An Efficient Deep Learning Approach for Detecting Alzheimer's Disease Using Brain Images

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A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science

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Declaration

It is hereby declared that

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2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Ethics Statement

We hereby declare that, all aspects of this thesis, from the research through the implementation of the suggested system ,model and overall work is being done by us. Any ideas, inspirations, datasets and all other external resources we used have been acknowledged.

Abstract

Alzheimer's disease (AD) is a disorder of the brain which causes the loss of memory. This is a successively growing disease which means the severity of it will be upward with the time. In this century, AD is one of the major concerns in the medical arena. The objective of our work is to improve a system that will be able to detect the disease at an early stage. We used efficient deep learning for our project as nowadays, deep learning plays a vital role in every research field. We used MRI of brain for our project using which, our model can identify whether there is sign of Alzheimer's disease or not. Besides, our model is multiclass classification related which means it can work on different stages of AD. We used different architectures of Convolutional Neural Network (CNN) that are VGG-19, Inception V3 and ResNet-101 and the accuracy we attained from our models are 88.02%, 89.62% and 91.49% respectively which are pretty decent scores. Since it is an irreversible disorder, we can perceive the significance of detecting the disease at an early stage with good accuracy. Thus, we can state based on the performance of our models that these might play some important role to detect AD.

Keywords: Deep Learning, CNN, VGG-19, Resnet-101, Inception v3, MRI Image Classification, Detecting Alzheimer Disease

Dedication

This thesis is dedicated to our beloved parents and our respected supervisor Dr. Md. Ashraful Alam.

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Chapter 1

Introduction

1.1 Overview

Alzheimer's disease (AD) is a kind of disease which is immutable as well as progressive disorder of brain that annihilates memory gradually and thinking ability and eventually destroys the capacity to remember the simplest things. It can appear anytime unlike any other diseases. It has been observed that the symptoms of AD usually appears after mid-age of the people. In the twenty-first century, it has become one of the challenges in the health sector. AD not only does reduces the memory of a person but also can be the reason of death due to its severity at the final stage. Among the older persons, it has become the most common disorder nowadays [1]. In USA, AD is the sixth greatest reason behind death and new projections are suggesting that it may soon be ranked third, behind cancer and heart disease as a cause of mortality for individuals at their mid-age. The medical and economic field of USA got impacted heavily as they had to spend $277 billion including all expenses in 2018 to manage AD (Alzheimer's Association, 2018). So, the severity of this disease is perceptible. We know, the population of developing countries are usually higher in number. So, the number of elderly people are huge and the number of AD affected people are being upward that creates a problem for public health. AD progressively declines cognitional action which causes the damage of learning capacity and thinking of the brain. The action of AD is far different from normal age-related decline of cognitive function. Where normal cognitive disorder is gradual with mild disability, AD occurs severe damage and can be devastating. As, it often starts with mild symptoms, it is hard to anticipate anything about it and the consequence can be severe damage of the brain. The rate of losing ability occurs at several rates over time. As, it is a progressive disease, people gradually experience severe memory loss with other cognitive difficulties. There are several stages of AD according to the status of the disease. It can be mild, moderate and severe. The symptoms of mid-stage can include trouble in the transaction of money, continually asking about the same thing or wandering and getting lost with changes in personality and behavior. Moderately affected people can behave abnormally and can have hallucinations. The people who are severely affected with AD cannot communicate properly with the people around them and become dependent on the other people for their look after. These persons spend most of their times on the bed as their body shut down due to improper functioning of the brain at the end of their life. It is apparent how important it is to detect AD early with accuracy to manage this.

Neuroimaging like MRI, CT as well as PET and SPECT can be used to check out other cerebral pathology or dementia subtypes [6]. Medical image processing and machine learning help neurologists to examine the state of this disease whether it is developing or not. Segmentation and classification of images are significant in MRI data analysis to detect Alzheimer's disease. Unnecessary info can be removed using segmentation to establish significant objects from processed images. To classify and generate the important patterns from data in different groups depending on the characteristics based on the previously trained data, classification can play a vital role [3]. Novel learning methods have been introduced in recent years with the progression of Machine Learning (ML). As deep learning helps to understand the representation of data for computational models using multilevel perceptions and it is getting better results, it started attracting the researchers in the arena of ML. Classification performance using DNN achieved extraordinary outcomes relative to other orthodox models. DNN shows its impact by solving problems with its advancement that resisted AI society for the past few years [4]. It has a lot more advanced features that attract the researchers to use this. In this work, an efficient deep learning to detect Alzheimer's disease using brain images is proposed which will have great accuracy. It will analyze the images and the data in a way that will provide the best result to detect AD at the initial level which is basically the main purpose to achieve in our research.

1.2 Research Problems

Maintenance and management of Alzheimer's disease is not only strenuous but also expensive. As the patients who are affected by AD are mentally unrested and are subsequently reach to the verge of death, it became mandatory to research in this field and invent some efficient systems to face the challenges of AD. Gradually research on AD initiated. These advance researches are basically based on Machine Learning (ML) where the system is trained with previous collection of data and images. Analyzing these data and images, system can predict targeted disease. Here, the efficiency and accuracy is very important which is tough to achieve. As this research aims to use brain images to detect AD, it is necessary to train the system accordingly. Earlier researchers in this field have gained unprecedented results after the completion of their research but they had to face difficulties to implement their work. There has difference between normal brain images and affected brain images. Train the system with the affected images to make a correct prediction not only sounds daunting but also tough to implement genuinely. It will be required to implement such algorithm what will provide us our expected outcome. Deep learning will be used for this research which is a part of Machine Learning. It is a very common scenario that many patient is treated whose result is false positive. Despite having such developed system, frequently these unwanted incidents are occurred. As a test report determines the destiny of a patient and it is a matter of one's life, it is vital to develop a system with higher accuracy. Though already there have systems to do this job, getting more and more accuracy in regular basis is important and challenging as well. Adding extra functionality and advanced features is also a challenging task as it is uncertain to the researchers whether these will work or not. The problems are immense but the target of this research is to overcome the difficulties and solving the problems as well as gathering knowledge on unknown things and clear the confusion throughout the gradual implementation of this project.

1.3 Research Objectives

This research aims to develop a system which will detect Alzheimer's disease efficiently with the best accuracy at the early stage. As we know how lethal AD can be if it cannot be detected early. Researchers are working on developing such system and already a good number of efficient system have been introduced which can detect AD with a commendable accuracy but this field needs more accurate system which will provide utmost accuracy. The damage of this disease is irreversible but early detection and treatment can reduce the percentage of damage as well as the death rate. Since only early detection does not work without higher accuracy, being more accurate is important for a system is important. The objectives of this research are:

- To know about Alzheimer's disease
- To acquire knowledge on the characteristics and impact of this disease
- To know about the existing researches and detection systems
- To develop a model that will be more efficient than previous systems
- To get better result from our system
- To evaluate the model
- To offer recommendations on improving the model

Chapter 2

Literature Review

As we already know how important it is to detect AD at the early stage with better accuracy due to its fatality, deep learning, which is an integrated and advance form of ML has already proven its capability in research field which will be used here as well for better outcome of this work. An efficient deep neural network will be used for this research.

2.1 Deep Neural Network (DNN)

Deep neural network is a neural network with some level of complexity, usually at least two layers. We know human brain consists of billions of neurons which take input and make a decision for a particular problem. Similarly DNN is a connection of innumerable layers that take input and make a decision which is considered almost as efficient as the decision of human brain.

2.2 DNN Architecture

The architecture of DNN is as complicated as brain. Every connection point is considered as nodes and these are part of the system which are like neurons of human brain. These nodes are interconnected like spider web. These complicated connections help to take the best decision for a system. These interconnected structures work so fine that replace human labor with autonomous work without compromising efficiency.

