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A Review on Alzheimer's Disease Classification Using Deep Learning

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Abstract

In recent years, there has been a substantial amount of research dedicated to using Deep Learning (DL) methods for the classification of Alzheimer's disease (AD) and other related tasks, specifically focusing on magnetic resonance imaging (MRI) data. According to a comprehensive analysis of recent studies, it seems that deep learning models, especially those that include the creation of different structures, have significant potential to improve the precision of identifying and classifying Alzheimer's disease at an early stage. This work aims to emphasize the importance of effective data preparation tactics and feature learning approaches, as well as the investigation of hybrid models using diverse deep learning technologies. This study primarily focuses on doing performance analysis of deep learning algorithms using the latest approaches. Finally, provide a concise overview and analysis of several methods that might enhance the effectiveness of identification and classification using deep learning.

A. Introduction

Alzheimer's disease (AD) is the most common kind of dementia that requires extensive medical attention and should be promptly addressed. In order to facilitate therapeutic advancements and assure appropriate patient care, it is essential to carry out a precise and timely research on the prognosis of Alzheimer's disease [1]. Research data indicate that there are annually reported 10 million new cases of dementia. The World Health Organization (WHO) has reported that Alzheimer's disease has surpassed cancer to become the fifth leading cause of death. By 2050, it is projected that the global prevalence of Alzheimer's disease would reach 152 million individuals [2]. Alzheimer's disease (AD) is a chronic neurological disorder characterized by the gradual and irreversible degeneration of brain cells. This results in amnesia and cognitive deficits, eventually hastening the decline in one's ability to do daily activities in reality [3].

Alzheimer's disease is the predominant cause of dementia in those aged 65 and above. Alzheimer's disease accounts for 60 to 80 percent of those diagnosed with dementia [4]. Dementia is defined as a decline in cognitive function that is necessary for performing daily tasks. The diagnosis of this disorder is based on the identification of plaques and tangles in the brain, together with the observation of cellular damage and death. The physician posthumously diagnosed her brain and saw the proliferation of many clusters. The brain's ability to communicate with the rest of the body was adversely affected due to these factors, which have been identified as the primary causes of the illness [5]. Consequently, persons afflicted by this ailment have challenges in doing routine tasks, such as driving and cooking. Early warning symptoms may manifest as difficulties in remembering names, misplacing essential items, and experiencing challenges in executing plans [6]. The symptoms of Alzheimer's disease reach their peak severity during the intermediate stage. The symptoms include significant fluctuations in mood, cognitive disarray, impulsive behavior, limited ability to focus, and challenges in identifying objects. The last stage is the most incapacitating [7].

The diagnosis of Alzheimer's disease is the duty of healthcare experts, and it is preferable to detect it within its first phases. Nevertheless, it is impractical to manually analyze medical photographs with both accuracy and speed due to the extensive data they include and the large number of patients. Each clinician or medical expert individually evaluates a small portion of the data to provide an analysis that is informed by their skill and knowledge. Additional complications may develop due to the potential for inaccurate analysis. An automated system is essential for efficiently analyzing the vast volume of imaging data obtained from patients. Several techniques, such as the Internet of Medical Things (IoMT), clinical treatment in labs using MRI or CT imaging, machine learning-based systems for analyzing large amounts of data, and deep learning approaches, are all making a substantial impact in the area of medicine. Furthermore, the MICCAI BRATS contests provide solutions that use deep learning and machine learning methodologies on MRI or CT images.

These machine learning (ML) approaches must be implemented using the proper architectural design and preprocessing procedures that have already been created. The classification study that utilizes machine learning typically involves four phases: feature extraction, feature selection, dimensionality reduction, and feature-based technique selection [9]. These activities need a substantial time commitment, as well as specialized skills and many stages of optimization. Conversely, there has been an issue about the reproducibility of these techniques. To clarify, the process of picking features entails choosing characteristics associated with Alzheimer's disease (AD) from different neuroimaging methods to provide more useful combined measurements. Characteristics such as subcortical volumes, gray matter densities, cortical thickness, brain glucose metabolism, and cerebral amyloid accumulation in specific regions of interest (ROIs), such as the hippocampus, may be seen. Several researches have shown that computer vision and deep learning models have achieved very satisfying outcomes in diagnosing viral or non-viral disorders via the analysis of medical imaging. Diffusion tensor imaging (DTI) may be used in the setting of Alzheimer's disease (AD) to analyze and track alterations in white matter across different time intervals. This approach may lead to new and valuable understandings about the progression of Alzheimer's disease. A pipeline is created by using test-reset procedures and the bootstrap approach. This pipeline involves doing forty scans of a subject at two distinct time periods. This enables a significant degree of precision in the prognosis.

Deep learning models, especially those using intricate neural network structures, have the capacity to enhance the precision and effectiveness of categorizing Alzheimer's disease (AD), specifically in the processing of magnetic resonance imaging (MRI) data. The AD classification, using DL methodologies, seeks to provide a comprehensive assessment of the latest advancements, challenges, and future possibilities in this rapidly expanding field. By thoroughly analyzing various research studies and approaches, our goal is to uncover the promising possibilities of Deep Learning (DL) in revolutionizing the detection of Alzheimer's disease and ultimately enhancing patient results.

B. Building Deep Leaning Model of Alzheimer's Disease Classification

Evidence has shown that deep learning methods has the capability to enhance the precision of Alzheimer's disease classification. Scientists are now working on creating advanced deep learning models that can accurately detect Alzheimer's disease by analyzing medical imaging data, such as MRI scans. These models are constructed with large datasets. In the following parts, we will analyze the procedure of creating deep learning models for Alzheimer's disease categorization. We will start by discussing strategies for data collection, followed by an exploration of data preparation, feature extraction, and ultimately, the development of classification models using deep learning methodologies.

Data Collection

To gather data, it is essential to get information from a diverse range of sources. The sources used in this study include clinical assessments, neuropsychological exams, imaging examinations (which include MRI and PET), biomarker analyzes (such as blood tests and CSF analysis), and genetic testing [10]. This collection includes T2-weighted magnetic resonance imaging (MRI) images of 2456 people, each representing a distinct stage of Alzheimer's disease (AD), Mild Cognitive Impairment (MCI), and other medical conditions [11].

Data Preprocessing

Preprocessing is an essential component of the Alzheimer's disease (AD) identification process as it entails applying appropriate procedures to enhance the quality and dependability of the data obtained from brain scans. Prior to proceeding with additional evaluation and interpretation, this section will focus on the fundamental preprocessing techniques used to prepare the acquired imaging data. Brain scans are matched to a common reference space via the process of image registration, which is a first step in the preprocessing process. This alignment guarantees the consistency of investigations across a diverse range of individuals and time periods by accounting for variations in placement and orientation [12]. Commonly used techniques for photo registration include affine transformations and non-linear transformations. Photographic identification and classification of Alzheimer's disease often need several data processing techniques.

