Alzheimer's Disease Prediction Using Resnet50

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Abstract--- Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by memory loss, cognitive decline, and behavioural changes. Early and accurate detection of AD is crucial for timely intervention and management of the disease. Deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been employed to analyse various types of data, including neuroimaging, genetic markers, and clinical data, to detect patterns indicative of AD. Deep learning models trained on large datasets of neuroimaging scans have demonstrated high accuracy in distinguishing between AD patients and healthy individuals, as well as predicting disease progression. Three sets of data were initially created: training, validation, and test. Only the training and validation sets were utilized to choose models. We use deep learning models to get the nearest accuracy as compared to the existing models.

Keywords *– Alzheimer's disease, Deep learning, convolutional neural networks, AD, Resnet50, early detection, diagnosis.*

I. INTRODUCTION

Alzheimer's disease (AD) is a devastating neurodegenerative disorder that affects millions of people globally, leading to progressive cognitive decline, memory loss, and functional impairment. The impact of AD extends beyond the individual, significantly impacting families, caregivers, and healthcare systems. Early detection and accurate diagnosis of AD are critical for providing timely interventions, personalized treatment plans, and improving overall patient outcomes.

In recent years, there has been a growing interest in leveraging advanced machine learning techniques, particularly deep learning, to enhance the diagnostic capabilities in AD. Deep learning algorithms have demonstrated remarkable success in various domains, including image recognition, natural language processing, and medical imaging analysis. These algorithms excel in automatically learning complex patterns and features from large-scale datasets, making them well-suited for analyzing neuroimaging data such as MRI and fMRI scans.

This paper introduces a novel deep learning-based approach tailored specifically for AD diagnosis and classification. The proposed methodology integrates state-of-the-art techniques in data preprocessing, feature extraction, model training, and interpretability to address key challenges in AD diagnosis. These challenges include handling imbalanced data distributions, ensuring data quality and reliability, improving model interpretability to aid clinicians in decision-making, and integrating multimodal data sources for comprehensive analysis.

By harnessing the power of deep learning and machine learning, this approach aims to enhance the accuracy, efficiency, and scalability of AD diagnosis. The ultimate goal is to provide clinicians with reliable tools that can assist in

early detection, prognosis assessment, and personalized treatment planning for individuals at risk or affected by AD. The contributions of this work extend to advancing the field of neuroimaging-based diagnostics, paving the way for more effective interventions and improved outcomes for AD patients and their caregivers.

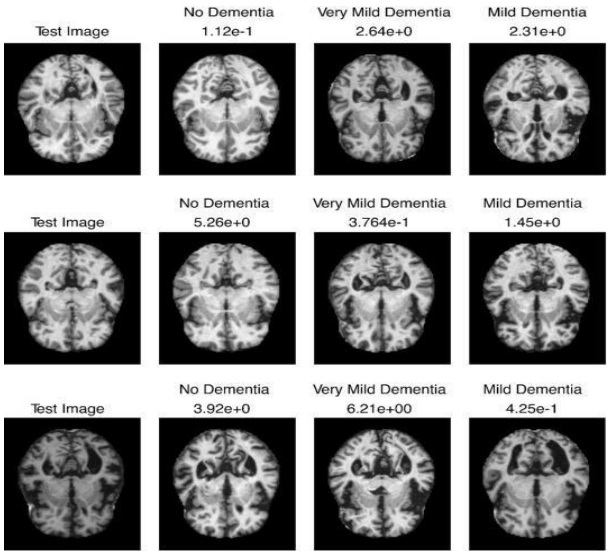

Figure 1: Stages of Alzheimer's disease

II. LITERATURE REVIEW

Z Breijyeh et al. [1] proposed a multifaceted approach to addressing Alzheimer's disease, recognizing its global health significance. They highlight the updated diagnostic criteria aimed at enhancing specificity and sensitivity for early identification of at-risk individuals. Despite symptomatic treatments, the disease's prognosis remains unchanged. Lifestyle modifications, such as diet and exercise, are advocated as first-line interventions, showcasing potential benefits for brain health. The research shift towards targeting AD's pathological features, particularly Aβ and p-tau, offers hope for disease-modifying treatments. However, numerous clinical trials targeting these pathways have failed to demonstrate efficacy in advanced stages. Promising avenues include the exploration of chaperone compounds and natural extracts from folk Chinese medicine, suggesting diverse therapeutic strategies.

