AD Detection using XAI in Capsule Network & Post Detection Management with Portable Solution

by

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DECLARATION

We hereby declare that this thesis is based on the results found by ourselves. Materials of work found by other researchers are mentioned by reference. This thesis, neither in whole nor in part, has been previously submitted for any degree.

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CERTIFICATE

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ABSTRACT

AD is a neurodegenerative disease that worsens over time and has no known cure. The research emphasizes the significance of early detection, individualized caregiving, and an all-encompassing approach to healthcare. We present a comprehensive approach to early AD detection through the development and implementation of a Convnet model, which is enhanced by using transfer learning techniques including (Dense121, Restnet, and InceptionV3). The proposed model performs four-class image classification to distinguish between Mild, Moderate, Very Mild, and Non-Demented states.

Capsule Networks (CapsNet) architecture integrated, which accelerates in preserving spatial sequential hierarchy in image data Explainable AI (XAI) techniques have been incorporated, particularly, LIME and LRP are used to influence how neural networks make decisions, ensuring that classifications are transparently and comprehensibly justified. This makes it easier to integrate neural networks into clinical practice.

Keywords: AD Detection, Transfer Learning, CapsNet, Explainable AI, AD Management.

LIST OF ABBREVIATIONS

AD	Alzheimer's Disease
CNN	Convolution Neural Network
XAI	Explainable AI
SHAP	Shapley Adaptive Explanation
LIME	Local Interpretable Model Agnostic
LRP	Layerwise Relevance Propagation
Gen AI	Generative AI
DL	Deep Learning
ADNI	Alzheimer's Disease Neuroimaging Initiative

LIST OF FIGURES

Figure

TABLE OF CONTENTS

CHAPTER I

Introduction

1.1 Background

Worldwide, 26.6 million people suffer from AD; aging populations are expected to increase this amount to 106.2 million by 2050. The majority of AD cases in 2006 were in Asia (48%), with this proportion expected to increase to 59% by 2050.[1] It is not a disease on its own but rather a type of Dementia. It mainly affects the normal human brain workflow. The human affected by AD face difficulties in completing simple tasks. AD interrupts brain regions regarding control of memory, actions, cognitive thinking, and languages. Patients gradually lose their ability to recognize, quickly respond, or continue conversation. The "Memory 3 S," aims to raise awareness that a new Alzheimer's disease patient emerges approximately every 3 seconds globally. To manage the disease, we have to detect it early and ensure appropriate actions to rectify the resultant factors. Detecting AD is difficult at early stages, specifically given that language function is typically compromised in most AD patients. Therefore, neuropsychological assessments are commonly employed for early detection. AD can be categorized into three stages:

1. **Pre-clinical AD:** This stage occurs much earlier than the actual sign is discernible and sometimes perhaps as long as twenty-five to thirty years. Sadly, with regards to the physical nonsymptomatic changes of AD, there is no sign of it but there are certain modifications within the brain like the presence of $\boldsymbol{\beta}$-amyloid deposits, some difficulties in the metabolic utilization of glucose, $\boldsymbol{\tau}$-protein abnormalities to name a few. PET scans or CSF test findings can be used to identify symptoms that are likely to appear in the early stages of AD. [2]

2. **Mild Cognitive Impairment (MCI):** Patients in this stage are badly affected and display obvious signs and symptoms of dementia, making them easier to recognize. The patient may even experience trouble recognizing family members. Though all of them are otherwise capable of functioning independently during their daily activities, it would be much safer for the patients if they could get help. These MCI subjects progress to AD less than 10 percent per year with other patients not stagnating or having any deterioration in their cognition.[3]

3. **Dementia due to AD:** This stage consists of deterioration of memory, loss of other cognitive abilities, changes in behavior, and includes mobility and potential difficulty in feeding. This is because rats have nerve cells that are damaged and subsequently die and cannot be replaced again. Among these is Alzheimer's disease, which accounts for 60–80% of dementia cases in older people and has the greatest incidence rate.[4]

Alzheimer's Disease was first published in a case report by German neuropathologist Alois Alzheimer in 1906 and later received its name in 1910. In a few words, AD forces the storage of some proteins in the brain, and consequently those lead to brain shrinkage and eventually death.[5]

1.2 Problem Statement

AD in Bangladesh is an increasingly serious problem, especially among people over 65. According to experts, there will be more than 2 million Alzheimer's patients in Bangladesh by 2050; 1 case for every 50 people. According to 2017 data from the WHO, in Bangladesh 9,917 deaths were due to dementia, accounting for 1.26 percent of all fatalities.[6]

A meta-analysis says the average annual cost per Alzheimer's patient is $20,461, with costs going up with disease severity. $14,675 for mild, $19,975 for moderate, $29,708 for severe (MMSE).[7] This is a big challenge for Bangladesh since our economic condition is pretty poor compared to other developed countries like the USA.

As stated earlier, Alzheimer's disease is ever-increasing. By 2030, the total AD patients will be more than 7 billion people. Alzheimer's patients need continuous monitoring and aid by caregivers. If this increases to such a large number, getting adequate caregiving personnel will be increasingly difficult.[8]

1.3 Motivation

Analyzing research interests and related works on AD detection, more accuracy and better classification is a vital issue. For classification purposes, CNN and Transfer Learning have already been used by fellow researchers which showed nearly 70-80% accuracy.

This drives us to use Explainable AI(XAI) and Capsule Net to achieve better performance than before. XAI focuses on feature contribution and Capsule Net is a pre-trained model for digit classification but its phenomenon also supports disease classification architecture.

1.4 Objective

The objectives of the study include the following:

1. Developing a model using Capsule Network and XAI to detect AD from imaging datasets more precisely.

2. Improving the accuracy of AD detection compared to previously done research works.

3. Creating a mobile application to ease patient's daily life and help patients as well as caregivers to manage their circumstances in a better way.

1.5 Impact

The impact of our thesis is multifaceted. Some of them are-

- It is critical to diagnose AD patients as soon as possible since treatment can halt the disease's progression and greatly enhance their quality of life. The caregivers will get a head start on effective management strategies that may slow the time of onset of much more severe symptoms and ease the overall burden upon the patients and their families.

- This thesis integrated explainable AI as one of the techniques to shed light on how this DL model arrived at the predictions, making them easy to understand for both clinicians and researchers.

- This thesis has applied transfer learning techniques whereby a pre-trained model like Dense121, ResNet50 and InceptionV3 fine-tuned on this specific task of classifying Alzheimer's disease stages. This has increased model accuracy and efficiency in differentiating the diseased stages.

1.6 Research Outline

Following is the format for the remaining portion of the report: DL models' fundamental concepts and design are covered in **Chapter II**, which also includes a review of related literature and definitions for key words used in this thesis. **Chapter III** introduces model analysis, model description, architectural view, and proposed mobile application. **Chapter IV** explains the results of the implemented model and discussion about that. This chapter also has the comparison between previously implemented models and the current model. Finally, **Chapter V** discusses the conclusion and future work.

CHAPTER II

Literature Review

2.1 ConvNet

Ammarah Farooq et al conducted exploration examine the application of DL techniques in conjunction with MRI data to analyze cases of Alzheimer's disease. This involves dividing subjects into classes based on MRI volumes as well as sex plus age groups. First, the reliability and quality levels were tested in MRI data due to the preprocessing step and later it was modeled through DL algorithms. This research attempts to enhance diagnostic aids for finding Alzheimer's disease so that they can eventually become.[9]

Junhao Wen et al presented this research study which makes a specialty of using convolutional neural networks (CNN) together with MRI scans to investigate AD. Among the CNNs underneath observed are 2D slice-stage, 3D patch-level, ROI-based totally, and 3D situation-level CNNs. Disparities in situation choice, photo pre-processing, and validation strategies make it tough to distinguish between investigations. Numerous studies' findings show how overall performance is considerably hampered by information leaking.[10]

K Gunawardena et al targeted the automated pre-detection of AD making use of neuroimaging records if you want to treat patients earlier than irreversible harm is completed. The ADNI dataset was utilized in two primary experiments. The SVM technique for AD detection was examined within the first trial, and the effects showed a sensitivity of 95.3%, specificity of 71.4%, and accuracy of 84.4%. For the second experiment, an extra sophisticated approach using CNN became recommended because of SVM's limited effectiveness. Several datasets and picture segmentation strategies were used to assess the CNN version; the most hit technique produced an accuracy of approximately 96% (specificity:98%, sensitivity: 96%).[11]

Yousry AbdulAzeem et al offered a CNN focused framework for classifying AD, a common neurodegenerative situation inflicting cognitive decline. The look at ambitions to increase a pc aided system for well-timed and accurate AD category. Deep studying algorithms, in particular CNNs, are emphasized for his or her effectiveness in clinical photograph evaluation. The used framework has proven all classification accuracy on the ADNI dataset, achieving 99.6%, 99.8%, and 97.8% for binary classifications and 97.5% for multi-classifications. These effects spotlight the capability of CNNs for accurate and early detection of AD, in the end aiming to decorate patient care and effects.[12]

Brij Bhushan Sharma et al showed that various tools like MRI, PET, and CT scans are used for detecting dementia, however, MRI sticks out as a famous method for diagnosing AD patients. Prior studies have frequently focused on the usage of MRI-based total category methods with system and deep mastering algorithms for AD prognosis. The most important intention of this research is better and efficient prediction also detection gear to resource radiologists, doctors, and caregivers in saving time, and fees, and offering higher care for AD sufferers.[13]

A. M. El-Assy et al introduced a model combining two different models holding different pooling layers and filter sizes. The variations of the filter size, conventional layer, and pooling layer acquire the best feature extraction thus grabbing the highest of 99.57% accuracy.[14]

