Diagnosis of Alzheimer’s disease Using Machine Learning

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Abstract:

Alzheimer's disease is a brain neurodegenerative illness that is becoming more and more irreversible. The Alzheimer's and Related Disorders Society of India (ARDSI) Dementia India Report 2020 projects that by 2020, 5.3 million Indians will suffer from dementia, and by the end of 2030, that number is predicted to rise to 7.6 million. Early detection of Alzheimer's disease can prevent significant harm to brain tissue. Numerous statistical and machine learning models have been employed by researchers worldwide to diagnose Alzheimer's disease. In order to distinguish between the various stages of Alzheimer's disease, magnetic resonance imaging (MRI) scans have proven invaluable in both medical and research.

In this study, we consider the importance of advancement in diagnostic imaging in Alzheimer's disease, such as feature extraction, LSTMs, and deep learning approaches. We will also try to develop an algorithm for detecting Alzheimer's disease using convolutional neural networks.

Keywords: Convolutional Neural Networks (CNNs), ResNet50 Model, InceptionV3 Model, a Xception Model, Histogram equalization etc.

1 Introduction

A neurodegenerative ailment that predominantly affects the brain, Alzheimer's disease (AD) progresses over time and causes cognitive decline, memory impairment, and ultimately the inability to perform daily tasks. Since being discovered for the first time by Dr. Alois Alzheimer in 1906, the illness has grown to be a significant public health

Issues, specially as the world’s population ages. One of the main clinical characteristics of Alzheimer's disease is the development of aberrant protein aggregates in the brain, such as tau tangles and beta-amyloid plaques. These degenerative alterations impair neuronal transmission and function, which eventually results in the death of brain cells.

As a result, the cognitive capacities of people with Alzheimer's disease gradually decline, which has an impact on their independence and quality of life.
For a number of reasons, an early and precise opinion of Alzheimer's complaint is essential. First of all, it makes prompt interventions possible, which could help reduce the complaint's course and ameliorate symptom operation. Alternate, early opinion empowers cases and their families to make well- informed choices regarding unborn legal arrangements and care plans. Eventually, it makes it easier for impacted people to be included in clinical trials, which promotes the creation of possible treatment results. still, diagnosing Alzheimer's complaint poses significant challenges. The symptoms of announcement, particularly in the early stages, can lap with those of other neurodegenerative diseases, making it delicate to establish a definitive opinion. also, current individual styles frequently calculate on clinical assessments, which may warrant the perfection demanded for early discovery.

This exploration paper aims to explore and estimate the current state of Alzheimer's complaint opinion, fastening on the challenges faced by clinicians, the advancements in individual ways, and the implicit part of arising technologies similar as neuroimaging and biomarker analysis. By critically examining the being individual geography, this exploration seeks to contribute to the ongoing sweats to enhance the delicacy and punctuality of Alzheimer's complaint opinion, eventually perfecting patient issues and advancing our understanding of this complex and ruinous condition. Alzheimer's complaint (announcement) stands as a redoubtable challenge to global healthcare systems, with its frequence steadily rising as populations age. As the major cause of madness, announcement poses not only a substantial burden on affected individualities and their families but also exerts significant profitable pressure on healthcare systems worldwide. Diagnosing Alzheimer's complaint directly and at an early stage is pivotal for initiating applicable interventions, offering support to cases and their families, and advancing our understanding of the complaint for effective remedial development.

Over the times, the geography of Alzheimer's complaint opinion has experienced significant elaboration. Traditional individual styles, primarily reliant on clinical assessments and neuropsychological tests, have been rounded and, in some cases, superseded by cutting- edge technologies and biomarker discoveries. This exploration paper aims to give a comprehensive overview of the current state of Alzheimer's complaint opinion, probing into the traditional approaches, arising technologies, and the pledge of biomarkers in revolutionizing how we descry and understand this enervating neurodegenerative complaint.
The trip towards effective Alzheimer's opinion is multifaceted, encompassing clinical, neuroimaging, and molecular perspectives. This paper will explore the strengths and limitations of each approach, pressing recent improvements and ongoing exploration sweats that hold the eventuality to reshape individual paradigms. likewise, the significance of early identification in relation to arising remedial interventions and substantiated drug will be addressed, emphasizing the vital part that accurate opinion plays in enhancing patient issues.

