Exploring Alzheimer's Disease Prediction with XAI in various Neural Network Models

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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.
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

Predicting the disease of an individual based on a probability provided by a Neural Network model without any further analysis or evaluation might provoke ethical dilemmas. Hence, we assured the transparency of the evaluation process and suggest an wise confirmation of a medical professional before finalising the result.

Abstract

Using a number of Neural Network Models, we attempt to explore and explain the prediction of Alzheimer's in patients in various stages of the disease, using MRI imaging data. Alzheimer's disease(AD) often described as dementia is one of the major neurological dysfunctionalities among humans and does not yet have a proven detection system; unless the final stage symptoms of AD starts to be seen. It is observed that multimodal biological, imaging and other available neuropsychological data can ensure a high percentage of separation among (AD) patients from cognitively normal elders. However, they cannot surely predict or detect early enough that patients with early signs of mild cognitive impairment (MCI) can develop into Alzheimer's disease dementia in the future. But the research done till date shows a high probable detection rate in which they used the pattern classifier built on various longitudinal data. So in this paper we experimented with the existing Neural Network models to detect Alzheimer's disease in its early stage by classification techniques; and will be using a recent hybrid dataset in the process to have four separate classification in total. And also explored the exact region for which that specific classification occurs for the patients, looking at the T1 weighted MRI scans from a hybrid dataset from Kaggle [21] using the LIME based XAI(Explainable Artificial Intelligence) framework. For the Convolution Neural Network Models we are using Resnet50, VGG16 and Inception v3 and received 82.56%, 86.82%, 82.04% of categorical accuracy respectively.

Keywords: Early Detection of AD, Alzheimer's Disease, CNN model for AD detection, Explainable Artificial Intelligence, XAI, LIME

Dedication

We would like to dedicate this thesis to our loving parents. As well as, all the amazing faculties we encountered and learnt from in the course of pursuing our Bachelors degree. It has been a journey worthwhile. . .

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At first, all praise to the Great Allah for whom our thesis have been completed without any major interruption.
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Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

AD Alzheimer's Disease

CNN Convolution Neural Network

DNN Deep Neural Network

DRN Deep Residual Network

JPG Joint Photographic Expert Group

$LIME$ Local interpretable model-agnostic explanations

MD Mild Demented

$ModD$ Moderate Demented

MRI Magnetic Resonance Imaging

ND Non Demented

$NIFTI/NII$ Neuroimaging Informatics Technology Initiative

VMD Very Mild Demented

XAI Explainable Artificial Intelligence

Chapter 1

Introduction

1.1 Overview

Alzheimer's disease is the most frequent neurological disorder that results in lifelong brain damage. Alzheimer's disease is named in honour of Dr. Alois Alzheimer, the man who noticed that a woman died of a common mental illness in 1906 due to changes detected in brain tissue. After examining the patient's condition, Dr. Alois discovered many abnormal fiber clumps and tangled fiber bundles, medically called amyloid and neurofibrillary plaques. This disease slowly erases memories, impairs their thinking ability, and prevents them from performing simpler tasks in daily life. Since this situation is irreversible, the longer the patient lives, the worse the disease gets[30]. Alzheimer's disease is a condition that worsens with time. Memory loss is a typical symptom of Alzheimer's disease and one of the first indicators. This could be an indication of a stroke, and a person should seek medical treatment. Alzheimer's disease causes memory loss, cognitive impairment, recognition difficulties, spatial awareness issues, speaking, reading, or writing challenges, and personality or behavior changes.

Alzheimer's disease has a wide variety of signs and symptoms, from mild to severe. Mild memory loss is at the bottom of the spectrum, followed by moderate memory loss and, finally, severe memory loss. The stages are divided into three categories: mild , moderate , and finally severe Alzheimer's. In the beginning phases of Alzheimer's disease, an individual can act independently. That person is still capable of driving, working, and socializing. In addition, the person may experience memory loss as a result of forgetting familiar words or the location of commonplace objects. Symptoms at this stage may not be as pronounced as Alzheimer's disease, so they may not be serious. Still, relatives and close friends can understand them, and doctors can diagnose the symptoms with appropriate diagnostic tools. People with dementia can live successfully in the early stages of the disease by managing their health and well-being and focusing their energy on the aspects of life that are most important to them. It is not predictable when mild AD will turn into moderate AD. Mid-stage Alzheimer's disease, on the other hand, is frequently severe and can endure for many years. People with Alzheimer's disease will demand more care as the condition progresses. In the middle stages of Alzheimer's disease, the indicators of dementia become increasingly evident and obvious. This person may be confused with known words. They act in odd or strange ways when they are disturbed or

angry, something they have never done before. Damage to nerve cells in the brain can also prevent a person from expressing coherent thoughts and performing daily tasks without help. In the medium term, Patients with Alzheimer's disease can still participate in daily activities with assistance. It's crucial to figure out what the person can still perform or how to make the activity easier. In the later stages of dementia, the symptoms are at their most severe. People's ability to react to their surroundings, control their conversations, and finally manage their physical actions is lost. They can still speak in words or sentences, but the pain makes communication difficult. Personality changes might become severe as memory, and cognitive abilities decrease, necessitating cautious therapy. Healthcare providers may desire to use support services, such as palliative care, at this point to focus on providing comfort and dignity at the end of life.

To be diagnosed with Alzheimer's, a doctor with experience with brain disease (neurologist) or a doctor who has received geriatric care (geriatrics) must be informed with a medical history, medications, and symptoms. The doctor can then perform various tests. The doctor starts to evaluate through these tests: Memory or thinking skills (cognitive) impairments, personality or behavior changes, memory impairment, or the degree of mental instability are all factors to consider. Additional laboratory testing is required, like brain imaging tests or submission of memory tests, which can provide doctors with useful diagnostic information. It has become an important field for researchers to come up with a new form of diagnosis to be able to identify signs of dementia earlier in the course of the disease, ideally, before they even appear. One such tool is a positron emission tomography (PET) scan that can detect TAU protein, the other abnormal protein characteristic of Alzheimer's dementia. However, it requires further research.

Prior to the COVID-19 pandemic, Alzheimer's disease was the third leading cause of death among the elderly in the United States, after only heart disease and cancer. The majority of developed countries identify Alzheimer's disease as one of the most serious economic threats. Alzheimer's disease will cost $7 billion in the United States alone in 2030, according to studies, including caregivers. In industrialized countries, the number of persons affected is currently higher, which coincides with the proportion of aged people [18], [31]. According to Alzheimer Disease International, around 44 million people worldwide have Alzheimer's disease or related dementia [19], with that figure anticipated to climb to 65.7 million by 2030 [28]. There is no motivation for the general people in Bangladesh to be concerned about Alzheimer's disease because the country is densely populated, with the majority of its citizens residing in rural areas.

In our paper, we present and discuss the methods of predicting and classifying MRI images of patients into four classifications- Non Demented, Very Mildly Demented, Mildly Demented, and Moderately Demented. As we believe it is imperative to identify the signs as soon as possible, identifying different levels of dementia in its physical manifestation may help treat it in various stages. The methods we explore are VGG-16, ResNet50, and Inception v3, each of which provides good levels of accuracy in our hybrid dataset, presented using the LIME-based XAI framework.

1.2 Importance / Usefulness

There is currently no possible cure process for Alzheimer's disease. Since brain cells cannot be revived, there is no way to prevent them from dying. On the other hand, treatments can try to alleviate symptoms, improve the patient's family's and carers' quality of life, and assist in managing the steep and unpredictable symptoms of the illness. Their health will inevitably deteriorate. There is yet to be discovered a medication that can reduce or stop the growth of Alzheimer's disease. Researchers are also unsure how to prevent the start of Alzheimer's disease. Doctors generally address the symptoms of the disease that traditional or alternative treatments can control, intending to improve people's quality of life. It's crucial to realize that the medical profession does not commonly accept alternative treatments for Alzheimer's disease. Anecdotal evidence has found some of these procedures beneficial, while some studies have suggested these treatments to be ineffective [13].

But this condition can be controlled if recognized early. With this in mind, we are examining the cervical patient's data and utilizing a hybrid dataset to identify the signs as soon as possible. Recognizing different levels of dementia in its physical manifestation may assist treat it at different stages. There have been several classifications to date, but medical specialists are still puzzled about why and how this model recognized the casualties. As a result, XAI is being used in our research. So that medical experts can figure out based on which regions these models are being classified. This would be extremely useful for medical professionals in informing their patients about their actual condition as well as the reasons for the projections made by various models.

1.3 Current Scenario and Motivation

The most common type of dementia is Alzheimer's disease (AD), which is defined as a loss of memory and other cognitive abilities that are severe enough to make daily life difficult for those affected. At this moment, there is no recognized cure for Alzheimer's disease, although there are treatments for the symptoms, and research is ongoing.

Alzheimer's disease is a difficult disease in case of detection. To detect this in an early stage is kind of impossible if the patient can not recognize the symptoms and consult with doctors. There is still no clear test for determining whether or not someone has Alzheimer's disease, so a careful medical evaluation is expected to help determine. In addition to physical tests and a review of medical history, the evaluation may include cognitive testing, neurological inspections, blood tests, or brain imaging studies. Memory loss is not always a sign of Alzheimer's disease; it could also be a sign of other conditions that are treatable, such as vitamin deficiency, depression, or a drug side effect or unpleasant response.

According to a recent study [20] done at the Mayo Clinic in Jacksonville, Florida, men are far more likely than women to be misdiagnosed. This disparity is exacerbated by the fact that men get Alzheimer's disease at a younger age than women,

that Alzheimer's disease affects different brain areas in men and women, and that men's symptoms are more commonly presented as behavioral or linguistic impairments.. In contrast, women's symptoms are more commonly manifested as memory issues.

In a separate study, the Keenan Research Centre for Biomedical Science which is established at St. Michael's Hospital in Toronto reported a 20% mismatch between clinical Alzheimer's diagnosis and brain autopsy findings. The existence of other illnesses, such as various types of dementia, was found to impact erroneous diagnosis in this study. Patients with Alzheimer's disease who have not been diagnosed on a regular basis may be suffering from other illnesses such as Parkinson's disease or vascular dementia, which have obscured their Alzheimer's symptoms.

Alzheimer's disease is widespread in developing and industrialized countries in Asia related to age, gender, social and cultural background [3], [4], [7], [15]. Alzheimer's disease has a number of risk factors, and the social and economic effects of this disease are unknown [3], [15]. Alzheimer's disease has been a major societal burden in some populous countries because of its effects on the elderly [6]. The role of nursing staff management has long been considered in these countries [5]. Some South Asian countries are also concerned about Alzheimer's disease. Our neighbor India is concerned about the consequences of Alzheimer's disease on the socio-economic structure Developed for a long time [1], [2]. Based on The Dementia India Report 2010, which is published by the Alzheimer's and Related Disorders Society of India estimates 3.7 million people in India have dementia. According to them, this number will be doubled in the next 20 years.

There are very little data available on the number of AD patients in Bangladesh. There are no accurate epidemiological data on AD in this country. Here, the recognition of AD is currently in its first stage. As a result, patients and their families are constantly faced with a variety of problems. Funding for conducting AD research is limited. This motivated us to work on a recent dataset from Kaggle so that in the near future, we can train the models using a dataset based on AD patients in Bangladesh.

1.4 Research Objectives

Alzheimer's disease (AD) is well-known due to the serious health risks it poses and the lack of a permanent solution. Alzheimer's disease attacks people in their older years and is one of the top causes of death in the modern era, exposing people to additional viruses like COVID-19. This has an impact on the health index of the people of Bangladesh and also its economy. Objectives of the paper are as follow:

1. The purpose of this research is to create awareness in people about Alzheimer's Disease. It will help to work with the patient to know the forecast of the danger level of the growth of dementia in an individual when they come for diagnosis or check-up; so that whenever related to initial dementia level, patients can

take necessary steps to prevent the final stage of AD in the long run.

2. This paper will help people to know about Alzheimer's Disease and help them understand the importance of it. Moreover, people will not hesitate to talk about this disease, because in Bangladesh though AD is prevalent in many cases, people often categorize it as the disease from old age more often than giving proper attention to cut down the prevalence of this disease.

3. Through our approach we are trying to predict Alzheimer's Disease in its earliest stage, so that people can use the benefit of taking care of this disease from the initial stage and prevent the extreme loss it can bear.

4. We aim to improve the physical and mental condition of Alzheimer's Disease patients and their family members to provide the highest accuracy through this research along with proper justification to some extent.

5. This study will enhance more legitimate and skillful broadcasting across the target AD patients.

6. Furthermore, methods that we are using, can detect and foresee the risk factors of Alzheimer's Disease , and it will furnish a better opportunity to the relevant contributor so that it tends to be extremely valuable for fast discovery and treatment.

1.5 Thesis Outline

The main goal of this thesis was to construct a model capable of predicting cervical cancer in the early stage based on patient's different symptoms. As well as to detect and predict the risk of being diagnosed. The aim of the authors was to construct the best model for achieving the task and enhance it for accuracy. In addition to it, provide visual reasoning behind the output.

To start with, in the first chapter (Chapter 1), an overview and the importance of our research. The existing situation and motivation for this research are also mentioned. Moreover, a brief discussion about the current situation of Bangladesh about the Alzheimer's disease (AD) and how our research will be a great assistance in medical sector.
Secondly, in (Chapter2) related work surrounding Alzheimer's Disease Classification and its predictions were discussed. Indicating significant results achieved by researchers. Also, the lacking of existing methods were over-viewed.
Thirdly, in (Chapter 3) we tried to provide a detailed explanation of the neural networks, residual networks, MRI scans that we used, and an architectural explanation of the CNN models that we used. In addition we discussed on explainable artificial intelligence in detail.
In (Chapter 4) we mentioned the overview of the data acquisition along with the data pre-processing techniques that we used for preparing them as usable data. We have given an idea about our train and validation dataset as well
Furthermore, in (Chapter 5) we mentioned how three of the CNN based model ResNet50, VGG16, Inception-v3 were built with the input setup and which training

parameters were used in the process of this model creation. We also showed some graphical representation for some of the metrics.
In (Chapter 6) the result were discussed in comparison to different epochs and we also cross compared the model with bar graphs for better understanding. And we also showed how the LIME based XAI framework helped to justify any generated result by the models.
Finally, in (Chapter 7) Conclusion, Limitations and Future works are mentioned in order.It also gives an insight about how we can add to our present research in the days to come.

