difficult task for our work.

1.2 Problem Statement

In modern society, the prevalence of neurodegenerative diseases is on the rise. There is still no cure for it, despite the fact that more cases are being discovered. Neurodegenerative diseases detection is one of the unavoidable areas to treat patients at an early stage. Identifying neurodegenerative disease with proper explanation is quite challenging. Deep learning is currently creating initiatives across a wide range of various sectors. Neurodegenerative disease detection is one of them. In this work, we designed a deep-learning-based neurodegenerative disease detection model using the collected data which will detect Alzheimer, Parkinson, and Dementia diseases. In our

work, we worked with a single deep learning model which can detect the three diseases for MRI data. However, until now, our system hasn't been proposed yet. This benchmark is being used for the first time in research. Therefore, it will create a new path in the medical field.

1.3 Problem Background

Over the past few decades, neuroimaging, in particular magnetic resonance imaging (MRI), has been crucial in helping us understand how the brain functions and the illnesses that can affect it. AD, PD and DD are three common neurodegenerative diseases, yet not many people in our country are aware of these diseases. Many people in undeveloped and developing countries view it as a normal aging issue. The present neurodegenerative disease detection system only detects one disease such as Alzheimer, Parkinson, Dementia, Huntington, Schizophrenia, etc. In this modern era, the medical field is now updated and technology-based while the existing system is quite backdated. Identifying neurodegenerative diseases and their reason for appearing is a deadly problem that needs to be solved. Diagnosis of Alzheimer, Parkinson, and Dementia diseases is very challenging due to the similarities in disease phenotypes, and accurate detection. Most importantly, finding a proper dataset was the critical challenge for our project.

1.4 Research Objectives

The objectives of our research work are as follows:

- Detection of three neurodegenerative diseases named Alzheimer, Parkinson and Dementia in a person.
- Build a single DCNN model to detect three neurodegenerative diseases.
- Get decent accuracy using a suitable MRI dataset.
- Comparing the existing architectures with the proposed one for neurodegenerative disease detection.

1.5 Motivations

Deep Learning (DL) is an emerging field that attracts researchers, specifically in the field of engineering and medical sciences. Deep learning techniques have opened up possibilities for enhanced analysis of neuroimaging data during the last decade. In this work, we provided deep learning architectures, applications, and the role of deep learning in the detection of neurodegenerative diseases like Alzheimer, Parkinson and Dementia. In general, we all know that using MRI to detect any of these three diseases is time-consuming and expensive. However, with our work, we can get results in a short period of time. As a result, we believe that detecting these three neuro diseases is essential in order to treat patients at an early stage. As a result, detection of neurodegenerative diseases is crucial in our society, as we have a significant number of elderly people who are suffering from these diseases. Therefore, in our work, we created a single model architecture that can detect Alzheimer, Parkinson, and Dementia diseases.

1.6 Flow of the Research

This research work is developed in several steps. First, we analyzed the research topics and then studied the basic theory of deep learning and learned about the application of neurodegenerative for the MRI dataset. Then we investigated the existing datasets and selected three different datasets for the three diseases. And then we preprocessed the datasets and convert them into six different datasets. After that, we build a model based on state-of-the-art deep learning approaches. Figure 1.1 illustrates the overall steps of the research procedure in the following diagram.

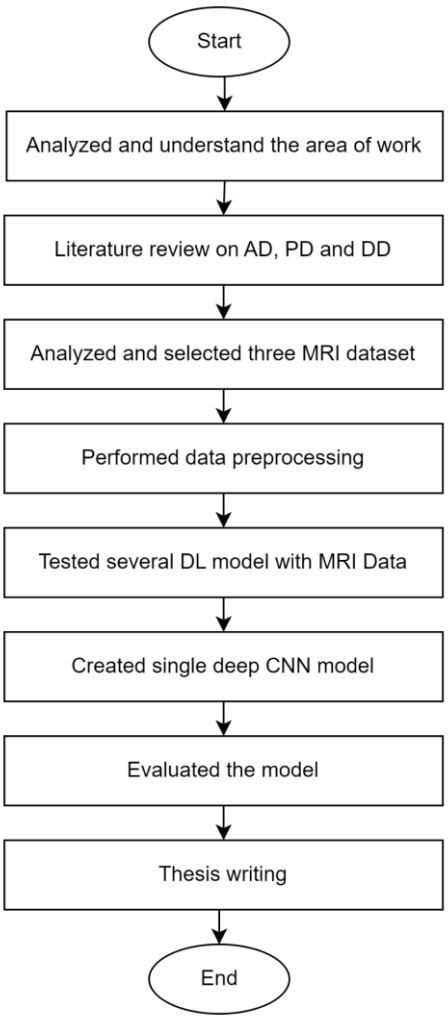


Figure 1.1: Flow of the work

1.7 Significance of the Research

We observed that most of the works for Neurodegenerative Diseases are on a particular disease. Therefore, this study introduces a new model to detect three NDs named Alzheimer, Parkinson and Dementia with a single deep CNN model. We used the MRI dataset as non-MRI data is less efficient than the MRI method. In our society, neurodegenerative diseases affect a significant percentage of the elderly population. The ability to recognize three diseases provided by this work will be beneficial to medical practitioners. This is a state-of-the-art architecture to estimate the detection of

ND significantly impacts society and the country. Our model can detect AD, PD and DD with great accuracy.

1.8 Research Contribution

The overall contribution of the research works can be summarized as,

- We investigated the existing deep learning algorithms to produce the best result possible for MRI data to detect three ND with a single model. Our research is the first research to perform this benchmark.
- We identified the present difficulty to detect Neurodegenerative Disease (ND) using the MRI dataset, and our proposed DL model can detect three neurodegenerative diseases with a single model by using a novel CNN approach.

1.9 Thesis Organization

The thesis work is organized as follows,
Chapter two highlights the background and literature review on the field of Neurodegenerative Disease (ND) detection for AD, PD and DD. Chapter three contains feasibility analysis and data preprocessing. Chapter four covers a detailed walk-through of the overall procedures and the details of the evaluations performed to evaluate our proposed architecture. Chapter five explains the Standards, Impacts, Ethics, Challenges, Constraints, Timeline, and Gantt Chart. Chapter six contains the overall conclusion of our thesis work.

1.10 Summary

This chapter includes a general overview of the problem that we aimed explicitly at our research work objectives, background, and research work motivation. This chapter also illustrates the overall steps on which we carried out our research work.

Chapter 2

Background

2.1 Introduction

When nerve cells in the brain or peripheral nervous system begin to lose their functionality over time and eventually die, this is known as a neurodegenerative disease. Although some neurodegenerative disease symptoms can be alleviated with particular medications, there is presently no cure. Advancements in the understanding of deep learning techniques, along with the rapid development of high-speed computing infrastructure and devices, have created opportunities for advanced analysis of MRI and other neuroimaging data. The majority of existing approaches focus on detecting one disease at a time. However, before this study, no work has introduced the detection of three neurodegenerative diseases at a time. In this project, we are going to present a single model architecture that can detect Alzheimer, Parkinson, and Dementia diseases using MRI image dataset.

2.2 Literature Review

Neurodegenerative diseases are affecting millions of people globally. Alzheimer, Parkinson and dementia disease are the most common neurodegenerative diseases. Therefore, there is large unmet demand for efficient treatments for ND like AD, PD and DD on a global scale. The development of early detection methods and efficient treatments for these diseases faces enormous difficulties due to the complexity of the molecular pathways behind neuronal degeneration and the variability of the patient population. A section of artificial intelligence called deep learning is allowing

researchers, doctors, and patients to tackle some of these problems. NDD using MRI data is the dominant in detecting diseases.

A few of the literature review are,
M. Biswas et al. [7] concentrated on a binary classification decision for brain MRI and observed better results compared to the other state-of-the-art studies for AD. Their proposed deep CNN achieves an accuracy of 99.38%. The model correctly identified 654 images out of 656 real Alzheimer images, with only seven misidentifications. Hence, the proposed classifier obtained the highest AUC score of 1.00, indicating the best deep CNN for high-class separation.

A. W. Salehi et al. [9] implemented a Convolutional Neural Network (CNN) for the earlier diagnosis and classification of AD using MRI images, and the ADNI 3 class of images were used. A significant accuracy of 99% was achieved in which the model performed well as we compared it with many other related works. Their purpose was to make the best prediction and detection tools with the help of radiologists, doctors, and caregivers to save time, and cost, and help the patient suffering from this disease.

J. Wen et al. [10] implemented and compared several deep models and configurations, including two-dimensional (2D) and three-dimensional (3D) CNNs and recurrent neural networks (RNNs). Their other contribution is the extension of an open-source framework for the classification of AD using CNN and T1-weighted MRI. The framework comprises previously developed tools to automatically convert ADNI, AIBL, and OASIS data into the BIDS standard, and a modular set of image preprocessing procedures, classification architectures, and evaluation procedures dedicated to deep learning.

Y. AbdulAzeem et al. [11] proposed a CNN based end-to-end framework for AD-classification. The proposed framework achieved 99.6%, 99.8%, and 97.8% classification accuracies on Alzheimer's disease Neuroimaging Initiative (ADNI) dataset for the binary classification of AD and Cognitively Normal (CN). In multi-classification experiments, the proposed framework achieved 97.5% classification accuracy on the ADNI dataset.

S. S. Kundaram et al. [14] proposed a method that classifies the disease as Alzheimer's disease (AD), mild cognitive impairment (MCI) and normal control (NC). They have achieved 98.57% accuracy on our dataset without using any handcrafted features for training the network. Experimental data was obtained from ADNI.

W. Wang et al. [18] introduced an innovative deep- learning technique to early uncover whether an individual is affected with PD or not based on premotor features. Specifically, to uncover PD at an early stage, several indicators have been considered in their study, including rapid Eye Movement and olfactory loss, cerebrospinal fluid data, and dopaminergic imaging markers. They also provided a comparative study and throws light on the performance of these advanced prediction methods when applied to small PD data sets. Their dataset was obtained from Parkinson's Progression. Markers Initiative (PPMI) and 97.92% accuracy were achieved using LeNet-5 architecture with batch normalization technique and dropout algorithm.

G. Solana-Lavalle et al. [20] proposed a method that provides high performance as an assisting tool in the diagnosis of Parkinson's disease. They used PPMI MR images with VBM, from controls and PD patients, providing high performance as a tool to assist in the diagnosis of PD. This study was conducted separately for male and female populations with good results in both cases. The results show that different regions are useful to classify PPMI MR images depending on gender. The areas more affected in men are the basal ganglia, the brainstem, fourth ventricle, lateral ventricle and cerebellum. The corresponding regions for women are the occipital lobe, thalamus basal ganglia, a small part of the cerebellum, and the frontal lobe.

