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Deep Learning-Based Early Prediction of Alzheimer's Disease

Mr. Nitin Barsagde[1], Kunali G. Atkare[2], Pranjali S. Sarode[3], Siddhi R. Malewar[4], Sonali P. Pradhan[5], Vaibhav N. Puri[6*]

[1]*Assistant professor, CSE Department, G H Raisoni College of Engineering and Management, Nagpur, Nagpur (Maharashtra), India*

[2,3,4,5,6]*Dept. Information Technology, G H Raisoni College of Engineering and Management, Nagpur, Nagpur (Maharashtra), India*

[*]*Corresponding author, vaibhav.puri.it@ghrietn.raisoni.net*

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Abstract

Alzheimer's disease (AD) is a progressively advancing neurological disorder that leads to irreversible degeneration of brain cells, affecting memory, cognition, and motor abilities. Early detection of AD plays a vital role in enabling timely medical intervention and slowing disease progression. However, limited public awareness and the complexity of neurological changes make early diagnosis challenging, particularly as symptoms worsen with age. For this study, the OASIS dataset obtained from Kaggle was employed, with 80% of the data allocated for model training and the remaining 20% reserved for testing to ensure a reliable evaluation process. To accomplish this objective, an efficient automated diagnostic framework was developed using transfer learning with the EfficientNet-B0 Convolutional Neural Network (CNN).
Furthermore, class-wise sensitivity analysis reveals that the proposed EfficientNet-B0 model performs consistently well across all three classes, including Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Normal Control (NC), confirming its robustness in stage-wise classification.

Keywords: Alzheimer's Disease Detection, EfficientNet-B0 Models, Brain MRI Analysis, CT Imaging

1. Introduction

Alzheimer's disease (AD) is a progressive neurological disorder that is most commonly diagnosed in individuals above the age of 60. The condition gradually affects memory, cognitive abilities, and an individual's capacity to perform daily activities independently. First identified by Dr. Alois Alzheimer in 1906, the disease is also associated with physical limitations, including difficulties related to walking, maintaining posture, and swallowing. Among individuals affected by dementia, particularly those diagnosed with AD, the ability to adapt to surroundings and communicate effectively declines over time. From a pathological perspective, Alzheimer's disease is characterized by brain shrinkage and the gradual loss of neurons.

Medical imaging techniques play a crucial role in identifying Alzheimer's-related abnormalities. Structural

brain changes revealed through magnetic resonance imaging (MRI) and computed tomography (CT) scans assist clinicians in detecting patterns associated with disease progression. As Alzheimer's advances, patients often experience impaired judgment and decision-making abilities, which may result in inappropriate behavioral responses, poor situational awareness, and difficulty managing routine challenges.

Conventional diagnostic strategies for Alzheimer's disease rely on the integration of multiple data sources, including brain imaging, positron emission tomography (PET), cerebrospinal fluid biomarkers, and clinical evaluations. Although such multimodal approaches aim to improve diagnostic accuracy, combining a large number of features frequently leads to overfitting issues within predictive models. Deep learning techniques address these limitations by automatically extracting and prioritizing relevant features from diverse datasets, enabling the identification of complex patterns within high-dimensional neuroimaging data.

In the healthcare domain, deep learning—particularly convolutional neural networks (CNNs)—has significantly transformed medical image analysis. These models support automated processes such as disease detection, image segmentation, and classification within computer-aided diagnostic systems. As an advanced branch of machine learning, deep learning utilizes multi-layered neural architectures to learn meaningful relationships between input data and output predictions through pattern recognition mechanisms.

In this work, a deep CNN-based framework is proposed for the detection and staging of Alzheimer's disease. The model is trained using appropriate datasets and demonstrates strong performance in identifying different stages of AD progression.

2. Literature Review

Ismail et al. (2023) proposed a novel multi-objective optimization approach for enhancing Alzheimer's disease detection through the combined use of different medical imaging sources, including magnetic resonance imaging and positron emission tomography**.** Utilizing the ADNI dataset, their research demonstrated that merging diverse data modalities significantly enhances classification precision compared to methods relying on a single modality [1].

To refine Alzheimer's diagnosis through MRI analysis, **Xu et al. (2021)** developed a 'Modified Tresnet' model. This approach incorporated a selective kernel model and transfer learning to more effectively capture multi-scale features. The experimental results reported in their study demonstrate improved performance in both segmentation and classification when compared with conventional CNN-based methods [2].

Balaji and Suresh (2021) performed a comparative study involving multiple machine learning techniques such as support vector machines, random forest models, and k-nearest neighbor classifiers, applied to neuroimaging and biomedical data. Their study concluded that ensemble-based techniques and SVMs achieved the highest performance in multiclass scenarios, highlighting the continued relevance and robustness of conventional machine learning in identifying neurodegenerative conditions [3].