1. Image Resizing: The act of adjusting the proportions of photos to ensure uniformity and consistency.
2. Noise Reduction: To enhance image quality, noise reduction techniques like blurring autoencoders or Gaussian blur are used.
3. Image Augmentation: Real-time image augmentation techniques are used during the data training phase of deep learning models. Diversifying the training data may be achieved by using these methods, which may include flipping, rotating, and adjusting the brightness, contrast, saturation, and hue.
4. Data Splitting: To partition the dataset, a specific sampling technique known as data splitting is used. Typically, around sixty percent of the dataset is allocated for training the model, while ten percent is allocated for validation (which entails assessing the model during training), and the remaining forty percent is allocated for testing. A 5-fold cross-validation approach may be used in certain situations, such as bagging studies. This approach entails using the whole dataset, allocating eighty percent for training and ten percent for validation, while reserving the remaining twenty percent for testing. The process of dividing data is influenced by both the amount of data available and the unique circumstances of the scenario [13].

Deep learning models for Alzheimer classification

To effectively distinguish between Alzheimer's disease, mild cognitive impairment (MCI), and normal cognition for early intervention purposes, advanced deep learning models employ complex neural architectures like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to evaluate medical imaging and clinical data.

Artifcial neural network

A neural network is a set of methods used to extract information from MRI datasets and uncover the underlying relationships within the data. It functions in a way that is similar to that of the human brain. The neurons in question are often known as perceptrons, and the neural network consists of many layers of interconnected neurons. The perceptrons in question are mathematical functions that categorize information obtained from the MRI image collection based on particular criteria and architecture [14]. Typically, a neural network consists of just two layers. However, this is not sufficient for processing large networks such as MRI images. To accomplish deep learning, extra layers are included into the ordinary neural network. The number of layers in a compute network might vary from 10 to one hundred, depending on its configuration. Within each layer, a neuron is responsible for storing and then transmitting information to the neurons located in subsequent layers. Upon transmission across the network, the secret information from the MRI photos is retrieved. Low-level neurons often have the role of gathering unprocessed data [15].

The VGG architecture, a two-dimensional convolutional neural network (CNN), is mostly used for image classification. The VGG model takes in an RGB image with a resolution of 224×224 pixels as its first input. The network consists of a series of convolutional layers, each of which consists of extremely small filters measuring 3×3. As the network increases in depth, the number of filters inside each layer will increase. VGG applies the rectified linear unit (ReLU) activation function after each convolutional layer to introduce nonlinearity into the model. The VGG technique utilizes a max pooling layer with a pool size of 2×2 after every pair of convolutional layers to reduce the spatial size of the feature maps and improve translation invariance. The last stage of the VGG method involves the output layer, which produces the classification probabilities for the output [16].

Convolutional Neural Network (CNN)

Employs hierarchical notions in order to acquire knowledge about complicated aspects. Suitable for the processing of picture data and the diagnosis of medical conditions We have achieved a good level of performance in the categorization of Alzheimer's disease. Incorporating Batch Normalization and Dropout into an Eight-Layer CNN: Model for the categorization of Alzheimer's disease that has been proposed. Every layer has been optimized to provide the best possible performance. The sensitivity, specificity, precision, and accuracy were all elevated to levels more than 97% [17]. Convolutional Neural Networks (CNNs) in Three Dimensions: MRI of the structure is used for the purpose of diagnosing Alzheimer's disease. Highly efficient in the processing of three-dimensional brain imaging data for categorization. Using medical imaging data, CNNs have emerged as useful tools for the classification of Alzheimer's disease (AD). They have the capability to automatically extract significant characteristics from raw pictures, they are resistant to spatial modifications, and they make optimal use of parameters, all of which make them well-suited for this purpose. Additionally, an improvement in performance may be achieved even when dealing with smaller datasets by using transfer learning in conjunction with CNNs that have been pretrained. CNNs with deeper layers are able to capture hierarchical representations, which helps in the detection of complex brain anomalies that are linked with Alzheimer's disease [18, 19].

C. Literature Review

A significant amount of research has been reported in the literature in recent times with the aim of enhancing the AD. This study involves detecting, categorizing, and performing a variety of tasks utilizing DL. Some of the methods that are used for Alzahaimers types, data collecting, data preprocessing, feature extraction, and classification are discussed in this section.

Through the use of MRI data from ADNI participants, Manhua et al. [20] reported their investigation into how algorithms using deep learning can segment the hippocampus and categorize illnesses. The segmentation findings, ROC curves, and classification performance of Alzheimer's disease and mild cognitive impairment are compared and contrasted. In the research, several α values are investigated for both single-task and multi-task learning, and the findings obtained are very encouraging. The process of retrieving relevant details from the ADNI database for people with Alzheimer's disease, mild cognitive impairment, and normal cognitive function is known as data preprocessing. Based on a number of references on hippocampus shape analysis and deep learning for the identification of brain diseases, the primary objective is to monitor the course of mild cognitive impairment and early Alzheimer's disease.

The minimalRNN and LSTM models were compared in research carried out by Minh et al. [21], who also included their respective state equations for the goal of providing a point of reference. Within the scope of the investigation, the simplicity of the minimalRNN and the positive influence it has on prediction performance were highlighted. By conducting ablation experiments, the researchers investigated the ways in which various characteristics influenced the accuracy of diagnostics. Several other research foundations provided financial support for this study, and it made use of resources from a number of different centers. As a result, the minimalRNN model shown promising promise in terms of predicting biomarkers associated with Alzheimer's disease and assisting in clinical diagnosis.

