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Alzheimer's Disease Detection using Deep Learning: A Review

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***Abstract*— Alzheimer's disease (AD) is a neurological illness that progresses over time and is a leading global health problem. Effective Alzheimer's disease treatments and better patient outcomes depend on early identification of the illness.Deep learning has become a powerful tool for analysing medical images, including detecting and assessing Alzheimer's disease. This survey analyses existing AD datasets, preprocessing methodologies, and feature extraction methods for deep learning models. We analyse the key contributions and limitations of numerous studies and provide insights into the challenges and opportunities in this domain. The usefulness of several deep learning architectures, including Convolutional Neural Networks (CNNs) and their derivatives, in classifying the MRI scans into mild demented, moderate demented, very mild demented, non demented is examined in our investigation.The paper also examines the role of preprocessing techniques, such as skull alignment and subtraction, in improving the accuracy of deep learning models for AD diagnosis. Additionally, we discuss the potential for further improvement through data augmentation and the collection of more extensive datasets.**

***Index Terms*— Advanced Deep Learning Methods, Convolutional Neural Networks (CNNs), Data Augmentation, MRI Scans.**

I. INTRODUCTION

Alzheimer's disease (AD) has been a long-standing challenge in the global healthcare system. With an aging population and its relentless trajectory, AD has emerged as a paramount public health concern, imposing a profound societal and economic burden. This progressive condition, marked by the gradual deterioration of cognitive function, strikes at the core of human cognition, memory, and reasoning, altering the lives of those afflicted and their families.

The timely and precise diagnosis of AD becomes crucial in this difficult situation. Prompt identification provides a number of crucial benefits. By providing patients and their families with the crucial opportunity to investigate interventions and support systems, it enables them to make informed decisions about their care and long-term goals. Timely identification can also improve response to treatment and potentially slow the unrelenting progression of the illness through targeted treatments and interventions.It is also essential for recruiting participants in clinical trials, which is an essential stage in developing novel therapies.

Clinical evaluations that involve caregiver interviews, cognitive tests, and medical histories are part of the process of detecting Alzheimer's disease. More advanced imaging techniques, such MRI, PET, and CT scans, are necessary to see changes in the brain, and genetic testing can identify mutations associated with Alzheimer's disease in close relatives. There are numerous techniques for using machine learning and deep learning to the classification of AD.

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Nevertheless, issues with excessive model parameters and unequal class distribution persist in the multiclass AD classification.

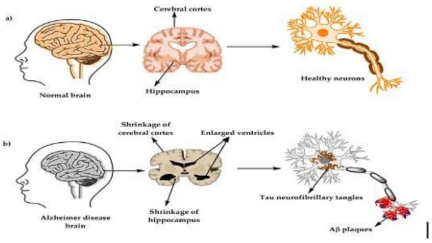

Figure 1. The structure of the brain and neurons in (a) healthy brain and (b) Alzheimer’s disease (AD) brain.

Source: Adapted from Breijyeh, Z., & Karaman, R. (2020). Comprehensive Review on Alzheimer’s Disease: Causes and Treatment. Molecules, 25(24), 5789. https://doi.org/10.3390/molecules25245789.

A new era in AD detection has been brought about by the extraordinary convergence of deep learning techniques and medical imaging in recent years. These days, magnetic resonance imaging (MRI) is the preferred diagnostic technique because it offers a non-invasive view into the structural changes in the brain that are the basis of Alzheimer's disease. At the same time, deep learning has made significant strides in medical image analysis and has the potential to completely change the field of AD diagnosis due to its capacity to identify complex patterns in data.

A. Problem Statement

The objective is to use structural magnetic resonance imaging (SMRI) to identify biomarkers for Alzheimer's disease (AD), to create and test a deep learning model for early AD detection using a dataset, and to categorize brain images into mild demented, moderate demented, non demented, very mild demented.

B. Objectives

- Develop a deep learning model using techniques such as CNNs to detect Alzheimer's illness.
- Optimize the model and hyperparameters for more accurate results.
- To identify the stages of Alzheimer's illness.

II. Literature Survey

This literature review examines research on detecting Alzheimer's Disease (AD) using MRI scans. It provides insights into diverse approaches and discoveries that contribute to our understanding of this important medical imaging analysis.The following summarizes key insights, methods, contributions, and limitations from the selected papers, drawing connections to the proposed project.

Fazal et al. have developed an innovative model for classifying MRI images into Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Cognitively Normal (CN) groups. Their method utilizes Convolutional Neural Network (CNN) features, leading to improved accuracy with fewer parameters, reducing computational complexity. The study employs the ADNI dataset and highlights the importance of preprocessing for optimal results, particularly in skull alignment and subtraction[1].