Chapter 2

Literature Review

2.1 Related Works

Many different forms of Neural Networks have been tested and used, in recent years, in attempt of early detection of the disease, in the combined field of computer science and medical science. A modified version of the 16-layer VGGNet architecture has been utilized by Sarraf and Tofighi, where they used the architecture in combination with the data preprocessing pipeline, to solve the classification problem of AD vs MCI [10]. They presented a solution to the binary classification of Alzheimer's Disease versus Healthy Controls from functional magnetic resonance imaging (fMRI) data. In another paper, Hongmin and Yong introduced recurrent neural networks (RNNs) to learn informative representation and temporal dynamics of the longitudinal cognitive measures of individual subjects [24]. They built a prognostic model for the progression of dementia by combining the RNN with the hippocampal MRI of the patients.. As they needed to learn informative and compact representations; the LSTM autoencoder proved to be ideal in reaching that goal.

To bypass issues like limitation of access to annotated medical data and issues leading to overfitting or underfitting of data, Jain et al [22] proposes the approach of transfer learning. This machine learning method uses a pre-existing model, computed for one task to be used as a starting point of a second task. In this case, a pre-trained VGG16, CNN architecture, trained on natural images is used as a base model to train on medical images. This cuts down training time from weeks to several hours, and also increases efficiency, regardless of the limited medical images. Using an entropy-based sorting mechanism to take slices of sMRI with most information to be fed to the CNN increases efficiency, and also accounts for overfitting. With higher efficiency and cutting down on time, transfer learning shows promise in being used with other, more accurate, methods and machine learning models.

Regarding the limitations of access of large amounts of data, Islam et al. [17] proposes a method to work with smaller data sets using a deep convolutional neural network that can identify Alzheimer's disease and classify the current disease stage, to increases chances of catching early symptoms of Alzheimer's. The proposed method is an ensemble of three, slightly different configurations of convolu-

tional neural networks, with each of which had several layers performing four basic operations- convolution, batch normalization [8], rectified linear unit, and pooling, following a connection pattern known as dense connectivity [14] to reduce overfitting. Here Batch Normalization is a method used to attempt to terrifically accelerate the training time of the networks. By removing the covariate shift and instead drawing power by integrating normalization in network architecture itself. Then, the normalization and optimization methods handle each other in being effective, yet cutting down on time. With the use of a 4 layered ensemble, speeding up the process and reducing complexity takes up a higher priority. Batch normalization takes only 2 extra parameters each time it is triggered, thus preserving the representation of the original network. Use of dense connectivity also allows feature reuse within the entire network, as a result, learning becomes more compact and subsequently an attempt to further increase accuracy. The method proved to have a total average accuracy of 93% regardless of the smaller dataset, but required a four tiered network, resulting in a higher training than most.

A joint research performed by the UK and China states they have tried to extract the most useful features of sMRIs by employing a deep convolutional neural network (DCNN). The data is then pre-processed, for convenience, in a strict pipeline. Before being fed into the DCNN, each volume is resliced. Finally, four stages of Alzheimer's are identified, with the average accuracy being 94.8% for LMCI versus EMCI, 94.5% for NC versus LMCI, 97.81% for EMCI versus AD, 97.2% for LMCI and AD, 96.9% for NC versus AD [28]. The paper also recognizes the limitations of the field with limited datasets available and how that affects the training accuracy of CNN. Therefore, it needs to be followed by a support vector machine (SVM) which, however, is a supervised machine learning method. For this reason the paper suggests a two part unsupervised deep learning method. The first part uses an unsupervised ML method, followed by an unsupervised classification method, to classify the final results. This is achieved by use of an unsupervised CNN called PCANet, which will take in a feed of 3 orthogonal views of MRI images, followed by a k- means clustering algorithm based unsupervised classification method for the final results, giving a relatively high accuracy of 92.5% on average [26].

On the other hand, a recent paper of October 2020 shows the use of neuroimaging techniques, which puts use of the fact that sMRIs reveal dramatic cerebral shrinkage as the brain structure degenerates as the disease progresses, and can give 91% of accurate data without a patient's past records by generating biomarkers for effective diagnosis [27]. Other Deep learning approaches, such that use CNNs or RNNs, that do not pre-process neuroimaging data for feature selection have yielded accuracies of up to 96.0% for AD classification and 84.2% for MCI conversion prediction [23].

Another system uses the data of two separate neurological experiments.. The first talks about the correlation between the switching cost of an individual and the frequency of the signal. The other experiment relates to the task switching capacities in people with AD and MCI. They used the spectral convolution-based ChebNet

model to classify the subjects in the ADNI dataset with an accuracy of 92.44% [19]. We can also observe a proposed CNN model which has 12-layers, with a new approach that can give an accuracy of 97.75% which is higher than most of the recent existing models. Moreover they have used different image segmentation methods to test out different datasets and the best among them is to be taken. Which, in this case, should come closer to 97.75% accuracy [28]. AD can also be detected through applying CNN (Convolutional Neural Network) on structural MRI data with the help of SVM (Support Vector Machine), which yielded an accuracy of around 96% [13]. Then again, Amin-Naji et al. [20] propose the use of Siamese CNNs, using axial view, specifically, of sMRI images, to further increase the accuracy of AD diagnosis, compared to previous computer-aided methods. The Siamese CNN contains multiple branches of CNNs which use a series of convolutional, pooling, ReLU, and fully connected layers. They are all simultaneously trained on multiple images of subjects and create the same feature vectors. The similarities between the input images are retrieved by calculations between the similarity and distance of the output feature vectors. Trained on the OASIS dataset of 235 subjects, 5 axial slices taken from each, gave an sMRI slice pool of 1645, an accuracy of 98.72% was obtained, which is considered to be the highest accuracy till date.

Chapter 3

Background Analysis

This part mainly discusses the different methods that have been implied on the backdrop of the Alzheimer's Disease prediction related research. It delves down into a finer detail about the previous studies scrutinizing the pros and cons of different methods, their limitation and extension. For classification and use of data set, many of these neural network models are statistically proven to give better results. The most difficult part is feeding the best selected and sorted MRI scans as data into these algorithms and training them. They should have all of the data set's relevant features. While there are numerous model training approaches available. Despite their ability to perform admirably, many model fall short of their expectations when it comes to achieving the desired outcome in case of AD research field as its quite dynamic in itself.

3.1 Weighted Magnetic Resonance Imaging

As the name suggests, MRI uses magnetic fields and radio waves to produce images of the tissues in the body. This is achieved by using a powerful magnetic field which causes the hydrogen protons' axes that are present in the water molecules in the body to line up. The uniform alignment of the magnetic field forms a magnetic vector which is oriented to the axis of the MRI scanner. Now, when radio waves are added to this magnetic field, this oriented magnetic vector is disturbed or perturbed. When this Radio Frequency is removed, the deflected vector returns back to it's resting state. And in doing so, it emits Radio Frequency energy. It is this signal that is received to be able to create the MR image. After a certain known time, the signals are computed.The frequency information from the signal, of the different areas, is extracted and using Fourier transformation, it is mapped as different shades of gray to a matrix of pixels, based on the intensity of the signals. Different variations of imaging are created by varying the sequence and frequencies of the Radio waves. Important variables here are the Repetition Time or TR, which is the time difference between successive pulse sequences implemented on the same slice. Another is TE the Time to Echo, this denoted as the time between the instance the Radio Signal is introduced and the moment the echoed signal is received. T1 And T2 are 2 relaxation times by which tissue imaging is characterized by. T1 is the longitudinal relaxation time, this is the measure of time difference between the moment the RF pulse is switched off and the time taken for the specifically aligned protons to realign with the external magnetic field. On the other hand, T2 is the transverse

relaxation time, defined as the time needed for the protons's axial spin to go back to the resting state. T1- weighted images use short TR and TE times, on the contrary, T2-weighted images use log TE and TR two both produce MR images, but are distinguishable by the different contrast and brightness of different tissues in the images. It can be cleared from the image below:

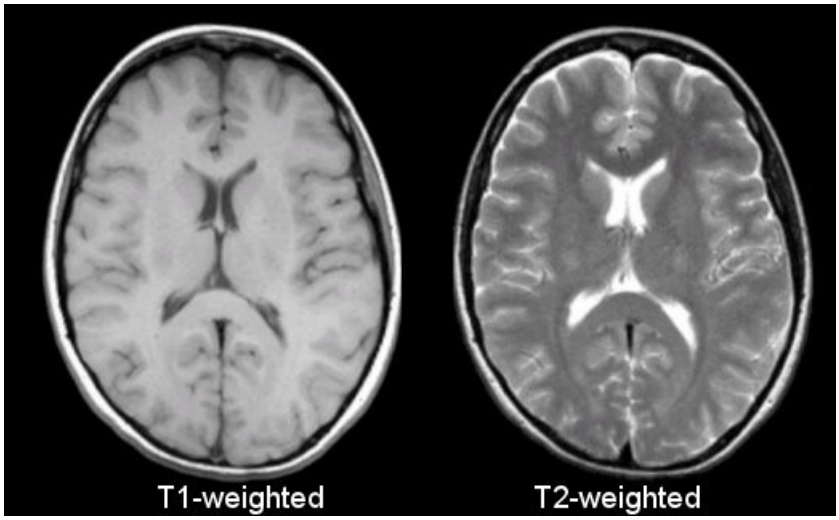

Figure 3.1: Comparison of T1 and T2 weighted images.

Differences of T1 and T2 weighted MRI		
Tissue	**T1-weighted**	**T2-weighted**
Cerebrospinal Fluid (CSF)	Dark	Light
White Matter	Light	Dark Gray
Cortex	Gray	Light Gray
Fat	Bright	Light
Inflamation (infections etc.)	Dark	Bright

Table 3.1: Comparison of colour of different tissues in T1 and T2 weighted images

The dataset we are using from Kaggle consists of T1 weighted MRI images and it is labeled as non demented, very mild demented, mild demented and moderate demented. One instance for each of the four classes is given below:

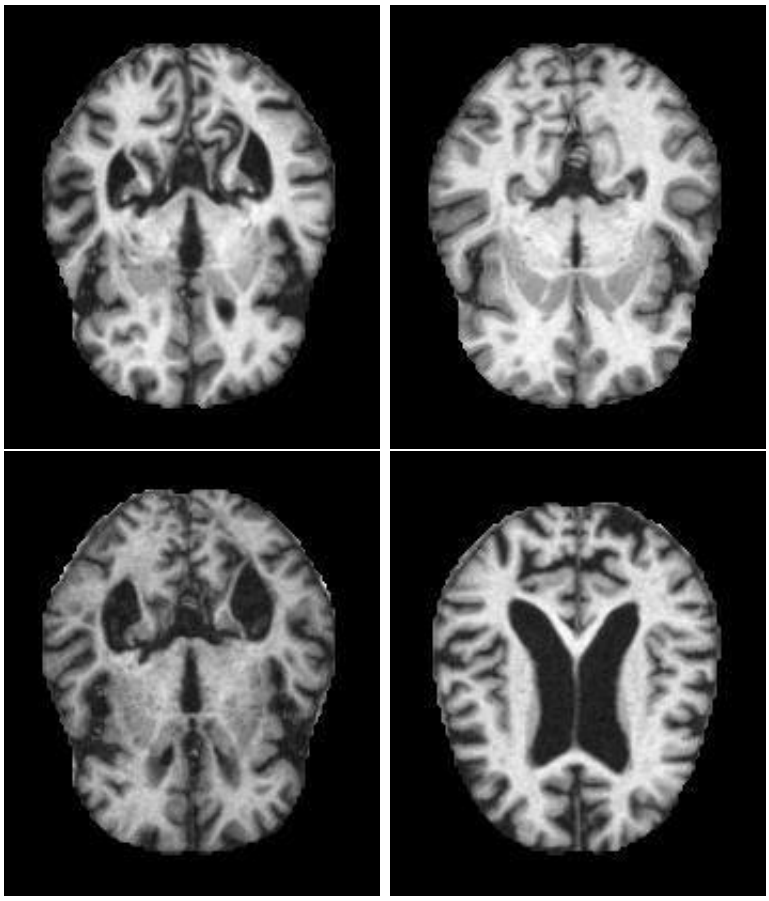

Figure 3.2: Sample MRI scans of non demented, very mild demented, mild demented and moderate demented patients (from left to right).

3.2 Convolutional Neural Network (CNN)

Neural Networks are a subset of machine learning which is a computational system modelled after the function patterns of the human brain. As like the connections of neurons in the brain neural networks use computational nodes as neurons which are interconnected in a distributed manner to process and extract information from an input to optimize the final output.
The most basic architecture of any Neural Network consists of an input layer, one or more hidden layers and an output layer. As can be seen in the figure below. The information is sent to the input layer, which will then distribute the data accordingly to the hidden layer(s). It is here where all computations and decisions are down before passing to the output layer. The fact that neural networks more often than not have multiple hidden layers which are stacked on each other classifies it as deep learning. [O'Shea, Keiron Nash, Ryan. (2015). An Introduction to Convolutional Neural Networks. ArXiv e-prints.]

