ADVANCEMENTS IN DIAGNOSTIC MODALITIES FOR ALZHEIMER'S DISEASE: A COMPREHENSIVE REVIEW

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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.

I. INTRODUCTION

The progressive neurological condition known as Alzheimer's disease (AD) mostly affects the brain. It causes memory loss, cognitive decline, and ultimately the inability to carry out daily activities. Since the disease's original discovery by Dr. Alois Alzheimer in 1906, it has grown to be a significant public health concern, especially as the world's population ages.

Alzheimer's disease (AD) is one of the most common types of dementia. Over five million people in India suffer from dementia of some kind. Dementia affects at least 44 million people worldwide, making the disease a global health crisis that cannot be ignored. [1] The presence of AD is guesstimated to be approximately 5% after the age of 65 and 30% after 85 years old in developing countries. Around 650 million humans are expected to be affected with Alzheimer's disease by 2050, according to the estimates. [2] Alzheimer's disease affects cells in the brain, which makes the patient lose their memories, psychological abilities, and the ability to carry out normal tasks like eating and walking.

Timely and accurate diagnosis of Alzheimer's disease is crucial for initiating appropriate therapy, offering assistance to patients and their families, and increasing our understanding of the illness to facilitate the creation of novel medicines.

This review paper aims to analyze and assess the current status of Alzheimer's disease diagnosis, emphasizing the difficulties faced by healthcare providers, improvements in diagnostic methods, and potential implications of recently emerging technologies like neuroimaging and biomarker analysis. Through a thorough analysis of the current diagnostic landscape, this study aims to support ongoing initiatives to enhance the precision and promptness of Alzheimer's disease diagnosis. Ultimately, the goal of this research is to better understand this debilitating and complex condition and to improve patient outcomes.
1.1 MRI:
The use of brain MRI to diagnose Alzheimer's disease has only recently become popular among doctors. The brain's hippocampus and cerebral cortex shrink, while the ventricles expand [3]. The hippocampus region is the part of the brain in charge of response inhibition, episodic memory, and spatial cognition. Also, it serves as a bridge across our bodies and minds. The loss of cells and harm to synapses and neurons occurs as the hippocampus region of the brain shrinks. As a result, neurons can no longer communicate via synapses. Due to this, the memory of short time, reasoning, planning, and common sense are all compromised [3]. The low intensity of degenerated brain cells in MRI images [4] makes it a feature that can be extracted using various techniques. Figure 2 depicts brain MRI scans for four different phases of AD.

![MRI images showing different stages of Alzheimer's disease](image)

(a) Non-demented; (b) Very mild dementia; (c) Mild dementia; (d) Moderate dementia

Figure 2: MRI images showing different stages of Alzheimer's disease

II. LITERATURE REVIEW

2.1 Classification 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 [5].

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. proposed 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 [6].

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) [7].

2.4 Optimization with LSTM

In their paper, Sethi et al. developed an enhanced deep learning model for Alzheimer’s disease prediction 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 [8].

III. 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. In T1w MRI pictures, fat will seem brighter while blood and water will appear darker, making fat appear white and blood gray [9].

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. Twenty percent of the training data will be utilised as the validation data to train the model after the training data was further divided.

A deep convolutional neural network model was built with reference to the article written by Islam et al. [10] in order to perform binary classification on the dataset. Many convolutional layers, pooling layers, dense blocks, and transition layers make up the model. The dense block is composed of several convolutional layers concatenated together. A combination of batch normalisation layers, a [1*1] convolutional layer, and a [2*2] average pooling layer with stride 2 make up the transition layer. The architecture of the deep convolutional neural network is depicted in Figure 1.

![Figure 3: Deep Convolutional Neural Network's Architecture.](image-url)
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 below gives the diagrammatic representation of the architecture used for training.

![Diagram of architecture](image)

**Figure 4:** Diagrammatic representation of architecture used for center slice input image

### IV. TECHNICAL ARCHITECTURE

The Alzheimer’s disease prediction incorporates a range of data sources, machine learning models, and preprocessing techniques. Data such as genetic information, neuroimaging pictures, and medical records are preprocessed and feature selected. Machine learning techniques like logistic regression and deep learning (Inception v3, Xception, ResNet 50, ResNet 101) are used to learn and evaluate predictive models. The prediction system generates risk evaluations and offers interfaces to users and clinicians based on the data entered. Security protocols, adherence to laws and regulations, and interaction with healthcare systems that ensures error-free data transfer all work to protect patient privacy. Scalability and speed advancements make accurate forecasting and efficient processing possible for improved patient care.