2.3 Convolutional Neural Network (CNN)

We know human brains consist of innumerable number of neurons. All of these are connected to each other. It is quite complicated formation. The main duty of neurons is to carry information throughout human body. Information is carried out through neurons inside human body and it travels from one layer of neurons to another and after a certain time, decision comes from human brain. During nineteen eighty, Convolutional Neural Network (CNN) was introduced following the working principle of human brain [17]. It is most popularly used to analyze images so far. We can consider CNN as an extended part of ANN that has some specialized features for being capable of detecting patterns as well as having sense of them.

As a result, this type of pattern detection capability makes CNN more usable for analyzing images. The hidden layers of CNN are called the convolutional layers and CNN became effective due to the precision of these layers. Though the base thing of CNN is convolutional layers, it can also have non-convolutional layers. What is the actual task of convolution layers? Just like the other layers, these layers take input and provide output to the subsequent layer by transforming the input in some way. This transformation layer with a convolutional layer is a convolution operation.

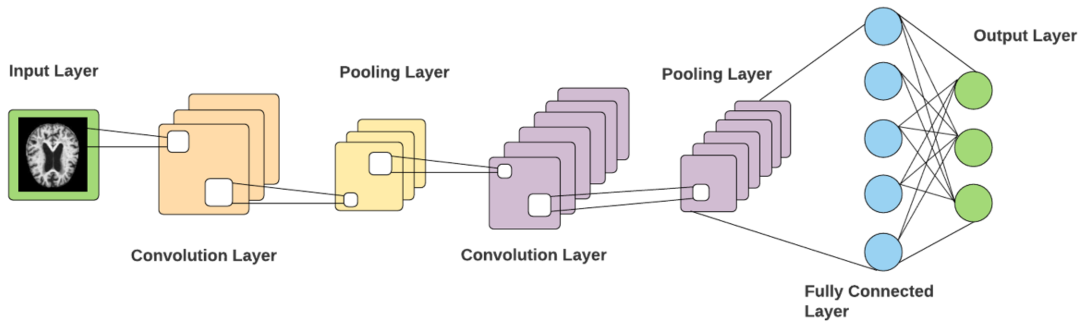

Figure 2.1: Architecture of CNN

We have already mentioned that CNN is a kind of design that can take almost human like decisions. A system properly trained with CNN algorithm can efficiently make a decision as like as human brain and to some extent, it can be more effective than human brain as humans sometime make mistakes. CNN is used not only for image data but also for other types of data. As our work is image based, we are mainly using image data. CNN basically has 3 layers which are (I) Convolutional layer, (II) Pooling layer and (III) Fully connected layer. The interesting thing about CNN is when it takes images as an input, it reduces the pixel size and quality of images but it takes the main features of images for which image data do not get affected. Besides, it reduces the time complexity and cost of a system. A filter with a determined size of n x n is applied to the image expressed as pixel matrices. Similarly, pooling layer provides ease of computation. Fully connected layer enhances accuracy by classifying images. If CNN did not have these functions, weak operating systems might get affected and to some extent systems could have crashed often.

2.4 Related Works

Islam & Zhang, 2017
We found that in their research paper, they have implemented a new deep learning model for AD detection and identification of different stages using brain MRI. They have used OASIS dataset for their research and there are four different data classification in the dataset. After being preprocessed, input is routed through a stem layer. The penultimate softmax layer for detecting and classifying Alzheimer's disease has been updated. They employed cross-entropy to calculate the suggested network's loss. Their solution is quicker, requires no created features, and can handle a small dataset of medical images. Finally, they have achieved 73.75% accuracy

in their research paper. [7]

Islam & Zhang, 2018
The effects of Alzheimer's disease on the brain follow a conventional pattern of earlier medial temporal lobe alterations, then there's neocortical injury, which gets worse with time. Years before the signs of Alzheimer's starts to emerge, such alterations take place. These gradual alterations in the brain related to AD may be measured using structural MRI . The goal of this study was to apply a deep learning model to analyze sMRI data in order to diagnose Alzheimer's disease with great accuracy. Machine learning models were used to develop diagnostic tools based on neuroimaging data. Deep CNN was utilized, which learns features from the structural MRI input. They used the OASIS database with only 416 structural MRI data to train their model but still give better accuracy for AD diagnosis which is 93.18 per cent with 94 percent precision. They convert the 3D image data to 2D by creating patches from 3 physical planes of imaging. While most research studies concentrated on binary classification, their proposed model provides great improvement for multi-class classification. [9]

Acharya et al., 2019
First of all, they have developed a CABD system in this research that can detect whether a brain scan reveals indications of AD based on MRI images. Then, for reducing noise in the MRI scans, they have used a filter that has improved the image quality. A feature extraction approach was being used to collect the key characteristics from the MRI images. To find the top features from each category's extracted features, they approach with a range of standard algorithms in their paper. The CABD system's ability to examine data is mostly determined by the classifier system's quality. They have also used the KNN model to find the classification of the MRI images to detect AD in this study. Finally, they have suggested ST+KNN methodology in their CABD system which gives accuracy, specificity, sensitivity and precision of 94.54%, 93.64%, 96.30% and 88.33% respectively. The results showed that the ST + KNN strategy outperforms other methods. However, by substituting different classifiers for the KNN, the system's performance can be enhanced.[11]

Jo et al., 2019
They conducted a systematic review of DL algorithms for the diagnostic classification of AD based on neuroimaging data in this research. Structural and functional biomarkers for Alzheimer's disease have been identified using multimodal neuroimaging data. To identify characteristics from neuroimaging data, deep learning algorithms were applied here. They have found the standard approach of ML with SAE achieved 98.8% accuracy to the classification of AD. Moreover, they have achieved accuracy rates of up to 96.0% for AD classification using CNN. Additionally, the MCI prediction without pre-processing the data was 84.2%. Here, the fluid biomarkers and various neuroimaging were combined to provide the best classification results. Deep learning methods are getting better, and they look to hold promise for diagnosing Alzheimer's disease using multimodal neuroimaging data. Furthermore, they have mentioned that comprehensive neuroimaging data become more accessible so research on detecting the categorization of AD using DL algorithms is turning away from hybrid methods.[14]

Lee et al., 2019
They integrated baseline cross-sectional neuroimaging biomarkers with ADNI longitudinal CSF and cognitive performance biomarkers. This framework is incorporating with longitudinal multi-domain data. We used four types of data: demographics, MRI-evaluated neuroimaging phenotypes, cognitive function, and CSF measurements. Item response theory is used to calculate the ADNI - MEM (memory) and ADNI - EF (executive functioning) composite scores from the ADNI neuropsychological battery. For Alzheimer's disease A1–42 peptide, CSF markers include total tau and tau phosphorylated at threonine 181. Two neuroimaging markers for Alzheimer's disease that are assessed using MRI are hippocampal volume and entorhinal cortical thickness.[15]

Chitradevi & Prabha, 2020
The results of this paper indicate that GWO can segment brain sub regions with a high degree of accuracy, with 98 percent similarity between the ground truth and segmented areas. The segmented areas are then categorized using a deep learning classifier, with a high accuracy of 95% as a result. Because the real-time photos are of poor quality, the proposed work has been pre-processed. Then, to boost the contrast of an image, histogram equalization is utilized, and Otsu's thresh holding techniques are applied for skull stripping. Segmentation of brain sub regions is a tough undertaking due to its anatomical alterations. To assess the performance of the segmentation technique, the segmented regions are checked with ground truth images after segmentation. Chettinad Health City provides ground truth photos based on the advise and consent of doctors. Deep learning classifier, a novel machine learning technology, was utilized to identify normal and AD photos for optimization strategies. The recommended research is able to examine the structural alterations in all the aforementioned regions employing four separate optimization algorithms and a deep learning classifier to identify normal and AD.[16]

Puente-Castro et al., 2020
The goal of this research was to detect Alzheimer's disease automatically by using sagittal MRI images and deep learning techniques. The study is done by using Transfer Learning (TL) techniques. . It has been found that, firstly, in sagittal magnetic resonance imaging, the harm is done by Alzheimer's disease and its phases can be distinguished. Second, and most importantly, the outcomes of sagittal Magnetic resonance imaging Deep Learning models are comparable to the existing modern Magnetic resonance imaging(MRI) horizontal plane. They get the maximum detection of 91.5% accuracy.[18]