The authors Ning et al. [22] describe an innovative ensemble learning strategy for the classification of Alzheimer's disease (AD), which is 4% more accurate than the techniques that are already in use. For the purpose of combining predictions from basic classifiers and managing interdependencies, this technique makes use of a stacking strategy in conjunction with Deep Belief Networks (DBNL). The research indicates that enhanced classifier performance may be achieved in decreased feature spaces by using a dataset consisting of 23,165 samples and 100 measures from the National Alzheimer's Coordinating Center. The relevance of feature learning across a wide range of base classifiers is emphasized, and the potential of this technique to improve primary care for Alzheimer's disease is brought to light. The findings that were provided by Halebeedu and Srirangapatna [23] highlight the critical significance of picture normalization and feature extraction in the process of detecting Alzheimer's disease (AD). They highlight the capabilities of the HOG-DNN model, in combination with the corrected Adam optimizer, to accurately categorize instances of Alzheimer's disease (AD). It is essential to detect Alzheimer's disease (AD) at an early stage in order to provide effective treatment, which highlights the need of sophisticated classification algorithms. The ongoing research efforts are aimed at improving the identification and categorization of Alzheimer's disease (AD) via the use of magnetic resonance imaging (MRI), highlighting the importance of having diagnostic tools that are both accurate and efficient in the healthcare industry. The findings that were given by Atif et al. [24] center on the use of a Siamese Convolutional Neural Network (SCNN) for the purpose of classifying the phases of Alzheimer's disease. In order to overcome the restricted availability of data, the study made use of the OASIS dataset and implemented strategies for data augmentation. Compare and contrast was done between a number of different normalizing approaches, with batch normalization providing the highest validation accuracy. In terms of dementia stage categorization, the SCNN model attained a test accuracy of 99.05%, which is higher than any other technique currently considered. Enhanced performance was achieved with the use of VGG16 and batch normalization inside the architecture of the model. In general, the significance of CNNs in Alzheimer's disease categorization via the use of MRI images is brought to light by the research.

Using MRI data, Jae et al. [25] introduced a novel ensemble technique for identifying Alzheimer's disease that was based on deep convolutional neural networks (DCNN). Improvements in classification accuracy were achieved as a consequence of the use of an optimization framework that was designed to determine the optimal ensemble weights. After being evaluated on the ADNI dataset, their strategy produced superior results in comparison to other approaches that were already in use. In addition, during the data processing phase, they used data augmentation and entropy-based sorting in order to choose MRI slices that included important information.

The study that was carried out by Samsuddin and colleagues [26] centered on the use of ensemble CNNs that were based on regions of interest (ROIs) for the categorization of Alzheimer's disease (AD) spectrum of symptoms. When it came to this categorization job, they stressed the significance of certain regions of the brain, including the insula, the amygdala, and the hippocampus. We were able to achieve a high level of accuracy in diagnosing attention-deficit/hyperactivity disorder (ADD), and we were able to recognize the relevance of characteristics from the left amygdala. Subjects with a wide range of cognitive problems were included in the statistical collection. Overall, the research exhibited efficacy that was equivalent to that of leading approaches in the classification of the Alzheimer's disease spectrum.

In their study on the categorization of Alzheimer's disease, Karim et al. [27] examined the use of data augmentation methods and transfer learning. When it comes to the analysis of medical pictures, they emphasize the relevance of cross-modal information transmission. Preprocessing processes, matrix decomposition methods, classification outputs, and assessment measures are all included in the scope of the research. This study is being conducted with the overarching objective of enhancing the diagnosis of Alzheimer's disease via the use of novel machine learning techniques. The R.C. the classification of Alzheimer's disease was the primary emphasis of et al. [28], who used pre-trained neural networks such as AlexNet, ResNet-18, and Google Net. These networks displayed a high level of accuracy via the utilization of deep convolutional neural networks. A strong emphasis was placed on the significance of picture preprocessing in the process of efficiently extracting features. In order to perform a comprehensive processing of input signals, deep learning requires the construction of neural networks that have numerous layers. Metrics like as Accuracy, Precision, Recall, Area Under the Curve (AUC), and F1 Score were applied by the researchers in order to assess the performance of the model. Moreover, they brought attention to Kaggle as a platform that facilitates the exchange of datasets and the promotion of cooperation within the area of data science. Additionally, a number of research projects are investigating the use of machine learning and deep learning techniques in the detection of Alzheimer's disease as well as in other domains.

A novel deep learning algorithm was developed by Morteza et al. [29] for the purpose of analyzing brain scans (MRI) in order to identify between Alzheimer's disease (AD) and normal controls (NC), as well as moderate cognitive impairment (MCI) and NC. Their solution, which combines two different deep learning algorithms, reached a high level of accuracy and surpassed other systems that were already in use. The researchers Gongbo et al. [30] provided a unique strategy in their work, which included the use of 2D CNN models with temporal pooling strategies to improve the detection of Alzheimer's disease by employing MRI data. The results obtained by this technique were superior than those obtained by a 3D CNN model, with an accuracy of 91% and an auROC of 0.91. There was a continuous demonstration of good performance from fusion approaches, especially late fusion with dynamic image pooling. In addition, there was a significant decrease in the amount of time spent on training, which was more than 89 percent. These results provide a strong foundation for future research initiatives that seek to enhance the detection of Alzheimer's disease via the use of CNNs to 3D MRI data.

Yousry et al. [31] centered their study on applying a variety of loss functions and CNN models in order to diagnose Alzheimer's Disease (AD) with a high degree of accuracy. In the process of training the models, they make use of techniques such as Fuzzy C-means and Weighted Probabilistic Neural Networks, while also placing an emphasis on the significance of data augmentation and cross-validation. It is usual practice to utilize the Adam optimizer for optimization, and it is responsible for evaluating performance parameters such as accuracy, precision, recall, area under the curve (AUC), and loss. In addition, their studies analyze the ways in which batch size and dataset split size influence accuracy, so underlining the significance of these aspects in the classification process.

The research that was provided by study in [32] delves into the most recent advancements in Alzheimer's disease (AD) categorization via the utilization of Deep Neural Network (DNN) applications. On the basis of brain MRI data, they suggest an improved version of the LeNet-DNN model in order to diagnose Alzheimer's disease. Their innovative strategy comprises merging the minimum and maximum pooling layers in order to enhance the selection of features. In addition, they investigate the use of the Squirrel Search Algorithm in conjunction with Statistical Parameter Mapping and stacked sparse auto-encoders for the purpose of feature extraction and optimization. In order to improve early Alzheimer's disease diagnosis, future work will concentrate on lowering the amount of memory space that is required and gathering data from a variety of sources. The individual, who holds the position of Associate Professor in the subject, brings a wealth of research expertise to the study.

A study conducted by Sanghyeop and colleagues [33] aimed to improve the diagnosis of Alzheimer's disease (AD) by using amyloid brain scans and the Genetic CNN Algorithm for the purpose of improving network design. In classification tasks, their method achieves a performance that is 11.73% higher than that of Genetic CNN, indicating its usefulness. These hyperparameters, which include activation functions and optimization techniques, are investigated in this work, which ultimately results in enhanced model optimization. The relevance of this technology in increasing Alzheimer's disease detection by picture analysis is highlighted by the findings, which demonstrate greater performance progression across generations at a higher level.