S. Sivaranjini et al. [23] attempted to classify the MR images of healthy control and Parkinson's disease subjects using deep learning neural network. The Convolutional Neural Network architecture AlexNet is used to refine the diagnosis of Parkinson's disease. The MR images are trained by the transfer learned network and tested to give the accuracy measures. An accuracy of 88.9% is achieved with the proposed system. The proposed methodology was not extended to deep fine-tuning of the AlexNet model to obtain improved performance levels.

S. Kaur et al. [25] proposed an approach to classify MR images of healthy and Parkinson's disease patients using a deep convolution neural network. The MR images are refined by normalizing before being fed with an advanced bilateral filter. For categorization, an Alex-Net model has been preferred as a convolution neural network. The classification results were achieved by employed in Deep CNN functioning upon the image synthesis vis-à-vis data augmentation.

M. Husaini et al. [27] detected PD by using a deep learning algorithm to discriminate between PD and controlled subjects. the diagnosis of Parkinson's Disease data was successfully performed, with and without batch normalization. 97.92% accuracy was achieved using LeNet-5 architecture with batch normalization technique and dropout algorithm. The model was trained using a big dataset containing 10,548 images. Implementation of this particular method for the purpose of diagnosing different stages of PD is viable. The accuracy of the model in which we did not apply batch normalization technique was 97.63%.

J. A. Akhila et al. [30] used Segmentation-based Fractal Texture Analysis (SFTA) technique for the extraction of features. Two threshold binary decomposition algorithm used for the decomposition. Classification of dementia is achieved with a feed forward artificial neural network. This algorithm was implemented successfully in images obtained from the OASIS database. A classification accuracy of 97.5% is obtained.

A. Bidani et al. [31] presented a new approach in the field of Deep Machine Learning, that comprises both DCNN (Deep Convolutional Neural Network) model and Transfer Learning model to detect and classify dementia disease. MRI images from the OASIS 1 dataset were used for their work. Total 416 subjects were used and each class contained 14 subjects for training. Using the DCNN model produced an important classification accuracy of 81.94%

H. Ucuzal et al. [33] aimed at developing an open source software for deep learning based-classification of dementia in magnetic resonance imaging scans. The image dataset encapsulates 1592 MRI scans for demented and 2032 MRI scans for non-demented subjects, respectively. The calculated performance metrics demonstrate that

the proposed Keras deep learning model can be used to successfully separate dementia patients and healthy individuals based on the T1-weighted MRI scans.

S. Murugan et al. [34] proposed a model that generates high-resolution disease probability maps from the local brain structure to a multilayer perceptron and provides accurate, intuitive visualizations of individual Alzheimer's disease risk. A Dementia Network (DEMNET) is proposed to detect the dementia stages from MRI. They used the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset to predict AD classes in order to assess the efficacy of the proposed model. The DEMNET achieves an accuracy of 95.23%.

S. Basheer et al. [35] intended to develop a novel algorithm by proposing changes in the design of capsule networks for the best prediction results and making the model computationally efficient. They used OASIS dataset with dimensions (373 X 15) to diagnose the labels into two groups, demented and non-demented.

2.3 Problem Analysis

Age significantly increases the risk of acquiring a neurodegenerative disease. We need to learn more about the root causes of neurodegenerative conditions including AD, PD, and DD. Through MRI neurodegenerative disease detection is a common and effective process. Generally, the existing approaches can detect one disease at a time which is time-consuming and expensive. In this project, we proposed a model to detect three ND with a single deep CNN model while maintaining a high level of learning performance.

2.4 Summary

This chapter investigated and reviewed the latest techniques of neurodegenerative disease detection for AD, PD and DD. The thesis's target is to eliminate imperfections as much as possible and introduce a new model to detect three neurodegenerative diseases at a time. This work will create a new path in the medical field as using this model we can detect three diseases at a time.

Chapter 3

Proposed Model

3.1 Introduction

This section discussed the feasibility analysis of neurodegenerative disease diagnosis at low cost and the requirements demanded in this structure. Additionally, this chapter illustrates the research methodology and data preprocessing.

3.2 Feasibility analysis

This capstone work needed five team members with one supervisor and took twelve months to develop. The capstone work required technical support in both hardware and software. This capstone work did not require any financial support from the institution or supervisor. The models were developed in a cloud environment for reducing hardware costs. To conduct the proposed architecture of the overall requirements, include:

- Cloud computing service.
- Open-source software libraries for scientific computations.
- Open-source software libraries to implement the deep learning models.

3.3 Requirement Analysis

Requirement analysis is significant and essential activity after elicitation. We analyzed, refined, and scrutinized the gathered requirements to make consistent and unambiguous requirements. This activity reviews all requirements and may provide a

graphical view of the entire system. After the completion of the analysis, it is expected that the understandability of the project may improve significantly. Here, we also use the interaction with the doctors & patients to clarify points of confusion and to understand which requirements are more important than others.

3.4 Research Methodology

In this section, the steps that have been taken to complete our capstone work have been illustrated. We used three different MRI data sets for the three diseases. For Alzheimer's Disease, we used a preprocessed dataset that we collected from Kaggle platform. We used Parkinson's Progression Marker Initiative (PPMI) dataset for Parkinson's Disease and for dementia we used Open Access Series of Imaging Studies (OASIS) dataset. We have to preprocessed Parkinson's disease and Dementia disease datasets. After that, we made them into six different datasets from the three collected datasets. As a model, we used a pre-trained ResNet50 model with transfer learning technique.

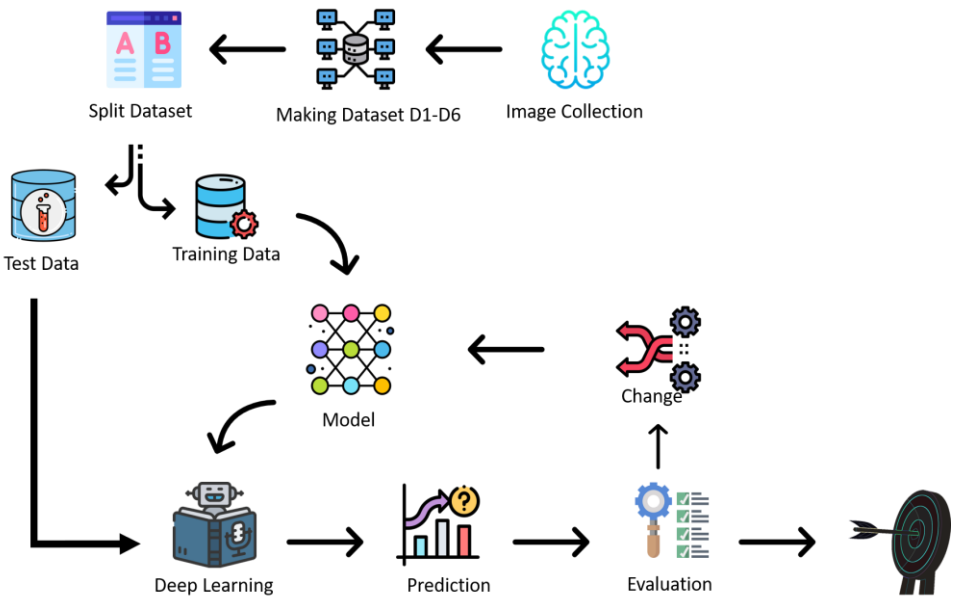


Figure 3.1: Research Methodology of our work

3.5 Dataset Details

Alzheimer MRI Preprocessed Dataset (128 x 128)

Source of dataset: www.kaggle.com

- The data is collected from several websites/hospitals/public repositories.
- The dataset is consisting preprocessed MRI Images.
- All the images are resized into 128 x 128 pixels.
- The dataset has four classes of images.
- The dataset is consisting of a total of 6400 MRI images:

  Class - 1: Mild Demented (896 images).

  Class - 2: Moderate Demented (64 images).

  Class - 3: Non Demented (3200 images).

  Class - 4: Very Mild Demented (2240 images).

We made two different classes named Healthy and Demented from the four different classes.

PPMI MRI Dataset

Source of dataset: www.ppmi-info.org/data

The Parkinson's Progression Markers Initiative (PPMI) study was launched in 2010 with a mission to identify biomarkers of Parkinson's disease (PD) onset and progression a critical next step in the development of new and better treatments for PD. The PPMI dataset originates from an observational clinical and longitudinal study comprising evaluations of people with Parkinson’s disease (PD), those people with high risk, and those who are healthy.

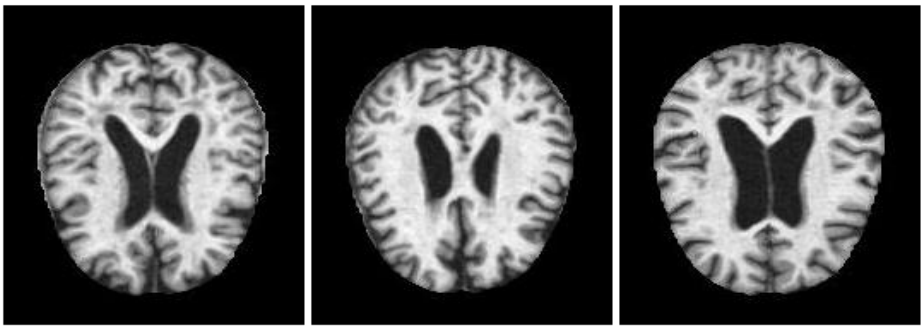
OASIS Dementia MRI Dataset

Source of dataset: www.oasis-brains.org

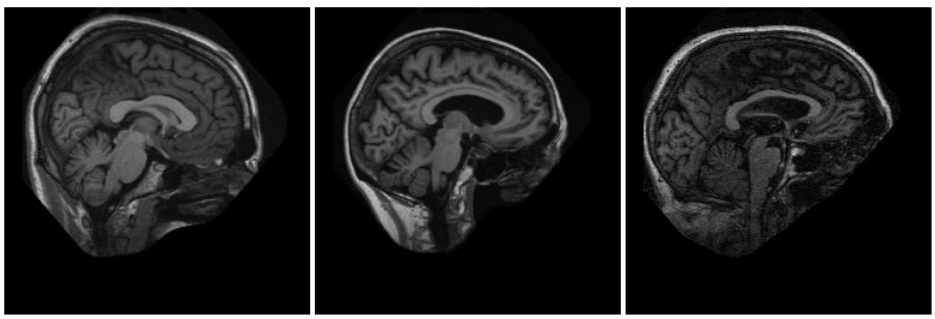
The Open Access Series of Imaging Studies (OASIS) is a project aimed at making MRI data sets of the brain freely available to the scientific community. By compiling and freely distributing MRI data sets hope to facilitate future discoveries in basic and clinical neuroscience. OASIS is made available by the Washington University Alzheimer's disease Research Center, Dr. Randy Buckner at the Howard Hughes Medical Institute (HHMI) (at Harvard University, the Neuroinformatics Research Group (NRG) at Washington University School of Medicine, and the Biomedical Informatics Research Network (BIRN).