As we embark on this disquisition of the current individual geography of Alzheimer's complaint, Admitting the collaborative sweats of scientists, croakers, and technologists is essential in their hunt to break the mystifications of this complex complaint. By synthesizing knowledge from colorful disciplines, we aim to contribute to the ongoing dialogue girding Alzheimer's complaint opinion and pave the way for unborn advancements that promise to bring us near to effective forestallment and treatment strategies.

2 Literature Survey

2.1 Classificatin based on embeddings generated from images

Feature-based classification is another name for classification that uses embeddings. Pictures with various modalities can be classified using features. For feature-based categorization, MRI (Magnetic Resonance Imaging) scans are utilized.
Ahmed et al. used visual similarity in their paper to compute characteristics found in structural MRI scans. Using the ADNI dataset, the images were classified according to the hippocampal areas of the brain. The terms "Alzheimer's Disease," "Mild Cognitive Impairment," and "Normal Control" were written on the pictures. [6]

2.2 Classification with Neural Network

Convolutional Neural Networks (CNNs) is mainly associated with image classification or computer vision tasks. CNNs make the use of spatial data with the use of convolutions and use less computing power for the training and testing. The major drawback of using CNN for AD classification is that there is very small training data available. However, there are a number of methods to solve this issue, including employing shallow neural networks, applying data augmentation, or applying transfer learning.
In their paper, Islam et al. presented a deep convolutional neural network. The results of the paper were then compared with the results of Inception-V4 and Resnet using the OASIS-1 dataset. There are four classes representing the four stages of Alzheimer’s Disease. [7]

2.3 Classification with 3D Neural Network

MRI being a 3D image, using 3D Convolutional Neural Networks makes more sense and it may provide a boost in the performance as compared to the traditional 2D convolutions.
In their research, Payan et al. used 3D convolutions combined with sparse encoders on the whole MRI scan to perform three binary classifications (AD v
NC, AD v MCI, NC v MCI) and ternary classification (AD v NC v MCI). [8]

2.4 Optimization with LSTM

In their paper, Sethi et al. developed an optimized deep learning model to predict Alzheimer's Disease in its early stage using binary and ternary classification. They have proposed 4 different 2-D and 3-D CNN frameworks and the models are optimized using Bayesian search optimization. Alongside the CNNs, they have also used long-short term memory (LSTM) in finding better settings for the model. [9]

1 Methodology

The assignment's primary focus is to categorize the photos into the HEALTHY and AD classifications. After the dataset was examined, it was discovered that there were 2568 and 821 photos for the relevant classes. MRI pictures were used to choose T1w scans. The longitudinal relaxation of tissues serves as the foundation for T1w MRI imaging. Blood will seem gray and fat will appear white in T1w MRI images because fat will appear brighter and water and blood will appear darker[12].

One MRI scan slice is binary classified as the first method. The brain's most comprehensive information should be found in the one slice that is used for classification. Therefore, the slice in the middle was selected.During training and testing, the slice situated at the brain's center along the axial view, also known as the z-axis, was selected from each scan. Every image was reduced in size to 224 by 224 pixels.

The data was partitioned in two parts, training and testing sets in the proportion of 80:20. The training data available was small. Hence, data augmentation techniques like rotation by 90 degrees and horizontal flip were used to increase the total images in the training data set. The training data was further split such that 20% of the training data will be used as the validation data for training the model.

The dataset is uneven as 2568 images are from the HEALTHY category and 821 images are from the AD category. Thus, this will cause the model to be biased towards the class having more images. This may reduce the overall accuracy. To overcome this problem, the class weights for each class were calculated and used during training.

While finding the slice along the axial view, it was observed that some MRI scans were oriented differently as compared to the entirety of the data set. To solve this issue, manual intervention was required. The images that were differently oriented were rotated accordingly to make the dataset similar.