The research reported by Robert et al. [34] investigates the evolution of neural network structures for the purpose of categorizing medical imaging. These structures have progressed from simple perceptron models to intricate CNN ensembles, and they have achieved a high level of accuracy in detecting Alzheimer's disease. Particularly noteworthy is the fact that pre-trained networks such as GoogleNet, ResNet-18, and ResNet-152 have shown remarkable performance in the classification of MRI data pertaining to Alzheimer's disease. Furthermore, the application of 3D CNN architecture for the purpose of classifying whole-brain MRI data has been shown to be beneficial. The results of these developments highlight the success that has been made in the use of deep learning models for the analysis of medical pictures, notably in the diagnosis of Alzheimer's disease.

The authors Peng et al. [35] provided a model that was developed for the purpose of categorizing Alzheimer's disease and mild cognitive impairment. Enhanced accuracy is achieved by the use of data denoising and a diagnostic network that is composed of many classifiers throughout this model. Through the targeted elimination of misclassified samples and the use of ensemble learning strategies, the objective is to achieve a higher level of accuracy. The findings indicate that there is a significant degree of accuracy in discriminating between Alzheimer's disease and normal controls, as well as between the various phases of cognitive impairment. When it comes to accurate diagnosis, the incorporation of MRI data is absolutely necessary, and the suggested technique outperforms traditional approaches in terms of performance.

ABOL et al. [36] suggested a unique technique that employs CNN and DNN models to identify Alzheimer's disease by examining volumetric characteristics derived from the left and right hippocampi in sMRI data. This method was developed in order to diagnose Alzheimer's disease. By automatically identifying the placements of the hippocampi and extracting characteristics with the help of the DVE-CNN model, this method achieves a high level of accuracy in discriminating between instances of Alzheimer's disease and non-cognitive disorders. The research highlights the significance of hippocampus volume atrophy as a key biomarker for Alzheimer's disease diagnosis. Furthermore, it outperforms the performance of earlier models, demonstrating the possibility of conducting automated classification of Alzheimer's disease. Implementing the approach on bigger datasets and combining it with other imaging modalities, such as PET scans, are also tasks that will be accomplished in the future. Nivedhitha et al. [37] presented their research in which they compared and contrasted many different gene selection strategies for the classification of Alzheimer's disease (AD). These methods included filter, wrapper, hybrid, and ensemble approaches. They use a gene selection pipeline that includes mRmR, Wrapper-based PSO, and Autoencoder techniques in order to pick genes. Within the context of Alzheimer's disease categorization using IDBN, autoencoder compresses selected genes. When dealing with datasets that have a large number of dimensions but a small number of samples, ensemble techniques are used to combine several feature subsets while maintaining robustness. The findings of this research highlight the necessity of early diagnosis via the use of deep learning and molecular data analysis for accurate diagnosis of Alzheimer's disease and prompt treatments. The processing of gene data in AD analysis is accomplished by the use of autoencoder procedures, which comprise encoding, decoding, and backpropagation error computation processes.

The use of machine learning, more especially CNNs, for the early identification of Alzheimer's disease was the primary emphasis of the research conducted by Vijeeta et al. [38]. CNNs have shown an accuracy rate of 98% when it comes to recognizing the illness in its early stages, which is an excellent achievement in recognition of their research capabilities. Nevertheless, there are still obstacles to overcome, notably in the detection of Alzheimer's disease in elderly people. Current research highlights the value of machine learning and neural networks in the advancement of both detection and treatment strategies for Alzheimer's disease. Early identification is essential for successful treatment, and current research emphasizes the significance of these technologies.

In their study, Shagun et al. [39] offered an examination of the usage of machine learning methods for the diagnosis of Alzheimer's disease. They highlighted the efficiency of a CNN model when it was applied to MRI scans. When assessing the performance of models, they examine a variety of models and datasets, putting an emphasis on the significance of measures like as accuracy, precision, recall, F1-score, and area under the curve (AUC). According to the ROC curves for both dataset 1 and dataset 2, the findings of their suggested model are promising and demonstrate higher performance in comparison to the results of earlier research.

Iqra et al. [40] provided a model that was designed to estimate the severity levels of problems based on summaries of all the bug reports that were received. For the purpose of improving the accuracy of their predictions, they make use of preprocessing techniques like as tokenization, the elimination of stop words, and lemmatization. For the purpose of fine-tuning hyperparameters, the model makes use of a Convolutional Neural Network (CNN) in conjunction with Harris Hawk optimization. According to the findings of the studies, the CNN-HHO model is superior than the Baseline-CNN model in terms of a number of metrics, including accuracy, precision, recall, F1-measure, and fitness value. The study highlights the necessity of forecasting the severity of bugs in healthcare software and recommends for the use of machine learning methods for the purpose of finding faults. In addition, it highlights the complex nature of software defects in Internet of Things (IoT) medical devices, underlining the significance of bug severity prediction in terms of assuring the operation of the device and the safety of an individual patient.

Using magnetic resonance imaging (MRI) scans, Kwok et al. [41] carried out a research with the purpose of identifying Alzheimer's disease (AD). In order to improve their performance, they made use of a convolutional neural network (CNN) model that was enhanced using transfer learning (TL) and a generative adversarial network (GAN). The sensitivity, specificity, and accuracy of their technique were greatly enhanced in comparison to the procedures that were previously used. Convolutional and pooling layers, fully linked layers, ReLU activation, and softmax activation were some of the major components that were included into the model. The model was able to obtain improved detection accuracy by using a two-tier transfer learning method and by including extra training data that was produced by GAN. The results of the performance assessment showed that there were significant improvements in sensitivity, specificity, and accuracy in comparison to their predecessors. In addition, the study investigated a variety of areas that are connected to Alzheimer's disease, including disease etiology, E-health frameworks, Alzheimer's disease detection, and diagnosis.

Convolutional Neural Networks (CNN) and Convolutional Autoencoders (Conv-AE) were reported by Saman et al. [42] as a method for the categorization of electroencephalogram (EEG) signals that are linked with Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Healthy Controls (HC). According to the findings of their research, CNN and Conv-AE models perform much better than other models when it comes to reliably identifying EEG signals. CNN models achieve a validation accuracy of 92.7%, while Conv-AE models achieve 89.3%. For the purpose of signal processing, the study makes use of wavelet analysis methods such as the Continuous Wavelet Transform (CWT) and the Discrete Wavelet Transform (DWT). Specifically, it highlights the significance of deep learning in the context of healthcare applications, notably with regard to improving treatment results and improving illness detection.