To overcome the limitation of small training datasets, **Amin-Naji et al. (2019)** introduced a Siamese CNN-based approach that learns similarity relationships between pairs of medical images instead of relying on conventional classification techniques. This methodology demonstrated improved performance over traditional deep learning models for identifying Alzheimer's disease, even when limited data samples were available [4].

Emphasizing the inherent strengths of deep learning, **Vinutha et al. (2018)** illustrated that CNN models possess the unique capability to automatically extract discriminative features directly from MRI data. Their

analysis confirmed that CNN-based classifiers reach higher accuracy levels than traditional machine learning methods, validating the shift toward automated feature extraction in medical diagnostics [5].

Islam and Zhangin (2018) investigated methods for detecting Alzheimer's disease at an early stage. Their study reported that convolutional neural network models can recognize subtle pathological changes that may be overlooked by traditional diagnostic approaches. These findings emphasize the importance of deep learning techniques for identifying Alzheimer's disease during its initial and more manageable stages [6].

Kulkarni et al. (2017) explored the application of Electroencephalography (EEG) as a cost-effective and non-invasive diagnostic tool. Their findings revealed that patients with Alzheimer's exhibit slower brain rhythms and distinct changes in EEG signal complexity, providing vital physiological markers for early-stage identification [7].

3. Problem Statement

Despite years of extensive research, Alzheimer's remains a complex and poorly understood condition, posing a significant challenge to global healthcare. The disease is characterized by a steady degeneration of brain tissue and the eventual death of neurons, which leads to physical and cognitive decline. As the condition progresses, individuals often lose their independence, struggling with essential motor functions such as walking or even the ability to swallow. Beyond the physical impact, the gradual erosion of memory and communication skills makes it nearly impossible for patients to convey their needs or discomfort. Consequently, those affected become entirely dependent on round-the-clock care, creating a profound burden for both the patients and their caregivers.

4. Methodology

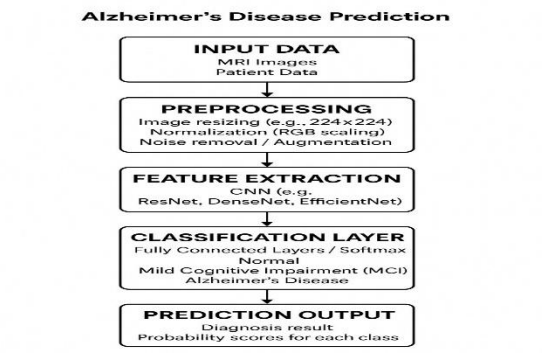


Fig 4.1 Flow Chart

A. Data Collection

For the present study, a publicly accessible MRI dataset was obtained from Kaggle in accordance with the OASIS (Open Access Series of Imaging Studies) guidelines. This dataset was selected due to its proven reliability and frequent use in research related to Alzheimer's disease and associated forms of dementia. A total of 2,239 brain MRI scans were included and organized into three distinct clinical categories. Among these, 1,279 scans correspond to non-demented individuals, 896 images represent subjects with mild

dementia, and 64 scans belong to cases of moderate dementia. For experimental evaluation and model training, the complete dataset was divided into training and testing subsets using an 80%–20% split.

B. Data Preprocessing

Before we began training, we put the MRI images through a rigorous preprocessing pipeline to ensure they were standardized and compatible with our deep learning architecture. We first resized every image to 256 x 256 pixels and then applied a center crop to achieve a final dimension of 224 x 224. This step was vital to maintain consistency across the entire input stream. After resizing, we converted the images into PyTorch tensors. In the final stage of preprocessing, input images were normalized using the standard ImageNet mean values ([0.485, 0.456, 0.406]) along with the corresponding standard deviation ([0.229, 0.224, 0.225]). This normalization strategy contributed to faster training convergence and enhanced overall model performance.

C. Model Design

In this study, the EfficientNet-B0 model was adopted as the primary deep learning architecture. EfficientNet-B0 is a convolution-based neural framework originally introduced by Google and is recognized for achieving strong predictive performance while maintaining computational efficiency, making it suitable for medical imaging tasks. The defining feature of this architecture is its compound scaling strategy, which uniformly adjusts network depth, width, and input resolution rather than modifying these parameters independently.

MRI scans supplied to the network are first represented in numerical form and passed through successive convolutional layers. These layers apply learnable filters that progressively extract informative characteristics from the images. Early stages of the network capture low-level visual patterns such as edges and textures, whereas deeper layers focus on identifying higher-level neurological features associated with dementia. The end-to-end processing pipeline, beginning with raw MRI data and concluding with clinical classification, is illustrated in Figure 4.2.