Shagun et al. proposed a deep learning model for detecting Alzheimer's disease using MRI data. They employ a CNN model with a VGG16 feature extractor and evaluate its performance on two datasets, achieving high AUC, accuracy, precision, recall, and F1-score. The paper suggests the potential for further improvement through the collection of more datasets[2].

Mian et al. created ADD-Net, a convolutional neural network architecture for early Alzheimer's disease diagnosis with few parameters. The method uses synthetic oversampling to correct class imbalance in the Kaggle MRI imaging dataset. The paper compares ADD-Net with other models using precision, recall, F1-score, AUC, and loss, emphasizing the challenges of imbalanced datasets on model accuracy[3].

Nagarathna et al. research focuses on categorizing Alzheimer's Disease into stages using an ensemble model. The objectives include preparing datasets, extracting features with a multi-layer feed-forward network, and using CNN for trinary classification. The study reported an accuracy of 93.38[4].

Marwa et al. developed a deep learning strategy for detecting Alzheimer's disease using CNNs and 2D T1-weighted MRIs. The method offers both global and local classification and suggests the use of advanced data mining algorithms on different datasets to enhance prediction effectiveness at earlier stages[5].

Jie Zhang et al. developed a 3D densely connected CNN with connection-wise attention mechanisms to classify Alzheimer's disease from pre-processed brain MRI data. The paper highlights significant improvements in diagnosis accuracy and MCI conversion prediction, emphasizing the effectiveness of 3D convolution for spatial information capture. Future work could explore integrating other modalities and address ethical considerations[6].
Hadee et al. have developed an E2AD2C framework for early Alzheimer's Disease detection using deep learning CNN architectures. It employs simple CNNs for 2D and 3D scans and transfer learning with the VGG19 model, achieving high accuracy. The paper recommends experimenting with different pre-trained models and augmenting datasets to increase performance [7].
Using systematic MRI analysis, V.P. Subramanyam et al. have proposed machine learning algorithms for classifying individuals into groups: mild cognitive impairment, Alzheimer's disease, and cognitively normal. The study achieves promising results, though not suitable for clinical diagnosis, suggesting further improvements and the integration of additional imaging modalities [8].
The HEMRDTL model was presented by M. Leela et al. for the purpose of detecting Alzheimer's disease. It combines transfer learning with VGG-19, resilient principal component analysis (RPCA), and modified RPCA (M-RPCA).
The model achieves high accuracy through the fusion of CT-MRI and EEG data. Future research aims to secure additional datasets and leverage diverse data sources for improved early AD detection[9].
Five levels make up the CNN-based system for classifying Alzheimer's disease that Yousry Abdul et al. described. These layers include MRI acquisition, adaptive thresholding, data augmentation, CNN model, and classification. The study emphasizes techniques for faster convergence and higher accuracy. Future directions include exploring transfer learning models, multi-classification, and further investigations into AD prediction[10].
In order to detect Alzheimer's disease (AD) and moderate cognitive impairment (MCI) in MRI data, Atif Mehmooda et al. have created a number of deep learning algorithms, such as layer-wise transfer learning and brain picture segmentation. It showcases the effectiveness of transfer learning with pre-trained VGG models, achieving high diagnostic accuracy, but it lacks clarity on dataset size and currency with recent advancements[11].
DH Chaitra et al. have proposed Convolutional Neural Networks (CNNs) and transfer learning with various architectures to obtain a 91\% accuracy in early AD detection and classification. While it highlights the potential of deep learning, it emphasizes the need for further refinement and clinical validation[12].
Srinivasan et al. have presented an approach for AD detection and classification from MRI using image processing and a modified k-Nearest Neighbour algorithm, achieving a 93.18% accuracy. Comparisons with existing methods would enhance its validity[13].
Dong Nguyen et al. have combined deep learning and machine learning, utilizing 3D structural features to diagnose AD. It effectively addresses overfitting and offers efficient and explainable predictions but may benefit from exploring data preprocessing challenges[14].
Rafsanjay kushol et al. have developed a novel approach using vision transformer networks to detect AD from MRI data. It emphasizes the fusion of spatial and frequency features, showcasing the value of transfer learning but calls for external validation on diverse datasets[15].
Renjith CV et al. have introduced ELDFL for detecting brain diseases, including AD, from MRI. It combines preprocessing, landmarks, hybrid feature learning, CNNs, and LSTMs. While it normalizes features and combines neural network architectures effectively, broader dataset testing is suggested[16].
S. Saravanakumar et al. have developed CNNs to classify AD stages using MRI scans and addresses overfitting through GAN augmentation. Despite high accuracy, it emphasizes the need for clinical validation and real-world integration[17].
Shiny Pershiya et al. have utilized CNNs, particularly the LeNet-5 architecture, to detect AD from MRI. While it emphasizes the clinical significance of accurate categorization, it lacks thorough comparisons with existing methods[18].
A CNN-based paradigm has been proposed by Subhankar Samanta et al. for the identification and classification of early AD from MRI. It emphasizes precise diagnosis and high-resolution mapping but requires further discussion on clinical validation[19].
Sanchit Vashisht et al. have developed CNNs to classify AD into stages from MRI, employing GAN augmentation. It shows potential for clinical support but requires discussion on clinical validation and practical utility[20].
Mohamed Ayman et al. have investigated the use of many CNN-based techniques, such as ResNetV2, VGG16, and Inception, for the classification of Alzheimer's disease using MRI scans at various stages of the disease. The study implements cross-validation techniques to ensure result reliability[21].