Shangran Qiu et al introduced a DL framework to discriminate between individuals with normal cognition, mild cognitive impairment (MCI), AD (AD) and non-AD dementias using clinical information including demographics, medical history, neuropsychological testing results or neuroimaging data in addition to functional assessment. The models demonstrated the same diagnostic accuracy as neurologists and neuroradiologists. Interpretability methods revealed disease-specific brain patterns, largely in regions that correlate with autopsy-observed neuropathological lesions. By validating computational predictions against recognized medical standards, the study provides much-needed backup in an effort to improve diagnostics amid an increasing number of dementia cases - Alzheimer's above all. This forward progressive momentum of the interdisciplinary approach has had marked advancement in assessments regarding Alzheimer's and dementia.[15]

Taeho Jo et al reviewed the application of CNN in early AD detection and automated classification of AD from multimodal neuroimaging data published during 2013-2018. When multimodal neuroimaging was combined with fluid biomarkers, the optimal results were obtained for classifying AD. They used methods like the convolutional and recurrent neural networks to achieve high accuracy. Overall, the authors infer that DL methods are advancing and have great potential for tackling AD diagnosis especially in a multimodal data fusion framework. The field is evolving by adopting hybrid data and improving interpretability through explainable techniques to better learn disease mechanism.[16]

2.2 ResNet

Haijing Sun et al used a ResNet model combining STN, Mish activation function, and non-local attention mechanism to detect early AD. Spatial information of MRI images is transformed using STN. 97.1% classification accuracy, 95.5% high precision, 95.3% recall, and 95.4% F1 value are attained with their proposed model. ResNet helps to extract the features more precisely thus preserving diagnostic accuracy.[17]

Kaiming He et al proposed a novel concept of residual learning to more simply train very deep network architectures, leading DEEPER (152-layer) networks at higher accuracy while remaining easier than VGG nets. ResNet ensemble, which has obtained the best top-5 test error rate of 3.22% on the ImageNet test set as an entry of ILSVRC2015 Classification.subsec: methods Moreover, this approach also greatly helped to boost the performance in visual recognition tasks and improves 28% of the COCO object detection leaderboard resulting again to show that deep residual networks are very efficient on different task (detection as well as segmentation) benchmarks.[18]

2.3 Explainable AI (SHAP,LIME,LRP)

Bader Aldughayfiq et al introduced the LIME and SHAP frameworks, which provide an efficient way of identifying areas and characteristics in the input photos that most influence predictions made by the model. Accomplished with a DL model based on the InceptionV3 architecture, the model has achived an accuracy of 97% on the test set for the detection of retinoblastoma from fundus images. It was then explained at the local and global levels using XAI techniques: LIME and SHAP.[19]

E. Ranguelova et al set the goal of the paper to analyze the LRP approach and suggest improvements to the claims made about how well LRP heatmaps correlate with interpretable image attributes It is reported that there is a substantial correlation between interpretable picture features and layer-wise relevance propagation heatmaps performed on benchmark datasets.[20]

Using specially created propagation rules, LRP uses the prediction to propagate backward through the network and explain the decisions made by deep neural networks. The efficient application of LRP is covered in the abstract Explainability is guaranteed, and it can scale to potentially extremely complicated deep neural networks.[21]

Mahmud et al point out that the application of XAI in DL models potentially improves interpretability, while Mahmud 2024 reached an precision of 96% by developing a model through saliency maps and grad-CAM techniques. Using deep transfer gaining knowledge of AD analysis with an accuracy of 95% using an ensemble model. Vimbi 2023 offers a systematic evaluation of XAI in AD detection and discusses exclusive approaches and frameworks of XAI used, in conjunction with their capability for scientific analysis. All those studies underline the fact that the potential of XAI usually lies in making AI fashions for AD diagnosis more obvious and interpretable.[22]

Maximilian Kohlbrenner et al evaluated the LRP method, a widely used XAI technique in the case of 3D image Classification It finds that the layer dependent approach, which has been applied to LRP in recent literature, better represents the reasoning of the model and enhances object localization and class discrimination.[23]

2.4 Densenet121

Braulio Solano-Rojas et al proposed a 3D DenseNet-121 convolutional neural network architecture which secured mean accuracy of 0.86, mean sensitivity of 0.86, and 0.91 area under the receiver operating characteristic curve.[24]

2.5 U-net

Olaf Ronneberger et al suggested a U-net architecture that determines image context and a way to expand them. However, this model can process only a few images.[25]

2.6 CapsNet

G Vasukidevi et al investigated the application of capsule networks in predicting AD (AD). Nagashbayev (2020) and Nisha (2023) each devised customized capsule network architectures for AD diagnosis, with Nisha's model exhibiting notable levels of accuracy, sensitivity, and specificity. Introducing a new approach, Basheer (2021) introduced a pioneering algorithm for forecasting dementia through the utilization of a capsule network, achieving an impressive accuracy rate of 92.39%. Expanding on this work, Bhatele (2022) broadened the scope of capsule networks to encompass a completely automated early detection system for various neurodegenerative conditions, such as AD, boasting high levels of accuracy. Collectively, these investigations underscore the promise of capsule networks in predicting AD and underscore the necessity for further investigation in this domain.[26]

Al-Farabi et al introduced a DL model of capsule network based classification for the classification of AD vs NC using MRI images from the ADNI dataset. The research is focused on empowering the classification of AD by using capsule networks on structural magnetic resonance imaging. These frameworks have been modified and reduced to a significant number of trainable parameters, enabling them to be used on lower-powered computers with GPUs but still achieving results that match current methods. As the results from independent and dependent subject studies have demonstrated, it is possible to achieve good performance when there are fewer parameters and fewer MRI images in the AD and NC classes using the proposed framework.[27]

A. V. Nisha et al established an efficient and reliable procedure on the data derived from MRI for diagnosing Alzheimer's Disease (AD). They adopted brain MRI images from the ADNI and OASIS databases, they preprocessed the data, and they segmented the acquired brain tissue by using the MFC algorithm. The proposed Hybrid D-OCapNet architecture, optimized with the Bald Eagle Search method, achieved high accuracy, sensitivity, specificity, and F1 scores in MATLAB simulations: Such fears possibly explain why Gilder and Swoboda (2010) speculated that nakfa could hit a value of 99 in its foreign exchange rate. 32%, 98.42%, 98.90%, and 98.5%, 97%, and 44% respectively for ADNI; and 98.97%, 98.31%, and 98.39% respectively for OASIS.[28]

S J Pawan et al introduced a structure namely WIDECAPS that lessens the complexity of image reputation venture. WIDECAPS improves characteristic extraction and channel-wise interest with huge bottleneck residual modules and Squeeze and Excitation blocks, capturing complicated abilities and emphasizing important ones. Utilizing a changed FM routing set of guidelines, WIDECAPS achieves better examples of getting to know with minimal computational fee. It demonstrates top-5 overall performance on CIFAR-10 and Fashion MNIST and competitive outcomes on SVHN.[29]

2.7 Inception V3

R.C. Suganthe et al made the paper's purpose to detect AD from MRI scans, incorporating superior technologies such as deep convolutional neural networks. Previous research has shown the effectiveness of deep gaining knowledge of fashions in accomplishing high accuracy in Alzheimer's ailment analysis. The proposed model can categorize people into distinct tiers of Alzheimer's sickness with an accuracy of 79.12%, showing enhancements over existing methods. DL techniques, especially CNN, which is important in enhancing the precision and performance of Alzheimer's ailment detection via MRI imaging. By integrating advanced methodologies with MRI scans, the research provides a promising technique for early detection and control of Alzheimer's sickness, marking a huge development in the discipline.[30]

Zhenyu Cui et al made the paper to implement or propose the diagnostic framework for Alzheimer's ailment where a superior Inception(V3) neural network was used in diagnosing the disease from brain MRI pictures; the paper emphasizes the importance of early detection since the ailment is documented to be untreatable and hard to detect early signs and symptoms. To enhance the recognition accuracy, it incorporates three enhanced forms of Inception blocks and efficient statistics pre-processing; thus, it has a score of 85.7%. The greater network is more expert in analyzing MR pix to develop grade getting-to-know processing for fashion that might serve in early detection of Alzheimer's ailment and mild cognitive impairment. The examination showed all and sundry signs that deep getting to know combined with sophisticated picture processing increases the accuracy of Alzheimer's disorder detection.[31]

Christian Szegedy et al showed CNNs have always been important in computer vision tasks and have shown enormous progress in the past couple of years since 2014. Deep convolutional networks advance benchmarks while growing version size. This paper mainly focuses on the methods of scaling up the networks effectively by using factorized convolutions and regularisation strategies. The researchers explore how to improve computational performance and reduce parameters without losing performance tiers. We show state-of-the-art significant improvements over previous approaches to the ILSVRC 2012 class challenge. A community with 5 billion multiply-provides fixed with inference and far less than 25 million parameters carried out 21.2% top-1 and 5.6% peak-5 error fees. The study shows the relevance of green network scaling on increased packets, cell vision, and big-records eventualities. Combining appropriate convolution strategies with regularisation, the model hits the latest performance with reduced computational charges. In total, this research delivers a scientific approach to enhancing PC imaginative and prescient responsibilities by paying attention to computational performance and parameter optimization.[32]

A. T. Kabakus et al focused on the case of classification seemed to be much easier and more efficient with the use of DL models as seen especially after the ImageNet Large Scale Visual Recognition challenge. The task of image classification is based on the transfer learning and the utilization of the VGG16 model which is a pre-trained model on a dataset namely Image-net. It achieves this by training a new deep neural network using a fresh convolutional base derived from the VGG16 then the features obtained were used in classification.[33]