The ADNI dataset and 18FDG-PET imaging were used by Ahila A et al. [43] in order to develop a computer-aided diagnostic (CAD) system for Alzheimer's Disease (AD). The CAD system was able to differentiate Alzheimer's disease (AD) patients from normal controls (NC) by learning characteristics from PET scans. This was accomplished via the use of a Convolutional Neural Network (CNN). Utilizing a confusion matrix, the system's performance on the ADNI dataset was evaluated, and the results revealed that it is effective in identifying Alzheimer's disease. Possible future study might focus on improving the computer-aided diagnosis (CAD) system and investigating its potential for early identification of Alzheimer's disease (AD) in clinical settings.

In order to address the issue of dataset imbalances in Alzheimer's Disease (AD) classification, Gulnaz et al. [44] introduced the ADASYN approach. This technique aims to improve accuracy by producing synthetic examples for classes that are not significantly represented in the dataset. Their DAD-Net model, which is constructed on a CNN architecture, has remarkable performance in the classification of AD. It achieves high AUC values and F1-scores in comparison to other models. The importance of fixing dataset imbalances in medical data cannot be overstated when considering the nature of Alzheimer's disease, which is a degenerative brain ailment that is characterized by memory loss. Future study will focus on improving the accuracy of Alzheimer's disease categorization via the use of deep learning models, with a particular emphasis on the crucial role that dataset equilibrium plays in medical picture analysis.

In their study [45], YUSERA and colleagues proposed a model called a Stacked Deep Dense Neural Network (SDDNN) that was developed for the purpose of predicting Alzheimer's disease. This model is superior than other models in terms of its efficacy since it integrates CNN, Bidirectional LSTM, and attention processes. Furthermore, the paper assesses performance using confusion matrices and reveals that Glove embedding is capable of producing high levels of accuracy via experimental analysis. Utilizing audio transcript data from DementiaBank is the approach that will be used in order to facilitate the early identification of Alzheimer's disease. Both Dr. Kumar and Dr. Ezaz Ahmed are listed as authors, respectively, and they contributed their respective academic backgrounds to the study effort.

A novel CNN architecture was presented by Gowhar et al. [46], which was developed for the purpose of diagnosing Alzheimer's disease by using MRI scans. The accuracy percentage that they achieve is 96.6%, and they do this by using transfer learning with models such as MobileNet. They use a variety of data augmentation strategies in order to combat the phenomenon of overfitting. According to the findings of the research, MobileNet is excellent in categorizing medical pictures because of its lightweight design and fast parameter reduction.

For the purpose of identifying Alzheimer's disease using magnetic resonance imaging (MRI) pictures, Faizal et al. [47] reported the use of Siamese architecture in conjunction with triplet-loss function. In their results, they show that this strategy is helpful in classifying Alzheimer's disease into four distinct categories. An analysis of the performance of the VGG16 model as an encoder is presented in this work, along with a discussion of the different machine learning approaches that may be used to diabetes categorization. With the end goal of improving AD categorization approaches via the utilization of deep learning strategies, the study endeavors to achieve its ultimate objective.

Both BATTULA and MUDIYALA. To identify Alzheimer's disease using magnetic resonance imaging (MRI) images and to segment brain areas, the approaches proposed in [48] make use of deep learning. A number of assessment measures, including TP, TN, FP, FN, and the Dice Coefficient, are used in order to evaluate the segmentation approaches. CNNs are an essential component in the process of detecting Alzheimer's disease based on brain scans, since they enhance both performance and accuracy. When it comes to tackling difficulties that are connected to data and computing, the scalability of deep learning is very necessary. In general, the use of deep learning algorithms improves the accuracy of brain MRI segmentation for the purpose of diagnosing Alzheimer's disease.

Ruhul et al. [49] discussed the construction and assessment of a hybrid deep learning model that was especially intended for the classification of Alzheimer's disease (AD). The study that they have conducted fully investigates a variety of deep neural network (DNN) topologies, demonstrating without a reasonable doubt that the hybrid model that they have proposed is better. This hybrid model surpasses the performance standards set by existing deep neural network models such as DenseNet-121. This is accomplished by combining components belonging to both LeNet and AlexNet. Its design blends convolutional and recurrent neural networks in a seamless manner, which results in better classification accuracy. In addition to this, the research emphasizes the significant significance that feature extraction has in improving the efficacy of the model as well as the computing efficiency of an algorithm.

Table 1: A Comparative Study among Several Studies for Brain Tumor Classification Using MRI

Ref	Year	Dataset	Method	Pros	Cons	Accuracy
[20]	2020	ADNI	A deep learning architecture was evaluated using structural MRI data from 449 individuals in the (ADNI). The approach included the process of dividing the hippocampus into distinct segments and performing activities related to categorizing diseases.	The approach demonstrates superior performance in accurately segmenting the hippocampus and classifying diseases, outperforming existing techniques.	The learnt characteristics have limited interpretability for therapeutic application. This constraint may impede the method's efficacy in offering comprehensive understanding of the fundamental biological underpinnings of the disorders.	The suggested method 's accuracy in categori zing people with Alzhe imer's Disease (AD) ag ainst Normal Control (NC) is as follows: For a single-task with α = 0, the acc uracy is 80.1%. The accuracy of multit asking, with a multitas king coefficient (α) of 0.5, is 79.9%. The adaptive alpha (m ulti-task) achieved an accu racy of 80.5%.
[21]	2020	The research used longitudinal data from 1677 individuals, which was gathered via the TADPOLE competition.	Utilizing a mac hine learning s ystem, this stud y aims to foreca st the progressi on of Alzheime r's disease by a nalyzing many i ndicators and c linical diagnosi s over time.	The technique of Effec tive Longitudinal Pred iction shown exceptio nal proficiency in man aging missing data an d diverse input timep oints. Versatility and adapta bility: Capable of forecasting an indefinite number of future timepoints, making it well-suited for longitudinal research including di verse participant data .	Implementation C omplexity: Proficiency in mac hine learning and data management is necessary for ef ficient usage. • Risk of Overfitti ng: Although having f ewer parameters t han LSTM, there is a potential for ov erfitting to the tra ining data.	Attained exceptional p recision in forecasting AD biomarkers over a prolonged period.
[22]	2020	National Alzheimer's Coordinating Center,	A novel approa ch for classifyin g Alzheimer's D isease (AD) is p roposed, which involves integr ating a stacking methodology	The capacity to surpa ss current methods by 4% demonstrates en hanced classifier perf ormance in smaller fe ature areas, while pre serving the accuracy o f clinical data.	The publication does not clearly state any drawbacks or restrictions of the suggested ensemble learning approach for	The suggested ensemble demonstrated a statistically significant level of accuracy, surpassing benchmarks with a p-value of less than

