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Unraveling Alzheimer's Disease Classification with Deep Learning: A Comprehensive Review

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Abstract: Alzheimer's disease (AD) is a neurological disease that progresses over time and is the primary global cause of dementia. Timely and accurate diagnosis is essential for therapeutic and interventional success. Conventional approaches, like clinical evaluations and neuroimaging procedures, are not always able to detect the illness at an early stage. This paper provides an extensive overview of current developments in using deep learning methods for AD early diagnosis and Identification. Numerous approaches have been put up, utilizing diverse forms of data such as MRI scans, eye-tracking actions, and text data that is clinically significant. Convolutional neural networks (CNNs), deep neural networks (DNNs), and long short-term memory networks (LSTMs) are just a few of the deep learning designs used by these models, which highlight how flexible and adaptive these methods are. Using cutting-edge methods to extract discriminative features from the data, feature extraction and selection have become essential components of these models. Additionally, a number of studies have concentrated on improving model performance through the use of methods such as depth-wise convolutional procedures, ensemble learning approaches, and particle swarm optimization for hyperparameter tweaking. Even with high accuracy rates attained, there is still opportunity for development, particularly with regard to managing data scarcity and model interpretability. This survey indicates possible routes for future research and offers insightful information about the state of deep learning applications in AD categorization.
Keywords: Alzheimer's Disease, Convolutional Neural Network, Deep learning, Deep Neural Network, MRI Images.

I. INTRODUCTION

Alzheimer's disease (AD) is the most frequent cause of dementia, accounting for 60–70% of cases globally. With time, AD worsens and causes cognitive decline, memory loss, and impaired reasoning. Eventually, daily functioning significantly deteriorates. There is still no treatment for the illness, even after much research. Nonetheless, symptoms can be reduced and the disease's course slowed with an early diagnosis and prompt treatment. The diagnosis of Alzheimer's disease requires the use of conventional diagnostic methods, such as cognitive evaluations and neuroimaging methods like CT, PET, and MRI. However, these methods are frequently subjective, time-consuming, and labor-intensive.

The development of deep learning techniques has brought about a revolution in a number of industries, including medical imaging and healthcare. These methods have demonstrated a great deal of promise in improving AD early detection and categorization. Deep learning algorithms provide a potent tool for assessing the complex and high-dimensional data involved in AD diagnosis because of their capacity to understand intricate patterns and relationships from massive volumes of data.

This paper offers a thorough review of recent advancements in the early detection and classification of AD using deep learning techniques. We investigate multiple approaches that make use of diverse forms of data, such as MRI scans, eye-tracking actions, and textual material with therapeutic relevance. We explore the wide variety of deep learning architectures used, including Long Short-Term Memory networks (LSTMs), Convolutional Neural Networks (CNNs), and Deep Neural Networks (DNNs), and talk about their benefits and drawbacks.

We also look at the creative methods for removing discriminative features from the data as well as the important parts of feature extraction and selection in these models. Moreover, we cover a range of optimization methods that improve model performance, such as depth-wise convolutional processes, ensemble learning strategies, and particle swarm optimization for hyperparameter tweaking.

Even with these models' excellent accuracy rates, there are still issues, especially with regard to handling data scarcity and model interpretability. The purpose of this survey is to offer insightful information on the state of deep learning applications in AD classification at the moment and to suggest future research directions. Our objective is to further our understanding of this complicated disease and improve patient outcomes by contributing to the continuing efforts to use deep learning for early AD identification.

II. LITERATURE SURVEY

'Biceph-net,' a novel deep learning framework for diagnosing Alzheimer's Disease (AD) using 2D MRI scans, is introduced in this research by H. Rashid et al. [1]. By modeling both intra-slice and inter-slice information, it tackles the problem of missing inter-slice information in 2D slices from 3D MRI scans. The technique compares the performance and computational efficiency of "Biceph-net" with other spatio-temporal neural networks and 2D CNNs. A neighborhood-based model interpretation feature is also included in the framework. In terms of CN against AD, MCI vs AD, and CN vs MCI vs AD, "Biceph-net" achieves 100% accuracy, 98.16% accuracy, and 97.80% accuracy, respectively.