Convolutional Neural Networks, or CNNs, are a specific type of Neural Network which is primarily specialized to be used to process pixel data. Image processing using traditional neural networks is not particularly ideal as the images must be inputted as reduced- resolution bits. CNNs, thus, has their nodes, or "neurons', arranged more similarly to that of the frontal lobe in the brain, since the frontal

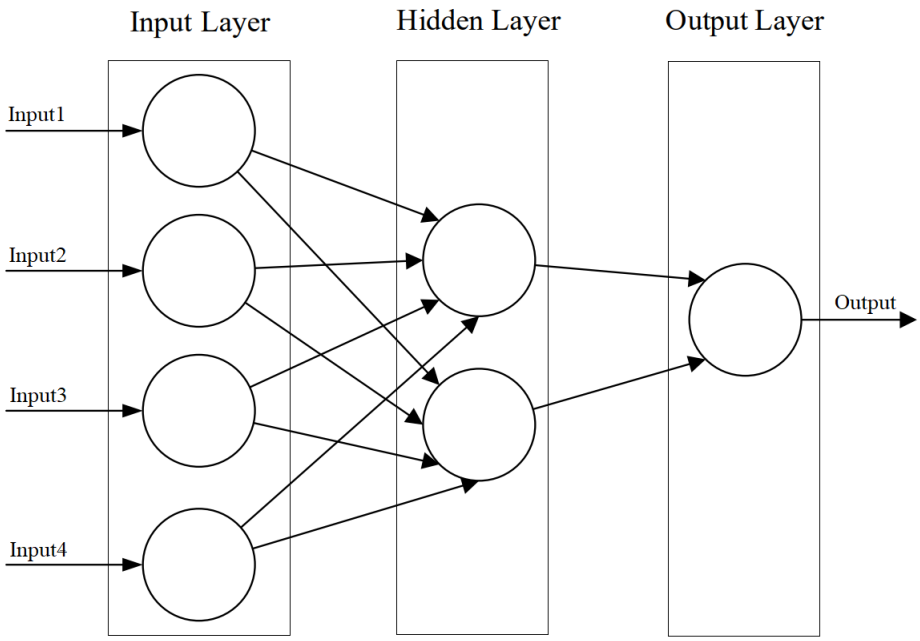

Figure 3.3: Simple three layered feed forward Neural Network.

lobe is responsible for visual stimuli processing in animals. In doing so, the layers are arranged to be able to processes the entire image at once instead of piece by piece. The neurons in layers within the network are arranged into three dimensions, 2 of which are dimensions of the input and the third being the activation volume.
Fundamentally, CNNs have three types of layers used in it's hidden layers- convolutional layers, max-pooling layers and fully connected layers. These layers are stacked, not necessarily in that sequence, to form a CNN architecture. The convolution layer always is the first one connected to the input layer, and essentially the most important ones. This layer applies a convolution function on the input before it is passed to the next layer. The convolution function converts the pixels fed into the layer into appropriate numbers to be processed. The parameters of the layers are dependent on the kernels that are used throughout the entire depth of the input. When the 2D map made of the input is processed, a scalar product is calculated for each kernel. An activation map is produced for each of these kernels, based on the activation functions. These maps are stacked, which forms the depth of the output volume from the layer. The stacking of layers is one of the 3 methods used to decrease the complexity of the model in the convolution layer. The other two hyper parameters are the stride and zero-padding. The depth of the output volume can be defined beforehand, similarly, we can define the stride. The higher the defined stride, the lesser the amount of overlapping as well as lower spatial dimensions of the output. Lastly, zero-padding is used to control the dimensions of the output, to maintain uniformity for ease of computation.
The pooling layers are used to downsize the dimensions of the incoming input between layers. It does so by comparing neighbouring information and producing a three dimensional matrix much smaller than the input, but still pertaining all information, to reduce the number of parameters within the activation. Pooling layers always follow convolution layers, however, not all convolution layers need to be fol-

lowed by a pooling layer. The fully connected layer consists of nodes where every input is connected to every activation node of the next layer. Fully connected layers usually are the last few layers of a CNN and compiles the data to be sent to the output layer.
Convolutional Neural Networks are defined by the functionality and differences of these layers and the total number of layers stacked and parameters of each network. For different operations, different numbers of stacks of layers can be applied for the same same model and achieve different levels of accuracy.

3.3 Deep Residual Network

Deep Residual Network is a network that is similar to convolutional neural network (CNN) which consists of many layers in the process of effective learning. Now when it comes down to residual network; then it can be described as an Artificial Neural Network (ANN) and generally it is the concept of stacking residual blocks one upon another in order to build a neural network. While going through recent studies we can notice some uncanny transformations or changes which were unimaginable a few years back in the research of computer vision, and it is solely because of the increased availability of modern technologies. Before this technological advancement humans were the basis for the expert classification and recognition or were involved in the process to a greater percentage for the authentic result. But the involvement of technologies in the computer vision sector has made the models possible to surpass the authenticity and efficiency achieved by human involvement in different problem solving like in the cases of image recognition, face detection, object detection and also image or object classification and so on. In this case we are seeing the convolutional neural network as the DNN in the up front in case of the contributions it marked. It has been possible to have visual image analysis and achieve very high accuracies because of the wide range of use of these networks. For our project since we are using the MRI scans for classification, we can see a glimpse of the working procedure below:

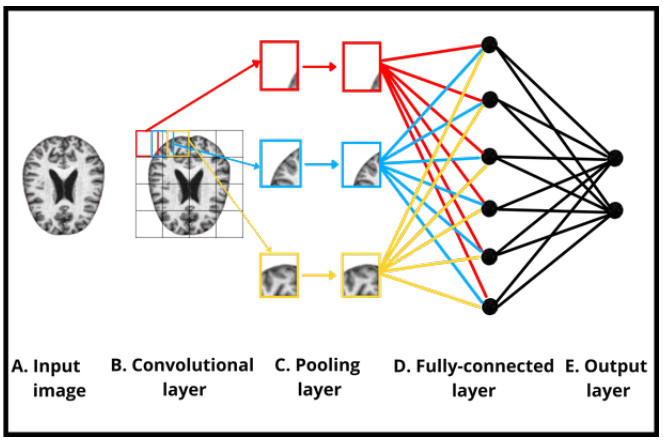

Figure 3.4: Convolution Neural Network (CNN) turn into Deep Residual Network

In the case of using networks like CNN, we have a very useful option to add more layers to these networks' available architecture in order to find solutions for even

more complex problems in various fields. And computer vision is exactly using that opportunity, but it also dealt with its arising issues too. While using the networks with additional layers, it has resulted in having difficulties while training the neural networks and with all the extra layers the optimum accuracy was becoming hard to meet in some cases. It is this time, when regarding to solve this exact issue, residual blocks were implemented to improve the accuracy of the models that were based on the previous convolution neural network concept; and this new network was introduced as Deep Residual Neural Networks.

3.4 ResNet 50

Residual Network, or more commonly known as ResNet is a well known neural network that serves as an essential part of many computer vision tasks. The use of deeper and deeper Neural Networks have become a common trend in the research community due to the fact that breaking the layers has proved to help reduce the problem of overfitting. However, deeper layers bring up another problem- the vanishing gradient problem. The repeated multiplication of the gradient as it is back-propagated through the previous layers, results in the gradient possibly being increasingly small. This problem becomes more and more evident as the layers go deeper. This results in the performance degrading through the layers.
ResNet deals with this particular problem by the use of the "identity shortcut connections" or "Skip Connections" or even residual connections. This effectively bypasses some of the connections in the network, creating blocks of layers, as demonstrated in the figure below:

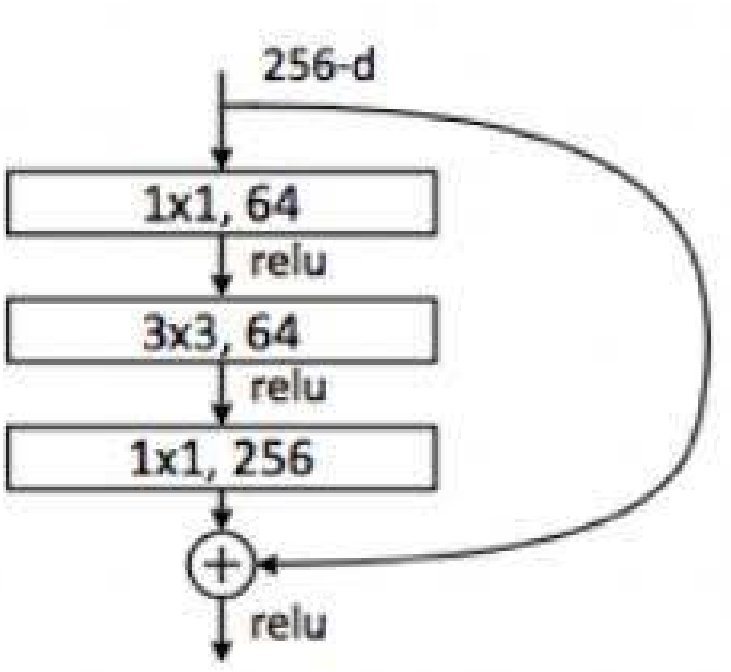

Figure 3.5: A residual block (for ResNet 50)

ResNet 50 in particular has 50 layers- 48 Conv. layers with 1 Maxpool and 1 Aver-

age pool layer. This model has 4 stages, each with one conv. block and one Identity block. Each block has 3 convolution layers (as seen in the figure above). The architecture uses 7x7 and 3x3 Kernel sizes respectively to perform the initial convolution and max-pooling.
Stage 1 of the model uses 3 residual blocks with 3 layers, it is here where batch normalization is usually implemented. The convolution here is performed with stride 2, reducing the size of the input but doubling the channel size. For the next stages, the 3 layers are stacked in each block, with 1x1, 3x3 and 1x1 convolutions in that order. The 1x1 layers reduce and then restore the dimensions of the data and the 3x3 layer serves as a bottleneck with smaller output dimensions. The Structure of the ResNet blocks are simplified and shown below:

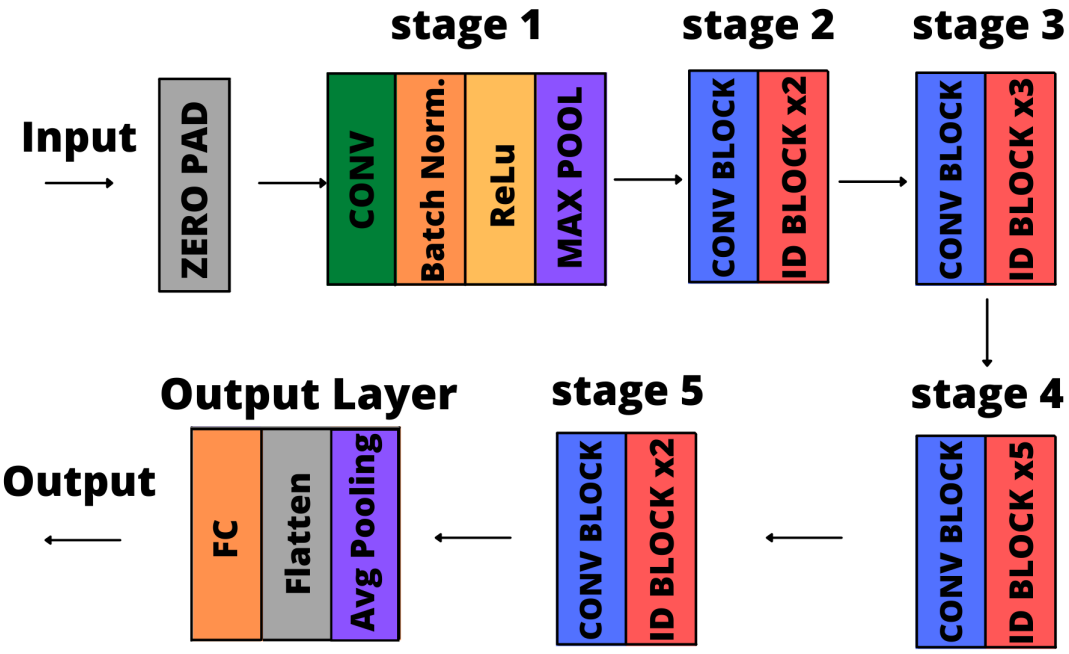

Figure 3.6: Model of ResNet-50 Architecture.

3.5 VGG16

Named after the Visual Geometry Group from Oxford, the group that came up with the convolutional Neural Network architecture, the VGG model has shown remarkable results with the ImageNet dataset. Instead of using large kernel-sized filters, the VGG model uses stacks of multiple 3x3 kernel-sized filters. There are 2 variations of the VGG model- VGG16 and VGG19 respectively, with 16 and 19 layers respectively. We will be working with VGG16, which requires less memory than it's deeper counterpart.

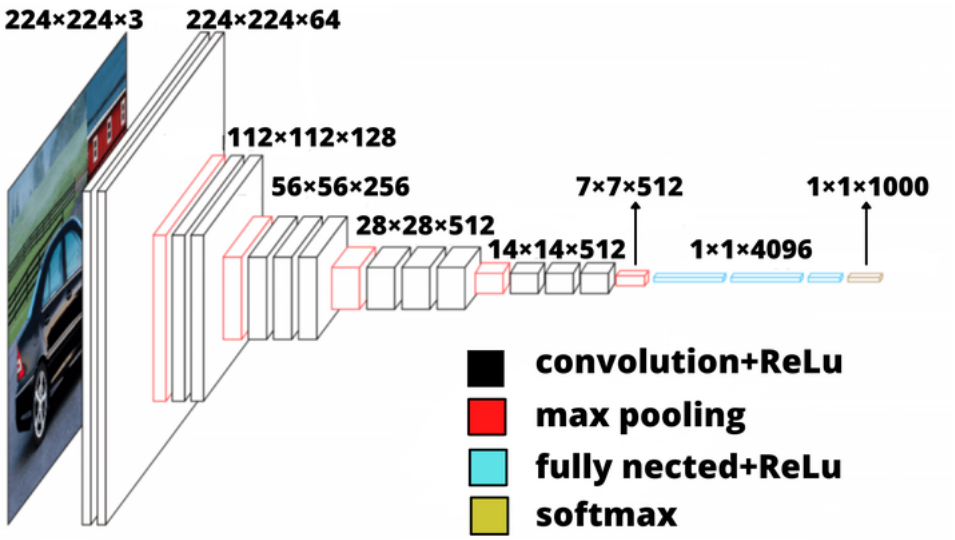

Figure 3.7: Model of VGG16 architecture.

The input to the network is predefined to always be 224x224 in dimension. This image is passed through multiple convolutional layers, with filters of the minimal size- 3x3 and a stride of 1. The padding always remains the same and the maxpool layers are all consistently of a size 2x2 with stride 2. This pattern of conv. layers and maxpool layers are carried out throughout the entire architecture. After a certain number of con. layers, max pooling is carried out, spatial pooling specifically. Out of the total 16 weighted layers, 3 of them are fully connected layers, which come at the very end of the model, right before the output is generated. The absolute final layer is a soft max layer. All of these hidden layers make use of rectification non-linearity.

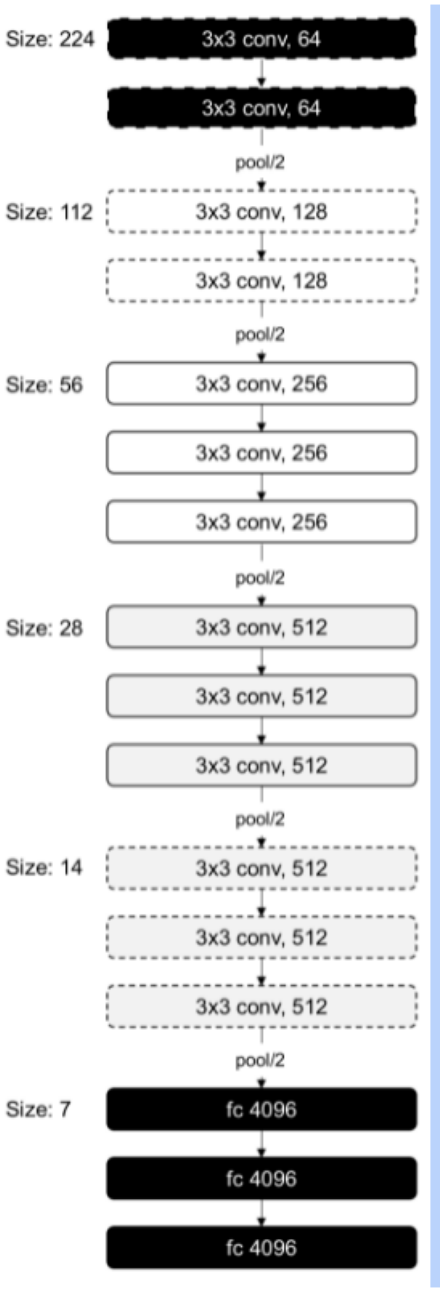

Figure 3.8: Block Diagram of the Layers of VGG16

We have considered VGG16 because of it's record of significantly outperforming it's predecessor models on the ImageNet dataset. It may be bigger in size, but generates a admirable accuracy.