			with Deep Beli ef Nets (DBN) t o merge predic tions from base classifiers and handle interde pendencies.		classifying Alzheimer's Disease (AD).	0.001.
[23]	2020	The datasets used in the study are the NIMHANS dataset, and the ADNI dataset.	The Hierarchic al Deep Neural Network (HOG-DNN) is being i mplemented fo r the classificat ion of Alzheime r's disease (AD) using MRI im age processing. The corrected Adam optimize r is being used f or this purpose .	Achieving a high classification accuracy of 99.5%	Sensitivity to parameters affecting classification performance	classification based on MRI image analysis is reported to be 99.5% on the ADNI dataset and 98.5% on the NIMHANS dataset.
[24]	2020	The study used the OASIS open-access dataset, including 382 photos sourced from the OASIS database.	I am creating a Siamese Convolutional Neural Network (SCNN) model to accurately diagnose Alzheimer's disease (AD) and Mild Cognitive Impairment (MCI) transition phases.	Convolutional Neural Networks (CNNs) have the ability to autonomously extract efficient features without requiring human feature extraction.	1. The process of training deep learning models on a large number of photos requires substantial computer resources. 2. Adequate training of the model requires a significant quantity of standardized training datasets, which may be costly and give rise to ethical privacy problems in the field of medical imaging.	The suggested model attained a classification accuracy of 95.9% in distinguishing between Alzheimer's disease (AD) and Mild Cognitive Impairment (MCI) conversion phases.
[25]	2020	ADNI	An ensemble of deep convolutional neural networks (DCNN) is used to classify Alzheimer's disease using structural MRI data.	The capacity to get exceptional classification accuracy for Alzheimer's disease utilizing structural MRI data.	The training method may be computationally intensive when compared to single Deep Convolutional Neural Network (DCNN) based techniques.	The AD vs. MCI and NC vs. MCI tasks had the most favorable outcomes, with enhancements of 4.52% and 8.89% respectively, in comparison to previously reported findings.
[26]	2020	ADNI	The paper	The capacity to	Inaccurate	The ability to

			employs a Convolutional Neural Network (CNN) model based on a Region of Interest (ROI) for the staging of Alzheimer's Disease (AD).	provide precise and effective categorization for the staging of Alzheimer's disease, focusing on particular brain areas such as the hippocampi, amygdalae, and insulae.	representation of human differences.	accurately and efficiently classify the progression of Alzheimer's disease, with a specific emphasis on key brain regions such as the hippocampi, amygdalae, and insulae.
[27]	2020	The research used the ADNI dataset, which included people diagnosed with Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and cognitively normal (NC) individuals.	structural MRI (sMRI) and Diffusion Tensor Imaging (DTI).	The aim of this study is to enhance the accuracy of Alzheimer's Disease (AD) diagnosis by using transfer learning, especially cross-modal transfer learning, with several brain imaging modalities.	The dependence on a restricted dataset might result in overfitting problems during model training.	Accuracy (Acc) = (tp + tn) / (tp + tn + fp + fn)
[28]	2021	Alzheimer's Disease Neuroimagin g Initiative (ADNI) database.	The objective is to create a Computer-Aided-Brain-Diagnosis (CABD) system that can accurately diagnose Alzheimer's disease using MRI images.	The capacity to get exceptional precision in the identification of different phases of Alzheimer's disease by using Convolutional Neural Networks (CNN) and the Inception ResNet V2 Architecture.	It is necessary to have a substantial quantity of samples for training and validation in order to enhance accuracy. Furthermore, the performance of the model might differ depending on the optimizer and learning rate parameters used throughout the training process.	The model attained a diagnostic accuracy of 79.12% in identifying Alzheimer's disease based on MRI scans.
[29]	2021	The dataset used in the study was obtained from the ADNI (Alzheimer's Disease Neuroimagin g Initiative)	Utilizes a deep learning framework using Convolutional Neural Networks (CNN) for the purpose of segmenting the	High Precision: Demonstrates exceptional precision and AUC in distinguishing between AD and NC as well as MCI and NC individuals, surpassing other approaches.	Computational Complexity: The deep learning model described may have a high level of computational complexity, necessitating substantial	AD vs. NC: Accuracy: 88.9% MCI vs. NC: Accuracy: 76.2%

		database.	hippocampus and classifying diseases in individuals with Alzheimer's disease (AD).		computer resources for both training and inference.	
[30]	2021	subset from the ADNI dataset, with a total of 100 cases - 51 cognitively normal (CN) samples and 49 Alzheimer's Disease (AD) samples.	Transforms three-dimensional imaging data into a two-dimensional format by using several fusion algorithms, with a special emphasis on leveraging temporal pooling approaches.	Enhances the accuracy of Alzheimer's disease categorization by 8.33% and decreases training time by more than 89%.	The limited amount of the dataset used may hinder the performance of the 3D model since it lacks adequate data for fine-tuning.	3D-ResNet: 0.84 Alex Early-Dyn: 0.90 Alex Late-Max: 0.91 Alex Late-Dyn: 0.90 Res Early-Dyn: 0.83 Res Late-Max: 0.84 Res Late-Dyn: 0.88
[31]	2021	Alzheimer's Disease Neuroimaging Initiative (ADNI) database.	Convolutional Neural Networks (CNN) used to classify Alzheimer's illness. The framework comprises a Convolutional Neural Network (CNN) model, data augmentation techniques, cross-validation, and optimization via the Adam optimizer.	CNN models do not need intricate picture pre-processing, hence conserving time and computer resources.	Training in medical imaging jobs need a substantial quantity of labeled data, which may be hard to acquire.	[Accuracy = \frac{TP + TN}{TP + TN + FP + FN}] where: TP: True Positives TN: True Negatives FP: False Positives FN: False Negatives
[32]	2021	The dataset used in the study was obtained from the Alzheimer 's Disease Neuroimaging Initiative (ADNI)	The research used an enhanced LeNet model for the categorization of Alzheimer's Disease (AD).	Optimize training by using a Python toolkit that incorporates data augmentation approaches.	Combining pooling layers may lead to increased computing time, thereby affecting the overall efficiency of the model. Architectural design.	The improved LeNet model achieved an average performance rate of 96.64%