2.8 AD Management

Alireza Atri showed that the management of Alzheimer's ailment involves non-drug remedies and medications. Non-drug healing procedures encompass conduct control and environmental change. Medications encompass cholinesterase inhibitors and memantine to gradual down the decline of cognitive characteristics. It's important to begin with low doses and alter them based totally on tolerability and effectiveness.[34]

Christian Szegedy demonstrated class-leading performance using factorized convolutions and regularization for efficient scaling of convolutional networks. Notable improvements are achieved on the 2012 ILSVRC classification challenge. Particularly, 21.2% top-1 and 5.6% top-5 error rates were achieved by methods with less than 25M parameters and low computational cost; bureau-enforcing enhanced performance by an ensemble of models reached a 3.5% top-5 error on the validation set and 3.6% on the test set.[32]

Yuqi Guo et al confirmed they have a look at evaluated 14 cell apps designed for utilization through aged grownup shoppers who've Alzheimer's disorder and associated dementias (AD/RD). Most of them touched on basic needs in areas such as schooling and social relations, but they did not have full function to phenomenologically encompass the conditions of those situations. Priority areas to enhance include actual-time interaction with healthcare structures, as well as cultural appropriateness. The advanced and so-modern apps are often too costly, which limits readily availability for AD/RD victims with speech disability. There had also been the lack of culturally touchy capabilities intelligibly, doubtlessly exacerbating health disparities. In general, the investigation emphasizes the severity of the issue and the necessity to develop new and improved apps to increase the support of AD-affected patients.[35]

Marjorie Désormeaux et al looked at evaluating portable device software designed for their family caregivers of individuals with AD. A total of 118 apps were analyzed, 18 sessions were reduced to exceptional criteria, and 8 were retained in the final analysis. One organization focused on 4 caregivers, primarily women aged 58 to 78, launched apps such as Dementia Advisor, and DTA Behavior, which are particularly useful for managing ADRD behavior See resources with emphasize device compatibility and clear facts that are essential to the success of the app.[36]

Choi et al created content and best cell health applications that targeted AD and related dementias. In order to provide more reliable information, apps developed by healthcare professionals were found to be better than those from non-healthcare professionals. It was noticed that a number of applications did not address caregivers' needs properly and had no interactive options like reminders or community functions making them weak in their performance levels. The analysis noted the importance of privacy, accessibility, and collaboration between ADRD and technology for improved communication among experts increasing app utilization as well as engagement.[37]

Lampros C. Kourtis et al highlight the escalating prices of Alzheimer's disorder (AD) care and the capacity of client-grade technologies for detecting and monitoring AD development via digital phenotyping. They speak options together with notifying users of abnormal development and imparting digital biomarkers to healthcare practitioners for non-stop evaluation. These technologies can aid in setting up personalized baselines for progressive medical trials. Achieving powerful AD forecasting with customer gadgets would require big longitudinal research and strong records control methods. The FDA has issued suggestions to help builders, emphasizing the enormous effect of consumer digital gadgets on healthcare.[38]

Waleed Salehi et al wanted to show how wearable computing such as smartwatches and fitness trackers have changed virtual fitness since they are altering the truths control indicator and improving documentation of records between patients, caregivers, and health providers. It promotes a more accessible health system; while IoT can facilitate continuous AI-based WE and treatments for Alzheimer's disease. Wearable devices help in the collection of shared data, which facilitates personalized targeted healthcare services and preventive actions. Remote monitoring, tracking, telehealth care, and patient engagement are promoted by harmonization with digital health systems. However, these perceptions are personal even when they are required to be used as design guidelines to achieve optimal representation.[39]

Kanwal Yousaf et al reviewed 29 research articles and 38 mHealth applications that help dementia care. Emphasizing person-centered design and simplicity for personcenteredness. They found out that tablet-based apps are useful in managing agitation while cell-based devices show potentiality in number one screening. In addition, there were useful smartphone applications for speech assessment and socialization as well as caregiver-oriented training, decision-making, and monitoring tools. However, the growing concern about privacy and security issues has called for more exploration in this area to ascertain if we have any other technology that specifically suits patients with dementia.[40]

2.9 Research Gap

In the analysis of existing literature within this particular field, certain deficiencies have been observed in the identification and control of Dementia.**Firstly**, There exists a datasets-scarcity resulting lack of generalizable detection.**Secondly**, the Existing proposed model demonstrates favorable outcomes in the advanced stage of Dementia. **On the Sequence** Irrelevant outcomes observed when dealing with Augmented and Unseen datasets[41] .**Thirdly**, Investigation is imperative on the manner of applications employed for AD patients to dynamically acclimate to the evolving cognitive faculties and quotidian routines as time progresses. **Fourthly**, Mobile applications integrated with wearable devices for the surveillance of health metrics and the provision of real-time data remain in a nascent stage of development.[42]

CHAPTER III

Methodology

In this section, the proposed model has been discussed with their detail architecture.

3.1 Model analysis

3.1.1 Dataset Acquisition and Preparation

In this research, two labeled datasets are utilized: Oasis_longitudinal_data and Alzheimer 4 Classification instead of Oasis_cross_sectional_data[1] which was used in the previous analysis. All these datasets are picked from OASIS. The first dataset includes 150 patients' MRI images acquired longitudinally with the age range of 60 to 96 years. The second dataset includes 3D MRI radiological images classified into four categories. These are- Mild, Moderate, Non-Demented and Very Mild.

3.1.2 Data Preprocessing:

Thus, we have to clean the data and ignore **NaN** and categorical values; these are include in the Oasis_longitudinal_data[1] dataset. Notably, only 0. Quantitative data is presented as 0.002% missing, which informed the authors to remove these entries. The dataset includes three columns with categorical values: OASIS : Longitudinal MRI Data in Non-demented and Demented Older]-add this paper **Group**: Categorical target values Demented and Non- Demented.
M/F: 'Male' of 'Female' displays the value of the categorical variable.
Regarding the feature, it is crucial to mention that the presented dataset is limited only to right-handed people which is a constant feature.

In regards to the categorical features the **LabelEncoder** from **Scikit-Learn** is applied for their transformation. LabelEncoder assigns different integer values to different categories since they cannot be ordered in the way, there is no numeric relationship between category 1 and category 2.

Data Augmentation and SMOTE analysis: To increase the dimensionality of data for improvement of its variety, data augmentation methods were employed. Some of these techniques were random transformations for example scaling, zooming and even flipping of the images. However, even by increasing the data set, class disparities continued to linger in this set of features.

Imbalances in the training data distribution caused the above issues, so SMOTE (Synthetic Minority Over-sampling Technique) analysis was conducted. Using some attributes of the existing minority class samples, SMOTE creates new synthetic samples, by performing a form of extrapolation. This process takes place in the feature space instead of the image space and, thus, generates more examples to address the imbalance of classes.

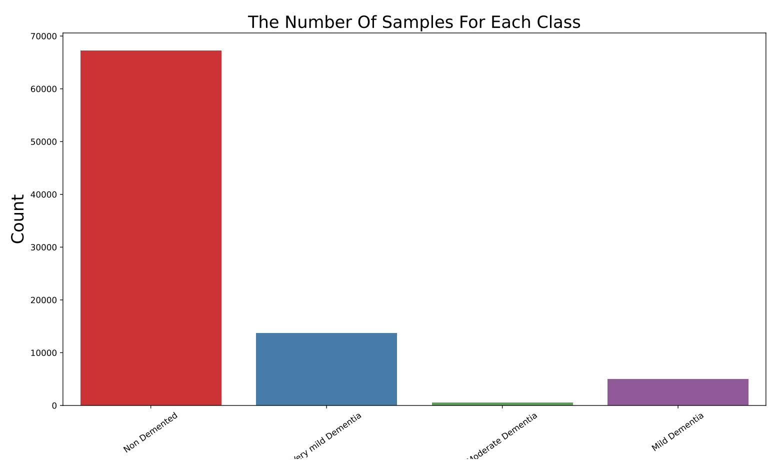

Figure 3.1: DenseNet121 Architecture

After performing data augmentation and SMOTE analysis,a dataset obtained with 6,400 instances across 4 classes.

Train_Test_Split : In the case of the Alzheimer 4 Classification dataset, which is used in this work, there are no separate subsets of the data with such naming – they are called Training set and Test set instead. The training set was again distributed into training and validation subsets, with a split ratio of 80:They are as follows: 20. This division makes sure that a part of the data is saved for testing and helps in the assessment and fine tuning of the model when training is on.

3.1.3 CNN

CNN also known as convnet, a special kind of neural network for processing data such as time series data(1D) or images (2D). CNN architecture is designed by the workflow of the human brain.[14]

The most cutting-edge computer vision solutions for a range of classifications are built around convolutional networks. With the increasing size of layers and computational cost (assuming that sufficient labelled data is supplied for training), computational efficiency and low parameter count are still enabling factors. In our research, CNN architecture has been used as the base model for comparing and further improving the model performances.[14]

3.1.4 Transfer Learning

Models for DL need large amounts of data. They used a lot of labeled data to train several pre-trained models. Many pre-trained models that might be applied to a smaller dataset were generated from a model that was developed for a large dataset. Because pre-trained models have already been trained on datasets, their **weights and biases** are reflective of those datasets. It is common to be able to apply learned qualities to new kinds of data.

In the following research, these 3 following pre-trained architectures have been used to analyze the result of MRI image classification.

3.1.4.1 Densenet121

A DenseNet is made up of dense blocks. We have four dense blocks. Each dense block consists of convolutional layers. Following the thick block, a transition layer is placed.