Salehi et al., 2020
We have found that they have implemented various DL algorithms for identifying AD. They evaluate the accuracy of several approaches and discovered that by utilizing a deep convolutional neural network learning approach on MRI and fMRI datasets, we may attain greater accuracy. They effectively obtained the AD data

from normal control with an accuracy of 96.86% by utilizing ADNI data and NC data using CNN and LeNet5 on fMRI data. Moreover, they indicate that applying advanced deep learning techniques in separate datasets (ADNI, OASIS) and integrating them into one by applying machine learning SVM algorithms for identifying AD patients from MRI can improve AD prediction at an earlier stage. They outperformed on two proven data sets utilizing binary classification, with 100% accuracy from the ADNI dataset and 97% accuracy from the OASIS dataset. They concluded that in future research, advanced deep learning algorithms can be applied to several datasets and combined into a single dataset to improve the efficiency and efficacy of AD prediction at an earlier stage. [19]

YİĞİT & IŞIK, 2020
In this research paper as a nonsurgical way for identifying Alzheimer's disease and dementia neuroimaging biomarkers was being used. As input for the AD detection model, sMRI images were being used. Via, for 3 alternative projections, they used a variety of preprocessing methods, magnetic resonance brain images with T1 weighted volumetric were reduced to 2D space. To increase MRI samples, researchers combined the OASIS and MIRIAD sets of data. They achieved maximum detection accuracy of 82 %. The suggested model does not need the use of any additional feature extraction or feature selection processes on the brain MRI. After constructing an optimal CNN model and defining its parameters, the model may be applied to new patient data without the need for human interactions.[20]

Kadhim et al., 2021
This article's main goal was to offer research on all new MRI approaches for Alzheimer's diagnostic studies from 2017 to 2020 in a comparative comparison. The demonstrated the necessity of detection of Alzheimer disease accurately by the implementation of DL. Necessity of identifying diagnosis for MRI pictures had been presented and described in this publication, followed by an introduction to Alzheimer's disease. Different sorts of procedures and explanations of the many 8 categories of Alzheimer's disease were also successfully detailed. Additionally, they also stated detection of AD depends on the extraction algorithm which being implemented..[22]

Chapter 3

Methodology

3.1 Work Flow

Firstly, we have collected dataset for our project. We pre-processed our data for the betterment of our project. Then, we augmented our data and later over-sampled these. Then the data have been split. After that, we selected models for our project. We trained and tested our models and finally evaluated these.

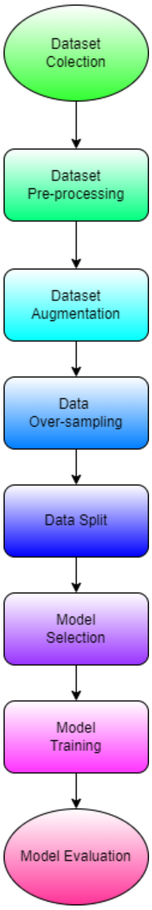

Figure 3.1: Work Flow Diagram

3.2 Description of Model

For our project, we decided to use Convolutional Neural Network (CNN). As the project we are working is brain image based, so CNN seemed to us suitable as it is used to analyze visual imagery. Nowadays, CNN is vastly accepted to work in image processing due to its efficient and friendly usability. There are different architecture of CNN among which we chose ResNet-101, VGG-19 and Inception V3 for our project.

3.3 ResNet-101

ResNet stands for residual network which was introduced in 2015 and it was so effectual that won first position in the ILSVRC visual recognition challenge [5]. What we generally do before solving a complicated problem is stack extra layers in DNN (Deep Neural Network) and think the result produced from it is improved and accurate with better performance which is to some extent a misconception. It has been noticed that fewer layers sometimes can show better performance than unnecessary extra layers [21]. ResNet which is actually residual network lessened the problem of training deep networks that reduced training time. It has residual blocks.

The interesting here is, a direct connection that can skip needless layers which can

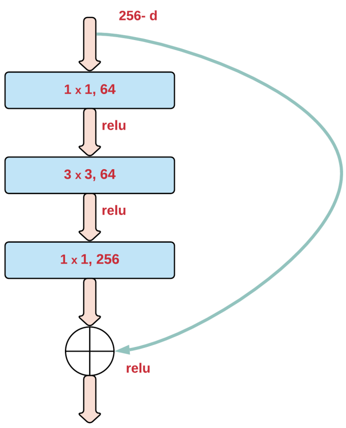

Figure 3.2: Residual learning: a building block

differ in various models according to the necessity. A stack of 3 layers is used for each residual function. 1x1, 3x3 and 1x1 convolutions are the 3 layers. ResNet-101 has depth of 101 layers.

$$[(Conv1)1*1+(Conv2_x)1*1+3*3+(Conv3_x)3*4+(Conv4_x)3*23+(Conv5_x)3*3] = 101 \tag{3.1}$$

It works as a feature extractor. RGB image is converted to a feature map from bottom layer and it is then provided to the next layer, and so on until the process is complete..

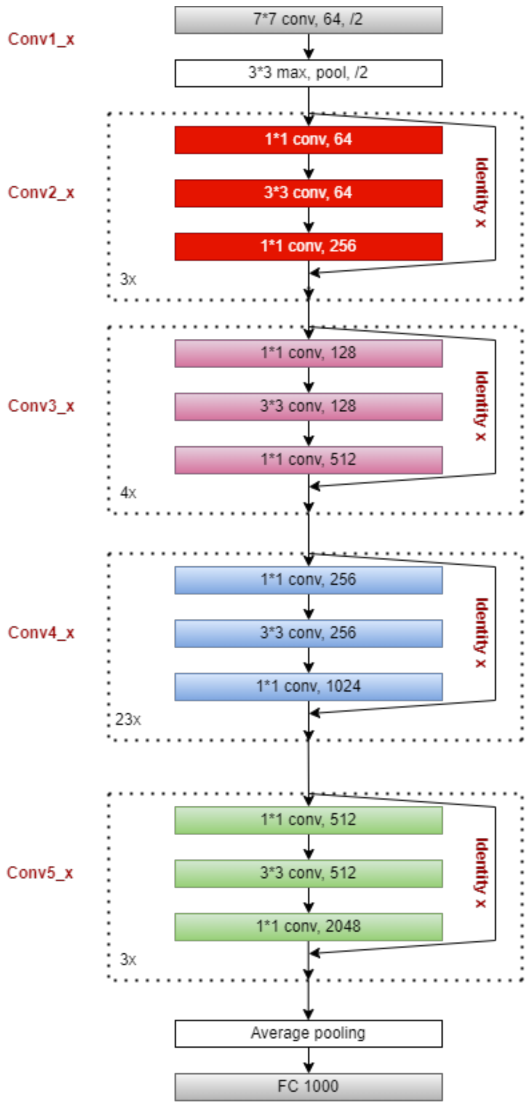

Figure 3.3: Architecture of ResNet-101

3.4 VGG-19

Before we can learn about VGG-19, we must first learn about VGGNet which is a pre-trained CNN model. [2]. VGG Net has learnt to extract characteristics (feature extractor) that can identify items and is being utilized to categorize things that aren't visible. The purpose of VGG was to increase the depth of the CNNs in order to enhance classification accuracy. For object recognition, VGG-16 has 16 layers and VGG-19 has 19 layers. The model achieves 92.7% top-five test accuracy using ImageNet, a dataset of over fourteen million photos belonging to thousand classes. The model that was submitted to the ILSVRC-2014 was a well-known one [8]. But although VGG-16 only has 16 layers, that is why VGG-19 is more efficient.

We know that VGG-19 is a 19 layers CNN model. The network can classify photographs into thousand distinct categories which includes objects such as mouse, pencils, keyboards, and a wide range of animals [24]. Thus, for a range of photos, the network has learned a number of rich feature representations. The network's images input size in term of pixels is 176×176. [10].