3.5.1 Sample images from the dataset

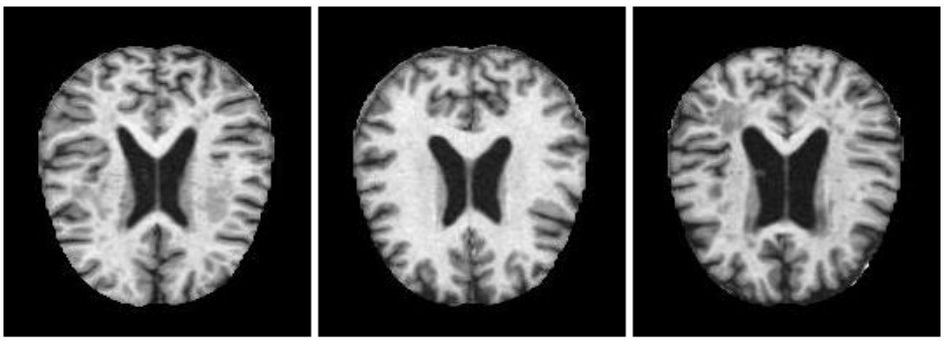
Class 1: mri_alzheimer's



Class 2: mri_dementia



Class 3: mri_healthy



Class 4: mri_parkinson's

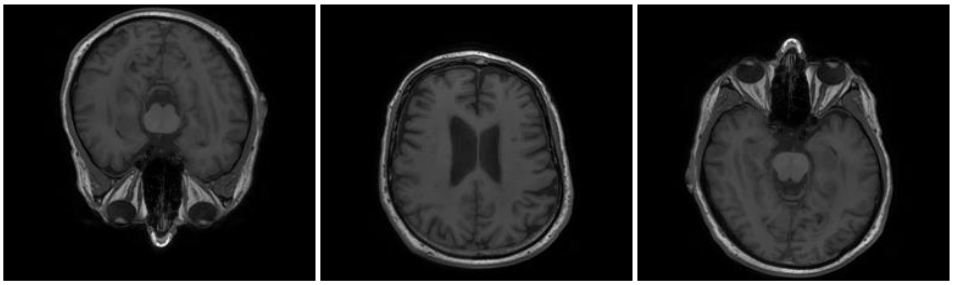


Figure 3.2: Sample dataset from each class of our study

3.6 Data preprocessing

In this section, we discuss data preprocessing. How to image read, resize and train test split.

3.6.1 Read, Resize and Covert Image to Array

In this part of our study, we preprocessed the dataset to increase the capability of the CNN models for better understanding. At first, we used OpenCV library to read every image from our dataset directory and resize them to 176 X 208 images. Then we converted each image into an array and inserted the image array in a list.

```python
def convert_image_to_array(image_dir):
    try:
        image = cv2.imread(image_dir)
        if image is not None :
            image = cv2.resize(image, default_image_size)
            return img_to_array(image)
        else :
            return np.array([])
    except Exception as e:
        print(f"Error : {e}")
        return None
```

Figure 3.3: Data preprocessing

3.6.2 Train test split

We had to perform the train test split and we kept 20% of our images for the test and 80% of our images for training. We used 500 images per class and for 4 classes the total dataset is 5646 images.

```python
print("[INFO] Spliting data to train, test")
x_train, x_test, y_train, y_test = train_test_split(np_image_list, image_labels, test_size=0.2, random_state = 42)
```

```
[INFO] Spliting data to train, test
```

```python
print(image_labels)
```

```
[[0 1 0 0]
 [0 1 0 0]
 [0 1 0 0]
 ...
 [1 0 0 0]
 [1 0 0 0]
 [1 0 0 0]]
```

```python
x_train.shape
```

```
(4516, 176, 208, 3)
```

```python
x_test.shape
```

```
(1130, 176, 208, 3)
```

Figure 3.4: Train-test split of the dataset

3.7 Summary

This section explains the feasibility analysis and research methodology of our work. The overall architecture uses several machine learning models and the combined Ensemble Architecture.

Chapter 4

Implementation, Testing and Result Analysis

4.1 Introduction

In this section, we emphasized the architectures of Convolutional Neural Networks. Here, we discuss the fundamental concepts of Convolutional Neural Networks and the CNN Models that we used. We discuss about the libraries imported for data processing, model building, and programming language. We have included side by side comparison of training and validation accuracy graphs, training and validation loss graphs, confusion matrices, precision, recall, F1 score, ROC AUC scores, ROC curves, and precision Vs recall curves for a better understanding of how the models are performing in all four classes.

4.2 Convolutional Neural Network

A deep neural network optimized for image recognition is called a convolutional neural network (ConvNet). This method demonstrates how important it is to improve the deep layers of information. Processing of (images) ConvNet is an old technology that was created in the 1970s. During the 1980s and 1990's It was, however, ignored for a while, as it was for real-world applications with complex graphics, this is obsolete. Since the year 2012, ConvNet has defeated most computer vision since it drastically revived the sectors, and it is rapidly expanding [36].

4.3 Architecture of Convolutional Neural Network

ConvNet isn't just a deep neural network with a lot of layers buried behind the surface. It's a deep network that mimics the way the brain's visual cortex analyses and recognizes images. As a result, even neural network professionals frequently have a problem. On their first meeting, they have a hard time grasping this concept [36]. ConvNet is different from previous neural networks in terms of idea and operation. ConvNet's basic architecture is briefly described in this section. Rather than developing the feature extractor manually, ConvNet incorporates it into the training process. ConvNet's feature extractor is made up of various types of neural networks, the weights of which are set by the training process. ConvNet's transformation of a manual feature extraction design into a main feature and benefit is the automated process. Figure 4.1 shows ConvNet's notion of training [36].

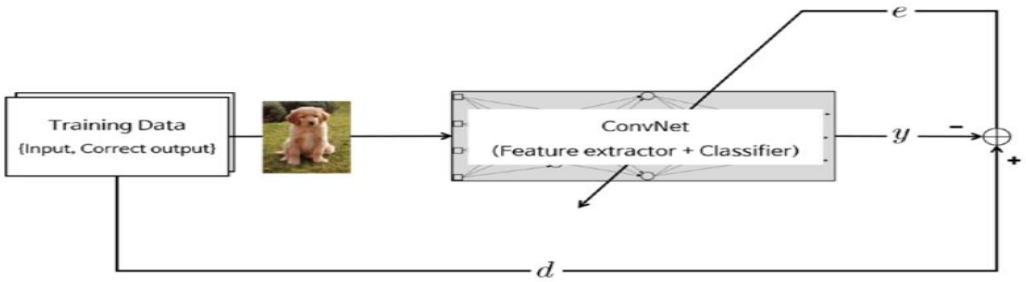


Figure 4.1: CNN feature extractor

ConvNet produces superior picture identification when its feature extraction neural network is deeper (has more layers), but this comes at the cost of training challenges, which made ConvNet impractical and ignored for a while. ConvNet is a neural network that extracts information. Features of the input image, as well as a second neural network that classifies the feature image. ConvNet's typical architecture is depicted in Figure 4.2 [36].

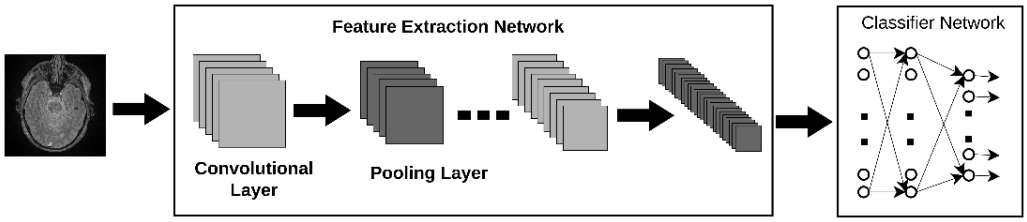


Figure 4.2: Typical architecture of CNN

The convolutional layer and pooling layer pairs are stacked in the feature extraction neural network. The convolution layer, as its name suggests, uses the convolution technique to convert the image. It's possible to think of it as a collection. The use of digital filters The pooling layer mixes adjacent pixels into a single image pixel. As a result, the pooling layer diminishes the image's dimension. As a result, the image is ConvNet's major interest, as are the convolutional procedures. Conceptually, pooling layers are in a two-dimensional plane. This is one of the options. ConvNet differs from other neural networks in several ways.

4.3.1 Convolution Layer

The convolution layer creates feature maps, which are new images. The feature map emphasizes the original image's distinct features. In comparison to the other neural network layers, the convolution layer works differently. There are no link weights or a weighted sum in this layer. Rather, Filters that convert photos are included. These filters will be referred to as convolution filters. The image is processed by convolution filters, and the result is a map of features. The process of the convolution layer is depicted in Figure 4.3 [36], where it is circled. [36] The convolution operation is denoted by the * mark, and the activation is denoted by the mark function. Between these operators, the square grayscale icons signify the Filters that use convolution. The convolution layer produces the same number of features as the previous layer. As the convolution filters, maps are used. As an example, if the convolution layer is It generates four feature maps because it has four filters.

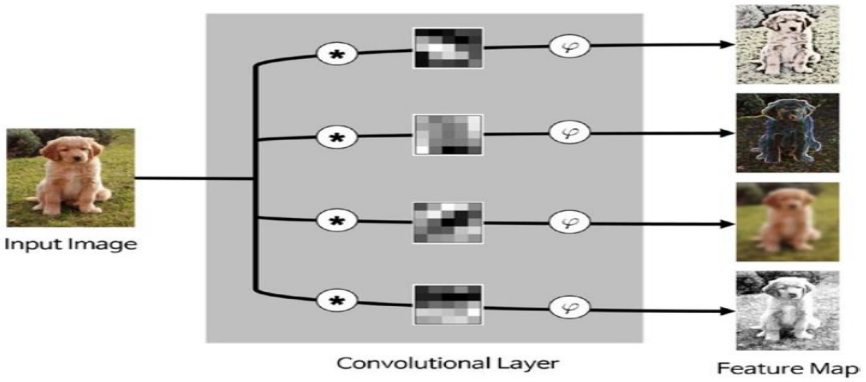


Figure 4.3: The convolution layer process

The filters of the convolution layer are two-dimensional matrices. They usually come in 5x5 or 3x3 matrices, and even 1x1 convolution filters have been used in recent applications. As addressed in the previous section, the values of the filter matrix are determined through the training process. Therefore, these values are continuously trained throughout the training process. This aspect is similar to the updating process of the connection weights of the ordinary neural network. The convolution operation begins at the upper-left corner of the submatrix which is the same size as the convolution filter (see Figure 4.4) [36]. It repeats the same process until the feature map of the given filter is produced, as in Figure 4.5 [36].