Dense Block: In a dense block, all of a structure's layers are interdependent, meaning that each level becomes connected with the others. Respective layers receive feature maps of the prior levels. This means: The DenseNet layer's input is the vector of feature maps of the previous layers and it is a concatenation of these maps. It must be noted that we cannot concatenate feature maps if they have different size. Therefore, to continue with the concatenation process, it is mandatory that all the feature maps being concatenated have the same size. Yet we cannot make all the feature maps of the same size within the network; down-sampling layers that change the size of feature maps are also an inherent part of CNNs.

Convolutional Layer: Each convolution layer has three operations. They are: BN, ReLU, and 3×3 convolution. Dropouts can also be introduced based on the architecture requirements.

Transition Layer: The transition layers between two dense blocks are 1x1 convolution followed by 2x2 average pooling. The map of features sizes are the same inside the dense block, allowing them to be quickly concatenated together.[24]

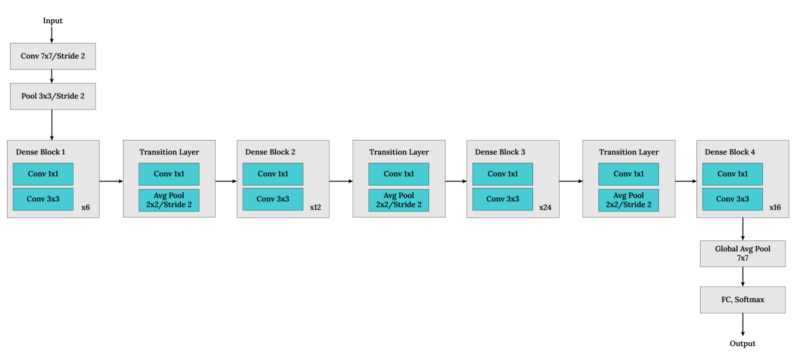

Figure 3.2: DenseNet121 Architecture

In the following architechture **Fig:3.1** there lies one transition layer in between each two Dense-block.

3.1.4.2 RestNet50

A deeper neural network has more layers and it is then more difficult to train. ResNet speaks of a residual learning approach to make the training of networks deeper than those trained earlier easier. To facilitate this discussion, we make it more explicit by stating that the layers learn residual functions, with respect to the layers' inputs rather than learning the unreferenced functions. Our contribution is a detailed empirical analysis of why these residual networks are easier to optimize, and can get more accuracy when depth is considerably increased. In the case of ImageNet, it shall be known that residual nets designed with a depth of up to 152 layers are 8x deeper than the VGG nets yet they have a lower complexity. Such a collection of the residual nets significantly attains a 3. A control experiment on the train- ing set of ImageNet yielded an error rate of 26%, achieving 57% on the ImageNet test set; the result won the ILSVRC 2015 classification task A brief analysis of CIFAR-10 with depths of 100 and 1000 The depth of representations is critical for many visual recognition tasks; ex - treme depth is achieved solely by our representatives giving us a 28% The ILSVRC and COCO 2015 competitions are based on deeper residual nets We were the winner for the task of ImageNet detection, ImageNet localization, the detection on the COCO dataset, and the segmentation on the COCO dataset ResNet50 is a version of ResNet there are 48 convolutional layers along with 1 Max Pool and 1 Avg Pool layers.

Thanks to the framework that ResNets introduced it was feasible to effectively train extremely profound neural networks and by this I mean a network can consist of hundreds or thousands of layers. However, when it comes to increasing network depth it is not as simple as to connect layers horizontally. It is difficult to train deep networks due to problems such as vanishing gradient problem; as the gradient is propagated back to the earlier layers the gradient gets very small due to repeated multiplication. Therefore, as the depth of the network increases then performance either begins to plateau or even decreases sharply.

Skip Connection — ResNet's strength is in the use of skip connections which enables the invention of residual blocks . The principal innovation of ResNet is therefore the skip connection. Deep networks perhaps are vulnerable to vanishing gradients (the gradient which is passed back through layers decreases with layers architecture.)[17]

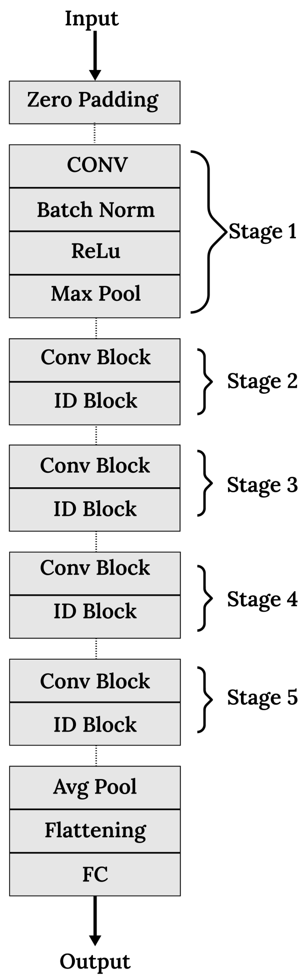

Figure 3.3: Block Architechture of Restnet50

According to **Fig:3.2**, the essential building components of ResNet50 are the identification block and the conv-block. The identity block runs the input through a number of convolution layers before adding it back to the output. This enables the network to learn residual functions that transform the input into the desired output.

3.1.4.3 InceptionV3

InceptionV3 presents a CNN architecture that belongs to the Inception family. The primary objective behind the development of this architecture was to facilitate the utilization of deeper networks while simultaneously constraining the growth of parameters. The network was trained using more than a million photos from the ImageNet database. The pre-trained network can categorize photos into 1,000 item categories. Now, a pre-trained model, InceptionV3 necessitates downloading along with Hyperparameter Tuning. The parameters entail various aspects such as input shape (224,224,1), which delineates the dimensions and color channels of the image, and weights that signify the dataset employed for model pretraining. This implies that the model has assimilated parameters from the pre-trained dataset for adjustment, subsequently enhancing computational efficiency and model performance. The inclusion of includetop= "false" parameter allows for the addition of customized layers to optimize model accuracy. The final layer consists of 10 dense layers with the activation function "softmax".

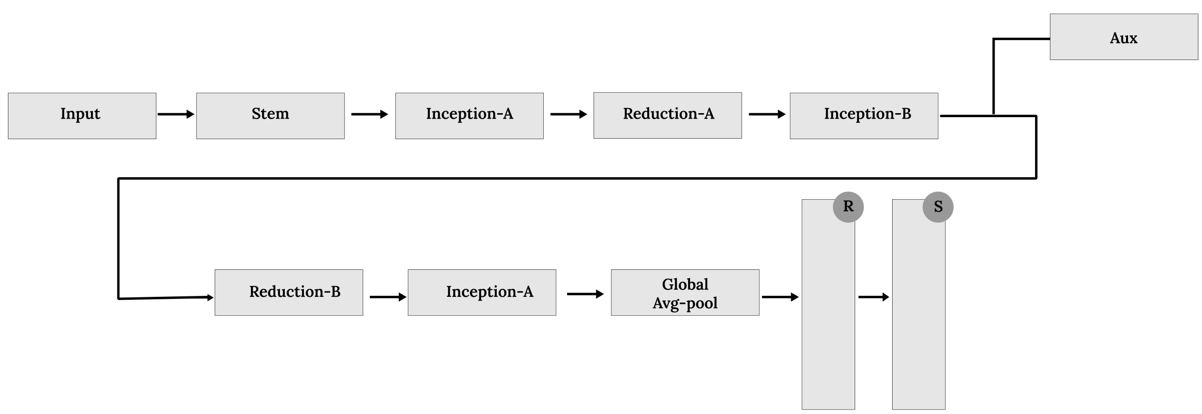

Figure 3.4: InceptionV3 Architechture

In **Fig:3.3** InceptionV3 is an updated version of Inception series that use filters making it deeply wider.

3.1.5 CapsNet

There are some problems with CNN like Translation Invariance or having poor performances with modified or augmented images like orientation changed or zoomed or resized data. As we already know CNN architecture is inspired by the visual cortex that helps in creating the Human Vision System. Also, CNN is a base architecture that needs a lot of data to have a generalized model with predicted performance.

Capsulenet is a layered neural layer in which neurons within the vessel record the attributes of a single thing in a picture. Images need to have a consistent size, typically used sizes are 64x64, 128x128, or 256x256.

Primary Capsules: Use convolutional layers to create primary capsules that extract low-level feature vectors.

Digit Capsules Build higher-level capsules that represent the specific conditions (different types of brain abnormalities). By adding a 128X3 filter it created another layer of vectors.

Finally, flatten the individual layer of vectors of each channel that will flatten into a 1D array then classify the 4 stages.

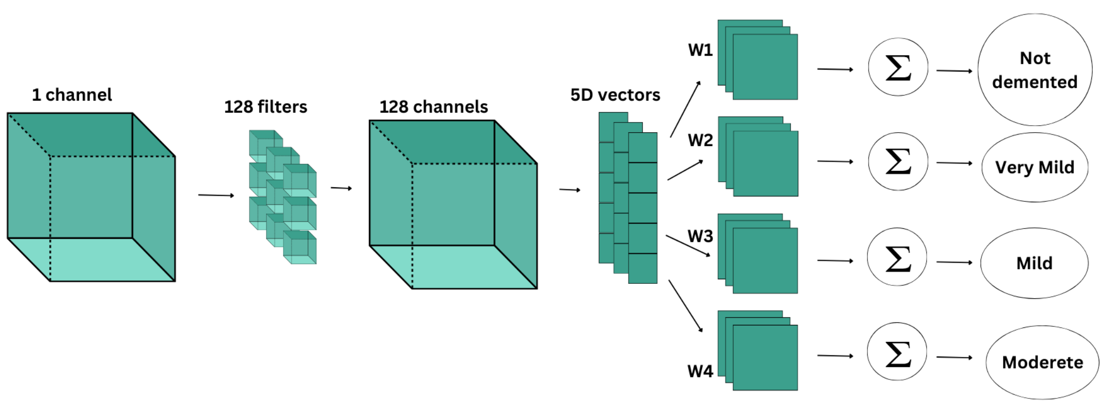

Figure 3.5: CapsNet Architechture

Fig :3.4 CapsNets architechture to replicate the hierarchical organization observed in biological neural systems.