This model was given a fixed size (224 * 224) as input where the shape of matrix (224,224,3). For a range of photos, the network has learned a number of rich feature representations. It used kernels with the size of 1 pixel and a size of 3 * 3 to cover the complete visual concept. To keep the image's spatial resolution, spatial padding was used.[26].

Because it uses an alternating structure of several convolutional layers and non-linear activation layers, VGG-19 outperforms a single convolutional layer. However, downsampling using Maxpooling, feature extraction from image, and ReLU as the activation function, which picks the largest value in the image region as the pooled value of the area, were all improved by the layer structure. The down-sampling layer's expression is. Among them,

$$\left(X_j^{(n-1)}\right)$$

is the maximum pooling sampling function, τ_j^n is the coefficient corresponding to the j-th feature map of the n-th layer, and

$\left(\tau_j^n \text{ down} \left(X_j^{(n-1)}\right) + b_j^{(n)}\right)$ is the ReLU activation function.

$X_{pj}^{(n)} = \text{f} \left(\tau_j^n \text{ down } \left(X_j^{(n-1)}\right) + b_j^{(n)}\right)$ [7] Although we customize and train the VGG-19 model. The remaining three layers of the VGG 19 deep transfer learning architecture are tweaked to conform to our issue domain and perform proper multiclass classification into the Alzheimer, healthy control ADNI, Parkinson, and healthy control PPMI classes.

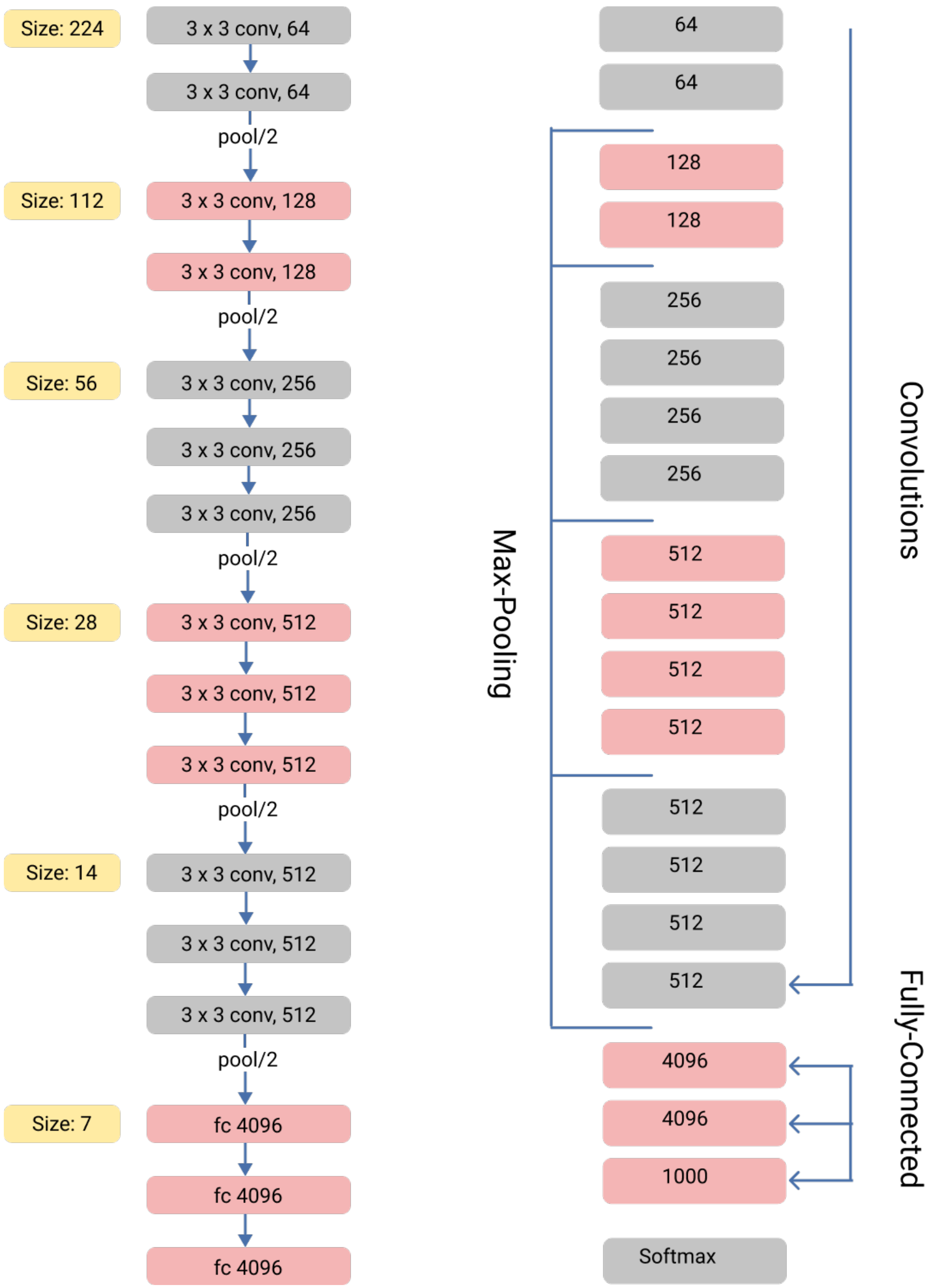

Figure 3.4: Architecture of VGG-19

3.5 Inception v3

Inception v3 is a CNN model that was created as a GoogLeNet plugin to help in object detection and image processing. The model is the result of years of work by a variety of researchers. It has settings that are a twelfth of what AlexNet has. It's a larger, more computer-friendly network. At the conclusion of the convolution layer, it replaced the fully connected layers with a basic average global pooling, in which the channel values are averaged over the 2D feature map whenever the end of the convolution layer is reached. Convolutions, average pooling, max pooling, concatinations, dropouts, and fully linked layers are only some of the symmetric and asymmetric building pieces that make up the model. The activation inputs are subjected to batch normalization, which is employed frequently throughout the model. Loss is calculated using Softmax[25].

At the very least, photographs must be decrypted and resized to fit the model. Photos for Inception must be 299x299x3 pixels in size.
TPU training sessions of Inception v3 has matched the accuracy curves that is generated by GPU workloads of equivalent configuration. In around 170 epochs, the model has achieved a 78.1% accuracy. During training, image preprocessing is a crucial component of the system that can have a significant impact on the model's maximum accuracy. However, achieving good accuracy requires more than simply decoding and scaling. An epoch is a single trip through the collection of training images. To improve its photo identification abilities, the model requires several passes over the training dataset during training [25]. SGD, momentum, and RMSProp are three types of optimizers in the current inception model. The simplest update is SGD. The weights are shifted in the direction of the negative gradient. Despite its simplicity, several models may nonetheless provide good results. The update dynamics may be described as follows: $w_{k+1} = w_k - \alpha \nabla f\left(w_k\right)$
Momentum is a standard optimizer that produces faster convergence than SGD. This optimizer modifies weights in the same way as SGD does, but it also adds a component that moves in the opposite direction of the previous update. The momentum optimizer's updates are specified by the following equations

$$\begin{aligned} z_{k+1} &= \beta z_k + \nabla f\left(w_k\right) \\ w_{k+1} &= w_k - \alpha z_{k+1} \end{aligned} \tag{3.2}$$

The component in the direction of the previous update is the last term.