3.6 Inception v3

Inception v3 of the Inception family is the third iteration of the inception family, which is an extended network of GoogleNet [9] which used transfer learning [12] to achieve improved classifications. Instead of going deeper and stacking more conv. layers on each other. Inception , instead used multiple layers on the same level. Essentially creating a wider network than deeper. The generalized model makes use to symmetric and asymmetric building blocks as required including conv. layers, dropouts, max pooling, average pooling, contacts and fully connected layers. Batch Normalization is also used thorough the entire architecture and applying to application functions. Below is an example of a fairly simple inception module.

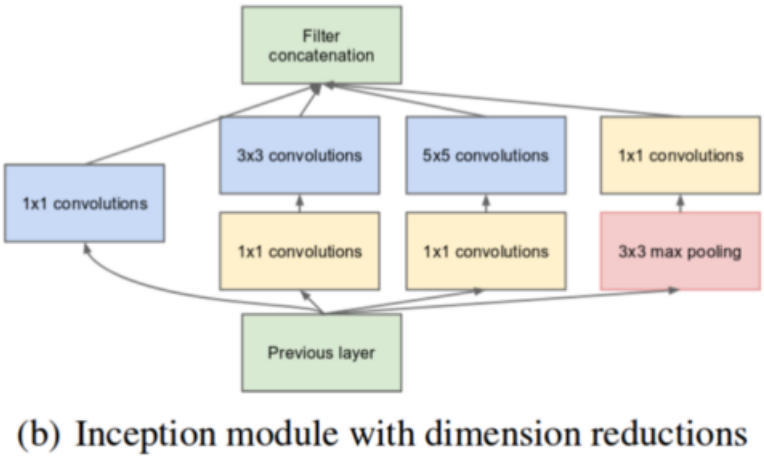

Figure 3.9: Inception module with dimension reduction.

This module is the basis that is stacked linearly to create the inception model. Stacking, inevitably increases depth, and as with any deep network, the model faces the vanishing gradient problem. For this, auxiliary classification was used to prevent loss of information from the middle. Filter banks in the module were also expanded in certain levels to avoid representational bottleneck, to cut on complexity and reduce excessive reduction in dimension. The inception v3 specifically added the following features over it's previous versions- RMSProp Optimizer, Batch Normalization in the auxiliary Classifiers, Factorized 7x7 convolutions and Label Smoothing. The last of which was added to prevent overfitting. Below are the simplified architecture of the layers of Inception v3, followed by a visual representation of the architecture-

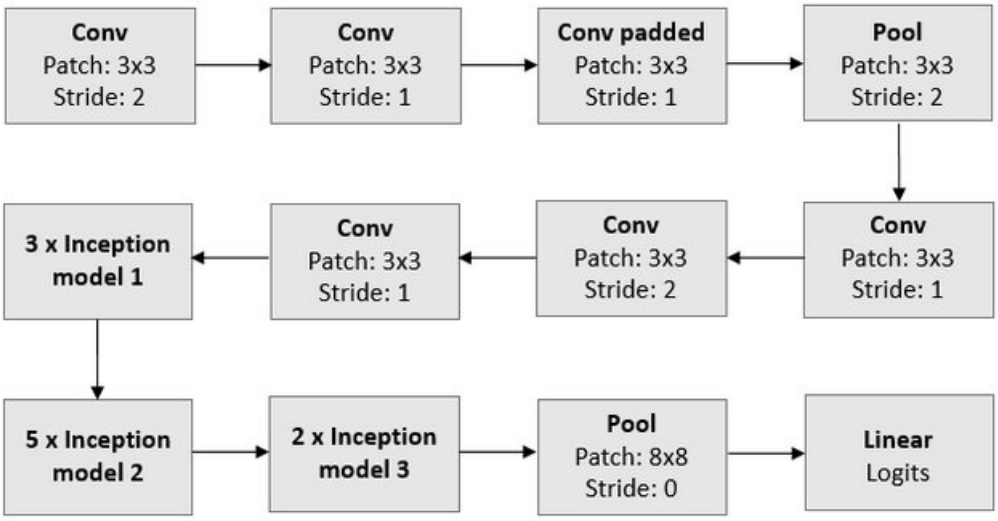

Figure 3.10: Basic layer blocks of Inception v3

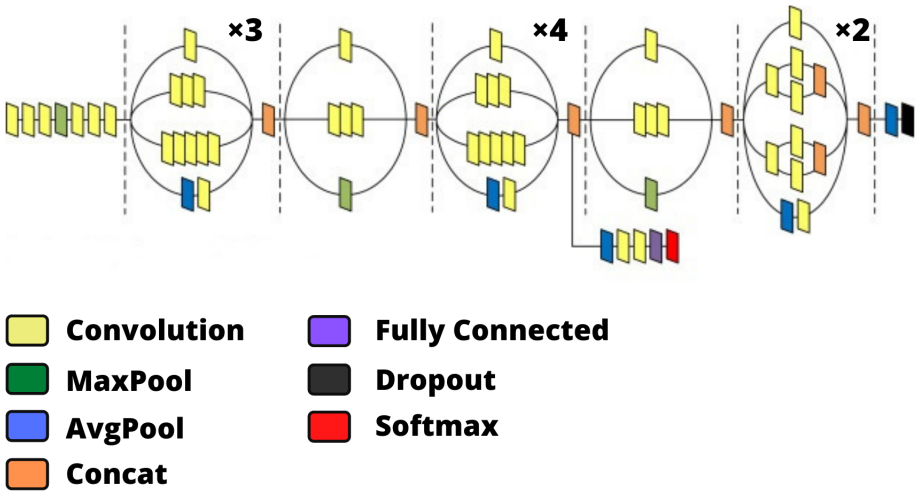

Figure 3.11: Visual orientation of the modules in Inception v3

Compared to most models, Inception Networks have fewer parameters and so are more economically efficient. However, due to it's complex and heavily engineered architecture, it is sensitive to changes and adaptability. Fine tuning the model for different use cases can prove to be a problem.

3.7 Explainable Artificial Intelligence (XAI)

Explainable Artificial Intelligence is known to be a series of steps and techniques that brings justification for the output or result generated by different learning algorithms and helps to build a trust around it. In this process the probable present biases and influences of any particular model can easily be portrayed with the help of Explainable AI. Not only this, but the accuracy and proper description of the

output is also obtained from any AI based decision making model or system. The use of Explainable AI is really helpful to build a bridge of trust between the service providers and receivers. Moreover, this explanation can be helpful in the future for the development that can enhance the system.

We know that any learning algorithm is trained with a training dataset at the initial stage by small or large dataset and from then the learning never stops, and as the process reaches its peak and generated result or makes decisions of its own; sometimes it becomes really difficult for us humans to trace or coagulate the algorithms end result. Here comes the concept of 'Black Box' which is widely known in the field of Neural Network or Artificial Intelligence; because the interpretation is somewhat impossible in some cases. Since these are solely derived from the data and those are built upon to be a model, often the developers and data specialists face a hard time understanding the procedure of how the model reached any of the results it is showcasing at the end of the chart. The knowledge matching or knowledge graph is the one that helps to generate both the cross-disciplinary explanations and interactive explanations. The neural network models that are passed through this knowledge graph can be really helpful to comprehend the decision and give better transparency to the result. The following block diagram can be helpful for better understanding of the process:

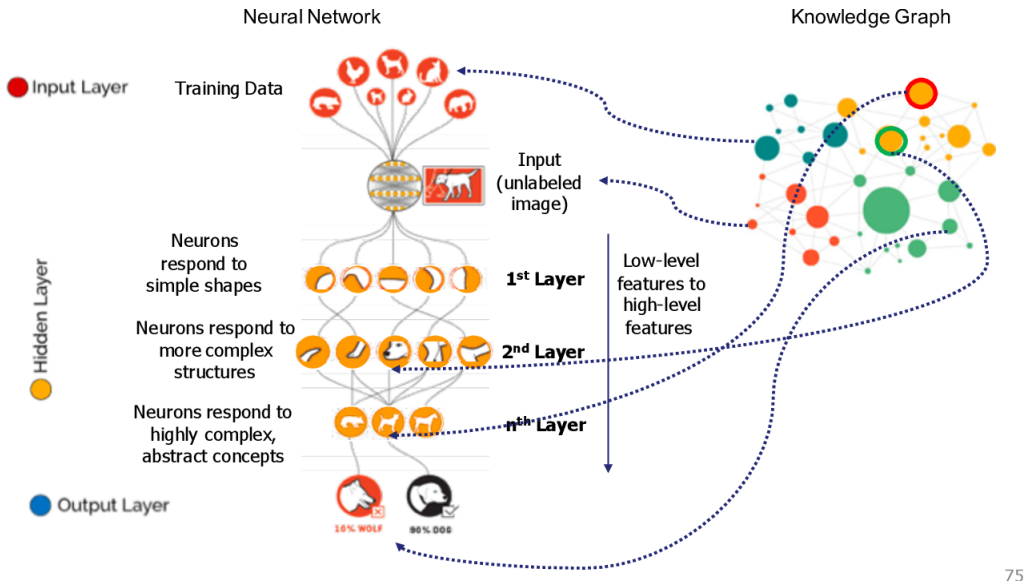

Figure 3.12: The explaining procedure of XAI

Any organization or system provider always prefers not to blind trust the model, rather they want to acquire a full understanding of the output generation process and try to monitor it as closely as possible since it often gets involved in making some very important decisions. Since the organizations and developers are to be blamed and held accountable for any discrepancies, this procedure makes their work less vulnerable to the model itself. The neural network models that are engaged in the image classification in our paper, can also be explained for the type of classes

they are assigning at the end of the process. The humans find it really troublesome when it comes to understanding any neural networks that are used in DNN specifically. And since interpreting those is nearly impossible, it is labeled as black boxes that are generating results for the model.

In the term Explainable AI, the explainable part means to generate the insights of the behaviour of the deployed model and generating both pros and cons in the model behaviors in line with the used data and complete the evaluation. In the field of health care systems, learning models are being developed with the neural network backbones in recent days. And it is actively in use for analysis and diagnosis of data and generating results. This is a kind of field where any wrong decision can bring in a deteriorating situation for any given patient, the black box concept of neural networks makes it difficult for the medical expert to believe in it. And in this limitation being observed in a significant manner, the explainable AI comes in play where it can explain the decision making process of any learning algorithm in a system; which can then meet the expert knowledge of doctors to bring out the combining decision that is beneficial to the patient.

Chapter 4

Dataset Analysis

In this chapter, first we describe the dataset acquisition for our experiments. In this section we do an in-depth discussion on data collection, data pre-processing, image conversion.

4.1 Data Acquisition

The meaning of data acquisition is to collect data from relevant sources before any of that data can be stored, cleaned and preprocessed. It is the process of retrieving relevant information from all the appropriate sources, transforming the data into a usable format for the machine to be able to get trained and be used to the decision making process. Our first target was to retrieve data from different Neurosciences Hospital, due to the current unfortunate circumstances, the actual data has not yet been collected. Therefore, for the data acquisition we opted for a reliable dataset extracted from Kaggle. Here the dataset is one of the recent dataset available online and the criteria which makes it stand out among other dataset is that it is prepared by combining several Alzheimer's Disease dataset available online. This dataset from Kaggle [21] was already split into test and train. The train dataset was already classified into 4 classes (Non-dementated, Very mild Demented, Mild Demented, Demented).

4.2 Data Preprocessing

Once we are done collecting all the necessary and appropriate raw data it needs to be preprocessed. Preprocess is a series of data transformations to reduce the noise in the raw data. Otherwise, our neural networks won't produce accurate forecasts, which will also affect our models' decision-making phase of our network.

Transformation and normalization are the two most widely used methods for preprocessing data. Transformation in creating a single net input to a net by manipulating the raw data. On the other hand, normalization is a transformation performed in a single data input to distribute the data evenly and scale it into an acceptable range for the network. To increase the network's ability to learn the association

between inputs and outputs we need knowledge of the domain to choose the best preprocessing method according to our dataset.