For the purpose of binary classification of the dataset, a deep convolutional neural network model was constructed with reference to the study written by Islam et al. [7]. The model consists of many convolutional layers, pooling layers, dense blocks, and transition layers. Concatenation of multiple convolutional layers makes up the dense block. The transition layer consists of a combination of batch normalisation layers, a [1*1] convolutional layer, and a [2*2] average pooling layer with stride 2. Figure 1 shows the deep convolutional neural network’s architecture.

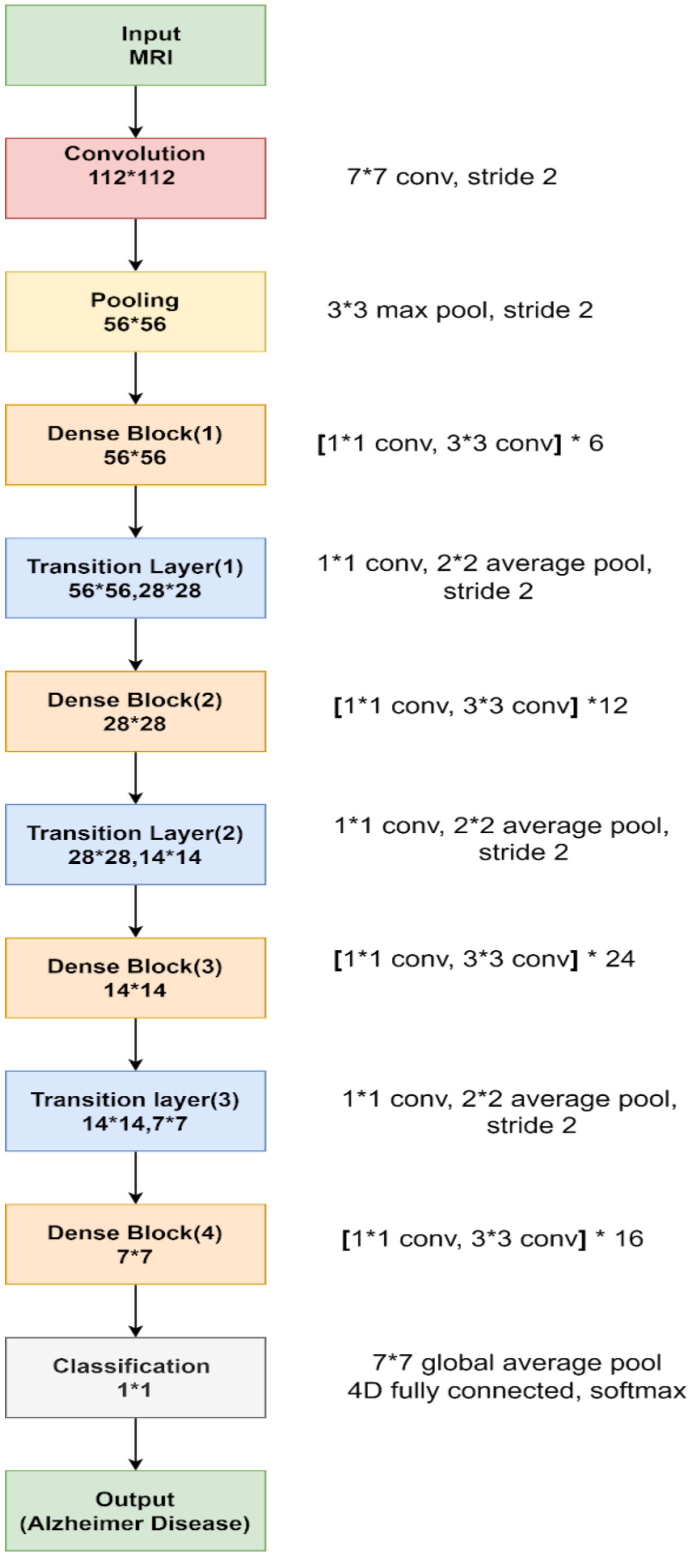


Figure 1: Architecture of deep CNN proposed in the paper authored by Islam et al.

The above-mentioned model was modified in the following way. The classification layer and output layer were removed and 4 layers were added as shown in Figure 2.