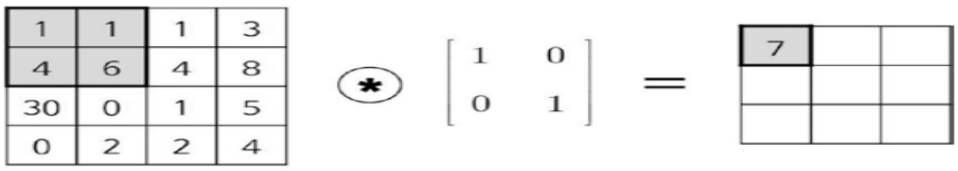


Figure 4.4: The convolution operation starts at upper-left corner

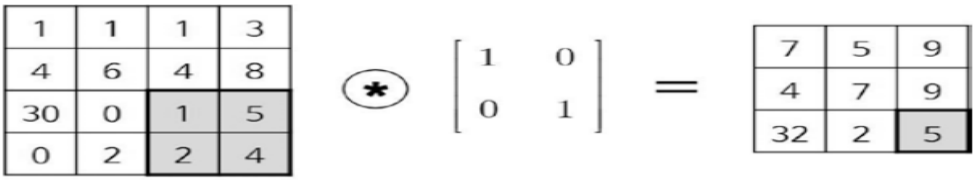


Figure 4.5: The feature map of the given filter in completed

4.3.2 Pooling Layer

Because it mixes neighboring pixels in a specific area of the image into a single representative value, the pooling layer decreases the size of the image. Pooling is a common approach used in many other image processing schemes. We must first establish how we will conduct operations in the pooling layer. The square matrix is frequently used to pick neighboring pixels, and The number of pixels combined varies depending on the difficulty. The mean or maximum of the selected pixels is usually used as the representative value. We combine the pixels of the input image into a 2-2 matrix without overlapping the elements. Once the input image passes through the pooling layer, it shrinks into a 2x2 pixel image. Figure 4.6 shows the resultant cases of pooling using the mean pooling and max pooling. A pooling process is a form of convolution operation in mathematical terms. The convolution filter differs from the convolution layer in that it is stationary and the convolution areas do not overlap. To some extent, the pooling layer adjusts for eccentric and slanted objects. The pooling layer, for example, can help with cat recognition which in the supplied image may be off-center. Furthermore, as the pooling process progresses, decreases the image size, which is very useful for reducing computational load, reducing the burden, and avoiding overfitting [36].

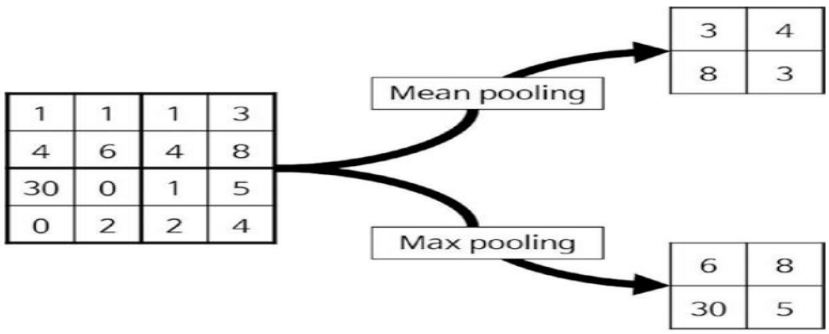


Figure 4.6: The resultant cases of pooling using two different methods

4.3.3 Fully Connected Layer

The fully-connected layer is similar to the way that neurons are arranged in a traditional neural network. Therefore, each node in a fully-connected layer is directly connected to every node in both the previous and the next layer as shown in Figure 4.7 [37], From this figure we can note that each of the nodes in the last frames in the pooling layer is connected as a vector to the first layer from the fully-connected layer. These are the parameters used with the CNN within these layers, and take a long time in training. The major drawback of a fully-connected layer is that it includes a lot of parameters that need complex computations in training examples. Therefore, we try to eliminate the number of nodes and connections. The removed nodes and connection can be satisfied by using the dropout technique [37].

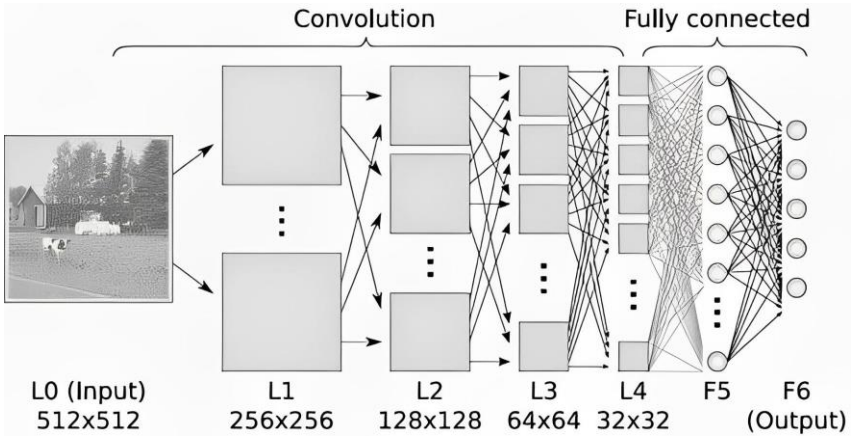


Figure 4.7: Fully connected layer

4.4 Popular CNN Architecture

In this section, we discuss the popular CNN architectures in detail which we have implemented in this thesis study. The names of the CNN architecture we use in our thesis are ResNet50 and VGG19.

4.4.1 ResNet50

The residual learning framework is developed to ease the training of networks that are substantially deeper than those used previously. Researchers explicitly reformulate the layers as learning residual functions regarding the layer inputs, instead of learning unreferenced functions. They provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset, they evaluate residual nets with a depth of up to 152 layers—8× deeper than VGG nets but still having lower complexity. An ensemble of these residual nets achieves a 3.57% error on the ImageNet test set. Their result won 1st place on the ILSVRC 2015 classification task. They also present an analysis of CIFAR-10 with 100 and 1000 layers. The depth of representations is of central importance for many visual recognition tasks. Solely due to our extremely deep representations, we obtain a 28% relative improvement on the COCO object detection dataset. Deep residual nets are the foundations of our submissions to ILSVRC & COCO 2015 competitions1, where they also won 1st place on the tasks of ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation [40]. Based on the above plain network, they insert shortcut connections (Figure 4.8, right) which turn the network into its counterpart residual version. The identity shortcuts can be directly used when the input and output are of the same dimensions (solid line shortcuts in Figure 4.8). When the dimensions' increase (dotted line shortcuts in Figure 4.8), they consider two options: (A) The shortcut still performs identity mapping, with extra zero entries padded for increasing dimensions. This option introduces no extra parameter; (B) The projection shortcut which is used to match dimensions (done by 1×1 convolutions). For both options, when the shortcuts go across feature maps of two sizes, they are performed with a stride of 2. They evaluate 18-layer and 34- layer residual nets (ResNets). The baseline architectures are the same as the above plain nets, except that a shortcut connection is added to each pair of 3×3 filters as in Figure 4.8 (right). They use identity mapping for all shortcuts and zero-padding for increasing dimensions (option A). So they have no extra parameters compared to their plain counterparts. The situation is reversed with residual learning – the 34-layer ResNet is better than the 18-layer ResNet (by 2.8%).

More importantly, the 34-layer ResNet exhibits considerably lower training error and is generalizable to the validation data.

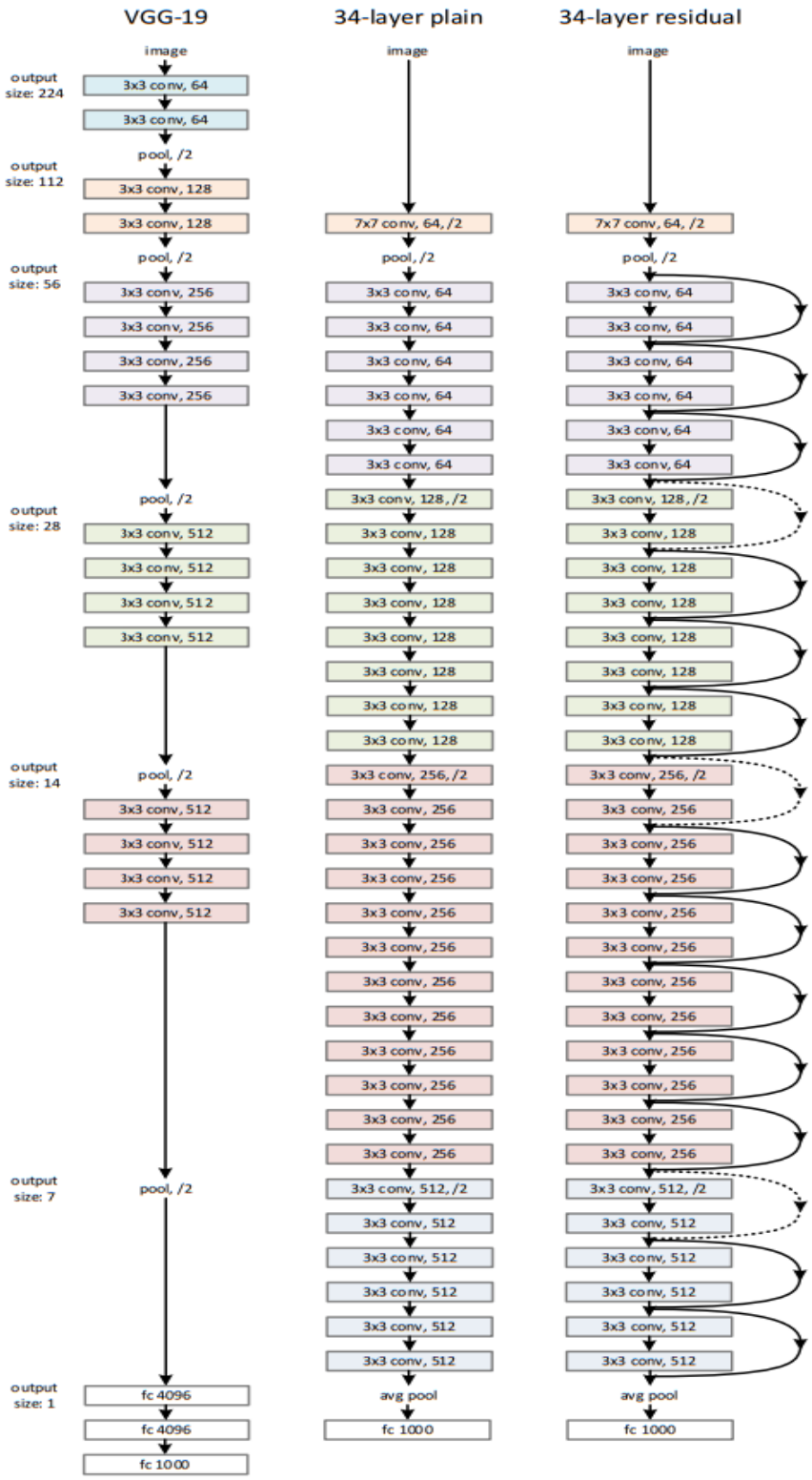


Figure 4.8: ResNet50 V2 Architecture

4.4.2 VGG16 and VGG19

Researchers investigate the effect of the convolutional network depth on its accuracy in the large-scale image recognition setting. Thorough evaluation of networks of increasing depth using an architecture with very small (3 × 3) convolution filters, which shows that a significant improvement on the prior-art configurations can be achieved by pushing the depth to 16–19 weight layers. These findings were the basis of ImageNet Challenge 2014 submission, where the VGG team secured the first and second places in the localization and classification tracks respectively. VGG representations generalize well to other datasets and they achieve state-of-the-art results.