CA Lane et al. [2] proposed a comprehensive understanding of Alzheimer's disease (AD), highlighting its multifactorial etiology and emphasizing early detection and diagnosis for effective management. They advocate for further research into biomarkers and imaging techniques to enhance diagnostic accuracy and stress the importance of personalized treatment approaches tailored to individual patient needs. Their proposal underscores the urgency of addressing the growing burden of AD and the necessity for innovative strategies to combat this challenging neurodegenerative condition.

A Serrano-Pozo et al. [3] stated that "Positive" lesions like amyloid plaques and cerebral amyloid angiopathy, neurofibrillary tangles, and glial responses, as well as "negative" lesions like neuronal and synaptic loss, are the hallmarks of Alzheimer disease (AD) neuropathology. Additionally, by demonstrating that there is a continuum between "normal" ageing and AD dementia and that amyloid plaque build-up primarily occurs prior to the onset of cognitive deficits, as well as the parallel progression of neurofibrillary tangles, neuron loss, and particularly synaptic loss, clinicopathological correlation studies have been instrumental in generating hypotheses about the pathophysiology of the disease. Significantly, longitudinal in vivo investigations employing contemporary imaging biomarkers like amyloid PET and volumetric MRI have substantially confirmed this cross-sectional neuropathological data.

R Mayeux at al. [4] proposed an estimated 24 million individuals worldwide are believed to be impacted by dementia, with projections indicating this number will increase every 20 years until at least 2040. As the global population ages, particularly the elderly, the number of individuals at risk is expected to rise significantly. Alzheimer's disease, the most common form of dementia characterized by memory impairment, is marked by neuropathological features including widespread amyloid plaques and neurofibrillary tangles in the brain. While the cause of Alzheimer's

remains unknown, environmental and genetic factors likely contribute. Looking ahead, there is a need for heightened awareness and research efforts to address the growing burden of dementia and Alzheimer's disease, focusing on early detection, effective treatments, and preventative measures.

DJ Selkoe et al. [5] proposed that the significant increase in life expectancy throughout the twentieth century has made Alzheimer's disease (AD) one of the most prevalent conditions in older age. A gradual decline in memory, thinking abilities, reasoning, and behavioral control inevitably leads to widespread dementia and premature death. During autopsy, numerous amyloid plaques and neurofibrillary tangles are found in brain regions responsible for memory and cognitive functions. These abnormalities have become the focus of extensive biochemical and genetic research into the disorder. Particularly, advancements in understanding the relationships between inherited forms of AD and genetic makeup strongly support the theory that the accumulation of amyloid-β protein (Aβ) in the brain is an early, consistent, and essential stage in the disease's progression.

RJ Castellani et al. [6] proposed that Diagnosing Alzheimer's disease involves clinical evidence of memory loss and cognitive impairment, alongside disruptions in social or occupational function. It's essential to differentiate AD from other dementia types. The initial clinical presentation varies depending on affected brain regions, affecting memory, personality, judgment, and more. Braak and Braak's stages outline a predictable progression of pathology. Mild cognitive impairment (MCI) refines early diagnostic features, identifying cognitive dysfunction before dementia onset, with subtypes like amnestic/single domain and non-amnestic/multiple domains.

AL Calderon-Garcidueñas et al. [7] proposed that the term AD can refer to either the neuropathological diagnosis or the clinical symptoms. To clarify, it has been suggested to distinguish between the pathophysiological process and the clinical phase of the disease (Sperling et al., 2011). The latest neuropathological criteria (Hyman et al., 2012; Montine et al., 2012) are centered on assessing AD neuropathologic changes. These criteria involve three scales: A for amyloid, B for Braak stages, and C for CERAD.