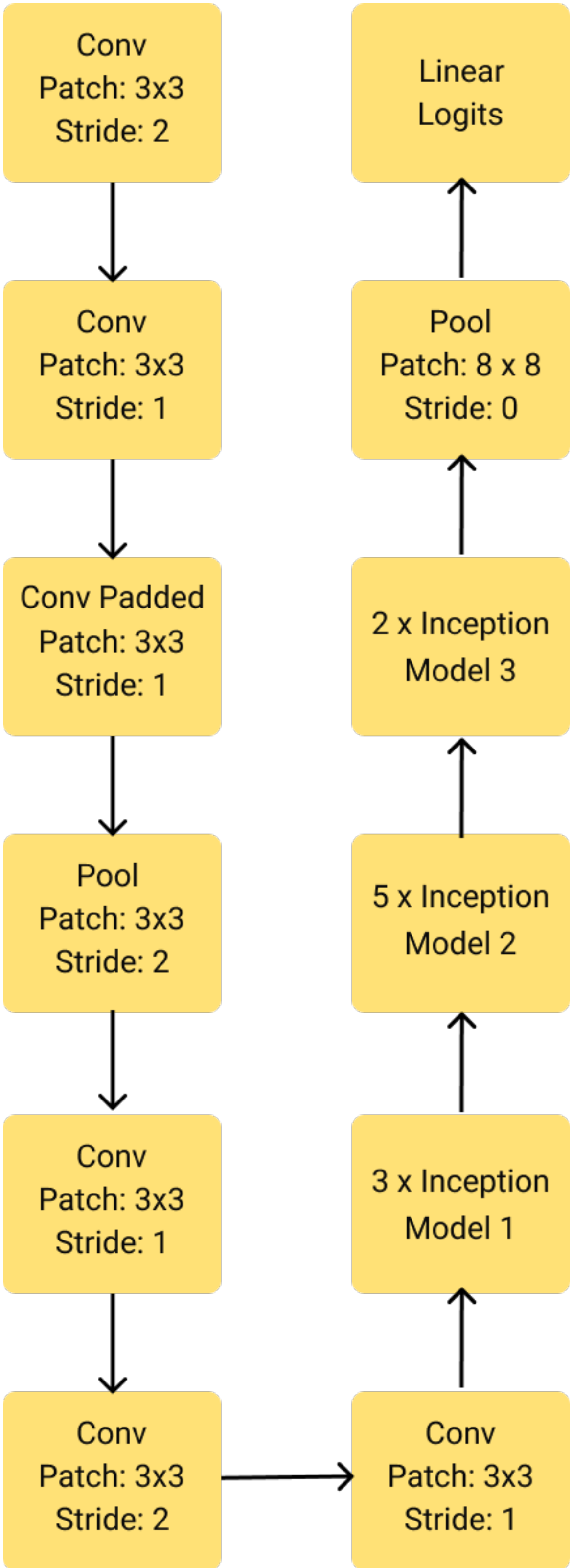

Figure 3.5: Architecture of Inception v3

We choose a value of 0.9 for the momentum. We know, RMSprop is a standard optimizer. Here:

$$\begin{aligned} g_{k+1}^{-2} &= \alpha g_k^{-2} + (1-\alpha) g_k^2 \\ w_{k+1} &= \beta w_k + \frac{\eta}{\sqrt{g_{k+1}^{-2} + \varepsilon}} \nabla f\left(w_k\right) \end{aligned} \tag{3.3}$$

Inception v3 testing has shown that RMSprop is the default optimizer and RMSProp gives the best performance to get the highest accuracy. The Inception v3 network differs from other deep neural networks in that it has parallel stacked convolutional layers. From top to bottom the neural network layers in the table are connected in the order they appear in the table. [12].

Chapter 4

Dataset Preparation

We intend to collect the datasets of MRI images for detecting Alzheimer disease at early stages and classify them into four different categories. Initially, we have started collecting the datasets from random websites. But, finding better datasets like MRI images, are difficult and the datasets must be sophisticated in order to accurately detect the early stages of Alzheimer disease. There are many datasets including OASIS and ADNI, are available on the internet. So, we have explored those resources to find reliable datasets of MRI images. Since we have wanted to detect Alzheimer's disease, the dataset of MRI images has to be highly accurate and validated by medical associations. After researching on those datasets, we found a standard dataset named "Dataset_Alzheimer" which is perfectly matched for our research purposes because it has four different image classifications [13]. As a result, we decided to use this dataset for our research.

4.1 Dataset Description

After fixing the datasets, we have downloaded the dataset from Kaggle. Then, we extract the dataset from the "Dataset_Alzheimer.zip" file and we found 6400 files of MRI scanned images. There are two folders in the datasets named "test" and "train". The dataset contains four different classifications of images such as mild demented, moderate demented, non-demented, very mid demented.

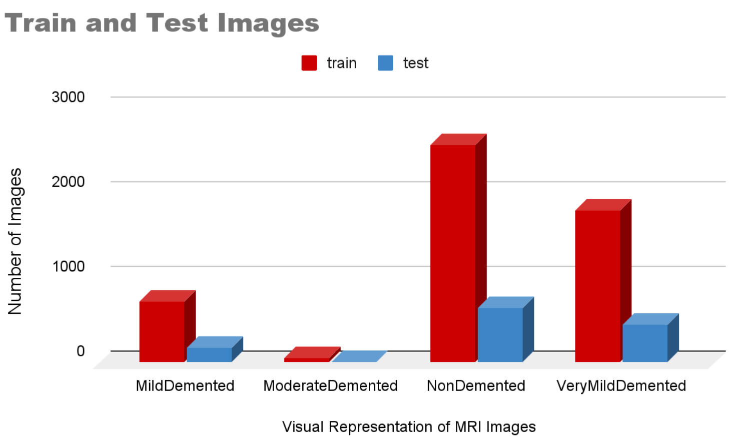

Figure 4.1: Train and Test Images

4.2 Data Preprocessing

Before preprocessing the dataset, we have ensured that all images have different unique ids. Secondly, all the images have been resized into (176x176) pixels. Moreover, we moved all images from train and test datasets in one single folder keeping their class identity. Then, we format the dataset by rescaling all images by 1./255 size.

4.3 Data Augmentation

By creating new instances to train datasets, data augmentation helps enhance the performance and results of machine learning models [23]. We process the dataset using the augmentation techniques such as rotation, flip and zoom. Firstly, we horizontally rotated and fliped all the datasets. Secondly, we have increased the zoom range from 0.99 lower limits to 1.01 upper limits and increased the brightness range from 0.8 lower limits to 1.2 upper limits. Furthermore, there were imbalanced data sizes in the classifications since the numbers of images are not equal in the dataset. So, to reduce the imbalances, we have done oversampling the dataset. As a result, we can double the 6400 images to 12800 images by oversampling and getting a new RGB dataset. Then, the whole dataset was split into train dataset and test dataset in 80:20 ratio.

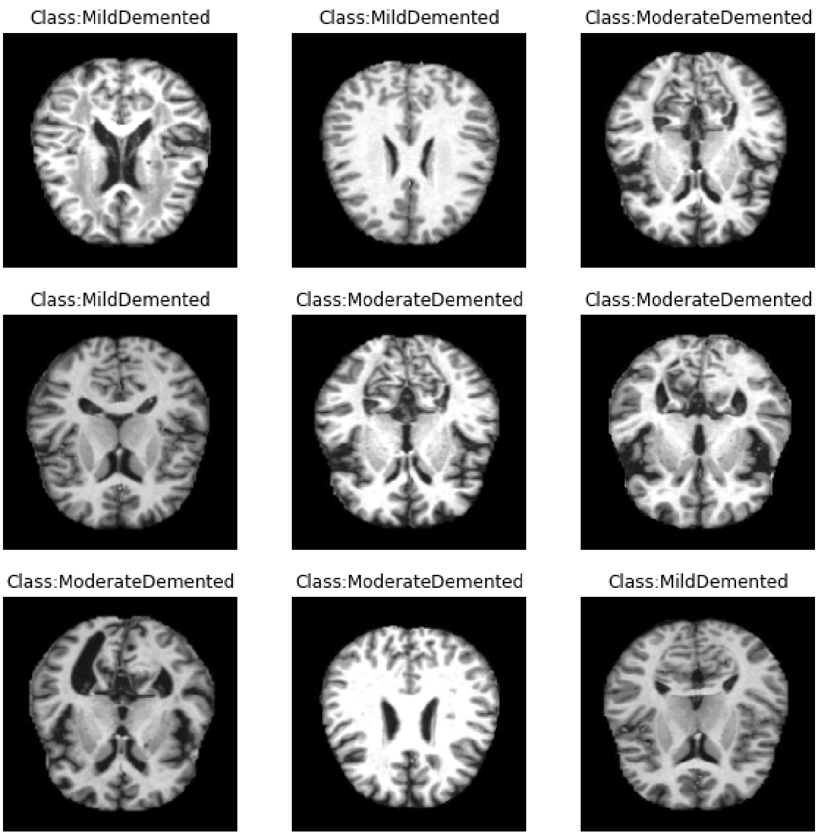

Figure 4.2: Augamentation of images

Chapter 5

Implementation

5.1 Set-up for the project

We used Google Colab Pro online platform for our project. Google Colab Pro provides Intel (R) Xeon (R) CPU and clock speed of 2.20 GHz with 24 GB ram and a GPU with 16 GB memory named "Tesla-P100". This is the brief idea about the platform that we used for our project. We have basically used 3 architectures of CNN that are Inception V3, ResNet-101 and VGG-19.