![Technical Architecture Diagram](image)

**Figure 5:** Technical Architecture
V. FEATURE AND FUNCTIONALITY

Data Integration
A variety of sources, including genetic data, biomarker data, medical records, and neuroimaging scans (MRI, PET) would be integrated into the project. These are the types of data that each model can handle, allowing for thorough analysis.

Preprocessing and Feature Selection
Preprocessing techniques tailored to the input specifications of each model would be used. For example, mean subtraction preparation steps could be required for ResNet models, whereas scaling and picture data normalization are usually required for Inception V3 and Xception. These models have pre-trained layers from which high-level representations of features important to Alzheimer disease prediction can be extracted.

Machine Learning Model
Convolutional neural network (CNN) architectures such as Inception V3, Xception, ResNet50, and ResNet101 are well-known for their effectiveness in image categorization applications. They can be improved upon or applied as feature extractors for the prediction of Alzheimer's disease. By using pre-trained weights, transfer learning saves training time and costs while utilizing the models’ acquired representations.

Prediction System
Based on features that are taken out of the input data, these models produce predictions. The project's objective is to develop a system that can evaluate model outputs and offer risk assessments and likelihood scores for Alzheimer's disease. Understanding model predictions and conveying them to patients and physicians can be made easier with the use of visualization techniques.

User Interface
The design of interfaces would allow for the viewing of Inception V3, Xception, ResNet50, and ResNet101 prediction findings. Through user-friendly displays, clinicians may analyze model results to assist with diagnosis and therapy planning. People may have access to streamlined interfaces for risk assessment and advice on health management.

Integration with Healthcare Systems
The project's seamless integration with existing healthcare systems, like EHRs, would enable data sharing and collaboration. APIs may safeguard patient privacy and ensure regulatory compliance by enabling communication between healthcare databases and the prediction system.

Security and Privacy
To protect patient data handled by ResNet50, ResNet101, Xception, and Inception V3, robust security measures would be implemented. Encryption techniques and access limits would safeguard confidential information and ensure compliance with HIPAA and other healthcare regulations.

Scalability and Performance
Prediction models' scalability and effective processing would be guaranteed by optimization strategies. Distributed computing and model parallelism are two techniques that can improve efficiency and make timely predictions even with big datasets and intricate algorithms.

Continuous Improvement
Mechanisms for model monitoring and updating in response to fresh information and research findings would be incorporated into the project. As information progresses, fine-tuning procedures and retraining schedules would guarantee that Inception V3, Xception, ResNet50, and ResNet101 continue to be successful in forecasting the risk of Alzheimer's disease.

VI. CHALLENGES IN IMPLEMENTATION

Addressing Data Heterogeneity
Dealing with the diverse nature of data sources and formats, and implementing preprocessing strategies tailored to handle variations in neuroimaging scans, biomarker data, and genetic information.
Managing Model Complexity
Overcoming the challenges posed by the intricate architectures of deep learning models like Inception V3, Xception, ResNet50, and ResNet101, and ensuring efficient utilization of computational resources during training and inference.

Ensuring Generalization and Adaptability
Tackling the task of fine-tuning pre-trained models to adapt them to the specific characteristics of Alzheimer's disease prediction, while also preventing overfitting and ensuring robust generalization to unseen data.

Interpreting Model Outputs
Addressing the inherent lack of interpretability in deep learning models and implementing techniques to explain model predictions, thereby enhancing trust and understanding among clinicians and stakeholders.

Integrating with Existing Healthcare Systems
Overcoming the technical challenges associated with integrating deep learning prediction systems with established healthcare infrastructure, while ensuring compliance with regulatory standards and data privacy regulations.

Continuous Monitoring and Maintenance
Putting in place procedures for ongoing assessment, upkeep, and monitoring of the prediction system in order to guarantee its efficacy and continued relevance over time, as well as adding updates derived from fresh data and research discoveries.

VII. 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.

VIII. FUTURE SCOPE
To further improve the models' accuracy, the following actions could be taken:

- The 3D CNN model might be trained with better resources to reduce the runtime.
- Since the previous prediction greatly influences the current prediction, a hybrid network incorporating LSTMs will perform better.
- Cascaded Convolutional Neural Networks could be used to reconstruct MRIs with some errors, potentially improving performance.
- There are multiple variables in the current MRI scan, those variables could be reduced using the dimensionality reduction techniques such as PCA or LDA to overcome the issue of the curse of dimensionality.

IX. REFERENCES