Model training was conducted using 80% of the available dataset, while the remaining 20% was reserved for validation on previously unseen samples. The trained network classifies brain images into three categories: Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Healthy Control (HC). Model effectiveness was ultimately assessed using commonly accepted evaluation metrics.

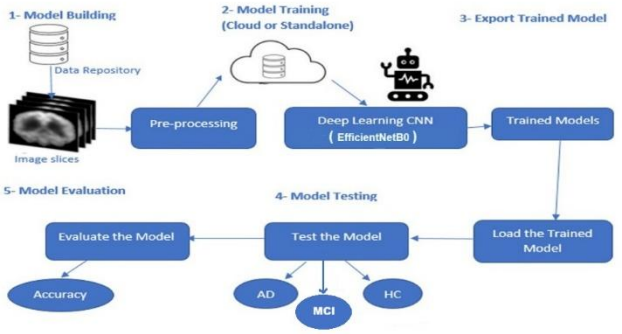


Fig 4.2*: *System Design

5. Result

The proposed system produces a final outcome in which brain MRI scans are categorized to determine the presence or absence of Alzheimer's disease.

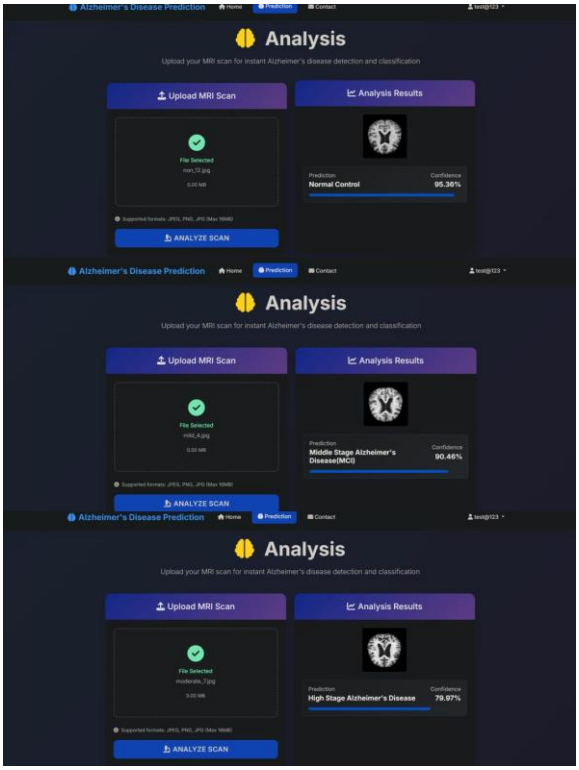


Fig 5.1: Result

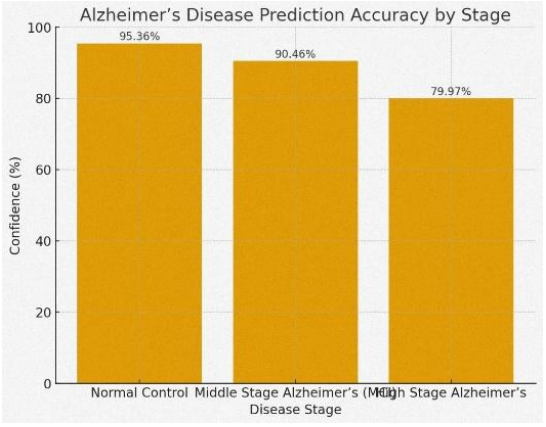


Fig 5.2: Bar chart for accuracy

6. Conclusion & Future Scope

Convolutional Neural Networks have been extensively utilized to predict Alzheimer's disease by examining patterns present in MRI brain images. Incorporating the EfficientNet algorithm improves prediction accuracy by allowing more efficient processing and interpretation of medical imaging data. This approach not only assits in disease identification by classifying individuals as either Alzheimer's patients or health control but also highlights the importance of dataset quality. The performance of the model is strongly influenced by quantity, quality, and diversity of MRI scan dataset, making them crucial for achieving reliable and accurate diagnostic outcomes.

Expanding the dataset with larger, more diverse, and multi-modal inputs such as PET scans, genetic data, and clinical records could improve the robustness and generalizability of predictions. There are several algorithm of CNN can be used as LeNet used for basic image classification. AlexNet that introduced deeper CNN layer and ReLU activation, improving image recognition accuracy. Continuous model optimization and cross-validation on international datasets will also be essential for achieving standardized and clinically acceptable performance in Alzheimer's disease detection.

Declaration of Conflicting Interests

The authors declare no potential conflicts of interest with respect to the research, authorship and publication of this article.

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