During training, the input to ConvNets is a fixed-size 224 × 224 RGB image. The only preprocessing we do is subtracting the mean RGB value, computed on the training set, from each pixel. The image is passed through a stack of convolutional (Conv.) layers, where we use filters with a very small receptive field: 3 × 3 (which is the smallest size to capture the notion of left/right, up/down, center). In one of the configurations, they also utilize 1 × 1 convolution filters, which can be seen as a linear transformation of the input channels (followed by non-linearity). The convolution stride is fixed to 1 pixel; the spatial padding of Conv. layer input is such that the spatial resolution is preserved after convolution, i.e. the padding is 1 pixel for 3 × 3 Conv. layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the Conv. layers (not all the Conv. layers are followed by max-pooling). Max-pooling is performed over a 2 × 2 pixel window, with stride 2. A stack of convolutional layers (which has different depth in different architectures) is followed by three Fully-Connected (FC) layers: the first two has 4096 channels each, the third performs 1000-way ILSVRC classification and thus contains 1000 channels (one for each class). The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks. The ConvNet configurations, evaluated in this paper, are outlined in Figure 12, one per column. In the following, we will refer to the nets by their names (A–E). All configurations follow the generic design and differ only in depth: from 11 weight layers in network A (8 Conv. and 3 FC layers) to 19 weight layers in network E (16 Conv. and 3 FC layers). The width of Conv. layers (the number of channels) is

rather small, starting from 64 in the first layer and then increasing by a factor of 2 after each max-pooling layer, until it reaches 512. The number of parameters for each configuration. Despite a large depth, the number of weights in VGG16/19 is not greater than the number of weights in a more shallow net with larger Conv. layer widths and receptive fields [42].

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 **LRN**	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					
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 4.9: VGG16 and VGG19 Model Architecture

4.5 Programming Language and Environment

In this section, we discuss the Libraries imported for data processing, model building, and programming language.

4.5.1 Libraries imported for data processing

NumPy (python library): NumPy stands for Numerical Python. It's a Python package and a library consisting of multidimensional array objects and a collection of routines to process those arrays. Logical and mathematical operations on the arrays can be performed with the help of the NumPy library.

Pandas (python library): It's a python data analysis library. It provides fast, flexible, and expressive data structures and is also designed to make working with "relational" or "labeled" data both easy and intuitive. Pandas aim to be the fundamental high–level building block for having practical real-world data analysis in Python.

CV2 (python library): OpenCV-Python is mainly used in computer vision problems for binding designs. cv2.imread() method loads an image from a specific folder if the image is present otherwise returns an empty matrix. It performs tasks like face detection, object detection tracking, landmark detection, and so on.

Listdir (python library): listdir() method is used to have the list of all the files and directories in the specific folder. It mainly returns a list containing names of the entries in the directory given by the path and if no directory is specified then returns the current directory.

Matplotlib (python plotting library): It's a comprehensive library for making static, animated, and interactive visualizations of numerical data in python. Matplotlib mainly provides an object-oriented API for embedding plots into applications using general-purpose GUI like Tkinter, wxPython, etc.

4.5.2 Model Building

TensorFlow framework (python): TensorFlow is Google's open-source AI framework for ML and high-performance numerical calculations. It's a python library that uses C++ to build and execute dataflow graphs. TensorFlow supports many classification and regression algorithms and more generally deep learning and neural networks.

Keras framework (python): Keras is a neural network library. TensorFlow provides both high–level and low–level APIs while Keras provides only high–level APIs. Keras is capable of running on top of TensorFlow, CNTK, or Theano.

4.5.3 Programming Languages

Python: Python is a general-purpose programming language that can be used on any modern computer operating system. It can be used for processing text, numbers, images, scientific data, and just about anything else you might save on a computer.

4.5.4 IDE

Jupyter notebook: The Jupyter Notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations, and narrative text. Uses include: data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning, and much more.

4.5.5 Execution Platform

Google Colab: Colab is a Google internal research tool for data science. They have released the tool sometime earlier to the general public with a noble goal of dissemination of machine learning education and research.

4.6 Hyperparameters

In this study, we implemented the above-mentioned dataset in a total of 2 different modes. We have pre-trained models where we used fine-tuning and transfer learning techniques. All the model parameters took input images in the size of $176 \times 208 \times 3$. The last layers of every model were four adjusting the output class numbers. Table 4.1 shows the hyper parameter details.

Total Number of Images	4000 (500 per class)
Test Image Percentage	20%
Number of Train Images	4516
Number of Test Images	1130
Number of Classes	4
Batch Size	8
Learning Rate	For Pre-train model 0.0001
Epochs	50
Optimizer	Adam
Image Shape	$176 \times 208 \times 3$
Multiclass Classification Loss	categorical_crossentropy

Table 4.1: Hyperparameters

We tried to evaluate the performance of pre-train models and evaluate which type of model performs better with our dataset in Table 4.1.

4.7 Models we Implemented

Our implemented models were based on pre-trained models with transfer learning. ResNet50, VGG19.

Pre-train models with transfer learning:

1. ResNet50
2. VGG19

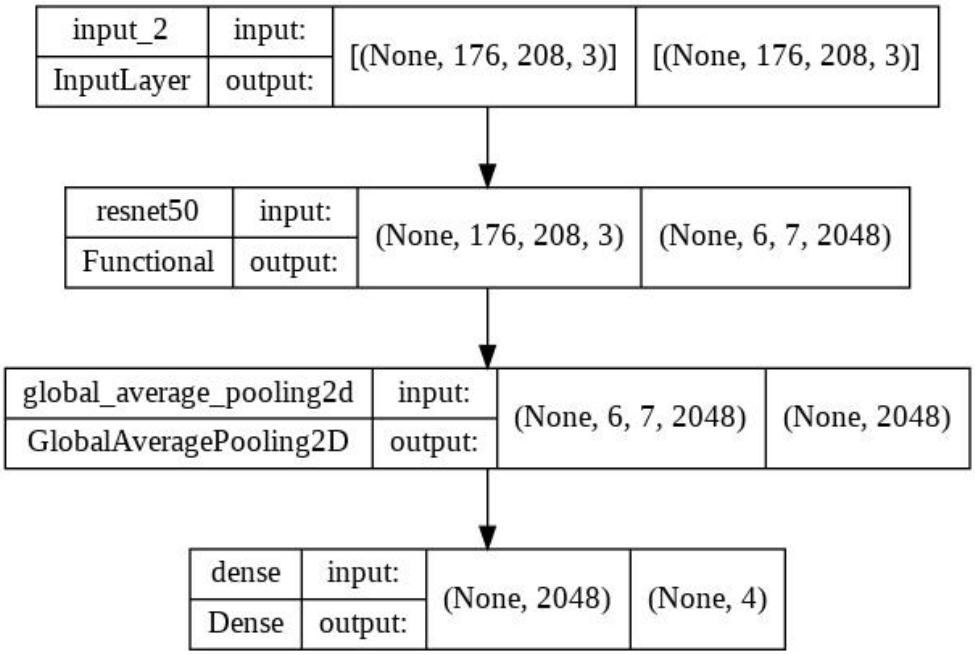


Figure 4.10: The architecture of pre-train ResNet50

4.8 Evaluation

We compared the result of the two experiments on different scales like Accuracy, F1 score, Recall, and Precision. It is essential to measure the models in different areas to evaluate them from different perspectives. Accuracy is the percentage of correct predictions for the test data.

The equations of Accuracy are,

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

Here, TP stands for True Positive, TN denotes True Negative, FP denotes False Positive, and FN denotes False Negative. However, Accuracy is not always the best scale to measure a model's performance. Precision tells us how many of the predicted positive results are positive.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall tells us how many of the positives are captured by our model. Recall is very important for a disease prediction model. Because we want to accurately identify as many positive patients as possible.

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

F1 score is used when we need to balance between Precision and Recall. The F1 score tells us which model has the optimal false positive and true positive rates. The equation for measuring the F1 score is,

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

We analyzed the Area Under the Receiver Operating Characteristics to determine which model best distinguishes classes. The model with the highest Receiver Operating Characteristic (ROC) – Area Under the Curve (AUC) value has the best separability.

4.9 Comparison of Results

Here we compare the outcome of all the models and try to evaluate which model is performing well with our dataset. We are comparing the results with the following:

1. Accuracy on the last 12 epochs.
2. Training and Validation accuracy graphs.
3. Training and Validation loss graphs.
4. Training and Validation accuracy and loss combine graph.
5. Confusion matrices on the test images.
6. Precision, Recall and F1 Score of each class.
7. ROC Curve and ROC AUC score.
8. Precision Vs Recall Curve.