5.2 Inception v3

For Inception v3, we used to import the library of it using keras of tensorflow. After that we provided the image size . And we used imagenet as pre-trained weight. We froze the layers not to train as we do not need to train these. We created a customized model of the Inception v3. Inception V3 extracts the features and the added fully connected layers classifies the extracted features into categories. It has a data dropout of 0.5 and a 2D global average pooling. The data has been flattened and from here fully connected layer forms. Batch normalization and dense network of 512 units were there and activation function was ReLu for each unit of dense network. We needed softmax activation function for the last layer for classification. As we had four classes (mild-demented, moderate-demented, non-demented, very mild-demented) in our dataset, we needed a dense layer of four unit for this and the activation function was softmax. We kept the batch size 16. We used adam as optimizer and used variable learning rate which was initially 0.002 which got reduced by half depending upon the loss.

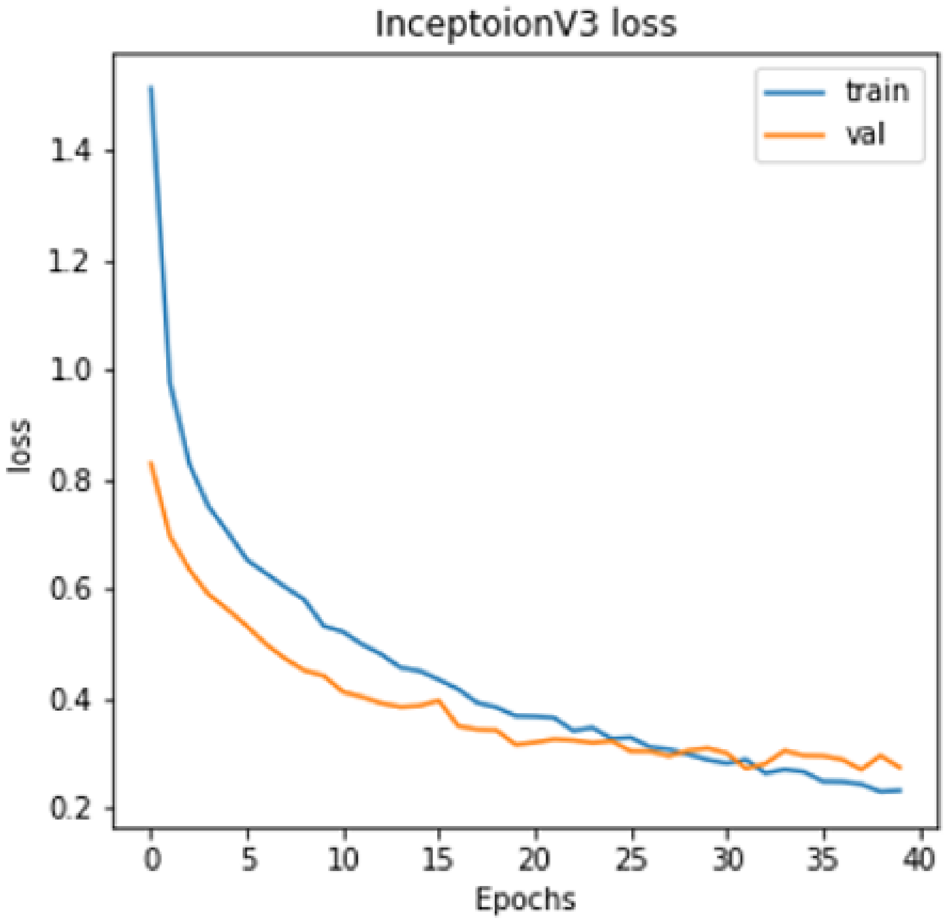

Figure 5.1: Training and Validation loss of Inception v3

5.3 VGG-19

We imported the library of VGG-19 from Keras of TensorFlow. We created a customized model of VGG-19. We used a flattened layer besides the base network for VGG-19. We used fully connected layers consisting of four dense layers of 512, 128, 64, 4 and the activation function was ReLu for the first three and for the last layer it was softmax. The other things were mostly similar like before.

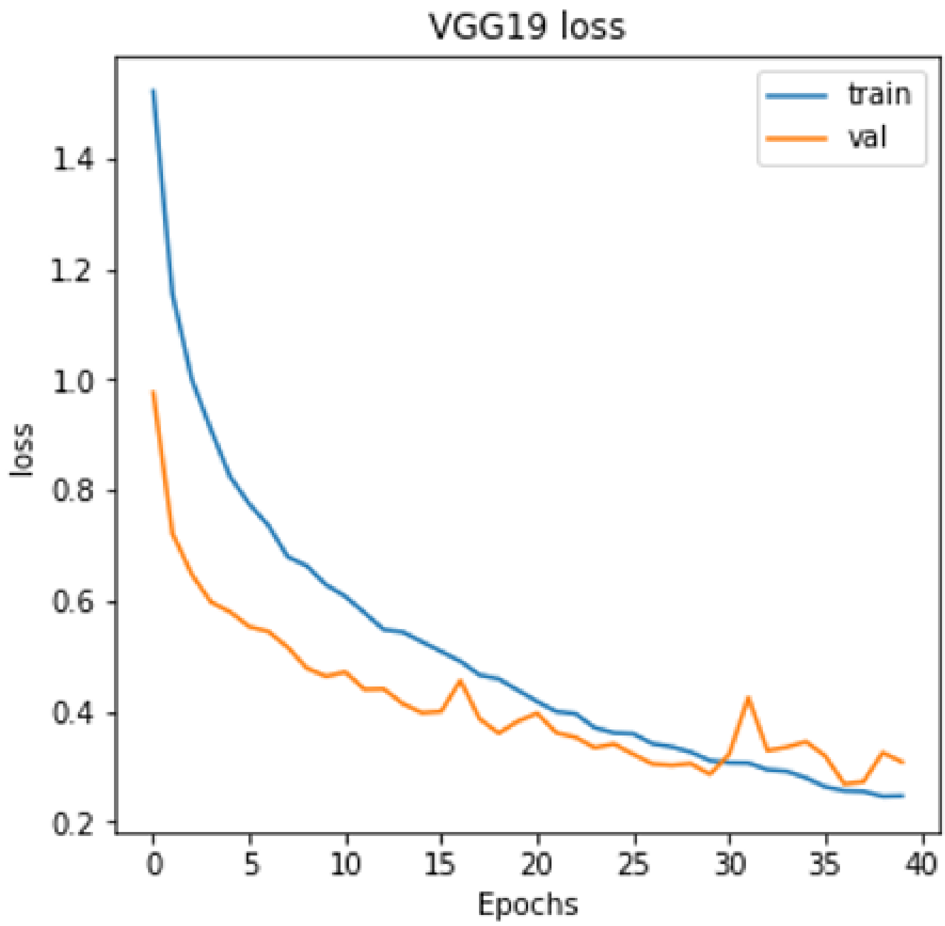

Figure 5.2: Training and Validation loss of VGG-19

5.4 ResNet-101

We followed almost the same procedure to implement the ResNet-101 architecture as well. We imported the library of ResNet-101 from Keras of TensorFlow. We created a customized model of ResNet-101. We used fully connected layers consisting of four dense layers of 512, 128, 32, 4 and the activation function was ReLu for the first three and for the last layer it was softmax. The optimizer and loss function was like inception.