In this paper, F. J. Martinez-Murcia et al. [2] offer a deep convolutional autoencoder-based exploratory data analysis of Alzheimer's disease (AD). High-level abstract features are extracted from MRI images and combined with results of cognitive tests, diagnoses, and other clinical data to build the approach. Regression and classification analysis are then used to examine and display the extracted features. With correlations above 0.6, the imaging-derived markers might predict clinical factors like the MMSE or the ADAS11 scores, with over 80% classification accuracy for the diagnosis of AD.

A approach for identifying Alzheimer's disease (AD) utilizing volumetric features taken from structural MRI data of the left and right hippocampi is presented in this study by A. Basher et al. [3]. Convolutional and deep neural networks are combined in this method, and a two-stage ensemble Hough-CNN is used for automatic hippocampal localization. The classification network is trained and tested using the extracted volumetric features. The suggested strategy beats existing approaches on the same dataset, with average weighted classification accuracies of 94.82% and 94.02% for the left and right hippocampi, respectively.

In this research, S. Bringas et al.[4] provide a novel technique that allows CNNs to learn from a constant stream of data from motion sensors tracking people with Alzheimer's disease, even when they don't have complete access to historical data. The CNN is able to self-configure and determine the stage of Alzheimer's disease thanks to this ongoing learning methodology. The technique was evaluated using data from accelerometers that tracked 35 Alzheimer's patients for a week at a daycare facility. Accuracy rates for the first two, third, and fourth encounters were 86.94%, 86.48%, and 84.37%, respectively. Deep learning solutions in medical situations where patients are continuously observed could benefit from this technique.

A dual attention multi-instance deep learning network (DA-MIDL) for the early identification of Alzheimer's disease (AD) and mild cognitive impairment (MCI) utilizing structural MRI scans is presented in this paper by W. Zhu et al. [5]. Enhancing the detection of discriminative characteristics in the brain is the DA-MIDL model, which consists of Patch-Nets with spatial attention blocks, an attention multi-instance learning (MIL) pooling operation, and an attention-aware global classifier. After being tested on two different datasets (AIBL and ADNI), the model proved to be effective at identifying problematic regions that are discriminative. It outperformed various state-of-the-art techniques in terms of accuracy and generalizability.

A novel patch-based deep learning network called sMRI-PatchNet is presented in this research by X. Zhang et al.[6] for the use of structural MRI scans in the diagnosis of Alzheimer's disease (AD). The network has a patch-based network for extracting deep features for AD classification, as well as an effective patch selection strategy for finding the most discriminative patches. The technique has been used to predict the transitory condition of moderate cognitive impairment (MCI) conversion and to classify AD. In comparison to current methods, the experimental evaluation demonstrates that the suggested method provides improved accuracy, computing performance, and generalizability while effectively identifying discriminative problematic regions with fewer patches used.

Sl no.	Author Name	Concept	Advantage	Disadvantage
1.	H. Rashid et al.	Deep learning models for dementia diagnosis	Automated diagnosis, potentially higher accuracy	Complexity in model training and validation, high computation
2.	F. J. Martinez-Murcia et al.	Transfer learning for Alzheimer’s classification	Leverages pre-trained models for efficiency	Might not generalize well to new, unseen data
3.	A. Basher et al.	MobileNet architecture for image classification	Efficient for mobile devices, lightweight architecture	Lower accuracy compared to larger models
4.	S. Bringas et al.	Use of MRI data for Alzheimer’s detection	Non-invasive and accurate diagnosis from brain scans	High cost of MRI scans, requires extensive pre-processing
5.	W. Zhu et al.	Model fine-tuning for Alzheimer's progression	Increased model performance through tuning	Risk of overfitting, needs extensive testing on varied data

Table 1: An Overview of the benefits and drawbacks of deep learning techniques for diagnosing Alzheimer's disease

A middle-fusion multimodal model for the early diagnosis of Alzheimer's disease (AD) is proposed in this study by S. K. Kim et al. [7]. Mix skip connection and sharing weight convolution blocks are used to apply middle fusion after a depthwise separable convolution block is used to extract features. The whole ADNI series, which includes tau protein PET, FDG PET, Aβ PET, and T1-weighted MRI, is used to assess the model. For areas that are known to be affected in the early stages of AD, a unique technique for extracting regions of interest is also suggested. For Alzheimer's disease vs. cognitive normal, the model's balanced accuracy was 1.00; for moderate cognitive impairment vs. cognitive normal, it was 0.76.