The required format for most MRI analysis tools is the NIFTI format. Our collected dataset was already cleaned when it was converted to NII format and then in JPG format, The noise reduced dataset did not need much pre-processing to begin with in our case. Next we re- scaled all the data for train, validate, test to 1./255 . Then we set a target input size of 244*244 for all the data. From this process we got 4098 usable images for training, 1023 images for validation and 1279 images for the test stage of our model. The four classes of images while training the model has similar scans shown below:

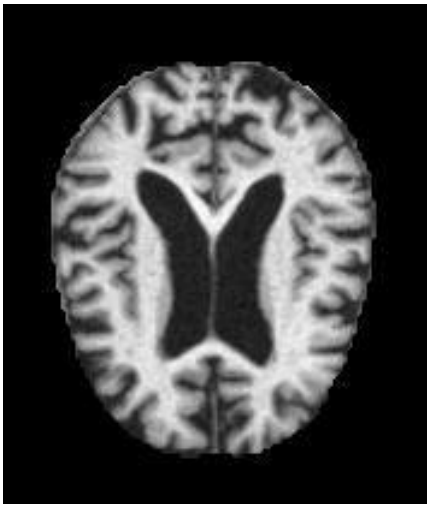

Figure 4.1: MRI Scan of a moderate demented patient

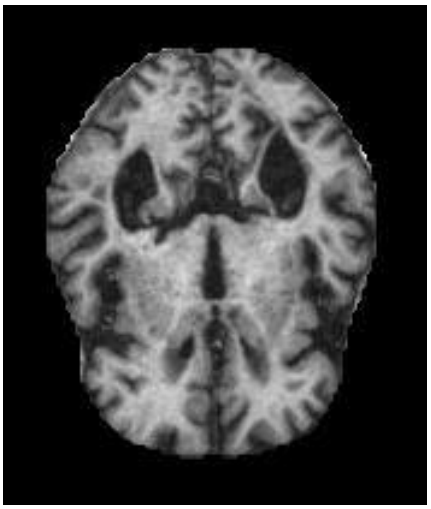

Figure 4.2: MRI Scan of a mild demented patient

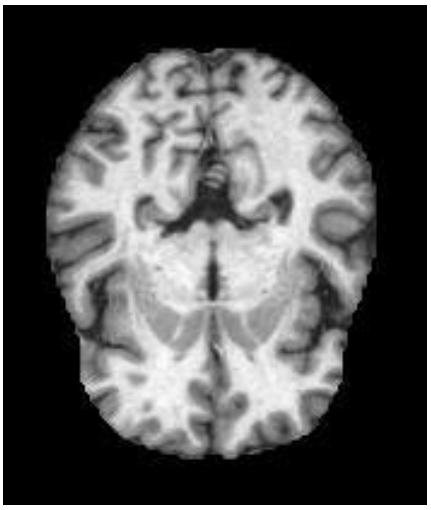

Figure 4.3: MRI Scan of a very mild demented patient

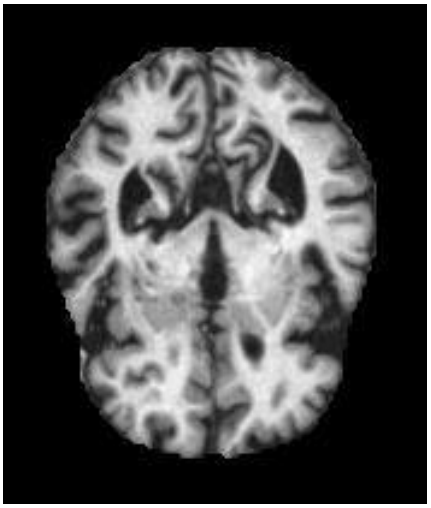

Figure 4.4: MRI Scan of a non demented patient

4.3 Train-Test Split

The train-test split is a technique for evaluating performance of a machine learning algorithm. It is used for supervised classification and regression models. This procedure involves dividing the whole dataset into two subsets. The first subset is called train and it is used to fit the model and the second subset is called test, it is not used in the training phase of the model rather it is used as input element of the dataset to provide to our model. Then it is used for making predictions and compared to the expected values. The objective of the test dataset is to estimate the performance of the machine learning on new data which was not used to train the model.

This train-test split is the expected use of these models. We want the models to fit it on available data with known inputs and outputs, then it will make prediction on

new examples on the future where we don't know the expected the output from an input. This methods works best when there is a large amount of data to work with.

Train-test split has only one main configuration parameter, that is the size of the train and test sets. This is normally expressed as percentages of between 0 and 1. for example if we set the training data to be .70 and test to be .30 it means 70% of the whole data will be used for training while the other 30% of the data will be used for the test. Some common splits are 80-20 split, 67-33 split, 50-50 split.

For our dataset we used the 80-20 split where 80% of the data was used for the training stage and the remaining 20% was used to test our model. On top of that we split our 80% train data into 80-20 again to create another sub dataset called validation. Validation is a data-set used to tune the hyperparameters of a classifier.

Chapter 5

Model Implementation

5.1 Proposed Model

At present, Deep learning is helping in advancing the computer based diagnosis in several critical diseases. Unlike machine learning, deep learning does not require any manual or expert based pre-selection of features. Rather it can integrate data from raw images in an efficient optimal representation. This attitude is really helpful in the healthcare system, since manual selection can be tiring in case of a huge dataset of patients for a particular disease detection. In any convolution neural network 150 or more layers can be detected and it is different from the simple neural network which only has a couple of layers. This feature of CNN helps to deal with large datasets and achieve higher accuracy in different fields.

From the illustration below we can visualize the generalized architecture for diagnosing Alzheimer's disease from the T1 weighted MRI scans and the required stages to pass on in order to match a proper detection. Firstly, we have collected our dataset from Kaggle [1], and after this data acquisition process we have pre-processed our data. We have fed the MRI dataset into the pre-processing phase where we have denoted and resized the dataset into appropriate portions. We used PCA (Principal Component Analysis) technique to increase the interpretability of the used dataset by dimensionality reduction and preserving information loss. OpenCV was used to denoise and resize the dataset.

Then we have split the dataset for training, validation, and testing data. We split it in a 80:20 ratio for training and testing consecutively. We have not created individual folders for validation requirements; rather we are using 20% data from the training dataset instead. We re-scaled all the data to 1/255 and set the target size to be (244,244) in order to run the models used.

By training the preferable system it is more likely to predict the AD patients in both earlier and later stages, because the fed training dataset instigates the system to make the right decision in the diagnosis process. For this purpose Deep Learning is second to none, as it is a good classifier which is also efficient with a large dataset as well. From many types of learning methods, we have used CNN (Convolution Neural Network) for the purpose of classifying our dataset which will also lead us

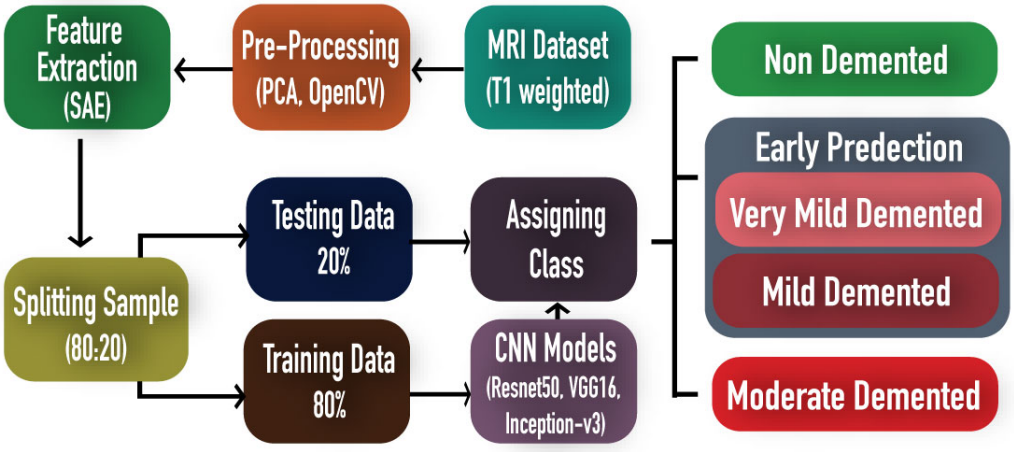

Figure 5.1: Proposed model for the early detection of AD.

to the accurate early detection of AD. Earlier we have said that Deep Learning is efficient with large datasets, and this property is essential for our case; as we have a large dataset with many T1 weighted MRI of a large patient base for a couple of years.

By training the preferable system it is more likely to predict the AD patients in both earlier and later stages, because the fed training dataset instigates the system to make the right decision in the diagnosis process. For this purpose Deep Learning is second to none, as it is a good classifier which is also efficient with a large dataset as well. From many types of learning methods, we have used CNN (Convolution Neural Network) for the purpose of classifying our dataset which will also lead us to the accurate early detection of AD. Earlier we mentioned that Deep Learning is efficient with large datasets, and this property is essential for our case; as we have a large dataset with many T1 weighted MRI of a large patient base for a couple of years.

In any CNN architecture feedforward layers are to be seen in the forefront and those are generally named as convolution layer filters and pooling layers. In a CNN architecture fully connected layers are implemented after these layers and it generates a single vector for the 2D image features in order to proceed with the classification. In order to have a high performance model CNN needs a very large labeled dataset for its feature extraction part and to get trained for the diagnosis [16]. From Fig.2 we can see that the CNN architecture consists of some building blocks and the first layer which is used for feature extraction from the MRI scans by learning from small squares segments is called the convolution layer. And the pooling layers are responsible for the parameter reduction as MRI scans are too large as an input. And since CNN has a fully connected network; all the neurons of the previous layer will be connected to the next. By this process CNN generates a single vector that consists of the probability of each label. These layers are stacked multiple times in a CNN architecture. Since we are having an output through all these layers from the input in a for-ward direction manner, this step is named as forward propagation.

As for pre-built models we have used Resnet50, VGG16 and Inception v3 for our experiment and result analysis.

5.2 Implementation of ResNet-50

5.2.1 Initial Setup

ResNet-50 is a CNN which is 50 layers deep which is a very classic approach for using it as a backbone for computer vision tasks. In our Alzheimer's disease prediction, we have used the ResNet-50 model to classify between the categories. Firstly we have autotuned our tensorflow such that the tensorflow runtime will be able to tune in into the values dynamically at run time. Then for the train ,test and validation dataset we have augmented our data according to the target size of 224,224 which is basically a tuple of integers height and width as all the image needs to be resized , the class mode is kept categorical as there are more than 2 categories of data and we have taken 32 image as batch size such that the training samples are controlled at and 32 image are used at each iteration. After this our train_dataset, validation_dataset and test_dataset is filled.

5.2.2 ResNet-50 Model Creation

Now diving into our base_model creation of ResNet-50 we have kept the input shape same as our target size 224,224 and also added 3 input channels at the end. Then we have specified include top as false as we don't want to include the fully connected layer at the top of the layer and added the pre-trained model 'imagenet' as the weights. Then we made a sequential model where we added our base_model of Resnet-50 and later added 3 dense batch normalization layers with 64 batches each and kernel initialization with uniform parameters and the rest 2 layers are of 32 batches each. All of the layers we used Dropout of 0.2 with the same activation function which is ReLu. Lastly we used a sixth layer of batch size of 4 and softmax activation function as this is our output layer and we want to predict in a multinomial probabilistic way. Then we defined two functions one is to calculate f1 score and the other is for exponential decay. F1_score method takes in the parameter of the y true value and the y predicted value where the true value and predicted value is multiplied and clipped to 0.1 and adding all this we get the true positive value. Then we clipped the y_true value to 0.1 scale and rounded up and then added all of them to get the possible positives. Similarly we have done it with y_pred value for predicted positives; the precision was calculated by dividing the true positives by the summation of predicted positives and the epsilon. Recall was calculated in the following manner where we divided the true positives by the summation of the possible positives and its epsilon. Then the f1 value was calculated using the below stated formula and then we returned it accordingly:

$$f1\_value = 2 * (precision * recall)/(precision + recall + epsilon) \tag{5.1}$$

5.2.3 Training Parameters

Moving on to our exponential decay where we lowered the learning rate while the training progressed. So in this function we take a learning rate then for each epoch we multiply the learning rate with 0.1 for epoch/sum of epoch times. Thus we make our own exponential decay by passing in 0.01 as the learning rate and the 5 while it runs for 50 epochs. We kept metrics where the recall, accuracy, precision and f1 score is kept. Then we compile the model taking in rmsprop optimizer, categorical_crossentropy as loss and passed in the metrics. Finally we train the model for 20 epochs using lr_scheduler as callback and saved it in history. After 20 epoch we see that the test set classification accuracy comes in at 82.56%.

5.2.4 Graphical Representation

For model metric visualization we used matplotlib to plot the values of history of accuracy , history of loss, history of AUC, history of precision, history of f1-score.

Accuracy is a metric for evaluating the accuracy of our model. In simpler terms accuracy is the number of correct predictions our model made from the total number of inputs. Loss in this scenario represents the prediction error of our neural network and then loss is used to update the weights of the neural network. Area Under The Curve (AUC) is used to measure the ability of a classifier to distinguish between classes. The higher the AUC is the better the performance of the model at distinguishing the classes. Precision is the ratio between the number of positive samples that were correctly classified to the total number of samples classified as positive. It calculates a model's accuracy in classifying a sample as a positive. F1-score is a measure of a model's accuracy on a given dataset. For each case we kept epochs in the x axis and the only thing we plotted against it in y axis is the training and validation for the accuracy, loss, AUC, precision and f1 score.

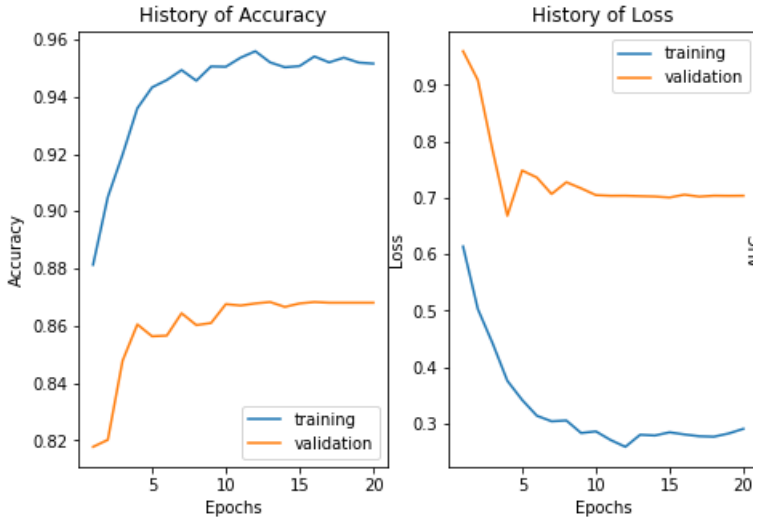

Figure 5.2: Metric Visualization of ResNet50 accuracy and loss.

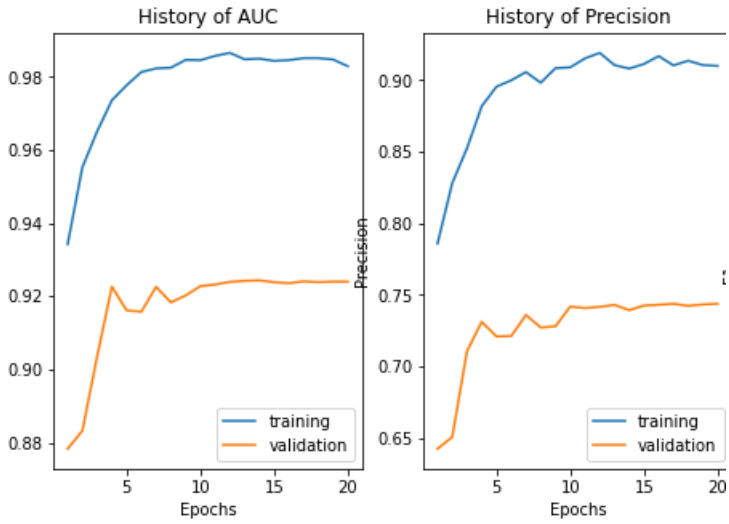

Figure 5.3: Metric Visualization of ResNet50 AUC and Precision.