C Duyckaerts at al. [8] proposed the continuum hypothesis suggests that certain tauopathies may severely affect the hippocampus, causing significant neuronal loss even when other brain regions are less involved. In the future, identifying such cases could involve comparing hippocampal lesion severity with the NFT stage, which is not currently part of the PART criteria. This omission might lead to confusion between early AD and specific tauopathies, as most tau-positive/Aβ-negative cases appear to represent a stage of AD rather than a distinct disease form, according to the continuum hypothesis.

RE Tanzi et al. [9] proposed that Family history stands as the second most significant risk factor for Alzheimer's disease (AD), trailing only advanced age. Studies involving twins and families suggest that genetic factors contribute to approximately 80% of AD cases. AD inheritance shows a two-fold pattern: rare mutations in APP, PSEN1, and PSEN2 almost certainly lead to early-onset familial AD (<60 years), accounting for about 5% of cases, while common gene polymorphisms like the ε4 and ε2 variants of the APOE gene influence susceptibility in roughly 50% of late-onset AD cases. These four genes contribute to 30%–50% of AD inheritability. Recent genome-wide association studies have identified 11 additional AD candidate genes, illustrating ongoing efforts to understand the complex and diverse genetic basis of AD.

A Kumar et al. [10] proposed that Cholinesterase inhibitors work by boosting acetylcholine levels, a crucial neurotransmitter for learning, memory, and cognition. Among these, donepezil, rivastigmine, and galantamine are FDA-approved for Alzheimer's treatment. Common side effects include gastrointestinal symptoms like nausea, vomiting, and diarrhea. Sleep disturbances are more frequent with

donepezil. Due to increased vagal tone, bradycardia, cardiac conduction issues, and syncope may occur, making these drugs unsuitable for patients with severe cardiac conduction abnormalities.

Table 1.1 - Comparative Analysis

Authors	Year	Methodology	Results
Payan A	2013	sparse auto-encoders and convolutional neural networks (CNNs)	Accuracy - 80%
Saraf S	2020	CNN	Accuracy - 96.85%
Bhatkoti	2022	hybrid multi-class Deep Learning (DL) framework	Accuracy - 83.4%
V.Patil	2019	18 layer-CNN 3D convolutional network	Accuracy - 98%

III. PROPOSED METHODOLOGY

Data collection of the people with Alzheimer's is collected of very well analysed brain images and other details of the patients with and without Alzheimer's, data pre-processing of the images and handling the missing values. We extract the required features of the dataset and other features to enhance the models performance, we set the appropriate evaluation metrics such accuracy, precision, and recall and F-1 score to assess the model's performance. We apply the required Deep learning and machine learning techniques for the available cleaned data.

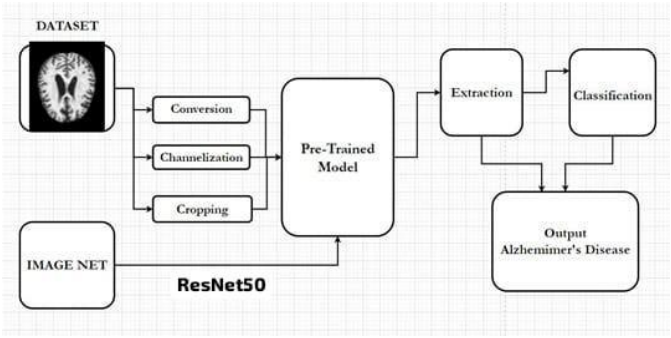

Figure 2: Model Architecture

Pre- processing:

Dataset:

In this step, the AD spectrum is divided into four stages:

- Mild Demented
- Moderate Demented
- Non Demented
- Very Mild Demented

A multi-classification approach is used to classify samples into these four stages. Additionally, separate binary classifications are performed between each pair of classes to further distinguish and classify samples within the AD spectrum.

The collected dataset suffers from imbalanced classes, meaning some classes have significantly fewer samples than others.