In this research, F. Zuo et al.[8] use eye-tracking behaviors, specifically visual attention, to propose a deep learning approach for early diagnosis of Alzheimer's Disease (AD). To obtain visual attention heatmaps, a non-invasive eye-tracking technology is used to administer a 3D comprehensive visual task. A multi-layered comparison convolutional neural network (MC-CNN), which encodes eye movement behaviors into a distance vector, is then used to analyze these heatmaps. The efficacy of the MC-CNN in diagnosing AD is demonstrated by its accuracy of 0.84, recall of 0.86, precision of 0.82, F1-score of 0.83, and AUC of 0.90.

A Stacked Deep Dense Neural Network (SDDNN) model for text classification and Alzheimer's Disease (AD) prediction is presented in this research by Y. F. Khan et al. [9]. The model, which consists of a Bidirectional Long-Short Term Memory (Bidirectional LSTM) and a Convolutional Neural Network (CNN), is trained using the DementiaBank clinical transcript dataset. GridSearch is used for hyperparameter tuning and Glove embedding is used for initialization in order to maximize the model's performance. With a noteworthy classification accuracy of 93.31%, the suggested model demonstrates its potential to support clinical specialists in the early diagnosis and detection of AD.

A deep learning method for the early identification of Alzheimer's disease (AD) is presented in this research by R. Ju et al.[10] using brain networks and clinically relevant text data, including age, gender, and ApoE gene. Using resting-state functional MRI data, the brain network is formed, and a focused autoencoder network is developed to discriminate between moderate cognitive impairment and normal aging. In comparison to conventional classifiers, the suggested method increases prediction accuracy by roughly 31.21% and decreases standard deviation by 51.23%, proving its stability and dependability in the classification of high-dimensional multimedia data in medical services.

AlzheimerNet, a refined Convolutional Neural Network (CNN) classifier for recognizing all five stages of Alzheimer's Disease (AD) and the Normal Control (NC) class using MRI images, is presented in this publication by F. M. J. M. Shamrat et al.[11]. Using data augmentation and the CLAHE image enhancement approach, the model prepares the raw data. The MRI scan dataset from the ADNI database is used for testing and training. The AlzheimerNet, which is based on the InceptionV3 model, performs best with a test accuracy of 96.67%. The model shows promise in early AD identification as it performs better than conventional approaches in identifying AD stages.

Using MRI pictures, Gamal et al.'s work [12] offers a novel method for dividing Alzheimer's disease (AD) into stages. Preprocessing the dataset, evaluating the effectiveness of several 3D classification architectures, and using an ensemble learning strategy on the best-performing models comprise the methodology. With AUC values of 91.28% and 88.42%, respectively, the suggested ensemble technique exceeds previous research in differentiating between AD, mild cognitive impairment (MCI), and cognitive normal (CN). The test was conducted on the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. The multiclass job of distinguishing between the three stages of the disease is also covered in the study.

In this paper, M. Kaya et al. [13] develop a deep learning model that uses magnetic resonance imaging to detect Alzheimer's disease (AD) early. The model adjusts important hyperparameters, such as the quantity of convolution layers and filters, using Convolutional Neural Networks (CNNs) and a particle swarm optimization technique. Using a public dataset, the suggested lightweight model successfully identifies AD with an accuracy of 99.53% and an F1-score of 99.63%, surpassing earlier research and maybe assisting physicians in their decision-making.

A unique Deep Convolutional Neural Network (DNN) model for differentiating Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI) patients from Cognitively Normal individuals is presented in this research by R. A. Hazarika et al. [14]. With 19 deep layers and the Dense-Block idea from DenseNet architecture, the model—which took inspiration from VGG-19—addresses the issues of vanishing gradient and information loss in backpropagation. For computational efficiency, depth-wise convolutional processes are also implemented in the model. With an average performance rate of 95.39%, the suggested model performs better than other DNN models.