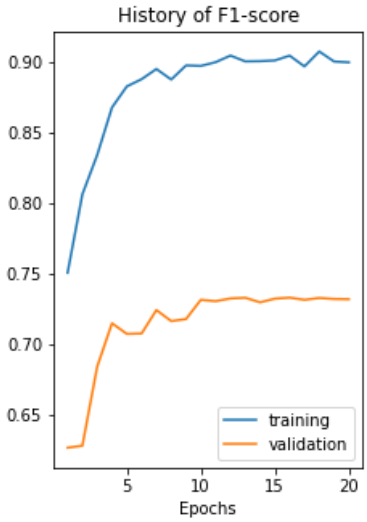

Figure 5.4: Metric Visualization of ResNet50 f1 score

5.3 Implementation of VGG16

Previously we have built our ResNet-50 base model, we've maintained the input shape the same as our goal size of 224,224 and added three input channels at the end. Then we set include top to false since we don't want the fully connected layer to be at the top of the layer, and we set the weights to the pre-trained model imagenet. Then we created a sequential model where we replaced our Resnet50 base model with VGG16, followed by three dense batch normalization layers with 64 batches each, kernel initialization with uniform parameters, and the last two layers with 32 batches each. We utilized the same activation function, ReLu, on all of the layers, with a Dropout of 0.2. The other training parameters remain the same as the previous model. So the metrics visualization of the VGG16 after the train and test is as below:

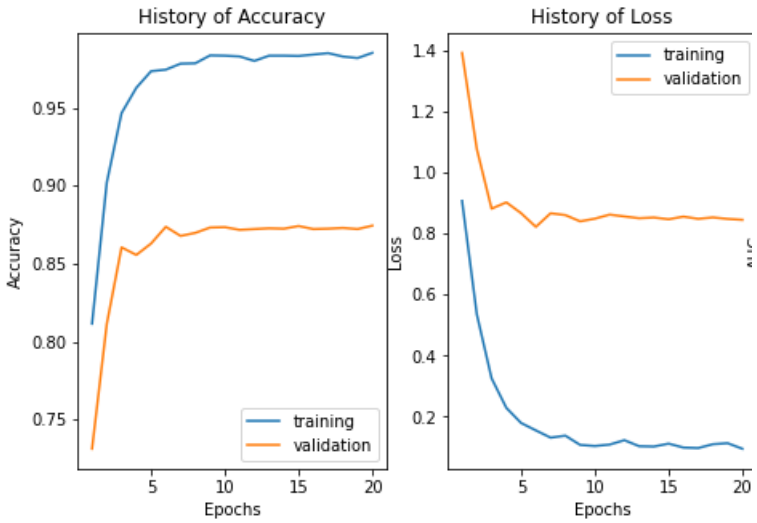

Figure 5.5: Metric Visualization of VGG16 accuracy and loss.

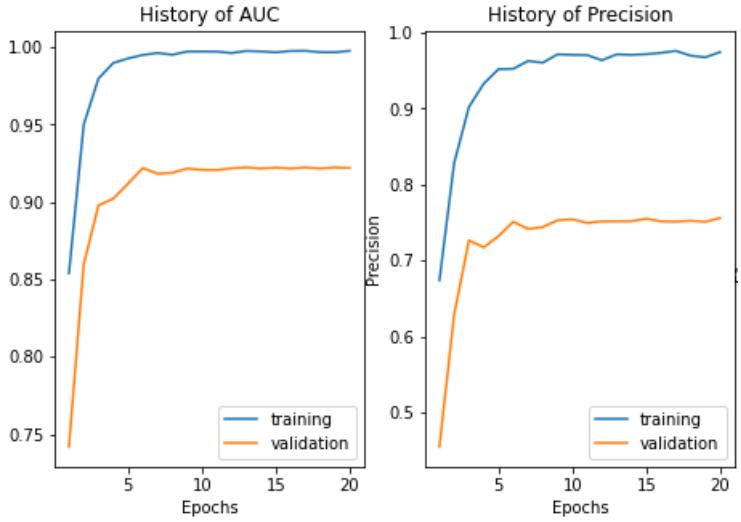

Figure 5.6: Metric Visualization of VGG16 AUC and precision.

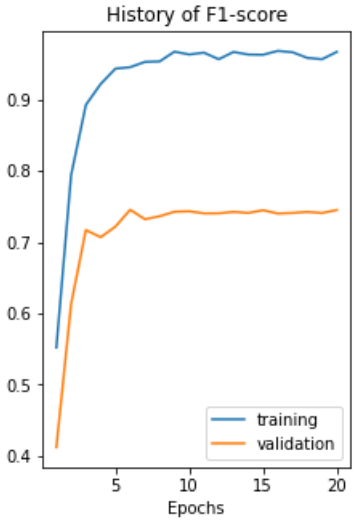

Figure 5.7: Metric Visualization of VGG16 f1 score

5.4 Implementation of Inception-v3

We created our ResNet-50 basic model previously and in case of the implementation of inception v3 we are maintaining the same initialization and input setup. So similarly we will keep the input shape the same as our 224,224 objective size and three input channels will be added at the end. Then, because we don't want the fully connected layer to be at the top of the layer, we set include top to false and the weights to the pre-trained model imagenet. After that, we built a sequential model in which we replaced our Resnet50 base model with Inception v3. Moreover like the two previous models we added three dense batch normalization layers with 64 batches each, kernel initialization with uniform parameters, and the last two layers with 32 batches each. On all of the layers, we used the same activation function, ReLu, with a Dropout of 0.2. The other training parameters remain the same as the previous models. So the metrics visualization of the Inception v3 after the train and test is as below:

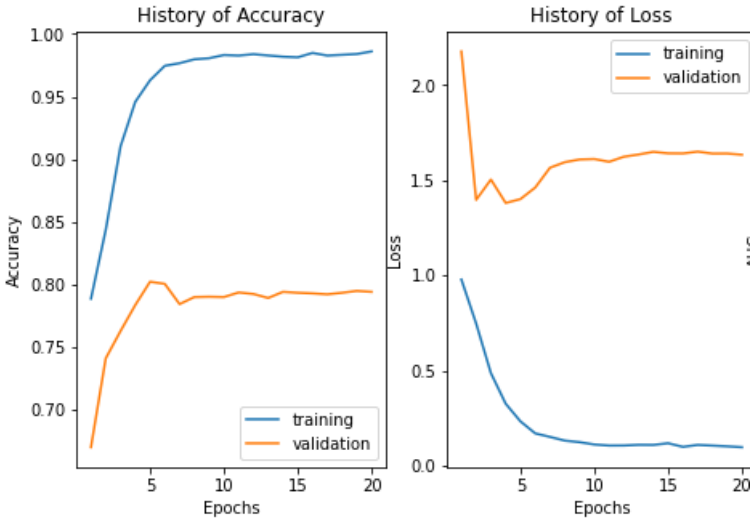

Figure 5.8: Metric Visualization of Inception-v3 accuracy and loss.

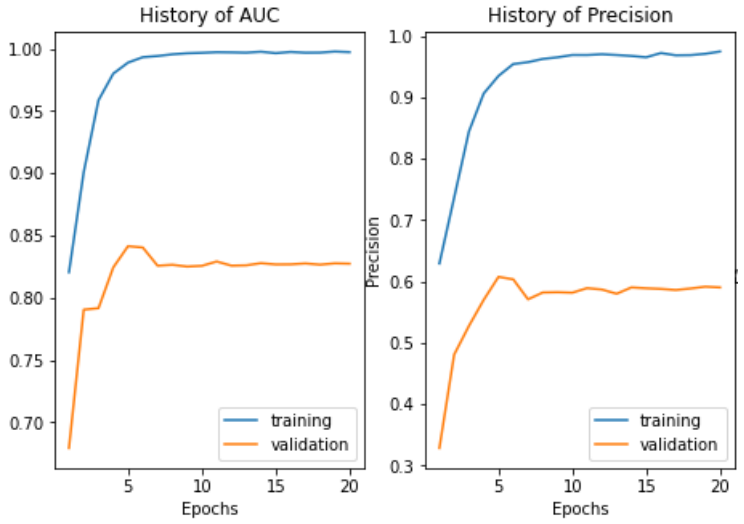

Figure 5.9: Metric Visualization of Inception-v3 AUC and precision.

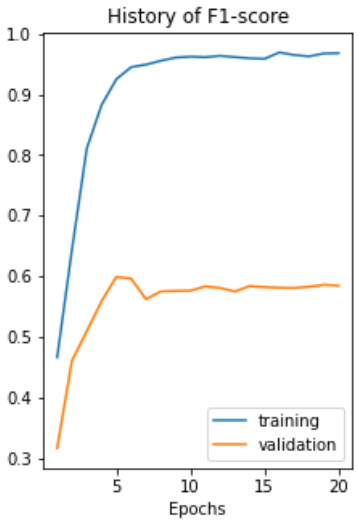

Figure 5.10: Metric Visualization of Inception-v3 f1 score

Here after closer inspection of the insights from the graph we can see that VGG16 outperformed other two models ResNet50 and Inception-v3 in the case of categorical accuracy with 86.82%, when ResNet50 and Inception-v3 scored 82.56% and 82.04% consecutively. But if we are focusing on the data loss, then ResNet50 outperforms others with lower value.

Chapter 6

Experimental Result and Analysis

6.1 Performance Evaluation

Before having a human-friendly explanation for the classification or prediction of certain MRI scans, we have trained three different models with our hybrid dataset and measured the categorical accuracy and test accuracy. These CNN based classification models were built using Keras. We have classified among four classes (ND: Non Demented, VMD: Very Mild Demented, MD: Mild Demented and Mod D: Moderate Demented) from which we are segmenting VMD and MD as the two classes which gives us the early prediction for AD. And in the classification AD patients are identified as Mod D and Normal patients with ND class.

We have shown the train and validation accuracy of the three models in the tables below with 10 and 20 epochs respectively. The accuracy does not change much for increased epoch, but we wanted to include the result for better understanding. The bar graph for each of the model depicting all the metrics in two different epochs are also shown consecutively.

Associated Numerical Metric Score for ResNet 50						
Train/Val	**Epochs**	**Accuracy**	**Loss**	**Precision**	**AUC**	**f1-score**
Train	10 epochs	0.9505	0.2867	0.9089	0.9846	0.8969
Train	20 epochs	0.9516	0.2912	0.9099	0.9829	0.8994
Validation	10 epochs	0.8675	0.7048	0.7417	0.9228	0.7311
Validation	20 epochs	0.8680	0.7036	0.7437	0.9240	0.7316

Table 6.1: Associated Numerical Metric Score for ResNet 50

Associated Numerical Metric Score for VGG16						
Train/Val	**Epochs**	**Accuracy**	**Loss**	**Precision**	**AUC**	**f1-score**
Train	10 epochs	0.9835	0.1038	0.9707	0.9972	0.9634
Train	20 epochs	0.9853	0.0946	0.9744	0.9976	0.9670
Validation	10 epochs	0.8734	0.8491	0.7543	0.9207	0.7434
Validation	20 epochs	0.8744	0.8454	0.7558	0.9220	0.7452

Table 6.2: Associated Numerical Metric Score for VGG16

Associated Numerical Metric Score for Inception-v3						
Train/Val	**Epochs**	**Accuracy**	**Loss**	**Precision**	**AUC**	**f1-score**
Train	10 epochs	0.9831	0.1110	0.9695	0.9968	0.9626
Train	20 epochs	0.9860	0.0958	0.9752	0.9973	0.9684
Validation	10 epochs	0.7901	1.6115	0.5818	0.8257	0.5762
Validation	20 epochs	0.7942	1.6341	0.5904	0.8274	0.5845