In medical imaging, variations between MRI scans of the brain can pose challenges due to differences in anatomy and positioning. Normalization addresses this by aligning images to a standardized brain template, known as the Montreal Neurological Institute (MNI) space. This ensures a consistent coordinate system, enabling direct comparison and analysis of brain structures. Denoising is crucial for accurate diagnosis, where deep learning models, like CNNs, remove noise patterns from images. Trained on pairs of noisy and clean images, CNNs generate denoised versions with

enhanced clarity, aiding precise analysis. Standardization involves scaling input data to have a mean of zero and a standard deviation of one, stabilizing training and improving model performance. Resizing images ensures uniform dimensions for model input, simplifying the data processing pipeline. Smoothing techniques, like Gaussian filters, reduce noise and enhance image quality, particularly in functional imaging. Finally, format conversion ensures compatibility with deep learning frameworks, converting images into suitable formats like NumPy arrays or standard image files

IV. EVALUATION METRICS

These references present various methods applied to different modalities (MRI, PET) for the identification of Alzheimer's disease, with accuracy ranging from 89% to 90%. The methodologies include Reinforcement Learning (RL), Deep Reinforcement Learning (DRL), Feed-forward Deep Neural Networks (DNN), 3D Convolutional Neural Networks (CNN), and AlexNet. The accuracy achieved by these methods demonstrates their potential in accurately diagnosing Alzheimer's disease based on medical imaging data.

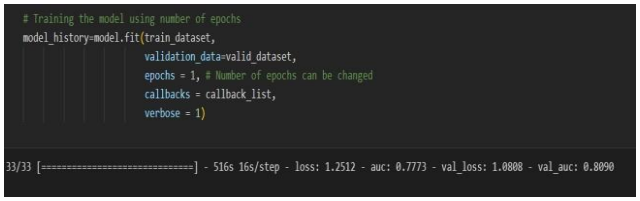

Figure.3: Accuracy

ResNet50 has been compared with other deep learning architectures, traditional machine learning methods, and even manual feature extraction approaches for Alzheimer's disease identification. The performance of ResNet has shown competitive or superior results in terms of accuracy and robustness, indicating its potential as a valuable tool for early diagnosis and understanding of the disease.

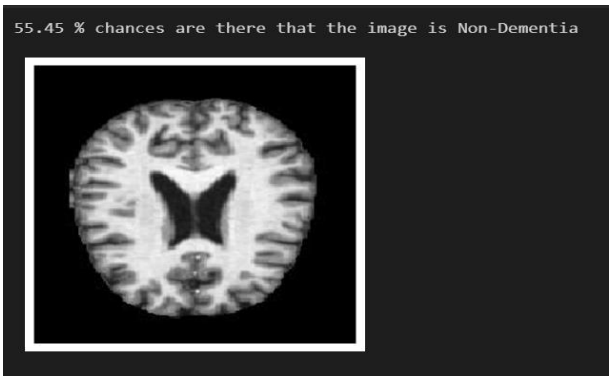

Figure .4: Prediction of Alzheimer's Disease

The deep layers of ResNet50 allow the model to automatically learn high-level features and hierarchical representations from the input data, making it well-suited for recognizing intricate patterns associated with the disease.

V. CONCLUSION AND FUTURE SCOPE

Finally, this research paper clearly explained the steps for using deep learning in the early detection of Alzheimer's. The explained steps are profound and detailed. We have concentrated on the algorithms CNN convolutional neural network and ResNet. Dataset is converted, channelized and cropped for only having the useful data. The data is also image processed using ResNet50.This data is pre-Trained model extracted and classified to give the accurate output on the Alzheimer's disease. Other sophisticated methods in the processing can be involved. Adding of the additional attributes in the required data, decreasing the noise data and clear attributes can make this much efficient than now. We followed the steps of data collection, data pre-processing, and image pre-processing eloquently for getting the accurate results.

Deep learning is the field of constable's development. Accuracy can be improved because of the advancements in deep learning and machine learning. Combining sparse regression and deep learning (DL) methods for diagnosing Alzheimer's disease (AD) can be

effective. Additionally, one promising technique for AD diagnosis is the manifold-based learning method. To improve the overall performance of AD diagnosis, data augmentation and scaling techniques are valuable. These methods can enhance the state-of-the-art performance by increasing the diversity and volume of data, making the models more robust and accurate. One of the challenges in Alzheimer's disease research is the difficulty in collecting brain-balanced and sufficient data. Obtaining a well-balanced dataset that adequately represents the different aspects and stages of the disease can be challenging.

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