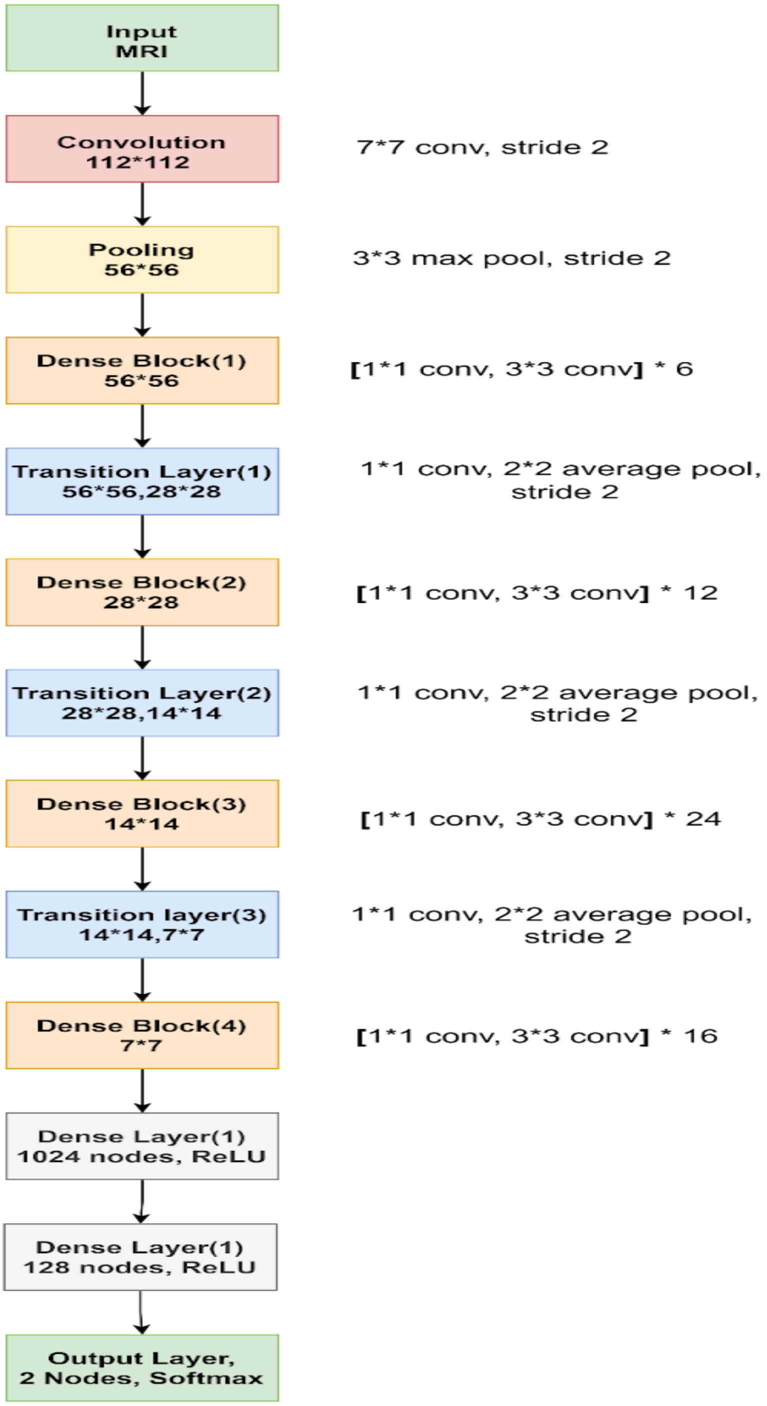


Figure 2: Architecture of the modified model

Other than this deep convolutional neural network model, we investigated multiple pre-trained CNNs and chose 3 CNN models which have performed well on the ImageNet dataset: ResNet50, InceptionV3, and Xception.
Custom layers were added on the top of pre-trained CNN models to generate a prediction from the Dense layers. Figure 7 gives the diagrammatic representation of the architecture used for training.