Table 6.3: Associated Numerical Metric Score for Inception-v3

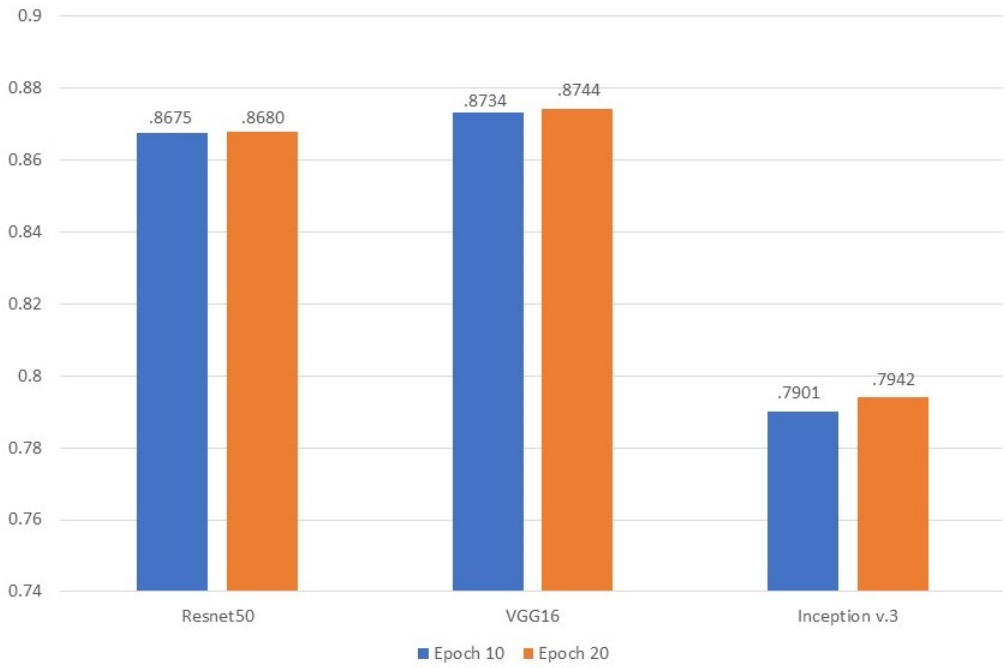

Figure 6.1: Comparison of three models based on accuracy

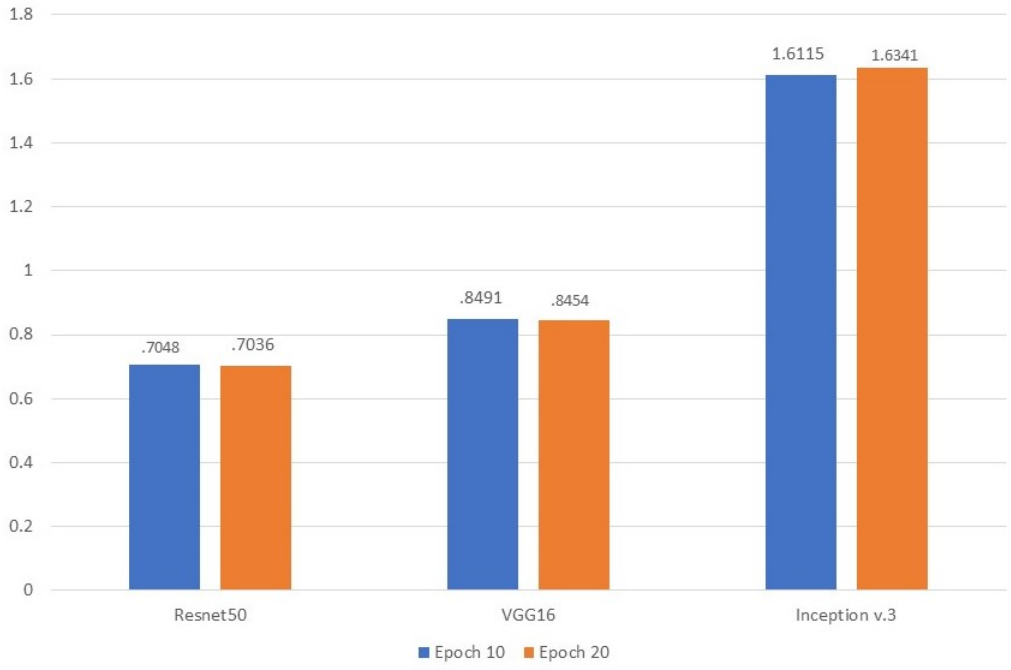

Figure 6.2: Comparison of three models based on loss

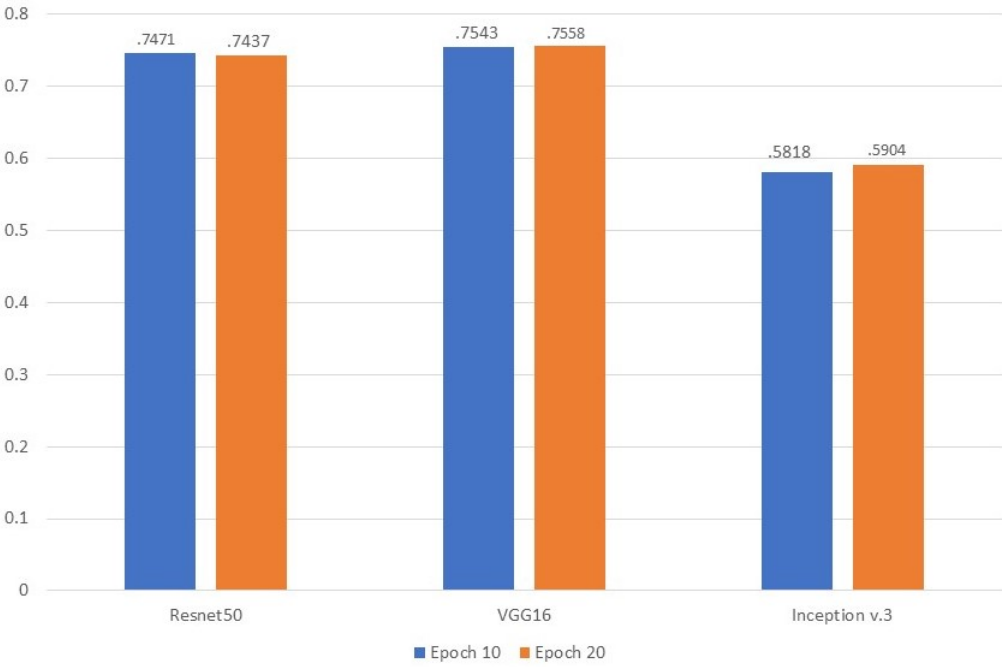

Figure 6.3: Comparison of three models based on precision

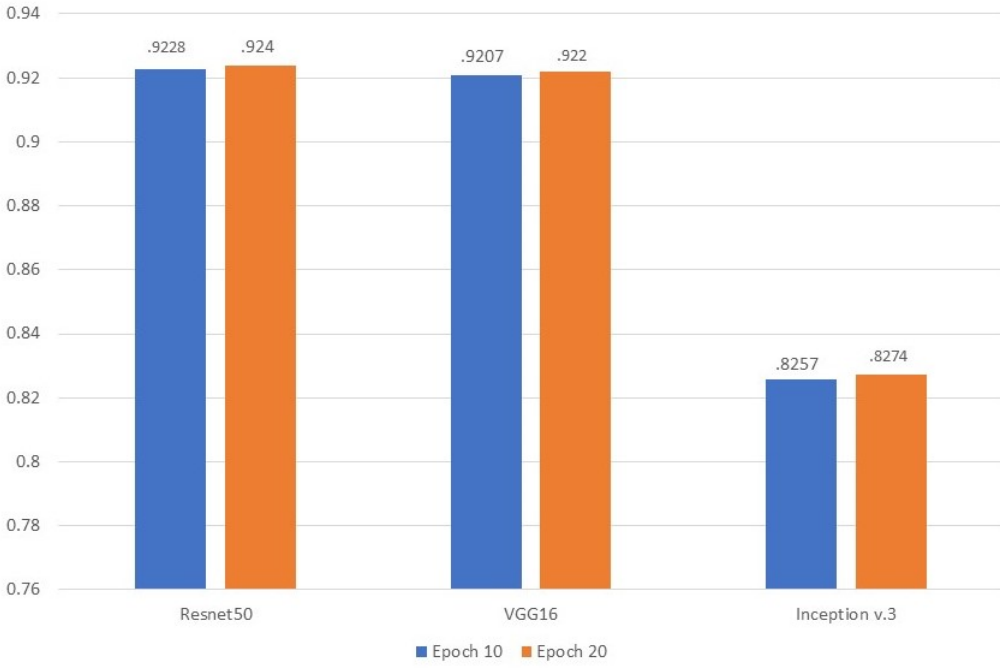

Figure 6.4: Comparison of three models based on AUC

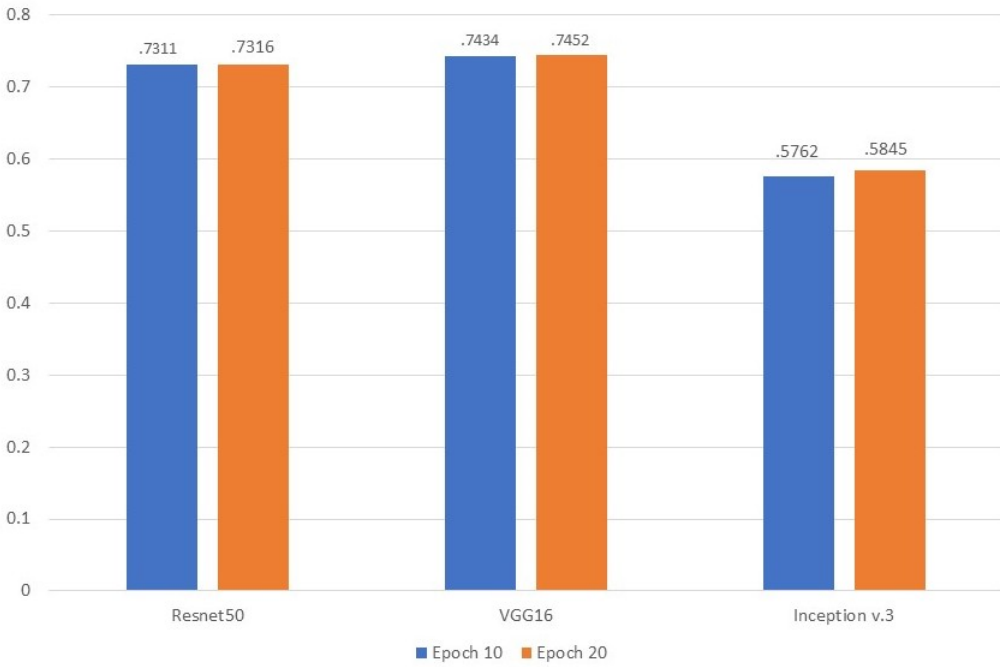

Figure 6.5: Comparison of three models based on f1 score

6.2 Result Analysis with LIME

Most of the decisions or predictions that are made in deep learning or machine learning in different researches around the world nowadays have a very cryptic method of presenting the end result. The coder or the researcher using a pre-built model cannot explain the decision/ classification/ prediction that a model or system is delivering. So this black box concept remains when we are using Artificial Intelligence as well, because it also generates the end result without any human understanding once it gets trained. But this concept can have a really negative effect in some sectors especially in the medical or health sector as the decision remains a mystery over all. Because the diagnosis or assistance that AI contributes to the medical sector can be questionable to the medical expert who has the in hand knowledge or degree to the process without any correct answer for why the detection was processed in such a way [25].

If this procedure of detection or analysis was explainable after the end result; it would be really easy to cross check and have a better understanding for the medical experts and it would result in delivering the maximum benefit and care for the patients. And keeping this concept in the background Explainable Artificial Intelligence (XAI) algorithm or framework came into use [16]. Now XAI can deliver the justification for any model's decision in a way that humans can understand and interpret it quite easily [29].

In our paper we used the LIME based XAI framework for the explanation purpose. LIME stands for Local Interpretable Model-agnostic Explanations which is popularly used to explain or visualize any particular solution or decision. LIME has a model sceptic approach and so it is usable for any model with supervised regression or focusing on classification in particular [11]. LIME has an approach of fitting only one observation around a simple model in use, and from there it tries to demonstrate how the global model would perform in that local measure. And the simpler model can act as an explainer for other complex models in that local measure.

After the testing with the testing dataset, we received 82.56%, 86.82%, 82.04% of categorical accuracy respectively for our Resnet-50, VGG16 and Inception v3 model. We are satisfied with the accuracy as we have worked with a new recent dataset with 6400 MRI scans of 2600 patients where we have tested 1279 scans for the experiment purpose.

Again when we are done with the training and testing of our CNN based model, we are focusing on exploring the regions with the help of LIME based XAI framework to know the exact regions which were key for the type of classification any model had performed. In any XAI framework many pixels are analysed for the explanation purpose. For our paper we are using LIME, and here for any explanation of an observation LIME disturbs that particular image N times and creates similar feature data. And this includes partial value moderation and the new generated data is considered fake data that is created around the observation in order to create a local linear model. Then LIME predicts the probable outcome for that new generated

data and calculates the distance of the original observation from it. After that the similarity valuation is retrieved from the converted distance calculated before. M features are selected from the new data that can describe the generated prediction to the fullest. Fitting a simpler model for the new data is the next essential step in LIME. The coefficients or assigned weights in the simple model are considered as explanations of the observation and thus justify the prediction of AD patients whether it is in the early stage or later. The colorful area signifies the regions that instigated the image classification models to make the prediction they have done in the process. Below we can observe four images for each of the models to have a strong ground on how the models predicted Alzheimer's disease under the CNN architecture.

In case of any images, LIME comparatively works differently than when it is applied on any tabular data. We are implementing LIME in our MRI scans, but it would have a different impact and explanation procedure when done with any csv file. Initially it would not portray much to perturb the pixels individually, because more than one pixel normally points towards one class. Which individual pixels are changing randomly, will not ideally bring the change in prediction as much as the other pixels would do. In LIME as we mentioned earlier different images are generated into superpixel by segmenting one image and also turning the superpixel on and off The term superpixels refers to the adjoined pixels that are mostly the same in colors and can be turned off by replacing the color of each pixel as gray or any user defined color for the pixels. In each permutation the user can also define the probability of getting the pixel's turned off.

From the images below we can observe the classification made by the ResNet50, VGG16 and Inception-v3 neural networks. The images attached below are some of T! Weighted graph that we used in the model when testing, and the model predicted them in any of the classes, ND, VMD, MD or Mod D. It is possible to have a handful of predicted labels for each image but here we will only explain the top labels. The top prediction colors the regions as green where it thinks that are demented and in the red parts are sliding towards non demented region. In calculation with the LIME explainer it then calculates the percentage of classifying the image in either of the four available classes when decided through any of the models.

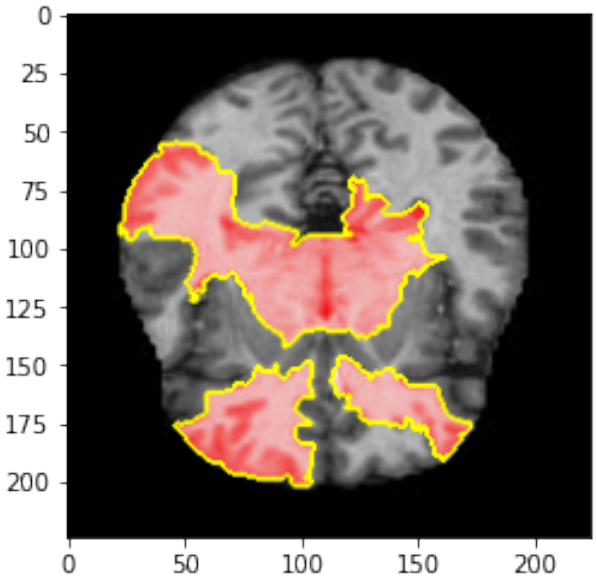

Figure 6.6: LIME regional explanation for classifying as ND in Resnet50.

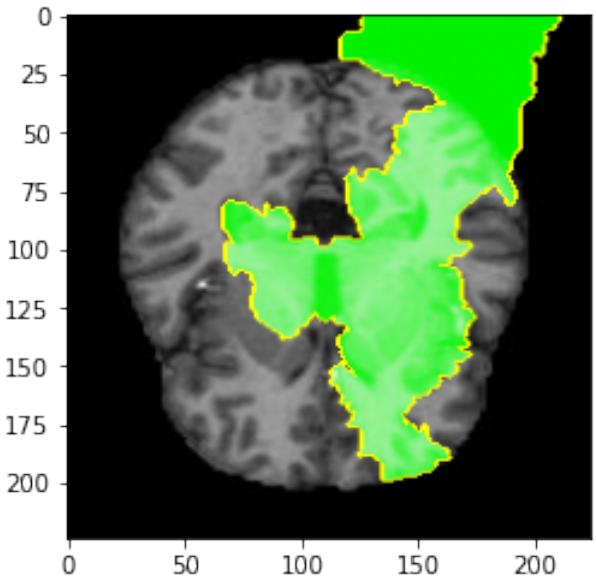

Figure 6.7: LIME regional explanation for classifying as VMD in Resnet50.