3.1.6 XAI

Nowadays model explainability becomes a basic part of the machine learning pipeline. XAI paves a way to increase the transparency and comprehensibility of AI models' decision-making processes for humans. Describe the particular methods for improving the explainability of selected models. Possible techniques encompass LIME or SHAP. Assessment criteria consist of the model's interpretability leading to the interpretation of the model within the research questions and hypotheses context.

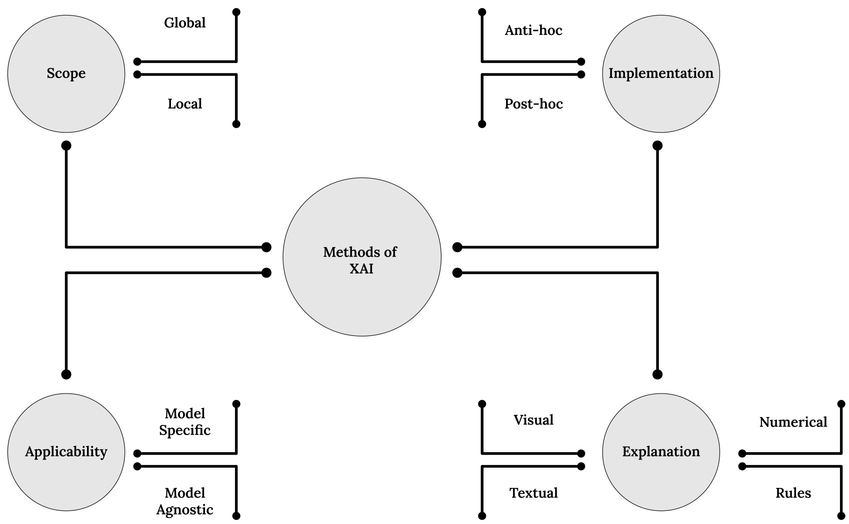

Figure 3.6: Methods of XAI

Fig:3.5 Following figure represents the Methods of Explainable -AI along with classification.

3.1.6.1 SHAP

Shapley Adaptive Explanation has been employed to calculate the contribution of meta-feature data (specifically Oasis_longitudinal). This method operates as a Model-Agnostic approach based on a rule-based system that facilitates the interpretation of predictions.

$$\phi_i(N, v) = \sum_{S \subseteq N \setminus i} \frac{|S|! \cdot (|N| - |S| - 1)!}{|N|!} \left(v(S \cup i) - v(S)\right)$$

3.1.6.2 LIME

LIME is a surrogate model or a new model is created as an explainer model to explain the prediction which focuses on the local proximity to the model prediction.LIME helps you explain the reason for a certain prediction by any model. Mainly Creates some inferences data.

$$\text{Explanation} = \arg\min_{g \in G} \left[L(f, g, \Pi_{x_+}) + \Omega(g)\right]$$

3.1.6.3 LRP

LRP explains the output of the Neural network, and highlights which input feature it uses to make the decision. According to our work image classification, provides a map of which pixel in the image contributes to the classification in the class.

- Layer-wise relevance Propagation for Neural Networks with Local RenormalizationLayer.[43]
- Framed LRP for Deep Networks(Computer Vision).
- Pixel-wise contribution is shown to highlight what pixels contribute most to model prediction. In computer vision pixel contribution, the model learns through
- spurious cues or
- grounding

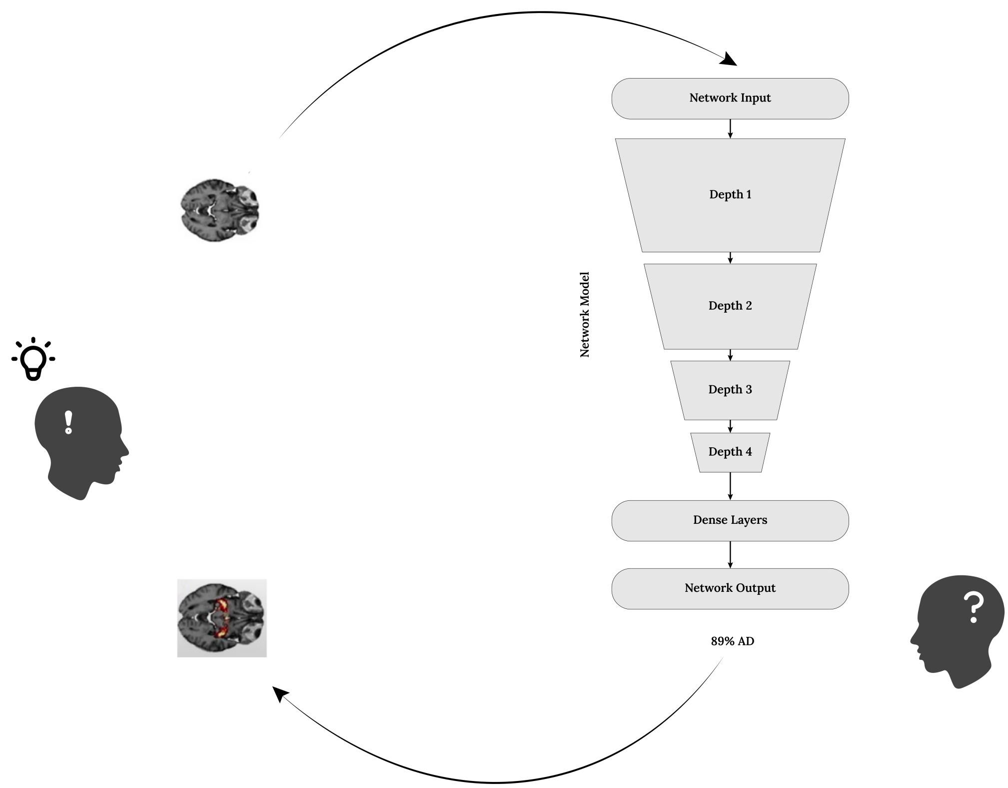

Figure 3.7: Architechture of LRP

The evaluation methods include Visual Inspection:

1. Fidelity: Precise showing of the output neuron of interest. Assuming the network has learned the problem in a ground truth manner.

2. Understandability: The result is easy to understand to a human.

$$R_i^{(l-1)} = \sum_j \frac{z_i^{(l)}}{z_j^{(l)}} R_j^{(l)}$$

Uniform LRP-0 accepts so many local artifacts thus creating noise. As a result, the focus on the object is not properly executed.

$$R_j = \sum_k \frac{a_j w_{jk}}{\sum_{0,j} a_j w_{jk}} R_k$$

3.2 Mobile Application

For better patient management, we created an extensive mobile app that possesses complex features. The app will solely focus on Alzheimer's patients and it aims to drastically better their everyday lives. The app helps with quick recall of important information and includes interactive exercises to engage patients in cognitive function-supporting activities. This has a two-fold function; it practices core knowledge and, at the same time, provides game scores to track how the patient is doing cognitively. Their novel solution allows both to be improved upon for a better life, whilst also providing the opportunity to monitor the advancement of mental health with quantitative data.

Figure 3.8: Note Books for Capturing Daily Routine

Fig : 3.7 This is a functionality of proposed app to keep regular work updates of Patients.