[33]	2021	The collection comprises brain pictures from 414 people who have been diagnosed with NC, MCI, and AD. These images were collected from 18F-Florbetaben Amyloid PET/CT scans.	The Genetic Algorithm (GA) method is used in the document.	Facilitates rapid convergence by choosing chromosomes with greater classification accuracies for the subsequent generation.	The convergence of a Genetic Convolutional Neural Network (CNN) to the most optimum network design may be hindered by constraints in hyperparameter selection.	The CNN model, which used a genetic approach, attained an average classification accuracy of 81.74%.
[34]	2021	The dataset used in the study contains MRI imaging data for healthy individuals and Alzheimer's disease patients.	The research used a unique ensemble model named DTE, which integrates deep learning, transfer learning, and ensemble learning methodologies.	capacity to get a high level of accuracy in classifying various types of Alzheimer's disease,	The intricacy involved in integrating deep learning, transfer learning, and ensemble learning approaches.	The DTE ensemble model had a peak classification accuracy of 99.09% for distinguishing between normal control and Alzheimer's disease, and 98.71% for distinguishing between moderate cognitive impairment and Alzheimer's disease.
[35]	2021	The dataset used in the study is from the Alzheimer's Disease Neuroimaging Initiative (ADNI).	The proposed diagnostic model consists of a data denoising module and a diagnosis network module, which operate together to enhance the accuracy of Alzheimer's disease diagnosis.	The diagnostic network utilizes many classifiers and employs fusion diagnosis methods. Consequently, this results in improved usage of samples, less noise in MRI images, and enhanced accuracy in tasks related to AD diagnosis.	need more processing resources and training time as a result of using several classifiers and fusion diagnostic approaches.	The suggested approach for diagnosing Alzheimer's disease has an accuracy of 95.2% when distinguishing between Alzheimer's Disease (AD) and Normal Control (NC), and an accuracy of 77.8% when distinguishing between stable Mild Cognitive Impairment (sMCI) and progressive Mild Cognitive Impairment (pMCI).
[36]	2021	Gwangju Alzheimer's and Related Dementia	An advanced method of deep learning is used to	Utilization of a two-stage Hough-CNN architecture	The results of this study may not be applicable to wider populations	The mean weighted accuracy for the testing set over all three folds in the

		(GARD) dataset	diagnose Alzheimer's disease (AD) by analyzing structural Magnetic Resonance Imaging (sMRI) data.		due to the small sample size of just 270 persons.	research study is 94.82%.
[37]	2021	The gene expression dataset used in the study is GSE5281 from the Gene Expression Omnibus (GEO) repository.	The hybrid technique incorporates the benefits of both filter and wrapper strategies.	Enhanced Performance: Utilizes the advantages of both filter and wrapper approaches to achieve higher accuracy in feature selection.	Complexity: The use of hybrid approaches in the feature selection process might lead to increased complexity.	The hybrid feature selection pipeline, mRmR-WPSO-AE, obtained a classification accuracy of 96.78% for Alzheimer's patients.
[38]	2022	ADNI Data Sets: Kaggle Data Set (Amnaya Pradhan et al., 2021): Data Collection by Year (Aakash Shah et al., 2020):	The Support Vector Machine (SVM) is used for the purpose of classifying Alzheimer's disease in detection tasks. Convolutional Neural Networks (CNNs) are used for the purpose of image analysis and feature extraction in Magnetic Resonance Imaging (MRI) scans.	Machine learning facilitates the rapid identification of Alzheimer's disease, allowing for early diagnosis and subsequent therapies, which ultimately enhance patient outcomes.	Machine learning models, particularly deep learning algorithms, might possess intricacy and present difficulties in interpretation, hence restricting their therapeutic use.	The performance of Convolutional Neural Networks (CNNs) has shown encouraging outcomes, achieving an accuracy of 98% with an 18-layered CNN and 88% with a 3D CNN network.
[39]	2022	Dataset 1: Collected from Kaggle with 6400 images divided into train and test folders. Dataset 2: Collected from Kaggle with 6330 MRI images divided into	The model employs a neural network that leverages VGG16 for both feature extraction and classification. The Adam optimizer is chosen for its efficient computational performance.	High Precision: Attained a precision rate of 90.4% for Dataset 1 and 71.1% for Dataset 2.	Overfitting refers to the risk of excessively tailoring a model to the training data, particularly when working with a small dataset. This may result in a decrease in the model's ability to accurately predict outcomes for new,	Dataset 1: Achieved an accuracy of 90.4%. Dataset 2: Attained an accuracy of 71.1%.

		train and test folders.			unknown data.	
[40]	2022	Kaggle is a platform for data science and machine learning competitions. The dataset is partitioned into training and testing subsets using 10-fold cross validation to mitigate the risk of overfitting.	Utilizes a controlled experiment to forecast the severity levels of bugs by analyzing summaries from a dataset of bug reports.	Achieves exceptional performance with a precision of 96.21% and other assessment measures.	The model's performance may be influenced by the quality of the dataset used for training and testing.	The bug severity prediction accuracy attained by the proposed CNN-HHO hybrid technique is 96.21%.
[41]	2022	OASIS-1: OASIS-2: OASIS-3:	The use of a mix of Generative Adversarial Network (GAN), Convolutional Neural Network (CNN), and Transfer Learning (TL) has been proposed for the purpose of detecting Alzheimer's disease (AD).	The approach used in the paper has the benefit of improving the precision of Alzheimer's disease (AD) detection models.	The intricacy of implementing and optimizing the combination	The precision varies between 74.4% and 97.3% across various categories and models.
[42]	2022	The dataset used in the study was provided by IRCCS Centro Neurolesi of Messina (ITALY).	The research u sed deep learni ng methodologi es, notably Con volutional Neur al Networks (C NN) and Convo lutional Autoen coder (Conv-AE).	The Conv-AE network exhibited a notable advantage i n the research by attai ning a validation accu racy of 89%, surpassi ng other methods and showcasing exception al performance in cate gorizing EEG signals a ssociated with AD, MC I, and HC.	The absence of int erpretability in he althcare applicati ons of deep neural networks (DNNs) arises from their non-linear character, r endering them "bl ack box" models.	The accuracy rates of t he Convolutional Neur al Network (CNN) wer e 70%, 91%, and 79% correspondingly. The Autoencoder-based CNN (AE-CNN) achieved accura cy, recall, and F1-score values of 70%, 8 8%, and 77% respecti vely.
[43]	2022	The research used the 18F DG-PET image col lection obtain ed from the A	The research u sed a Convoluti onal Neural Net work (CNN) to create a Compu ter-	The primary advantag e of a CAD system usi ng a Convolutional Ne ural Network (CNN) f or diagnosing Alzhei mer's Disease (AD) is	The computationa l complexity and r esource demands linked to deep lea rning models.	The accuracy was reported to be 96%.