Xiao Cao et al. have introduced ADResNet, a CNN model based on ResNet-18, designed for efficient and accurate Alzheimer's disease detection through MRI image analysis. ADResNet outperforms other architectures such as VGG16 and ResNet-18, achieving exceptional results[22].

Using the hippocampal areas in MRI images, Junaidul Islam et al. have investigated different YOLO versions for the identification and classification of Alzheimer's disease. It highlights the potential of YOLO variants for accurate identification of the hippocampus region, with potential applications in AD detection and diagnosis[23].

D. Thamaraiselvi et al. have focused on utilizing DenseNet 169, a CNN variant, to detect Alzheimer's disease through MRI scans. It emphasizes the potential of DenseNet 169 for accurate AD detection and highlights its societal well-being implications[24].

Omar Elgendy et al. have demonstrated the effectiveness of deep learning methods, including custom CNN, ResNet50, and VGG16, for Alzheimer's disease detection. The research discusses strategies to address overfitting during model training. It acknowledges the limitation of dataset availability and encourages efforts to collect or augment more data for comprehensive research[25].

The use of deep learning for early Alzheimer's disease (AD) prediction and classification has been the focus of Priyanka Datta et al. It emphasizes how Deep Learning is better at early AD diagnosis than traditional machine learning models. It highlights the superiority of Deep Learning over conventional machine learning models in early AD diagnosis. The research delves into various biomarkers and datasets, emphasizing ethical considerations in medical data research[26].

Convolutional Neural Networks (CNNs) have been used by P. Praveen et al. to identify and stage Alzheimer's disease using MRI brain imaging. It introduces a novel approach using MRI data from Kaggle and underscores the significance of leveraging large datasets. The study suggests exploring clinical validation and real-world implementation challenges[27].

Ruchika Das et al. have presented a deep learning method that uses MRI brain image analysis to categorize Alzheimer's disease stages. It successfully divides MRI scans into four disease stages but lacks discussion on ethical considerations related to patient data privacy and informed consent[28].

Using deep learning models and mobility data, Santos Bringas et al. have determined the stages of Alzheimer's disease. It achieved promising results, but limitations include a small sample size, controlled data collection, and labeling inaccuracies[29].

A CNN-based method called DEMNET has been presented by Suriya Murugan et al. for the early identification of Alzheimer's disease from MRI pictures. It achieves high accuracy and performance metrics. However, it acknowledges the need to address dataset class imbalance and optimize pre-processing while exploring advanced models and robustness across datasets in the future[30].

III. Methodology

Our extensive survey report offers a thorough summary of all the methods applied in the field of Alzheimer's disease detection.

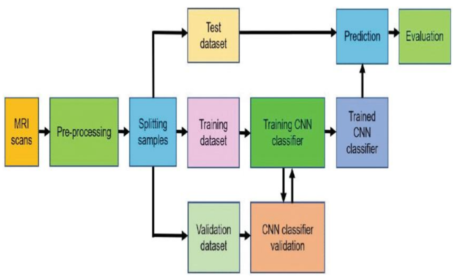

Figure 2. System Design.

Source: Adapted from Islam, J., & Zhang, Y. (2018, January 1). Deep Convolutional Neural Networks for Automated Diagnosis of Alzheimer's Disease and Mild Cognitive Impairment Using 3D Brain MRI. Lecture Notes in Computer Science. https://doi.org/10.1007/978-3-030-05587-5_34.

A. Data Collection

The first step is collecting a substantial dataset of MRI brain images, comprising scans from both Alzheimer's disease patients and healthy individuals. Diverse data sources such as ADNI and OASIS are integrated to ensure a representative sample.

B. Data Preprocessing

The MRI images undergo rigorous preprocessing, which includes image augmentation, and alignment to create standardized input data for the deep learning model. This step ensures that the model operates on consistent and informative image data.

C. Model Selection

An effective model for Alzheimer's disease detection is Convolutional Neural Networks (CNNs) due to their well-established track record in image evaluation tasks. The selection of an appropriate CNN architecture plays a pivotal role to achieve the best possible results.

