Alzheimer’s Detection Through MRI Scan Classification

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Abstract

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder that significantly impairs memory, cognitive function, and daily activities, making early detection critical for effective intervention. This project presents a novel deep learning architecture designed to enhance the accuracy and reliability of AD diagnosis using MRI scan classification. The proposed system integrates dual convolutional neural network (CNN) branches—Upper for fine-grained spatial features and Lower for global contextual information—fused through a concatenation layer for robust feature representation.

To address limitations in traditional approaches, the model incorporates advanced preprocessing techniques such as histogram matching, SMOTE-based class balancing, and DCGAN-generated data augmentation, which collectively improve data quality and model generalization. Extensive experimentation on the OASIS MRI dataset demonstrates that achieves superior classification performance across various stages of cognitive impairment. Ensemble learning methods and interpretability tools like heat maps further strengthen the model's diagnostic potential.

This project not only achieves state-of-the-art accuracy (99.01%), but also proposes a scalable and explainable framework that can be integrated into real-world clinical workflows, represents a significant step toward automating and improving the early detection and management of Alzheimer's Disease through artificial intelligence and medical imaging.

Keywords:

- **Alzheimer's Disease (AD)**
- **Convolutional Neural Network (CNN)**
- **MRI Scan Classification**
- **Data Augmentation**
- **Early Detection**

Introduction

Alzheimer’s disease (AD) is a progressive brain disorder that mainly affects older adults, causing memory loss, reduced thinking ability, and difficulties in daily life. As the global population ages, the number of people with AD is rising quickly, creating major social and economic challenges. MRI scans are important for early detection because they can show changes in brain structure linked to the disease.

But analysing these scans manually takes a lot of time and can vary between different doctors, making it harder to manage as more cases appear. Traditional machine learning methods often depend on manually selected features and expert knowledge, which limits how well they can be scaled or standardized. New progress in deep learning, especially through Convolutional Neural Networks (CNNs), has shown strong results in automatically diagnosing diseases from images with high accuracy.

To address this, we introduce this model, a new deep learning model built to improve how accurately and efficiently Alzheimer’s can be identified from MRI scans. It uses two CNN pathways to capture features at different levels and includes steps like image preprocessing, data augmentation, and balancing to deal with common data issues. This project aims to help create faster, more dependable, and practical tools for diagnosing Alzheimer’s disease in clinical settings.

Problem Statement

The escalating prevalence of Alzheimer's disease poses a significant societal and economic burden. With projections indicating a substantial increase in affected individuals, there is an urgent need for advanced diagnostic tools and efficient healthcare management. Current manual analysis of MRI images for Alzheimer's disease detection is time-consuming, exacerbating the strain on medical infrastructure as patient numbers rise exponentially. The research identifies the need for an automated AD classification and grading system to streamline the evaluation process, enabling quicker and more accessible preliminary diagnosis and guidance for neurologists. This paper addresses the challenge of enhancing accuracy and efficiency in AD detection by proposing the innovative model, surpassing the limitations of existing methodologies.

Review on existing systems

Magnetic Resonance Imaging (MRI) plays a vital role in the diagnosis and monitoring of Alzheimer's Disease (AD), enabling clinicians to assess structural brain changes such as hippocampal atrophy. However, manual MRI interpretation is often challenging due to the high dimensionality and variability of scan data [1]. Traditional machine learning (ML) methods have been widely used over the past two decades, often outperforming expert diagnosis. These approaches typically rely on manually extracted features from voxel-based, region-of-interest (ROI)-based, or patch-based inputs [2]. While such methods are interpretable and robust, they depend heavily on expert domain knowledge and specialized software, which can limit reproducibility and scalability [3].

Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a superior alternative by enabling end-to-end learning from raw imaging data. CNNs automatically extract multilevel features through stacked convolutional layers—shallow layers capture low-level textures while deeper layers extract abstract semantic features [4]. Architectures like AlexNet [5], VGGNet [6], ResNet [7], DenseNet, DarkNet, and EfficientNet have been successfully applied to AD classification tasks [8]. For instance, Conv-Swinformer [9] integrates CNN with Swin Transformer modules to capture planar and spatial MRI features with high accuracy. Image preprocessing using spatial alignment with ICBM templates and registration tools like 3D Slicer ensures consistency across patients [10][11].

In [12], CNN models such as VoxCNN and ResNet were evaluated on ADNI datasets for multi-stage classification using 3D tensors, achieving high accuracy across several binary classification tasks. Preprocessing pipelines often include skull stripping, bias correction, and affine registration using tools like FreeSurfer, FSL, and FLIRT [13][14][15][16]. The ISDL model [17] utilizes iterative sparse dictionary learning on parcellated cortical areas using AAL mappings and LASSO regression for feature selection.