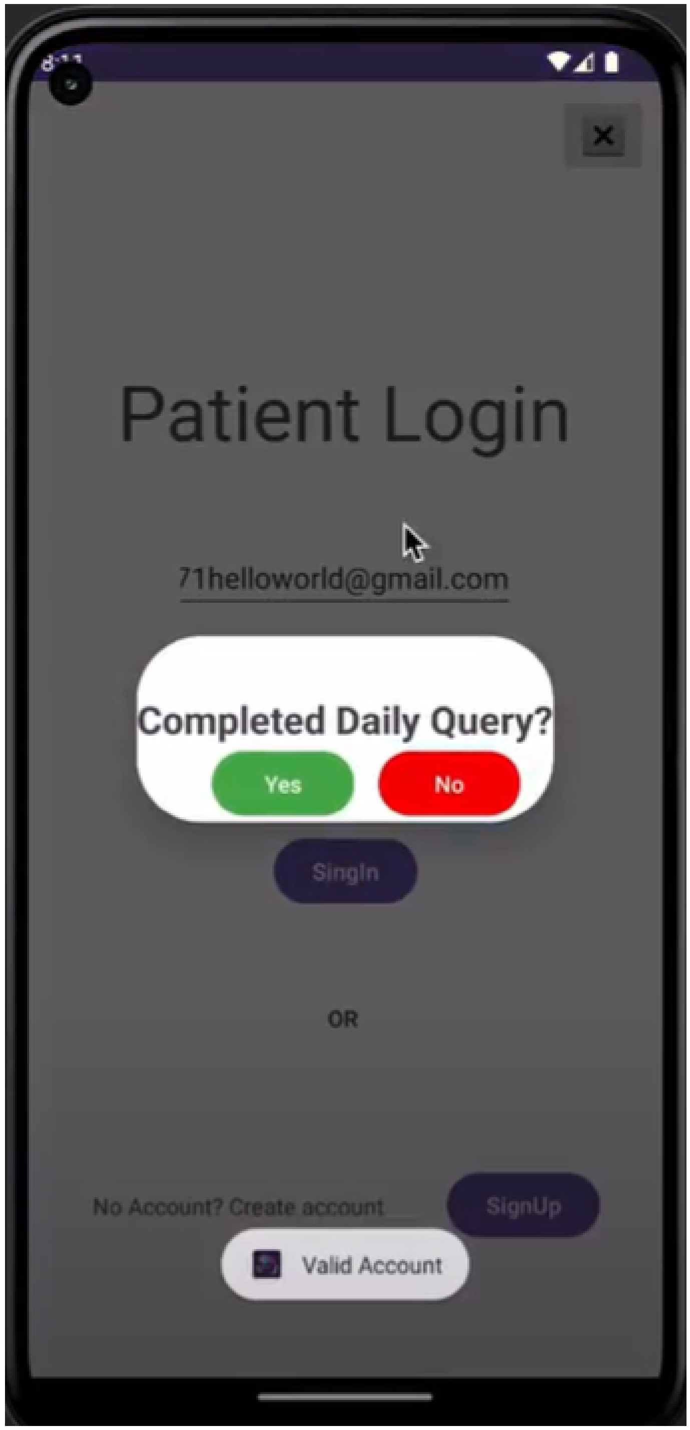

Figure 3.9: Regularity Checking

Fig : 3.8 This functionality of app refersto ensure the maintainability of regular task.

CHAPTER IV

Result and Discussion

4.1 Result

4.1.1 ConvNet

As base architechture CNN has used.The model has trained with **Adam** optimizer with value =(1e-4). Since it's a multiclass classification `sparse_categorical_crossentropy`, has been calculated as loss, and "accuracy" has been specified as evaluation metrics

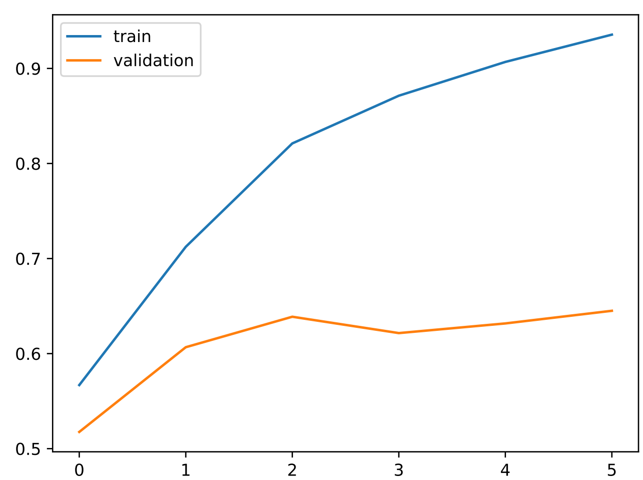

Figure 4.1: Training and Validation Accuracy for total 50 epochs

The following **Fig: 4.1** Training and Validation Accuracy is increasing with the growing number of epochs.

Initialzed epochs number is 50.With the increasing iteration of each epoch on train and validation data training loss decreases but the testing accuracy increases which tends to overfitting tendency of the model that indicates poor performance.

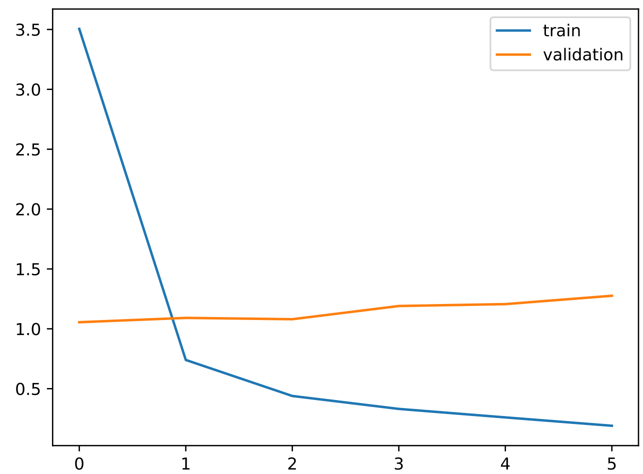

Figure 4.2: Training and Testing Loss

The following **Fig: 4.2** Training and Validation loss is decreasing with the growing number of epochs.

The CNN Model have used as base model to compare the performances further.Since CNN has implement without balancing the dataset.

4.1.2 Transfer Learning

According to the previous graph, it is ensured that CNN provides poor performance for a larger Augmented dataset(6400 data with 4 classes). It leads to some additional changes in layer architecture. However, it is computationally expensive to run the model from scratch. It is already mentioned that DL techniques need a lot of data to learn, so it's not feasible to work with smaller and raw datasets using DL methods like CNN. The solution comes from the technique known as "Transfer-Learning".

4.1.2.1 Densenet121

DenseNet-169 is a collection of DenseBlocks with many layers. It's Configuration is: [6, 12, 24, 16] layered layers, yet the CNN architecture's fundamental elements are all the same. Its structure is multilayered and distinct. DenseNet-121 is capable of object diagnosis and detection.

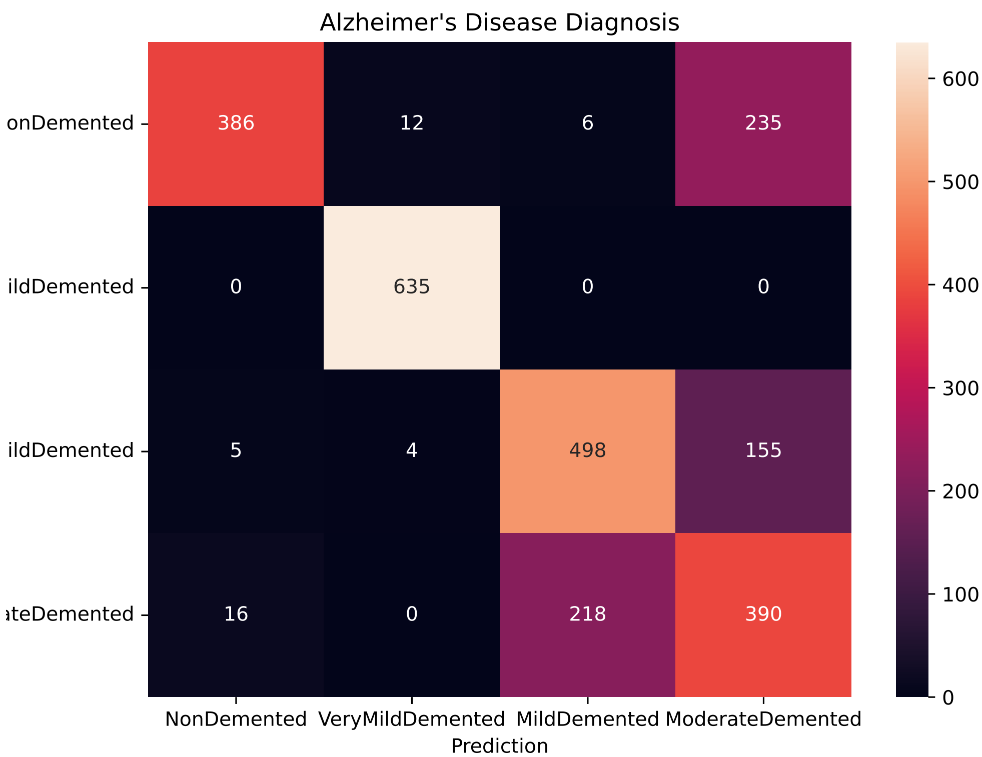

Figure 4.3: Dense121 model's Confusion Matrix

After Handling the Imbalanced Dataset of the output become more precise according to each classes.

4.1.3 Resnet50

While evidently derived from the DenseNet structure, Resnet-50 is also a CNN architectural derivative. It is important to note there are 48 convolutional layers in ResNet-50. However, it has only one Ap layer and one MaxPool(MP) layer and on the same layer and the MP layer is of 2×2 size. Other attributes of ResNet-50 includes 3. It can achieved 8 times 10 to the power 9 floating operations.

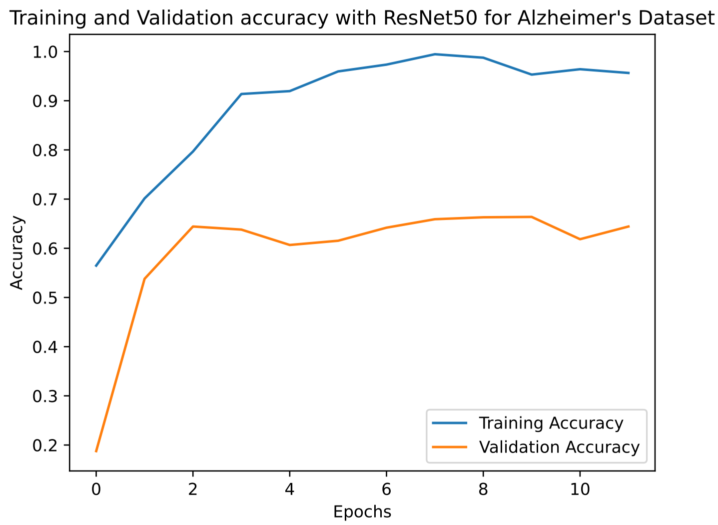

Figure 4.4: Training and Validation Accuracy for the increasing number of epochs

Training and Validation Accuracy is decreasing with the growing number of epochs.