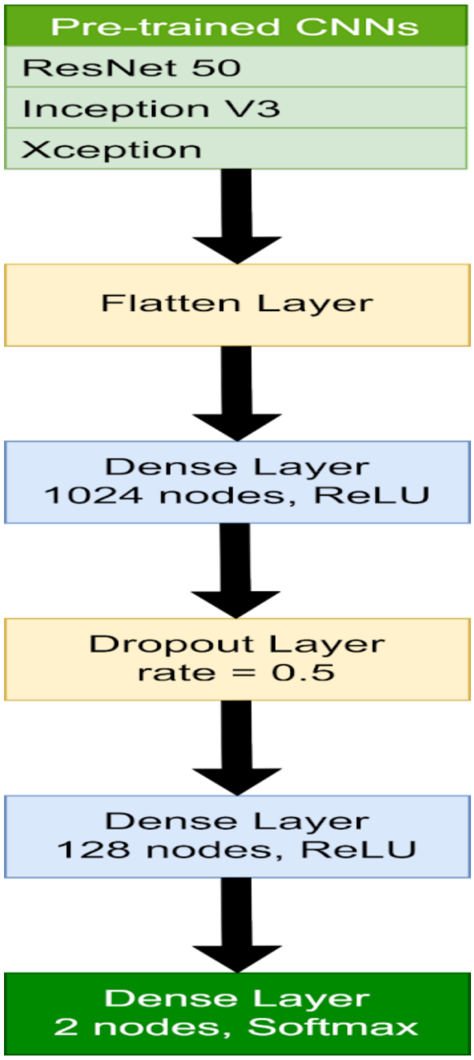


Figure 8: Diagrammatic representation of architecture used for center slice input image.

In the above approach, only the center slice (axial view) of the scan was used, giving the Top-1 binary classification accuracy of 0.71. The downside of just selecting the middle slice was that the potential data from the other slices were being missed. In order to overcome this problem, the second approach is to use multiple slices. The 3D MRI scan must be reduced to a 2D image (mosaic) containing multiple slices. All the slices from the sagittal view of the MRI scan were used to create a 2D image otherwise known as a mosaic. The slice from the sagittal view was of pixel size 256 * 256. The mosaic was to be created of 14 * 14 slices, this was found out by assessing the images present in the dataset.

Since some of the 3D images were poorly oriented and of a different shape than the others, those images were dealt with by swapping the axes of 3D images and resizing each slice in one of the axes.

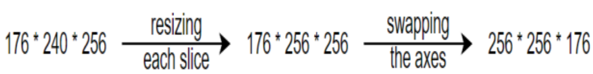
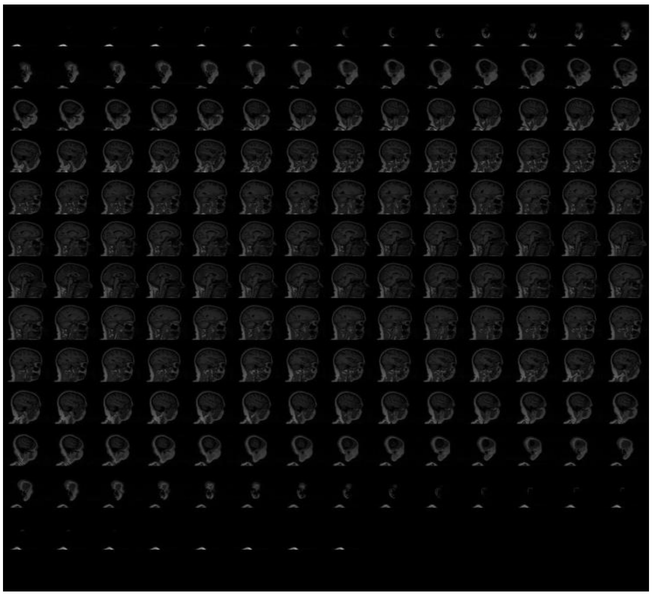
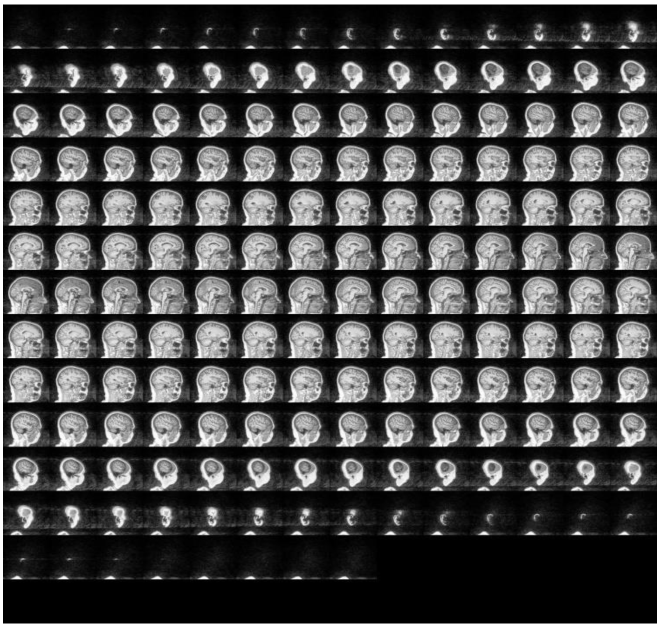