4.9.1 Accuracy on the last 10 epochs

An epoch is the total number of iterations required to train the machine learning model using all of the training data at once. It is measured in cycles. The picture below shows the accuracy on the last 10 epochs:

```
Epoch 10/50
564/564 [==============================] - 59s 105ms/step - loss: 0.1066 - accuracy: 0.9581 - val_loss: 0.1610 - val_accuracy: 0.9319
Epoch 11/50
564/564 [==============================] - 57s 100ms/step - loss: 0.1192 - accuracy: 0.9523 - val_loss: 0.0897 - val_accuracy: 0.9646
Epoch 12/50
564/564 [==============================] - 58s 102ms/step - loss: 0.0931 - accuracy: 0.9645 - val_loss: 0.3168 - val_accuracy: 0.8938
Epoch 13/50
564/564 [==============================] - 59s 104ms/step - loss: 0.0815 - accuracy: 0.9669 - val_loss: 0.0927 - val_accuracy: 0.9726
Epoch 14/50
564/564 [==============================] - 56s 98ms/step - loss: 0.0832 - accuracy: 0.9669 - val_loss: 0.2051 - val_accuracy: 0.9478
Epoch 15/50
564/564 [==============================] - 58s 102ms/step - loss: 0.0791 - accuracy: 0.9665 - val_loss: 0.1228 - val_accuracy: 0.9575
Epoch 16/50
564/564 [==============================] - 58s 102ms/step - loss: 0.0576 - accuracy: 0.9758 - val_loss: 0.0679 - val_accuracy: 0.9805
Epoch 17/50
564/564 [==============================] - 57s 100ms/step - loss: 0.0738 - accuracy: 0.9705 - val_loss: 0.1108 - val_accuracy: 0.9717
Epoch 18/50
564/564 [==============================] - 56s 99ms/step - loss: 0.0536 - accuracy: 0.9798 - val_loss: 0.0740 - val_accuracy: 0.9717
Epoch 19/50
564/564 [==============================] - 56s 99ms/step - loss: 0.0555 - accuracy: 0.9798 - val_loss: 1.7547 - val_accuracy: 0.7434
Epoch 20/50
564/564 [==============================] - 57s 101ms/step - loss: 0.0549 - accuracy: 0.9789 - val_loss: 0.0772 - val_accuracy: 0.9796
Epoch 21/50
564/564 [==============================] - 59s 105ms/step - loss: 0.0601 - accuracy: 0.9769 - val_loss: 0.0398 - val_accuracy: 0.9903
<tensorflow.python.training.tracking.util.CheckpointLoadStatus at 0x7fb8520ca350>
```

Figure 4.11: Accuracy on the last 10 epochs of ResNet50

4.9.2 Training and Validation accuracy graph

We trained the model using the training data and check its performance on both the training and validation sets (the evaluation metric is accuracy). Running the code generates a similar plot of the training and validation accuracy curve to the one given:

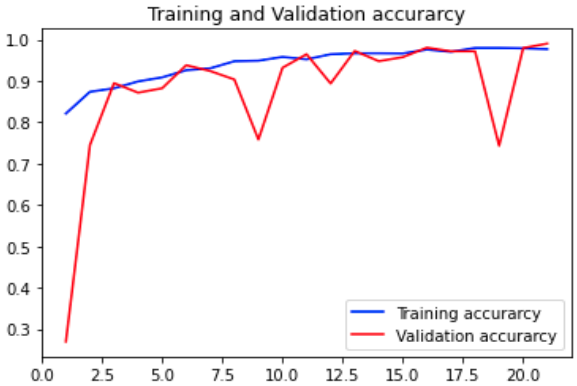


Figure 4.12: Training and Validation accuracy graphs of ResNet50 Model

4.9.3 Training and Validation loss graph

We trained the model using the training data and check its performance on both the training and validation sets (the evaluation metric is loss). Running the code generates a similar plot of the training and validation loss curve to the one given:

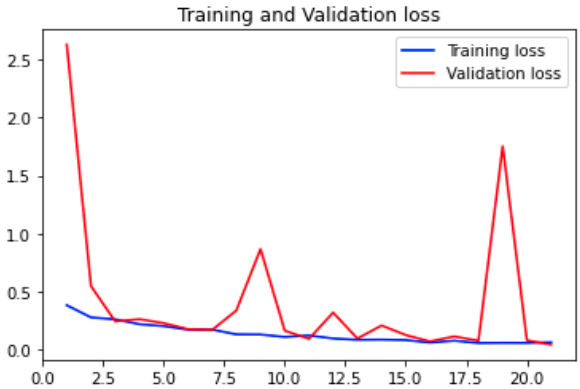


Figure 4.13: Training and Validation loss graphs of ResNet50 Model

4.9.4 Training and Validation accuracy and loss combine graph

To check our model performance on both the training and validation sets (the evaluation metric is accuracy and loss). Running the code generates a similar plot of the training and validation accuracy and loss curve to the one below:

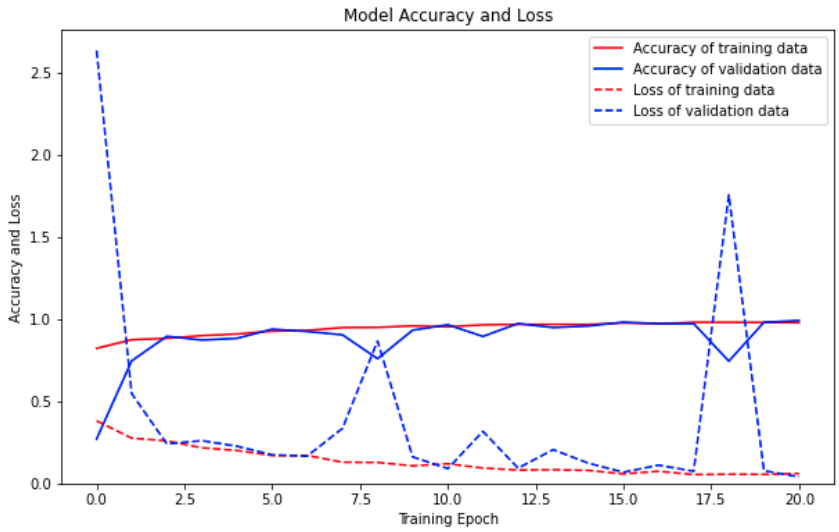


Figure 4.14: Training , Validation accuracy and loss combine graph of ResNet50

4.9.5 Confusion matrix on the test images

The confusion matrix on the test images is a performance measurement for classification problems where the output can be two or more classes. It is extremely useful for measuring Recall, Precision, Specificity, Accuracy and most importantly AUC-ROC curves. The confusion matrix itself is relatively simple to understand, but the related terminology can be confusing. The given picture illustrates the confusion matrix of our project:

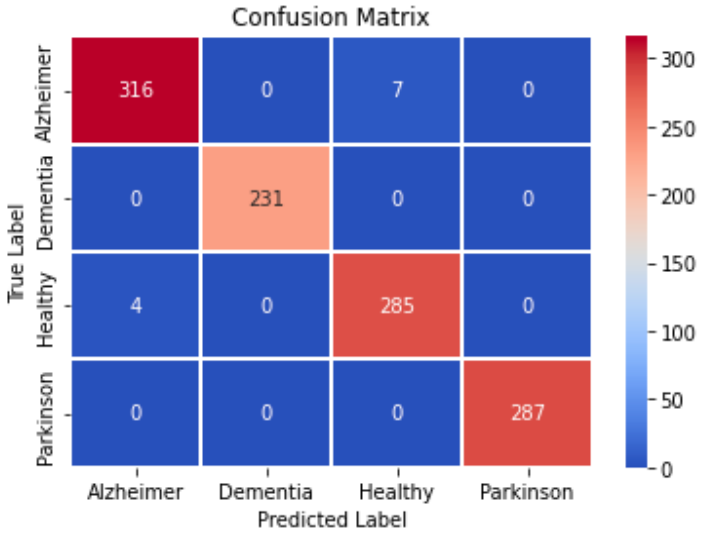


Figure 4.15: Confusing matrix of the model

4.9.6 Precision, Recall, F1 Score of each classes

Precision is a measure of how many of the positive predictions made are correct (true positives). The recall is a measure of how many of the positive cases the classifier correctly predicted, over all the positive cases in the data. F1-Score is a measure combining both precision and recall. The picture below illustrates the Precision, Recall, and F1 scores of our project.

	precision	recall	f1-score	support
0	0.99	0.98	0.98	323
1	1.00	1.00	1.00	231
2	0.98	0.99	0.98	289
3	1.00	1.00	1.00	287
accuracy			0.99	1130
macro avg	0.99	0.99	0.99	1130
weighted avg	0.99	0.99	0.99	1130

Figure 4.16: Precision, Recall, F1 Score of the model

4.9.7 ROC Curve and ROC AUC score

AUC stands for "Area under the ROC Curve." That is, AUC measures the entire two-dimensional area underneath the entire ROC curve. The picture below illustrates the ROC curve and ROC AUC score of our project:

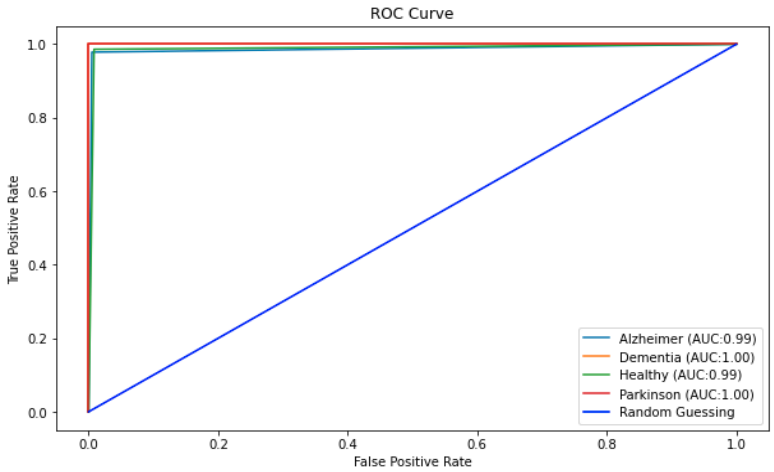


Figure 4.17: ROC Curve and ROC AUC of the model

4.9.8 Precision Vs Recall Curve

The picture below illustrates Precision Vs Recall Curve of our project:

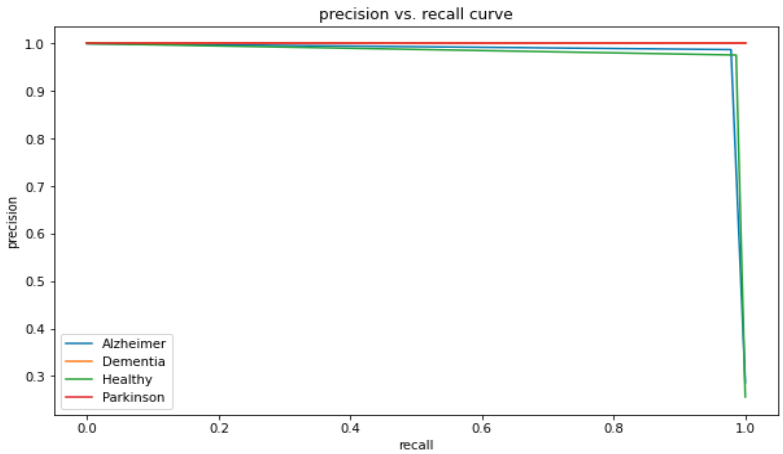


Figure 4.18: Precision Vs Recall of the model

4.10 Result Analysis

According to the visualization of the model outcomes of our model. We can conclude that the pre-trained model ResNet50 with transfer learning technique provides the best accuracy of 99.03% and AUC Score of 94.1%, and VGG19 has reached the second closest outcome accuracy of 64% and AUC Score of 62.5%. Though the ResNet50 pre-trained model with transfer learning reached 99.03% accuracy and 94.1% ROC score from both the training and validation accuracy and loss graph VGG19 is having very high loss spikes. That is why we are considering ResNet50 better than VGG19. We found that ResNet50 performs the best in classifying the images with an accuracy of 99.03%. Our study found that ResNet50 pre-trained model with transfer learning resulted better performance for the classification of MRI images for detecting neurodegenerative disease. We summarize our outcome in Table 4.2 and Table 4.3.