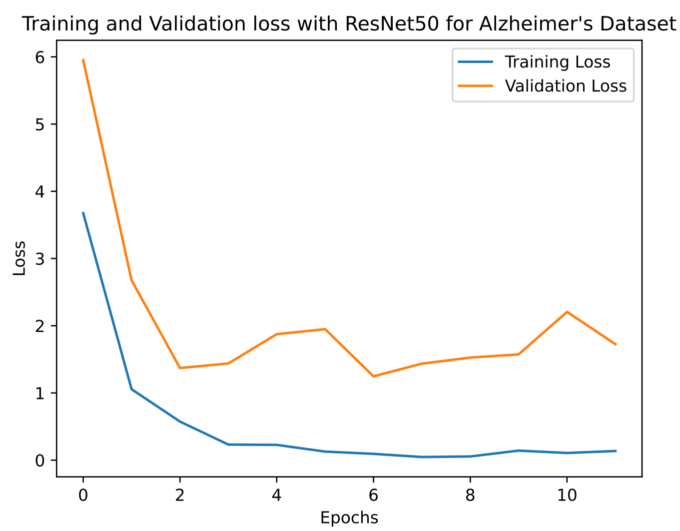

Figure 4.5: Training and Validation Loss for the increasing number of epochs

Training and Validation loss is decreasing with the growing number of epochs.

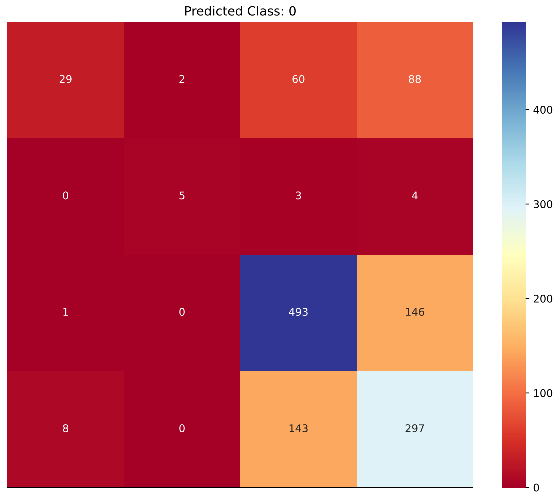

Figure 4.6: Confusion Matrix of Resnet50

It provides the higher correlation of **Moderate Dementia**

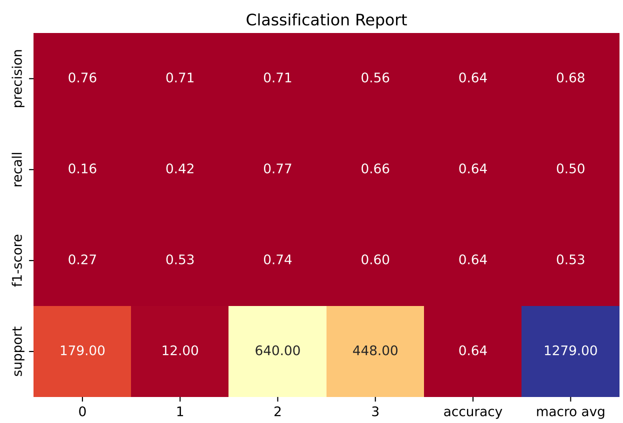

Figure 4.7: Classification Matrix for Resnet50

4.1.3.1 InceptionV3

All the convolutions, including those inside the Inception modules, use rectified linear activation.

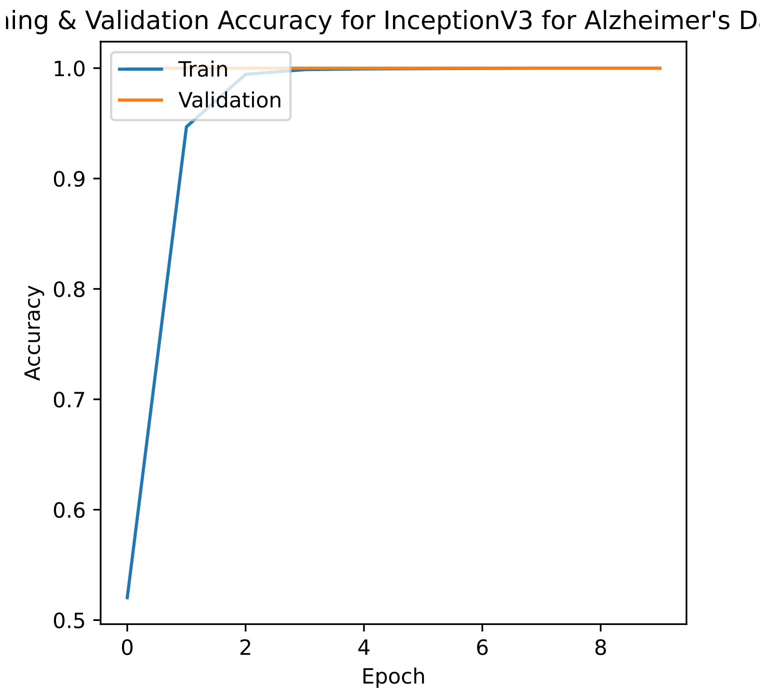

Figure 4.8: Training and validation Accuracy of InceptionV3

Here Validation Accuracy becomes constant with the number of Epochs.

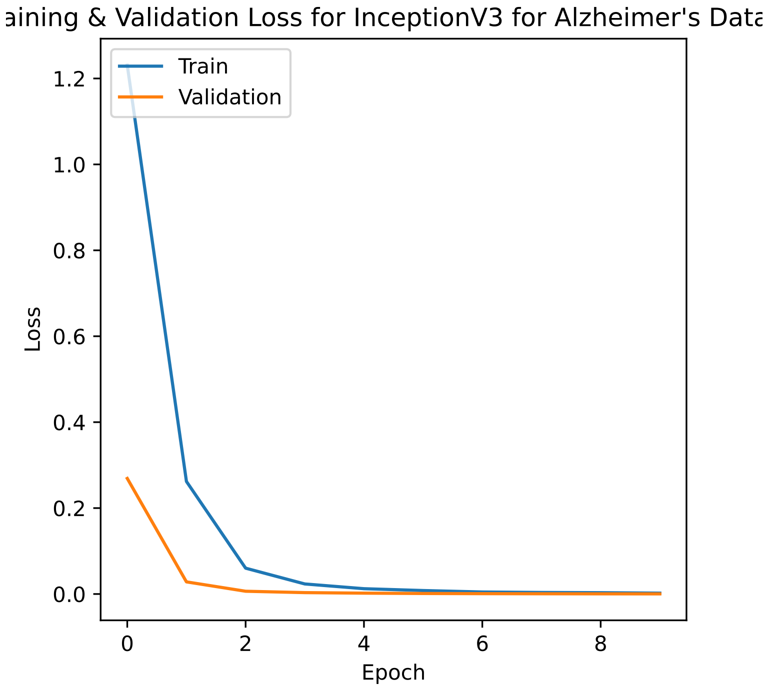

Figure 4.9: Training and validation Accuracy of InceptionV3

Here also Training and Validation loss have decreased with the increasing number of Epochs.

4.1.4 Capsule Network

The Dense layer is similar to the capsule layer. The dense layer has four output neurons with the scalar inputs of 128X3 for each neuron which shows the neuron's output from the previous layer. The neuron's output is merely augmented to vector form by the capsule layer but with significant impact on the model. Hence, it is seen that the number of capsules and vectors forming the input shape and size of a vector and number of capsules collectively define its output shape. For Dense Layer, input shape = [128, 128, 1], number of channels = 4 The training and validation accuracy is growing along with increasing epochs. On the other hand, The testing and validation loss is reducing along with increasing epochs. That means there lies no Vanishing-Gradient Problem.

Translation Invariance means the equivariance makes a CNN understand the rotation or proportion to change and adapt itself accordingly.

Classification report along with cbar for the 4-stage classification.

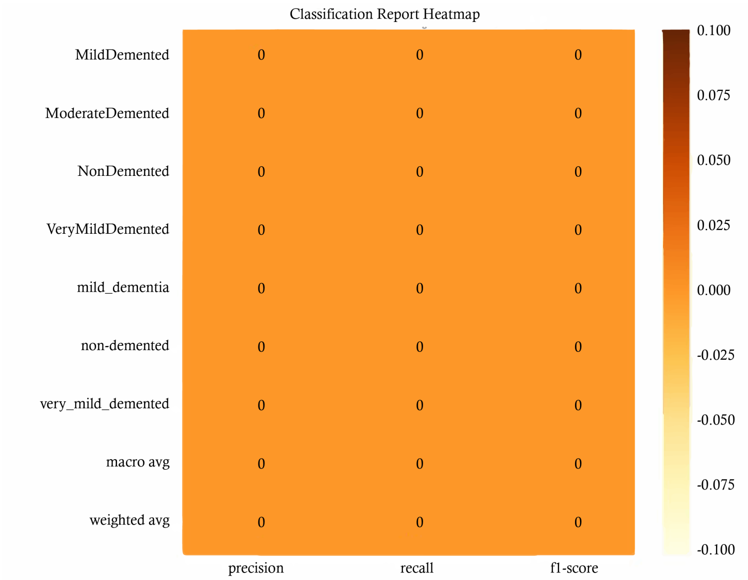

Figure 4.10: Classification heatmap for capsule net

4.1.5 Explainable AI

DL models, particularly convolutional neural networks (CNNs), are often perceived as augmented entries due to their complex internal structures. This lack of transparency presents a challenge for healthcare professionals in understanding and trusting the predictions generated by the model, especially when identifying specific impacted areas. Explainable AI (XAI) methodologies can interpret the "Black Box" equations within DL models. Conversely, LRP breaks down the predictions of a DL model into the contributions of individual pixels or regions, thus tracing back the prediction score through the network to determine the importance of input features.