Figure 3: Changing the dimensions of input images for 2D CNN

The mosaic was built by concatenating all the slices starting from the beginning. But, the mosaic had issues where the prominent features were inhibited due to the lack of clarity in the image. Hence, the image processing technique ‘Histogram Equalization’ was used to enhance the contrast. Histogram equalization is a process of adjusting contrast using the image’s histogram of pixels. The pixels having low intensity are given higher contrast and likewise to make the image’s histogram evenly distributed. The images are enhanced as shown in Figure 4.



(a) Original Mosaic



(b) Mosaic after using Histogram equalization

Figure 4: Comparison between original Mosaic and enhanced Mosaic

There were still some erratic images that needed to be eliminated manually. Now, the dataset was fed to the 2D pre-trained CNN models Inception V3 and ResNet101 models. For training, the pre-processed mosaics of slices were reduced to pixel size 128 * 128, and data augmentation was applied. Customized layers were applied on the top of Inception V3 and ResNet101 models as shown in Figure 5.

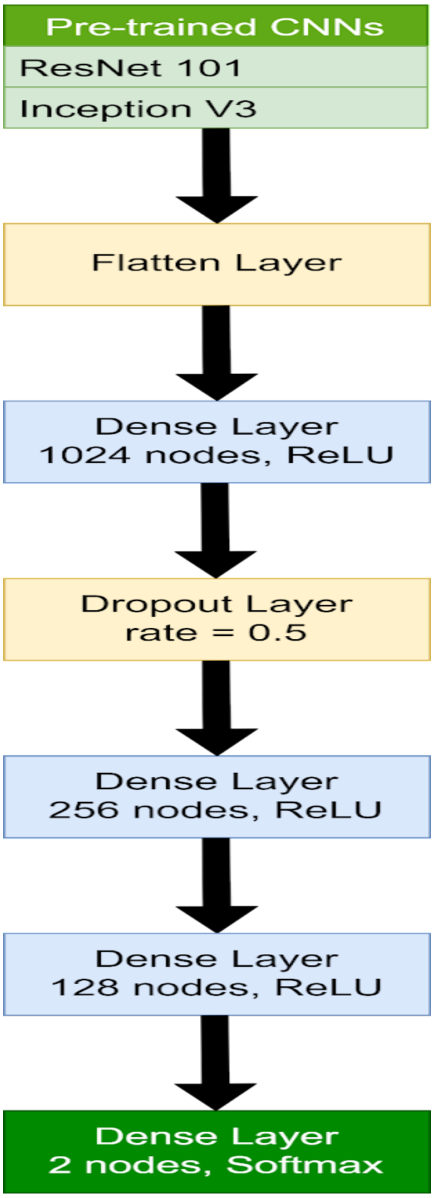


Figure 5: Diagrammatic representation of architecture used mosaic input image

For the binary classification purpose, a layer of softmax activation function was applied as the final output layer to the CNN models with counts of nodes equal to two (output classes). 16 batches were used to train the models and a planned rate of learning of 1e-3, which was reduced by a magnitude of 1e(-0.1) per epoch. As an optimizing function and a loss function, the Adam optimizer and binary cross-entropy were utilized, respectively.