CNN Architecture	Epoch	Training Accuracy %	Validation Accuracy %	Training Loss %	Validation Loss %
ResNet50	50	97.69	99.03	06	03
VGG19	50	63.34	78.24	07	05

Table 4.2: Result Analysis (Accuracy, Loss)

CNN Architecture	Precision	Recall	F1 Score	AUC
ResNet50	0.99	0.99	0.99	94.1
VGG19	0.64	0.64	0.64	62.5

Table 4.3: Result Analysis (Precision, Recall, F1 Score, AUC)

4.11 Summary

Neurodegenerative disease like Alzheimer's, Parkinson's and Dementia has been detected separately using deep CNN models. For our work, we use a single deep CNN model to detect three ND. We used pre-trained model ResNet50 with transfer learning technique. The model obtained a decent accuracy.

Chapter 5

Standards, Impacts, Ethics and Challenges

5.1 Introduction

This section demonstrates the Standards, Impacts, Ethics, and Challenges of the work. Then, the Constraints and Alternatives are illustrated. Finally, the Schedules, Tasks, and Milestones of the proposed work are presented.

5.2 Standards

Through our proposed approach we ensure that our work will be sustainable for many years. Detecting neurodegenerative is a very popular field of study and it will remain popular as the cure to these diseases are yet to be found. In our study, we used deep learning which is one such field that is considered to analyze the problem. The reason behind the decision of using Deep Learning is to get a better result after analyzing all related previous work and obtaining results. Just choosing an algorithm doesn't make a model efficient and smooth. It also needs a standard dataset. To make standard data, the dataset needs to be prepossessed which means there will be no redundant data, no null data, no inconsistent data, and no duplicate data. After that, the necessary features will be extracted. As our used resources will be available for more extended periods of time, we can say this thesis work will be sustainable for many years.

5.3 Impacts on Society

The detection of neurodegenerative diseases has a wide area of influence in the medical field. In this paper, detecting three diseases named Alzheimer's, Parkinson's, and Dementia using one model at a time is a great effective system. The early-stage detection of neurodegenerative diseases is quite tough, costly & time-consuming. However, a low-cost system will open doors for all and potentially save lives. It can also be used as a tool for raising awareness.

5.4 Ethics

In our study, we worked on detecting neurodegenerative diseases: Alzheimer, Parkinson, Dementia. We got our datasets from Kaggle, PPMI and OASIS. Our collected datasets are open source. From their written description these datasets were approved to show openly. In that case, we can say we didn’t break any law or regulation.

5.5 Challenges

Although the field of neurodegenerative disease research has come a long way, there are still several challenges in this field. The biggest challenge, of course, is to develop a cure for the diseases. A lack of trained professionals is also a big challenge. Low awareness and misconception about the diseases are also challenges moving forward, as people are reluctant to diagnose Alzheimer, Parkinson, and Dementia.

5.6 Constraints

Different constraints such as design constraints, component constraints, and budget constraints are presented in this section. The overall structure is proposed based on training deep learning models.

- **Design Constraints:** The overall structure of the recommended architecture can be executed based on MRI data. The model needs systems with high processing capacity to detect neurodegenerative diseases.
- **Component Constraints:** We developed our system on Google Colaboratory to reduce hardware constraints. However, we still faced some issues with the free version of the Google Colaboratory. We could not run more than one process simultaneously, so it took more time to 31 train the models. A stable internet connection was also an issue, as models needed to train from the beginning if we were disconnected from the Google Colaboratory.
- **Budget Constraints:** The cost of completing our research which is the Single Deep CNN Features to Detect Neurodegenerative Diseases: Alzheimer, Parkinson, and Dementia don't need any additional purchases for hardware and software.

5.7 Timeline

Our thesis work timeline is divided into three segments based on the three semesters we got to complete our work. Each semester is four months, and we have one year to complete our thesis. We have carried out our work following the guidelines of our supervisor. In The first semester, we submitted a proposal and reviewed the related work of the thesis work. In the second semester, we implemented the model partially. Finally, we implemented the overall architecture in the third semester, benchmarked our results, and reported the overall work. Figure 5.1, Figure 5.2 and Figure 5.3 contain the Gantt charts describing the work execution process of the thesis work.

5.8 Gantt Chart

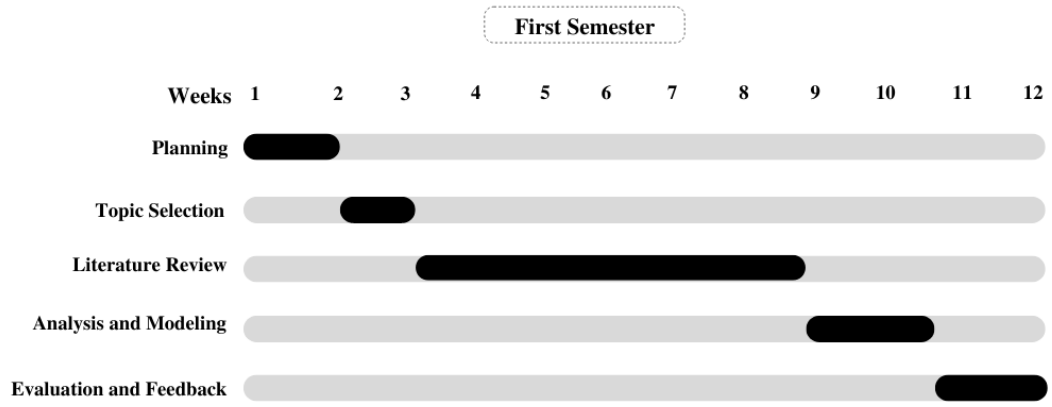


Figure 5.1: Gantt chart of the work execution process for the first semester

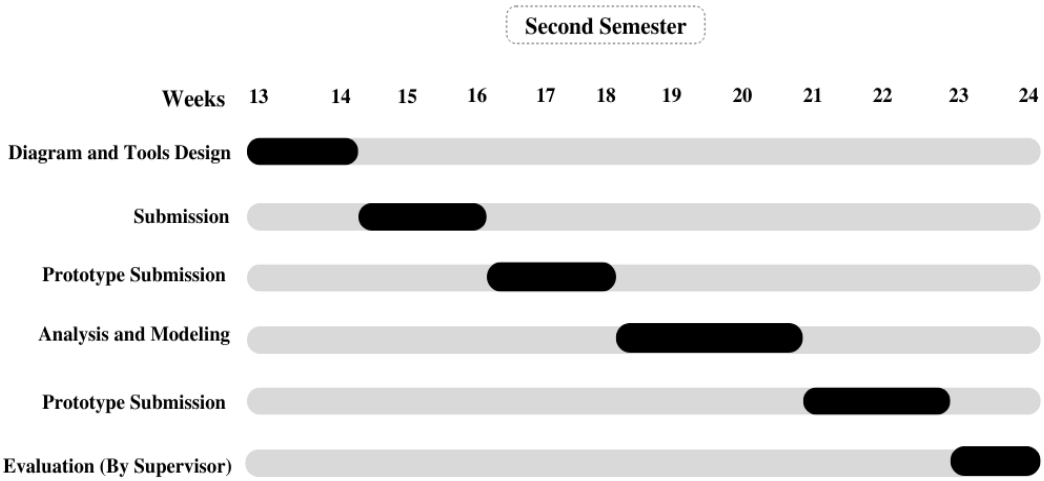


Figure 5.2: Gantt chart of the work execution process for the second semester

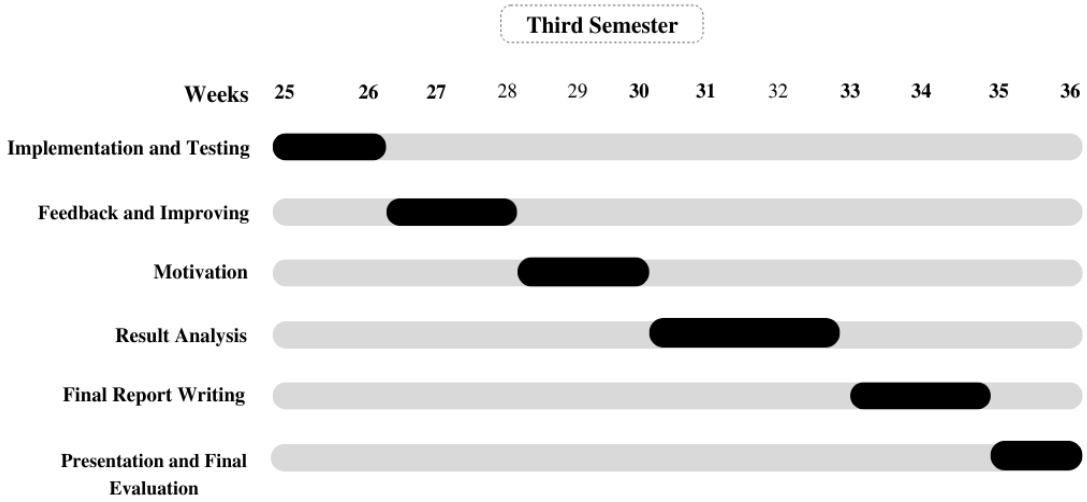


Figure 5.3: Gantt chart of the work execution process for third semester

5.9 Summery

Neurodegenerative Disease is a condition that affects neurons in the brain, causing symptoms such as memory loss, moodiness, anxiety, and depression. Our model accuracy is quite good. Also, it isn't guaranteed that only our model is the best to detect three diseases at a time. In this chapter, we briefly explained the standards, impacts, challenges, constraints, schedules, tasks, and milestones of the proposed work are demonstrated.

Chapter 6

Conclusion

6.1 Introduction

This paper experiments with and evaluates a low-cost diagnostic model of Alzheimer, Parkinson, and Dementia. Through this, it will also save wasting time. We tested and benchmarked the MRI data to detect three diseases and healthy MRI images correctly. This is the first research to perform this benchmark of this kind.

6.2 Future Works and Limitations

We build a model that works for three neurodegenerative diseases at a time. This can be an extensive field of research. We had to face a model overfitting problem. We have worked with a comparatively decent amount of dataset. This method can be tested for large datasets. In the future, we will operate this work based on the place (NDs situation in Bangladesh) or based on age. We couldn't implement explainable AI. In the future, we will implement XAI. Then we can explain how and why our model makes a particular prediction. Therefore, in this field, there is sufficient scope to work.

Reference

[1] A. D. Gitler, P. Dhillon, and J. Shorter, "Neurodegenerative disease : models , mechanisms , and a new hope," pp. 499–502, 2017, doi: 10.1242/dmm.030205.

[2] C. Singh, "Medical Imaging using Deep Learning Models," *Eur. J. Eng. Technol. Res.*, vol. 6, no. 5, pp. 156–167, 2021, doi: 10.24018/ejers.2021.6.5.2491.