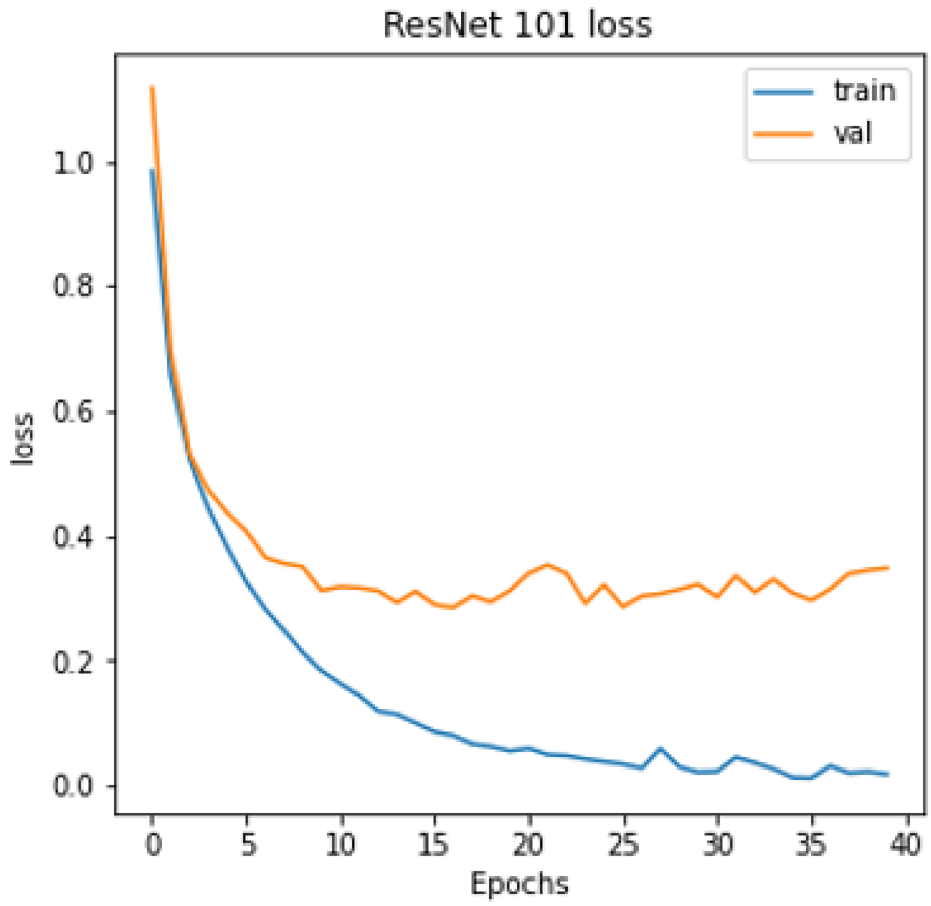

Figure 5.3: Training and Validation loss of ResNet-101

Chapter 6

Result Analysis

We have total 12800 images after doubling the size of the dataset where the images are MRI scan of the brain. Our project is basically multiclass classification based, it would not be fair to judge this project only with accuracy rather it should be judged upon several other parameters. The prime focus is classification performance and we are assessing this model on the classification metrics.
Accuracy: The degree that determines the efficiency of a model is the accuracy. When we provide the test data to the model, it can be truly positive or truly negative among the number of samples. The formula of checking accuracy is,

$$\text{Accuracy} = \frac{(\text{True Positive+True Negative})}{(\text{True positive+False positive+True negative+False negative})} \tag{6.1}$$

The final accuracy we got from our model is 91.49%. There exists imbalance of classes in the dataset. So, this model should not be judged only with accuracy.

6.1 Categorical Accuracy, Precision, Specificity, F1 Score

True positive- when the model accurately identifies the positive class is true positive.

True Negative- when the model accurately identifies the negative class is true negative.

False positive- incorrect identification of positive outcomes by a model.

False negative- incorrect identification of a negative outcomes by a model.

Loss Function-the evaluation of how perfect our algorithms models our data. It will be depending upon the prediction of the models. If predictions are lower, loss function will give a higher number and give lower number for higher predictions.

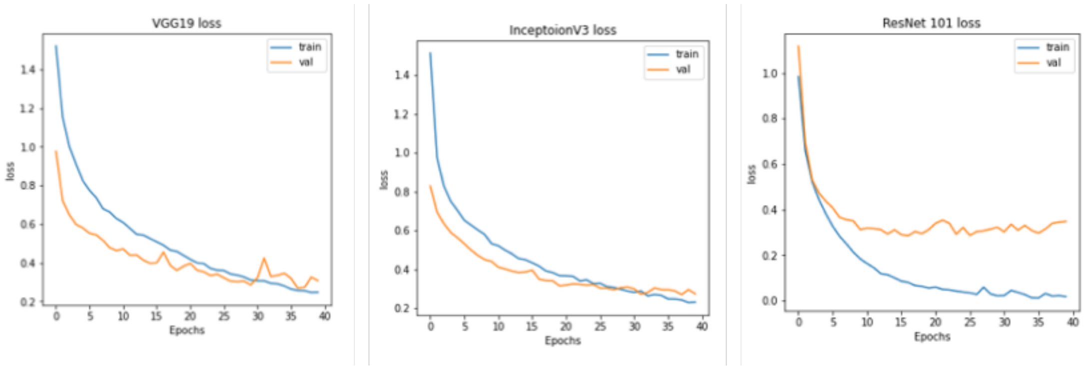

Figure 6.1: Loss Function

Categorical accuracy- determines how often a system make a perfect prediction. If the value is 1, that means the predictions are perfect. The formula for categorical accuracy:

$$\text{Categorical accuracy} \;=\; \frac{\text{(Number of correct predictions)}}{\text{(Total number of predictions)}} \tag{6.2}$$

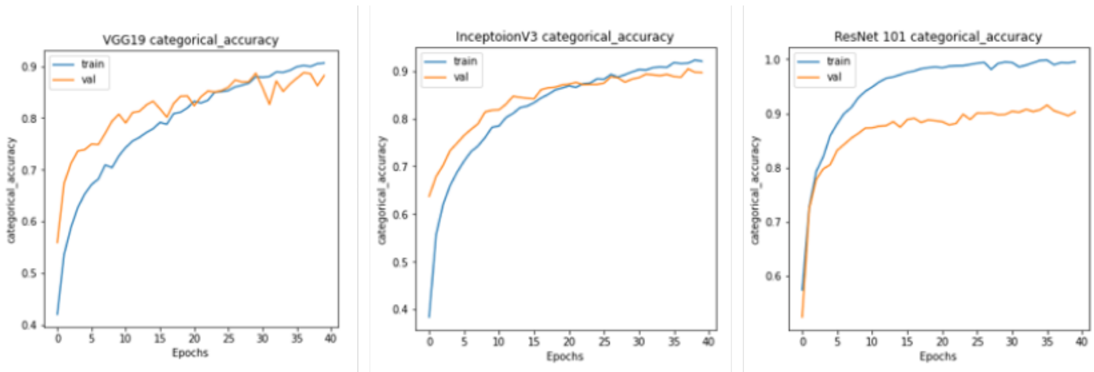

Figure 6.2: Categorical Accuracy

Precision- among all the positive instances, it ensures to find the percentage of actual positive samples. The formula of precision:

$$\text{Precision} \;=\; \frac{\text{(True Positive)}}{\text{(True positive+ False positive)}} \tag{6.3}$$