D. Training the CNN

The CNN model is trained on the preprocessed MRI dataset. This involves presenting the model with labelled images, allowing it to learn and recognize patterns associated with Alzheimer's disease stages.

E. Validation

To evaluate the model's performance and prevent overfitting, utilize a validation dataset. This dataset ensures that the model can handle new data effectively and helps with hyper parameter optimisation.

F. Testing and Evaluation

The trained CNN undergoes assessment using a separate test dataset that it hasn't been exposed to previously. Then analyse its accuracy, precision, recall, F1-score, and other pertinent metrics to measure its diagnostic performance.

G. Future Enhancement

As part of our system design, ensure scalability and adaptability for future improvements. This includes the incorporation of additional datasets, advanced deep learning techniques, and continuous model updates to enhance accuracy and clinical utility.

IV. Datasets Used

The Datasets used are ADNI dataset containing 1167 MRI scans, MRI dataset(Kaggle) containing 6400 MRI scans, OASIS dataset containing 6400 MRI scans.

V. Result Analysis

This analysis looks at the findings of a comprehensive review of the literature on using deep learning techniques to MRI data for the diagnosis of Alzheimer's disease (AD). This analysis aims to provide a thorough grasp of the conclusions, significant trends, advantages, and disadvantages of the selected research publications.

Convolutional neural networks (CNNs), in particular, have emerged as the main method for AD diagnosis from MRI images in a number of studies. These techniques regularly produced excellent recall, F1-score, accuracy, precision, and AUC values. In addition, a wide range of deep learning architectures were investigated by the researchers, many of which demonstrated accurate and promising results. These designs included VGG16, ResNet, DenseNet, and bespoke CNNs.

Techniques for augmenting data were widely used to overcome the drawbacks of small sample numbers and uneven class distribution. These techniques, which included preprocessing images and synthesizing data, significantly enhanced the model's performance. Transfer learning also enabled researchers to alter and refine pre-trained models such as VGG and ResNet for the purpose of AD detection, resulting in high accuracy and efficiency.

Nonetheless, a number of issues were raised in the literature, most notably the issue of unbalanced datasets in AD categorization. Techniques like class-weighting and synthetic oversampling were frequently used to lessen this problem. A few papers acknowledged ethical issues, such as patient data protection, informed permission, and the responsible application of AI in healthcare; nonetheless, in-depth talks on these subjects are still required.

Alzheimer's disease (AD) is a progressive neurological condition that is one of the major global health issues. Numerous investigations confirmed the efficacy of their methods by highlighting the models' strong performance across a range of datasets. The problem of limited datasets was shown to be greatly mitigated by data enrichment strategies, which improved model performance and generalization. Furthermore, using pre-trained models in transfer learning showed how successful and efficient knowledge transfer is in identifying Alzheimer's disease.

Still, restrictions remained. Small dataset sizes were one of the main obstacles, highlighting the need for bigger and more varied datasets to guarantee model generalizability. Even if several studies acknowledged them, ethical issues needed more focus, especially when it came to patient data privacy, informed permission, and moral AI procedures in medical research. The majority of research focused on how crucial clinical validation is in proving practical applicability and adhering to medical norms. The interpretability of deep learning models, which is critical to building confidence in healthcare decision support, was one major issue that continued to be raised. Confirming the resilience of the model and its ability to generalize beyond training datasets required external validation on independent datasets, which was also considered essential.

The findings of this review of the literature demonstrate the profound influence of deep learning, especially CNNs, on the early identification of AD using MRI images. The obstacles that have been identified encompass the requirement for increasingly extensive and varied datasets, ethical deliberations, meticulous clinical validation, and comprehensibility. Future studies should concentrate on improving the quality of datasets, giving ethical data usage first priority, guaranteeing clinical utility, creating AI models that can be easily understood, and investigating multi-modal strategies for better early AD detection accuracy. Addressing these issues is essential to converting research results into clinically useful instruments for Alzheimer's disease diagnosis and monitoring, even as it highlights advancements and promise.

VI. CONCLUSION

The revolutionary potential of deep learning is highlighted in this thorough overview paper, which focuses on convolutional neural networks (CNNs) in the field of MRI scan processing for Alzheimer's disease diagnosis. The study's findings emphasize the possibility of early diagnosis, which offers the prospect of improved patient outcomes and higher treatment efficacy. In addition, the integration of several data sources, such as genetic data and clinical evaluations, offers a promising path to improve diagnostic precision. However, the area still confronts significant obstacles, such as class disparity and a lack of data, which can be overcome by pursuing bigger, more varied datasets and creative approaches. It is essential to transfer research into practical applications and promote multidisciplinary collaboration among computer scientists, physicians, and neuroscientists in order to fully achieve these advancements. In conclusion, this survey summarizes important findings, highlights the importance of continuing research, and outlines future options for further improvement.

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