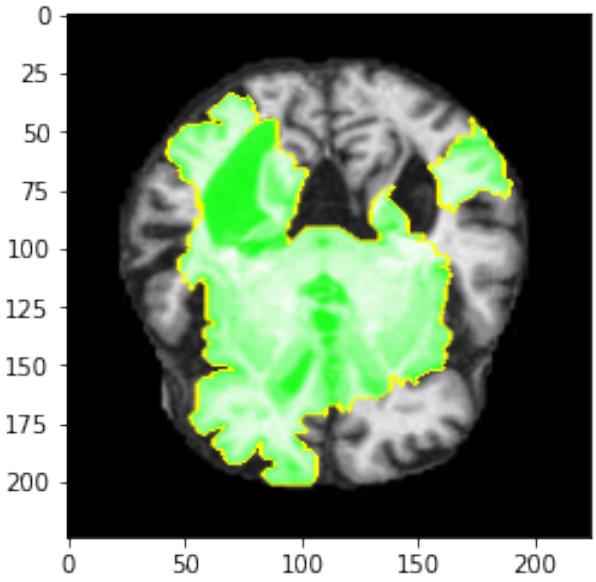

Figure 6.8: LIME regional explanation for classifying as MD in Resnet50.

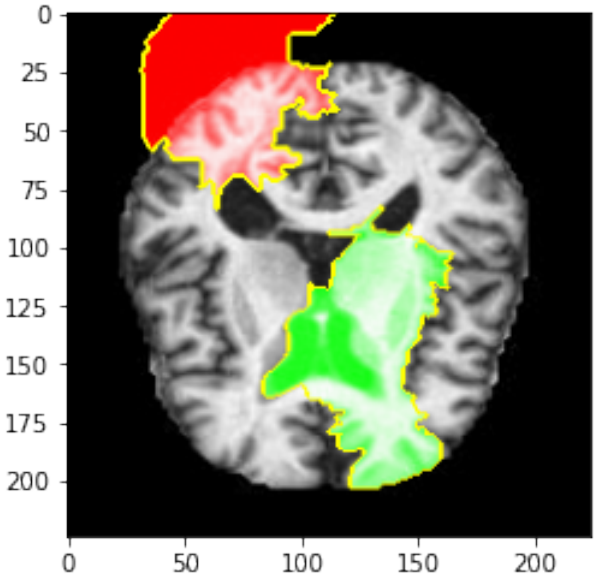

Figure 6.9: LIME regional explanation for classifying as Mod D in Resnet50.

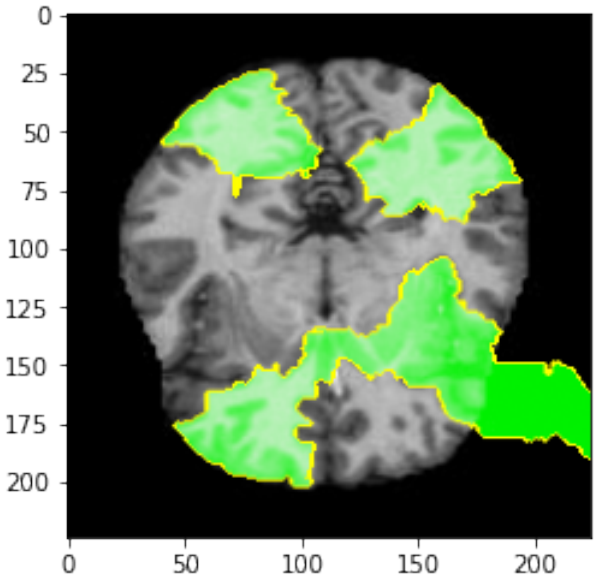

Figure 6.10: LIME regional explanation for classifying as ND in VGG16.

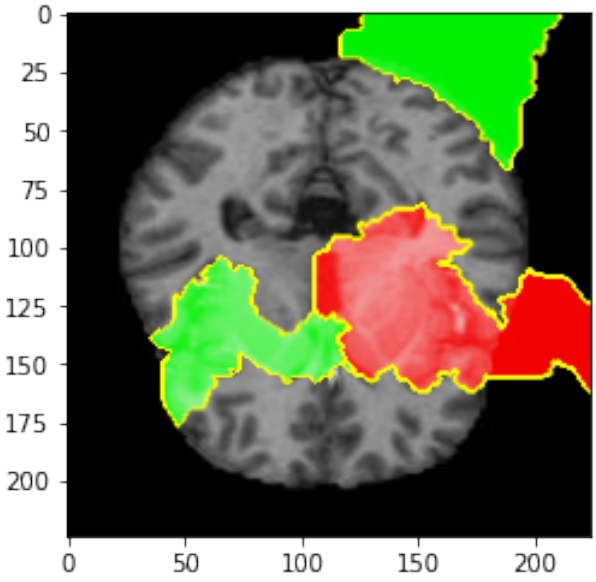

Figure 6.11: LIME regional explanation for classifying as VMD in VGG16.

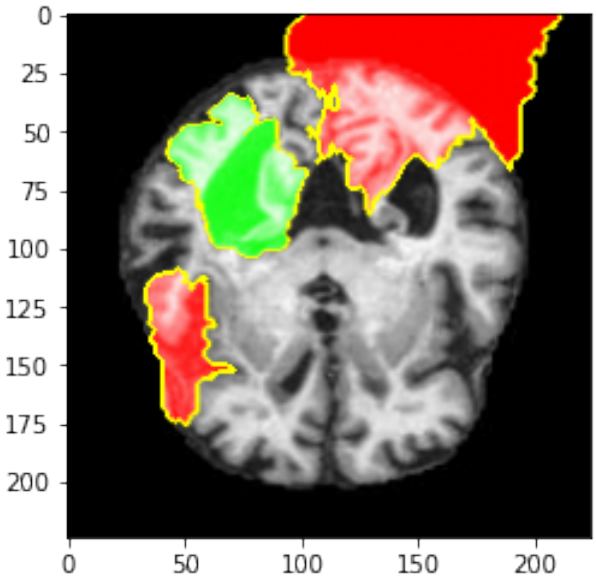

Figure 6.12: LIME regional explanation for classifying as MD in VGG16.

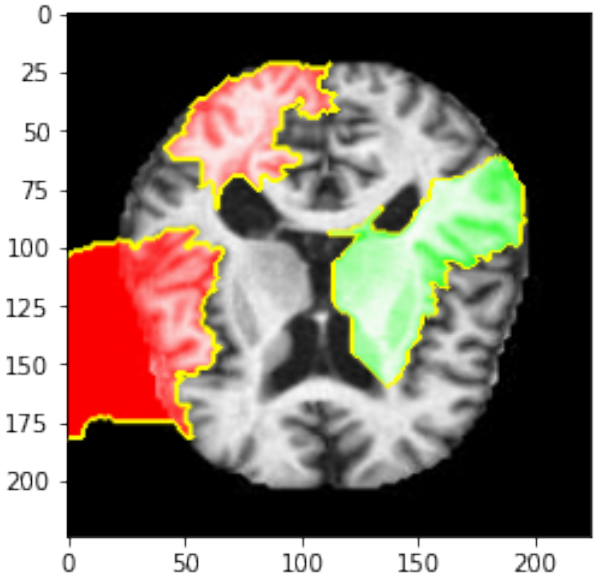

Figure 6.13: LIME regional explanation for classifying as Mod D in VGG16.

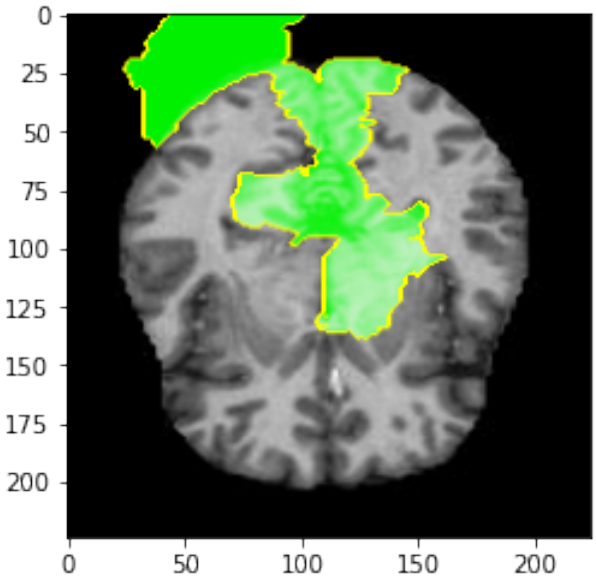

Figure 6.14: LIME regional explanation for classifying as ND in Inception-v3.

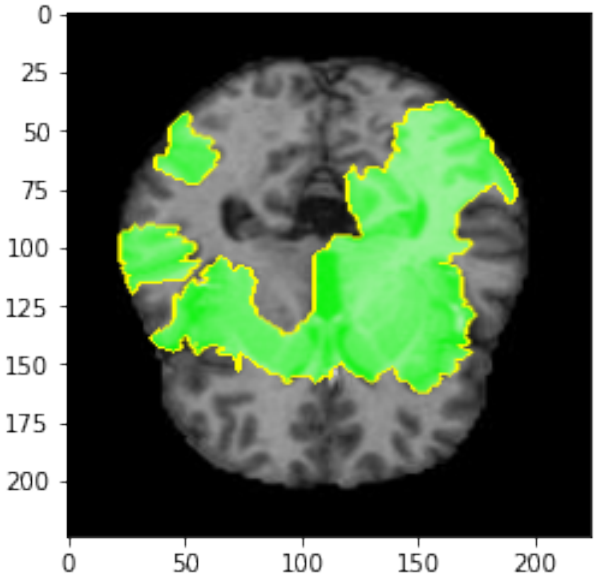

Figure 6.15: LIME regional explanation for classifying as VMD in Inception-v3.

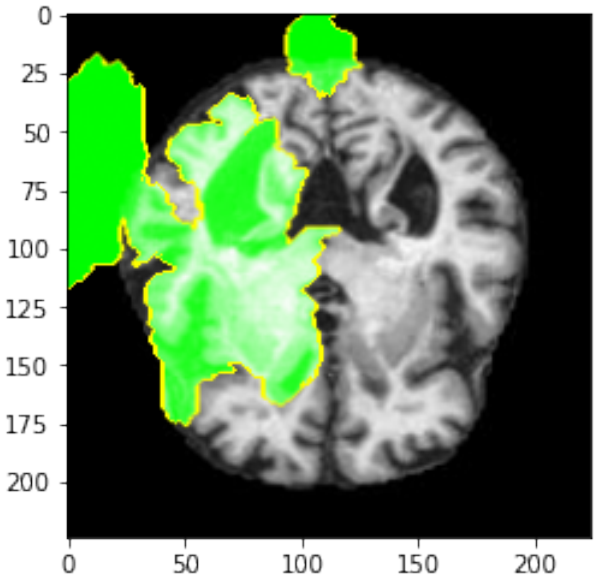

Figure 6.16: LIME regional explanation for classifying as MD in Inception-v3.

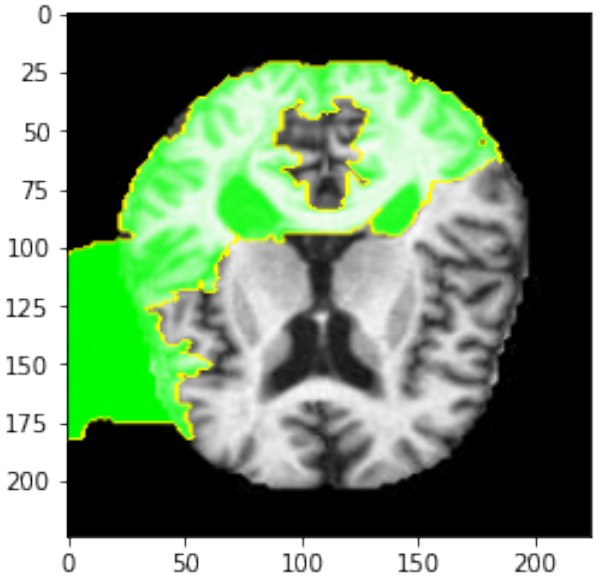

Figure 6.17: LIME regional explanation for classifying as Mod D in Inception-v3.

Chapter 7

Conclusion

7.1 Conclusion

A progressive and incurable neurological disease like AD is extremely common and the brain cell degeneration that results from it is irreversible. Over 500 million people suffer from AD, globally. These numbers are predicted to exceed 152 million by the year 2050. With little known about how to prevent the disease, we must also focus on predicting or detecting the disease as early as possible, and also strive to make diagnosis more accessible and comprehensible to more and more people. Thus, we explore and present the prediction of early stage AD by different neural network models. We put forth many related works and previous experiments conducted on different datasets. In our work, we ran the data through ResNet50, VGG16 and Inception v3 and presented the information using the LIME based XAI framework. We used 80% of our data for training and 20% for testing. In the end, we reached an accuracy of 86.68% using VGG-16, 82.26% using ResNet50 and 82.04% with Inceptionv3 for predicting the 4 classifications. This also presents promising results to improve upon and also be used in other fields. The ease of use with our LIME base framework also is a means to make the low level data more easy to use and comprehend, which is a principle that can be extended to other fields of data processing.

7.2 Limitations

There were certain problems and drawbacks that we faced while working on this project. First and foremost, our initial plan was to collect MRI data locally from institutions in Bangladesh to also incorporate local statistics and conditions in the country. However, due to the pandemic and health risks, we were unable to collect the data that we needed. Next, the accuracy percentages that we acquired from our training models, even though significant, leaves room for improvement, since our initial goal was to achieve values over 90%. Lastly, the margin of loss is also an area where the values were less than satisfactory and we can also cut down the loss here by analysing some of the insights we get from the models and try to change it further for better accuracy with available regularization techniques like L1 and L2. Because the approach we are focusing on is mainly focusing on the health sector, the increased accuracy and lower data loss is crucial for serving the patients with

proper diagnosis of AD.

7.3 Future Work

With regards to our analysis and work, we achieved a significant level of accuracy from the models we trained and presented. Our current work can serve as a baseline to extend and work on Alzheimer's Disease in Bangladesh. Our primary goal is to first fine tune and improve the models to achieve greater accuracy on them, to make it more reliable. Another factor to be improved upon is the percentage of data loss that we faced during data processing, which we will work on to lower and thus make it more efficient. We also plan on working with local data to understand and predict the data statistics in our country, which we could not due to the current pandemic. Furthermore, we plan to implement XAI to other fields of research being conducted in the combined computer and medical fields to make information more accessible for more and more people.

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