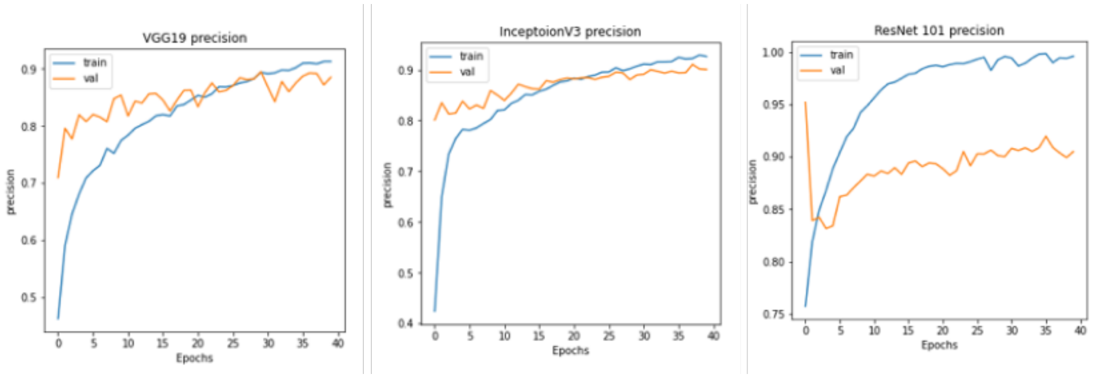

Figure 6.3: Precision

Recall/Sensitivity- how correctly the model identifies true positive is recall. The formula of recall:

$$\text{Recall} \ = \frac{(\text{ True Positive })}{(\text{ True positive } + \text{ False negative })} \tag{6.4}$$

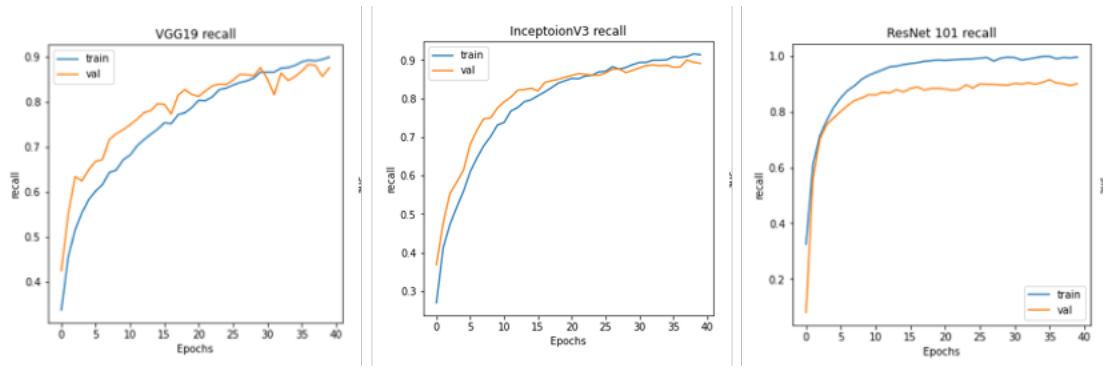

Figure 6.4: Recall/Sensitivity

Specificity- among the prediction of negative, how many of them are actual negative is the specificity. The formula of specificity:

$$\text{Specificity} \ = \frac{(\text{ True Negative })}{(\text{ True negative } + \text{ False positive })} \tag{6.5}$$

F1 score- it ensures symmetry between precision and recall. This is the weighted average of recall and precision. Formula of F1 score:

$$\text{F1 score} \ = \frac{(2 * \text{ Precision } * \text{ Recall })}{(\text{ Precision } + \text{ Recall })} \tag{6.6}$$

AUC - The full form of AUC is area under the curve that measures the performing ability of classification model. It assists to perceive the efficiency of a model to distinguish the classes. The efficiency will be higher if the model performs better otherwise the scenario will be the reverse. In our case, we could bring out decent results. The curves for our models are:

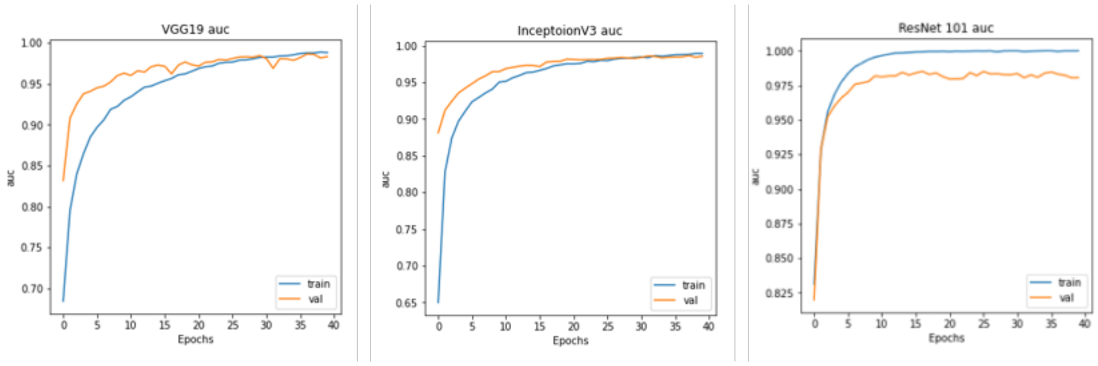

Figure 6.5: AUC Curves

6.2 Accuracy scores

	Loss	Categorical accuracy	Precision	Recall	AUC score	Specificity	F1 score
VGG-19	0.3083	0.8821	0.8854	0.8753	0.9833	0.9988	0.8802
Inception V3	0.2731	0.8962	0.9006	0.8912	0.9856	0.9985	0.8962
ResNet-101	0.2972	0.9153	0.9195	0.9144	0.9847	0.9973	0.9149

Figure 6.6: Category based accuracy score

6.3 Comparison among the Models

We have used three models for our research that are VGG-19, Inception V3 and ResNet-101. We can acknowledge from the result we got that, we moderately attained a good result. Though we declared our project should not be judged only with accuracy, nevertheless, if it is judged based on accuracy, it can be asserted the model performed well. The accuracy we got from ResNet-101 is 91.49%. We could achieve 89.62% accuracy using Inception V3 which can be considered as an excellent outcome. Also we got 88.02% accuracy from VGG-19 model. Among all these three models, we can observe that ResNet-101 produces the best accuracy. Other than that, the result we are getting from Inception V3 is closure to the accuracy of ResNet-101. The result we are getting from VGG-19 is relatively lower than the other models. We could have achieved better results if we found more relevant data related to our research but the data we found did not seem relevant to our research. So, observing all the parameters we can come to the decision that ResNet-101 is the best model for our research.

Chapter 7

Conclusion and Future Works

7.1 Conclusion

Alzheimer's disease is one of those kinds which are usually asymptomatic. Most of the times, nobody can anticipate about a patient affected by AD. Subsequently, when the patient gets affected severely, people understand it from his abnormal behavior that something happened that causes the patient making unusual behavior. Initial stage of AD is not much harmful. Though the symptoms are very mild at the beginning, if anybody is suspected should be sent for diagnosis. The early detection will not favor the patient, but will surely help to mitigate the rate of damage.
Likewise, the detection system should be efficient to predict the disease from its symptoms with good accuracy. AD generally occurs after a certain age. Most of the people affected by AD are middle-aged. However, it is understandable that detection with the highest accuracy can benefit the patients as well as the physicians to provide better treatment that can save life and resist wastage of money and suffering of the people around the patients. Using deep learning to build such detection system can be effective what we can assert to conclude and we practically got to understand by implementing such things in our research.

7.2 Future Work

We are eager to involve ourselves for further improvement in this field in future. If we actually get the opportunity, we will first try to develop our models that will be more advance than the current ones. We will try to collect some reliable and relevant data that will help us make a very fruitful system. In this project, we have used MRI of the brain as our data, but hereafter we might use other type of image data for the development purpose. Then, we will have the enthusiasm to make our project the best amongst the existing systems around the world. We will not only confine ourselves in this (AD related) field but also try to develop something of new arena that will be helpful for the human being.

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