While this method gave an improvement in performance, the results were still not satisfactory. Thus, a new approach was devised to implement a 3D convolutional neural network that allows the model to detect spatial data across various slices. All the MRI scans had to be of the same dimension to implement 3D CNN. The different shapes of the images were handled the same way it was handled before, just that this time, only 70 middle slices were chosen to bring all the images to the same dimension and reduce computational complexity as shown in Figure 5.

2 Problem Statement

Alzheimer's disease (AD) is a neurological illness that worsens with time and is marked by functional impairment, memory loss, and cognitive decline. The prevalence of AD is increasing with the aging of the world population, which presents a significant challenge to healthcare systems and necessitates efficient detection techniques for early management. Advanced imaging tools, neuropsychological tests, and clinical assessments play a major role in the present diagnostic landscape. But despite tremendous progress, difficulties still arise in getting a prompt and accurate diagnosis, which limits the possibility of early therapeutic interventions and individualized care.

One critical issue lies in the limitations of traditional individual styles, where reliance on private clinical evaluations and cognitive tests may lead to delayed or inaccurate judgments . also, the complex etiology of Alzheimer's, involving inheritable, molecular, and environmental factors, necessitates a more nuanced and comprehensive approach to opinion.

The hunt for dependable and accessible biomarkers, both in neuroimaging and molecular analysis, is ongoing but faces obstacles in terms of standardization, availability, and cost-effectiveness. likewise, the practical perpetration of arising technologies in different healthcare settings poses challenges, with issues similar as resource constraints, moxie vacuity, and the need for technical outfit affecting their wide relinquishment.

The restatement of promising exploration findings into routine clinical practice remains a chain, limiting the impact of innovative individual approaches. Addressing these challenges is pivotal not only for accurate and timely Alzheimer's opinion but also for easing advancements in treatment strategies and furnishing support to individualities and families affected by the complaint. This exploration aims to critically examine the current state of Alzheimer's complaint opinion, identify gaps and obstacles in being methodologies, and look into ways to introduce and get better. In the face of this expanding global health extremity, this study aims to support ongoing sweats to ameliorate individual delicacy, availability, and ultimately patient issues.

Table 1 : Values of Class-wise Precision , Recall, F1 Score tested by Res Net 50 Model

Class	Precision	Recall	F1-score
HEALTHY	0.25	0.16	0.19
Alz. Disease	0.75	0.84	0.80

3 Result

The following accuracy was achieved using the middle slice of axial view tested on all the models described above:

Table 2: Models and their accuracy

Model	Accuracy
Base Paper Model	0.69
ResNet 50	0.67
Xception	0.70
Inception V3	0.71

The following classification reports were produced using the middle slice of axial view tested on different models:

Table 3: Values of Class-wise Precision, Recall, F1 Score tested by Base Paper Model

Class	Precision	Recall	F1-score
HEALTHY	0.28	0.16	0.20
Alz. Disease	0.76	0.87	0.81

Table 4: Values of Class-wise Precision, Recall, F1 Score tested by Xception Model

Class	Precision	Recall	F1-score
HEALTHY	0.28	0.14	0.19
Alz. Disease	0.76	0.89	0.82

Table 5: Values of Class-wise Precision, Recall, F1 Score tested by Inception V3 Model

Class	Precision	Recall	F1-score
HEALTHY	0.31	0.16	0.21
Alz. Disease	0.76	0.88	0.82

As evident from the classification reports, Inception V3 gave the best performance among the four models, giving the classification accuracy of 71.44%.

The following accuracy was achieved when the mosaic (created from voxel) was tested on the models mentioned:

Table 6: Accuracies produced by Inception V3 and ResNet 101 Model

Model	Accuracy
Inception V3	0.7868
ResNet 101	0.7740

4 Conclusion

This paper focuses on the binary classification of healthy brain MRI scan and the MRI scan of Alzheimer's disease-affected brain using the OASIS-3 dataset. A total of 3 approaches regarding the same have been discussed and implemented. Image preprocessing for each of the three approaches has been discussed. It is evident from the results that the CNN model Inception-V3 gave the best performance among all the other models implemented. The better result of approach 2 indicates that there is a lot of information in the other slices than the center slice of the brain, which could have been missed if approach 1 had been used.

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