A unique approach for the early prediction of Alzheimer's disease using machine learning techniques is presented in this study by S. Basheer et al. [15]. The study makes use of the Open Access Series of Imaging Studies (OASIS) dataset and suggests modifying a capsule network's architecture to enhance computing efficiency and prediction accuracy. Comprehensive feature importance identification, correlation analyses, and exploratory data analysis of data density are all part of this work.

When compared to cutting-edge deep learning classifiers, the model obtains an accuracy of 92.39%, proving its efficacy and precision in predicting Alzheimer's disease early on.

III. SURVEY FINDINGS AND INSIGHTS

Different kinds of data are employed in the classification of AD. These consist of eye-tracking behaviors, MRI scans, and text data that is therapeutically relevant, such as age, gender, and the ApoE gene. Preprocessing this data is an important stage, where the raw data is prepared for analysis using methods like data augmentation and the CLAHE image enhancement approach. Novel region-of-interest extraction techniques have also been suggested by several research for areas known to be impacted in the early stages of AD.For AD categorization, a variety of deep learning architectures are being used. These comprise Long Short-Term Memory networks (LSTMs), Convolutional Neural Networks (CNNs), Deep Neural Networks (DNNs), and even cutting-edge architectures like "Biceph-net," "AlzheimerNet," and "sMRI-PatchNet." The high-dimensional and complicated nature of the data used in AD diagnosis may be handled by these architectures with ease.

A crucial component of these models is efficient feature extraction. To extract discriminative features from the data, methods such as targeted autoencoder networks, Dense-Block idea from DenseNet architecture, and depthwise separable convolution blocks are being used. In order to speed up and improve the accuracy of the model, some research have also carried out extensive re-examinations to determine the significance of features and executed feature selection.The goal of several investigations has been to maximize model performance. Model performance and computational efficiency have been improved by the application of methods such as depth-wise convolutional processes, ensemble learning strategies, and particle swarm optimization for hyperparameter tweaking. These optimization methods are essential for managing the sizable and intricate datasets used in the diagnosis of AD.

The models have classified various phases of AD with good accuracy rates. There is still space for development, particularly with regard to managing data scarcity and model interpretability. Certain research have employed methods such as 10-fold cross-validation to guarantee that their models operate as expected across different contexts. Some have carried out ablation experiments to support their model's predictions.

Subsequent investigations may concentrate on tackling present issues such limited data availability, interpretability of models, and the incorporation of multimodal data. Furthermore, further research might be conducted to investigate the possibilities of deep learning in forecasting the course of AD and creating models that are able to continuously learn from fresh data.

IV. CONCLUSION

In summary, deep learning methods hold great potential for early detection and classification of Alzheimer's disease (AD). The mentioned studies have put forth a range of innovative models and techniques, each with a distinct focus and methodology. The multi-modal character of AD diagnosis has been demonstrated by these models' excellent utilization of many data sources, such as MRI scans, eye-tracking behaviors, and clinically important text information.These models' designs, which include Long Short-Term Memory networks (LSTMs), Convolutional Neural Networks (CNNs), and Deep Neural Networks (DNNs), are made to manage the complicated and high-dimensional data used in AD diagnosis. Novel architectures including "Biceph-net," "AlzheimerNet," and "sMRI-PatchNet" have also been proposed by several studies, demonstrating the continuous innovation in this sector.

A key component of these models is efficient feature extraction, which is accomplished by using methods like targeted autoencoder networks, depthwise separable convolution blocks, and the Dense-Block concept from DenseNet architecture to extract discriminative features from the data. Additionally, a number of studies have concentrated on improving model performance through the use of methods such as depth-wise convolutional processes, ensemble learning strategies, and particle swarm optimization for hyperparameter tweaking.Even though these models have demonstrated good accuracy rates in categorizing various phases of AD, there is still need for development, particularly regarding model interpretability and managing data scarcity. Subsequent investigations may concentrate on resolving these issues and investigating the possibilities of deep learning in forecasting the course of AD and creating models that are able to continuously learn from fresh data.

All things considered, the knowledge gathered from these research projects has the potential to greatly assist medical professionals in making decisions and even enhance patient outcomes. The development of deep learning methods for early detection and AD classification holds great promise for the future of medical research and healthcare. To fully exploit its potential and overcome current limitations, more research is necessary. Every step we take on the path to developing a more precise, effective, and understandable model for AD diagnosis advances us toward our objective.

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