4.1.5.1 LIME

LIME is model agnostic means that can work with almost any model where predictions are supervised in nature and an explanation is required for the prediction by the model. Here LIME has implemented with Inception V3 image classification model. That makes a similarity check and make the prediction by detecting mostly defected areas.

- **LIME with InceptionV3**

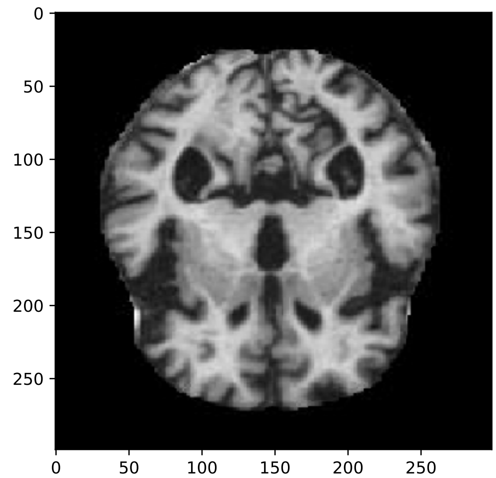

Figure 4.11: Input image of for LIME

Here LIME highlights the affected area for classifying.

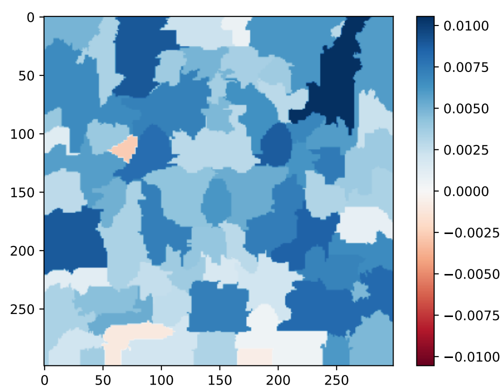

Figure 4.12: Weighted Correlation for detecting the affected area for making the Prediction

The higher Correlation value refers to the most affected area of the brain.

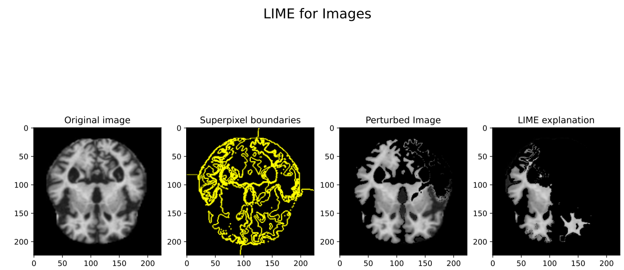

Figure 4.13: LIME Explaination Output

4.1.5.2 LRP

LRP is a technique of such explainability and scales to potentially highly complex deep neural networks.This makes it applicable to a large number of practical scenarios where explanation is needed.[44] Basic **LRP-0** based on the following equation :

$$R_j = \sum_k \frac{a_j w_{jk}}{\sum_{0,j} a_j w_{jk}} R_k$$

It is a uniform application across the entire network and produces an explanation equivalent to **"Gradient x Input"**

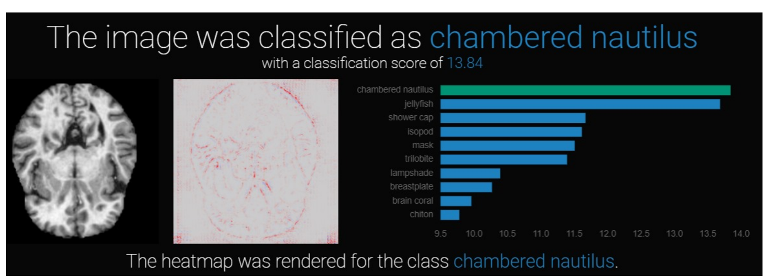

Figure 4.14: Classification score with LRP-0 pre-trained Model of Demented Image

The previous figure **Fig :4.14** calculates the classification score with the weights and bias of mentioned pre-trained model names LRP-0.

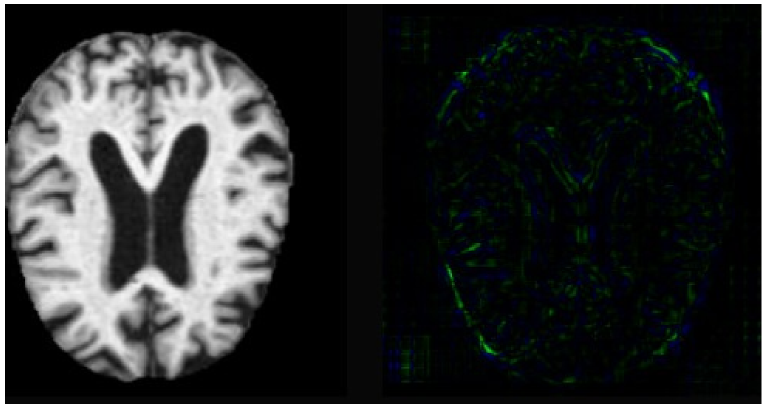

Figure 4.15: Output of LRP-0 pre-trained Model of Non-Demented Image

4.1.5.3 SHAP

Another way of decomposing the impact that each attribute has on the forecast of a certain observation is by use of the force plot. This plot has positive SHAP values on the left side and negative on the right as though they are in competition with each other. The forecast for that observation is the value that is boxed.[45]

SHAP's sum and base value interprets the reason for making the classification. For being Classified as "Non-Demented" these features along with their contribution are responsible.

Figure 4.16: SHAP Force Plot, that reasoning part of the classification with their feature contribution

The following stack plot shows the feature importance for making each classification. The graph shows that **CDR** - Clinical Dementia Rating has the highest feature Importance for making the classification. The sequence "Hand Gesture" has no significance for making the classification.

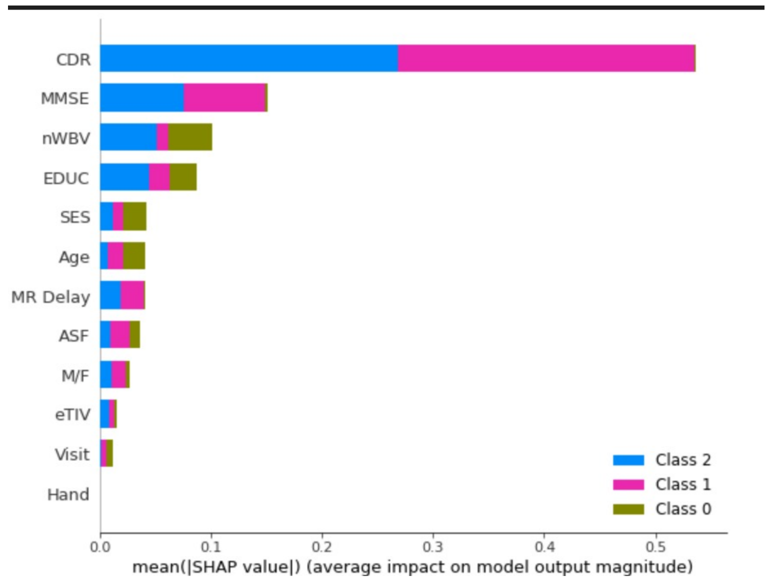

Figure 4.17: Measurement of SHAP value along with the impact on the magnitude of each feature

In the following Stacked-Bar chart represents the higher contribution percentages according to target- category.

CHAPTER V

Conclusion and Future Work

5.1 Conclusion

To sum up, this study has investigated the applicability of machine learning approaches to the screening of AD at an early stage. The analysis emphasizes the necessity to comprehend the model's actions to achieve accurate and interpretable results. In this study, two kinds of Explainable AI (XAI), including model-based and post hoc, have been used to reveal model performance and decision-making. More notably, SHAP, LIME, and PDPs have made it possible to dissect contributions and relationships of features better.

A notable component of this work included identifying data leakage, which may cause a notable increase in performance metrics and lead to misleading findings. In this manner, it was guaranteed that all the evaluations of the model were valid because data leakage was not easily done due to the vigorous tests that were conducted. It was vital to avoid situations whereby resources are utilized based on wrong results by ensuring the validity of outcomes.

Resource regulation was the other important aspect, where the concern was to optimize the use of computational resources in terms of training-validation of the selected models. The application of LRP provided additional increased interpretability of the models we have been developing. LRP, given by the formula permits to define the origin of each input attribute and is tuned to the final output of the constructed neural network, that is, explains the totality of the opinion formation process.

In summary, this thesis is useful to the area of early AD detection as it provides an extension of knowledge regarding the behavior of machine learning model, enhances the process of method validation and evaluation due to the ideas to detect data leakage, as well as addresses the issue of how to regulate resources sustainably. Not only have SHAP, LIME, PDP, and LRP increased model interpretability, but they have also opened the door to more accurate and understandable diagnostic tools in healthcare. More areas of research in this context should include replication and extension of these methods to different databases and different populations in order to enhanceAD diagnosis.

5.2 Future Work

The proposed Mobile Application can be updated to serve various points further to achieve more acceptability. Our future works can be:

- Enhancing the CapsNet architecture for the processing and analysis of 3D and color images
- Incorporate patient meta-data (additional information) to determine the root cause and provide more accurate preventive recommendations.
- It is necessary to gather additional image data.
- The App will have an advance guidance system which will help the patient finding his way to home.
- Using Generative AI(GEN AI) the app will have a speech to text or text to speech functionality. This functionality enables patients who have problems reading or typing to be able to listen to written content and at the same time, to translate their spoken words to writing.

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