[3] K. Suzuki, "Overview of deep learning in medical imaging," *Radiol. Phys. Technol.*, vol. 10, no. 3, pp. 257–273, 2017, doi: 10.1007/s12194-017-0406-5.

[4] X. Zhao and X. M. Zhao, "Deep learning of brain magnetic resonance images: A brief review," *Methods*, vol. 192, no. August 2020, pp. 131–140, 2021, doi: 10.1016/j.ymeth.2020.09.007.

[5] M. Binth, T. Noor, N. Z. Zenia, M. S. Kaiser, S. Al Mamun, and M. Mahmud, "Application of deep learning in detecting neurological disorders from magnetic resonance images : a survey on the detection of Alzheimer ' s disease , Parkinson ' s disease and schizophrenia," *Brain Informatics*, 2020, doi: 10.1186/s40708-020-00112-2.

[6] L. Zhang, M. Wang, M. Liu, and D. Zhang, "A Survey on Deep Learning for Neuroimaging-Based Brain Disorder Analysis," *Front. Neurosci.*, vol. 14, no. October, pp. 1–19, 2020, doi: 10.3389/fnins.2020.00779.

[7] M. Biswas, M. K. Mahbub, and M. A. M. Miah, "An Enhanced Deep Convolution Neural Network Model to Diagnose Alzheimer's Disease Using Brain Magnetic Resonance Imaging," *Commun. Comput. Inf. Sci.*, vol. 1576 CCIS, pp. 42–52, 2022, doi: 10.1007/978-3-031-07005-1_5.

[8] L. Yue *et al.*, "Auto-detection of alzheimer's disease using deep convolutional neural networks," *ICNC-FSKD 2018 - 14th Int. Conf. Nat. Comput. Fuzzy Syst. Knowl. Discov.*, pp. 228–234, 2018, doi: 10.1109/FSKD.2018.8687207.

[9] A. W. Salehi, P. Baglat, B. B. Sharma, G. Gupta, and A. Upadhya, "A CNN Model: Earlier Diagnosis and Classification of Alzheimer Disease using MRI," *Proc. - Int. Conf. Smart Electron. Commun. ICOSEC 2020*, no.Icosec,pp.156–161,2020, doi:10.1109/ICOSEC49089.2020.9215402.

[10] J. Wen *et al.*, “Convolutional neural networks for classification of Alzheimer’s disease: Overview and reproducible evaluation,” *Med. Image Anal.*,vol.63, p. 101694, 2020, doi: 10.1016/j.media.2020.101694.

[11] Y. AbdulAzeem, W. M. Bahgat, and M. Badawy, “A CNN based framework for classification of Alzheimer’s disease,” *Neural Comput. Appl.*, vol. 33, no. 16, pp. 10415–10428, 2021, doi: 10.1007/s00521-021-05799-w.

[12] A. Ebrahimi, S. Luo, and for the A. Disease Neuroimaging Initiative, “Convolutional neural networks for Alzheimer’s disease detection on MRI images,” *J. Med. Imaging*, vol. 8, no. 02, pp. 1–18, 2021, doi: 10.1117/1.jmi.8.2.024503.

[13] A. D. International and M. University, “World Alzheimer Report 2021,” *Alzheimer’s Dis. Int.*, pp. 2–314, 2021, [Online]. Available: https://www.alzint.org/resource/world-alzheimer-report-2021/.

[14] S. S. Kundaram and K. C. Pathak, *Deep Learning-Based Alzheimer Disease Detection*, vol. 673. Springer Singapore, 2021.

[15] C. L. Saratxaga *et al.*, “Mri deep learning-based solution for alzheimer’s disease prediction,” *J. Pers. Med.*, vol. 11, no. 9, 2021, doi: 10.3390/jpm11090902.

[16] M. Zaabi, N. Smaoui, H. Derbel, and W. Hariri, “Alzheimer’s disease detection using convolutional neural networks and transfer learning based methods,” *Proc. 17th Int. Multi-Conference Syst. Signals Devices, SSD 2020*, pp. 939–943, 2020, doi: 10.1109/SSD49366.2020.9364155.

[17] E. Hussain, M. Hasan, S. Z. Hassan, T. Hassan Azmi, M. A. Rahman, and M. Zavid Parvez, “Deep Learning Based Binary Classification for Alzheimer’s Disease Detection using Brain MRI Images,” *Proc. 15th IEEE Conf. Ind. Electron. Appl. ICIEA 2020*, pp. 1115–1120, 2020, doi: 10.1109/ICIEA48937.2020.9248213.

[18] W. Wang, J. Lee, F. Harrou, and Y. Sun, “Early Detection of Parkinson’s Disease Using Deep Learning and Machine Learning,” *IEEE Access*, vol. 8, pp. 147635–147646, 2020, doi: 10.1109/ACCESS.2020.3016062.

[19] B. Heim, F. Krismer, R. De Marzi, and K. Seppi, “Magnetic resonance imaging for the diagnosis of Parkinson’s disease,” *J. Neural Transm.*, vol. 124, no. 8, pp. 915–964, 2017, doi: 10.1007/s00702-017-1717-8.

[20] G. Solana-Lavalle and R. Rosas-Romero, “Classification of PPMI MRI scans with voxel-based morphometry and machine learning to assist in the diagnosis of Parkinson’s disease,” *Comput. Methods Programs Biomed.*, vol. 198, p. 105793, 2021, doi: 10.1016/j.cmpb.2020.105793.

[21] P. M. Shah, A. Zeb, U. Shafi, S. F. A. Zaidi, and M. A. Shah, “Detection of Parkinson disease in brain mri using convolutional neural network,” *ICAC 2018 - 2018 24th IEEE Int. Conf. Autom. Comput. Improv. Product. through Autom. Comput.*, no. September, pp. 1–6, 2018, doi: 10.23919/IConAC.2018.8749023.

[22] S. Soltaninejad, I. Cheng, and A. Basu, *Towards the identification of Parkinson’s disease using only T1 MR images*, vol. 11010 LNCS. Springer International Publishing, 2018.

[23] S. Sivaranjini and C. M. Sujatha, “Deep learning based diagnosis of Parkinson ’ s disease using convolutional neural network,” 2019, [Online]. Available: https://doi.org/10.1007/s11042-019-7469-8.

[24] S. Chakraborty, S. Aich, and H. C. Kim, “Detection of Parkinson’s disease from 3T T1 weighted MRI scans using 3D convolutional neural network,” *Diagnostics*, vol. 10, no. 6, pp. 1–17, 2020, doi: 10.3390/diagnostics10060402.

[25] S. Kaur, H. Aggarwal, and R. Rani, “Diagnosis of Parkinson’s disease using deep CNN with transfer learning and data augmentation,” *Multimed. Tools Appl.*, vol. 80, no. 7, pp. 10113–10139, 2021, doi: 10.1007/s11042-020-10114-1.

[26] T. A. Mostafa and I. Cheng, “Parkinson’s Disease Detection Using Ensemble Architecture from MR Images∗,” *Proc. - IEEE 20th Int. Conf. Bioinforma. Bioeng. BIBE 2020*, pp. 987–992, 2020, doi: 10.1109/BIBE50027.2020.00167.

[27] M. Husaini and B. Nadri, “Signal using Deep Learning Algorithm,” no. Icicv, pp. 1467–1470, 2021.

[28] Donahoe, “NIH Public Access,” *Mol. Cell. Biochem.*, vol. 23, no. 1, pp. 1–7, 2012, doi: 10.1162/jocn.2009.21407.Open.

[29] E. M. Alkabawi, A. R. Hilal, and O. A. Basir, “Computer-aided classification of multi-types of dementia via convolutional neural networks,” *2017 IEEE Int. Symp. Med. Meas. Appl. MeMeA 2017 - Proc.*, pp. 45–50, 2017, doi: 10.1109/MeMeA.2017.7985847.

[30] J. A. Akhila, C. Markose, and R. P. Aneesh, “Feature extraction and classification of Dementia with neural network,” *2017 Int. Conf. Intell. Comput. Instrum. Control Technol. ICICICT 2017*, vol. 2018-Janua, pp. 1446–1450, 2017, doi: 10.1109/ICICICT1.2017.8342782.

[31] A. Bidani and M. S. Gouider, “Dementia Detection and Classi fi cation from MRI Images Using Deep Neural Networks and Transfer Learning,” vol. 1, pp. 925–933, doi: 10.1007/978-3-030-20521-8.

[32] A. J. Astell *et al.*, “Technology and Dementia: The Future is Now,” *Dement. Geriatr. Cogn. Disord.*, vol. 47, no. 3, pp. 131–139, 2019, doi: 10.1159/000497800.

[33] H. Ucuzal, A. K. Arslan, and C. Colak, “Deep learning based-classification of dementia in magnetic resonance imaging scans,” *2019 Int. Conf. Artif. Intell. Data Process. Symp. IDAP 2019*, pp. 1–6, 2019, doi: 10.1109/IDAP.2019.8875961.

[34] S. Murugan, C. Venkatesan, M. G. Sumithra, S. Member, and X. Gao, “DEMNET : A Deep Learning Model for Early Diagnosis of Alzheimer Diseases and Dementia From MR Images,” *IEEE Access*, vol. 9, pp. 90319–90329, 2021, doi: 10.1109/ACCESS.2021.3090474.

[35] S. Basheer, S. Bhatia, and S. B. Sakri, “Computational Modeling of Dementia Prediction Using Deep Neural Network: Analysis on OASIS Dataset,” *IEEE Access*, vol. 9, pp. 42449–42462, 2021, doi: 10.1109/ACCESS.2021.3066213.

[36] P. Kim, “Convolution Neural Network,” no. Network. MATLAB Deep Learning, 2017, doi: 10.1007/978-1-4842-2845-6_6.

[37] S. Albawi, T. A. M. Mohammed, and S. Alzawi, “Layers of a Convolutional Neural Network,” *Icet2017*, pp. 1–6, 2017.

[38] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, “Rethinking the Inception Architecture for Computer Vision,” *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2016-December, pp. 2818–2826, 2016, doi: 10.1109/CVPR.2016.308.

[39] F. Chollet, “Xception: Deep learning with depthwise separable convolutions,” *Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017*, vol. 2017-January, pp. 1800–1807, 2017, doi: 10.1109/CVPR.2017.195.

[40] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2016-December, pp. 770–778, 2016, doi: 10.1109/CVPR.2016.90.

[41] T. Akiba, S. Suzuki, and K. Fukuda, “Extremely Large Minibatch SGD: Training ResNet-50 on ImageNet in 15 Minutes,” 2017, [Online]. Available: http://arxiv.org/abs/1711.04325.

[42] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” *3rd Int. Conf. Learn. Represent. ICLR 2015 - Conf. Track Proc.*, pp. 1–14, 2015