Hybrid deep learning approaches, such as combining Darknet53, ResNet101, and InceptionV3, have also shown promise, achieving up to 99.1% classification accuracy when optimized with feature selection techniques like mRMR [18]. Similarly, [19] proposes a 3DCNN model trained on brain-region patches, further improved by genetic algorithm-based ensemble learning (GA-EL). Structural and functional features extracted from sMRI and rs-fMRI modalities were used in [20], where SVM and Random Forest classifiers achieved strong results using features selected by LASSO, SVM-RFE, and JMI. Finally, [21] introduces NMF-TDNet, which replaces PCA with Non-negative Matrix Factorization (NMF) for filter training and uses Tucker decomposition for dimensionality reduction, achieving both classification and MMSE score prediction using LIBSVM-based SVC and SVR

Objective

The objective of this project is to develop a deep learning-based model for the early and accurate detection of Alzheimer's Disease using MRI scans. By using a dual-branch convolutional neural network architecture, advanced preprocessing techniques, and data augmentation strategies, the model aims to enhance diagnostic precision, address class imbalance, and provide a scalable, automated solution for real-world clinical application.

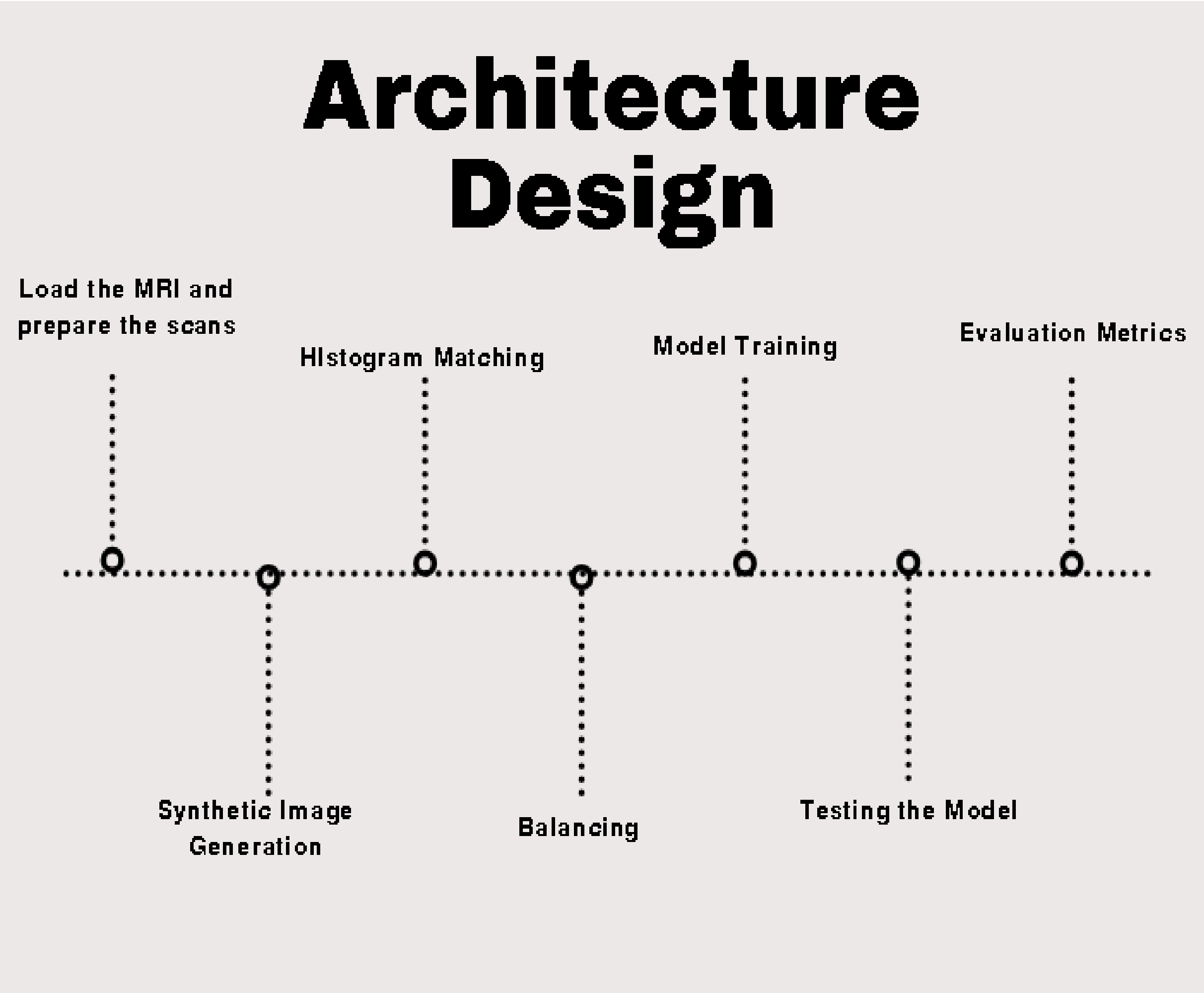
Motivation

Alzheimer's Disease is a serious illness that slowly takes away a person's memory and ability to think. By the time it is usually diagnosed, it's already too late to slow it down. Early detection can make a huge difference in a patient's life, allowing for better care and treatment. However, checking brain scans manually is slow and can be difficult, even for experienced doctors. This motivated us to build a smart system that can look at MRI scans and help detect signs of Alzheimer's quickly and accurately. By using artificial intelligence and deep learning, we hope to support doctors and make early diagnosis easier, faster, and more reliable.

Proposed Methodology

1. **Load MRI and prepare the scans from dataset.**
2. **Synthetic Image Generation**
3. **Histogram matching**
4. **Balancing**
5. **Model Training**
6. **Testing the Model**
7. **Evaluation Metrics**

Architecture Diagram



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