		lzheimer's Disease Neuroimaging Initiative (ADNI) database.	Aided Diagnosis (CAD) system. This system was designed to distinguish between patients with Alzheimer's Disease (AD) and normal control (NC) patients by analyzing 18FDG-PET images.	its exceptional precision and efficacy in distinguishing AD patients from normal control participants.		
[44]	2022	The dataset used in this study comprises 6400 samples of unidentified individuals with MRI scan pictures and accompanying class classifications.	The article presents a strategy that leverages the ADASYN oversampling methodology to balance the dataset and enhance classification accuracy.	The projected DAD-Net offers a distinct benefit. Through Utilizing ADASYN for up-sampling enhances the ability to learn from difficult data and mitigates the bias resulting from class imbalance, resulting in more dependable classification outcomes.An inherent drawback of the system is that it necessitates more processing resources and training time owing to the intricate neural network structure and oversampling procedure.	In the research, accuracy is defined as the quantification of the degree to which a measurement or result corresponds to the true value or standard.	The suggested DAD-Net model with ADASYN attained accuracy values of 99.22%, 98.67%, and 98.10% when applied to the balanced AD dataset. These results indicate a high level of accuracy in classifying Alzheimer's Disease.
[45]	2022	Source: DementiaBank	Pre-processing of Audio Transcript Data involves the removal of symbols and the retention of solely alphabetic characters.	Improved Precision: By using deep neural network models with Glove embedding, the accuracy of categorizing patients with Alzheimer's disease was enhanced.	Data Limitations: The model's generalizability to larger populations or various language patterns may be limited due to its reliance on a single dataset (Dementia Bank).	The accuracy of the models is calculated using the formula: [\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}]
[46]	2023	Alzheimer's Disease Neuroimaging Initiative (ADNI) database.	The article outlines a methodology that utilizes CNN architectures, such as VGG19, ResNet50, and DenseNet121, for transfer learning. It also incorporates data augmentation methods and implement	The MobileNet paradigm, often used for mobile applications, is utilized for the development of lightweight neural networks.	The paper does not specifically address any potential limitations or downsides of the unique approach or technique offered in the study.	The suggested model had a precision rate of 96.22%.

			s the MobileNet model for illness detection.			
[47]	2023	The research used the ADNI (Alzheimer's Disease Neuroimaging Initiative) and OASIS (Open Access Series of Imaging Studies) databases.	Developing a Siamese Convolutional Neural Network (SCNN) structure for the purpose of classifying Alzheimer's disease. The SCNN used a triplet-loss function to generate k-dimensional embeddings of MRI images, resulting in a high level of accuracy in Alzheimer's disease (AD) classification on the ADNI and OASIS datasets.	The capacity to accurately categorize Alzheimer's disease (AD) by using the triplet-loss function for k-dimensional embeddings of MRI images.	Scarcity of training samples in the data-limited field of Alzheimer's disease classification	The suggested models in the research demonstrated accuracy ranging from 85.31% to 91.83% on the ADNI dataset and from 89.00% to 93.85% on the OASIS dataset.
[48]	2023	OASIS ADNI IBSR MICCAI	The use of simulated and phantom images for validation, coupled with deep learning approaches, namely Convolutional Neural Networks (CNNs), for Magnetic Resonance Imaging (MRI) segmentation, and the assessment metrics include Dice coefficient, True Positive, True Negative, False Positive, and False Negative.	The scalability of deep learning methods is essential for effectively processing vast amounts of data.	The restricted availability of data presents challenges in following and analyzing the evolution of Alzheimer's disease over time.	The publication highlights the significance of precision in MRI image processing for the diagnosis of Alzheimer's disease.
[49]	2023	ADNI	The research used Deep Learning (DL) models to classify Alzheimer's Disease (AD) by using a hybrid methodology that combines the LeNet and AlexNet	architectures.Attains a commendable performance rate of 93.58% in AD classification while maintaining computational efficiency.	Additional optimization and modification may be necessary to further optimize its performance.	Here is a summary of the accuracy values for different AD classification approaches: Region growing: 0.62 Histogram based: 0.85 Fuzzy C means: 0.53 K-Means: 0.64

D. Recommendations

Previous research has covered a variety of deep learning models that are used for detecting Alzheimer's disease, such as those that make use of MRI data. Each individual research presents a unique set of approaches and developments, which together contribute to the continuous effort to improve the accuracy of Alzheimer's disease early detection and categorization. Based on the many works that were examined, the suggestions and solutions that should be implemented in order to progress the diagnosis of Alzheimer's disease should be to construct a powerful deep learning model that is capable of detecting, recognizing, and classifying diseases with a high degree of accuracy.

There are a number of research that indicate encouraging outcomes in terms of classification accuracy, specificity, and sensitivity. These studies suggest that model performance is improving. A number of different methods, including ensemble learning, CNN architectures, recurrent neural networks (RNN), and hybrid models, have repeatedly shown advantages in comparison to more conventional approaches, often known as machine learning algorithms.

During the data preprocessing step, it was shown that successful preprocessing approaches, including as picture normalization, feature extraction, data augmentation, and cleansing data from noise, have a significant role in improving model performance while simultaneously lowering the amount of computing time required for training the model and the general level of complexity. In contrast, the process of feature extraction and deep feature learning approaches contribute greatly to the efficacy of classification models such as transfer learning, autoencoders, and CNN help in identifying and selecting informative features for classification correct diagnosis. These techniques are used to find and choose features that are relevant to the classification.

It is essential to make use of a variety of methods, including parameter tuning, select and stable weights, and loss function selection, in order to optimize models in classification tasks in fit DL models. These strategies are essential for performing the best possible model performance. The proposals include the development of hybrid approaches, such as CNN with RNN and CNN with GAN algorithms, in order to create classification models that are more reliable and accurate. In addition, it is vital to conduct rigorous validation on a variety of datasets as well as external validation in clinical settings in order to guarantee the generalizability and dependability of the presented models. It is essential for researchers working in DL and clinical practice to work together in order to translate model improvements into diagnostic tools and therapies that can be used in clinical settings. In the context of real-world clinical settings, longitudinal studies that monitor the evolution of illness and the results of therapy may give very helpful insights about the effectiveness of diagnostic tools that are based on DL. Finally, the most important takeaway from this study is that there is no particular deep learning algorithm that can accurately diagnose and categorize Alzheimer's disease or any other kind of dementia. Building a strong model architecture that is based on the algorithms that are most suited for a certain illness condition is thus the most effective method for making recommendations for potential treatments.

E. Conclusion

In conclusion, the developments in deep learning models for the diagnosis of Alzheimer's disease using functional magnetic resonance imaging (MRI) data show tremendous potential for enhancing the accuracy of early detection and categorization. The many approaches and procedures that were investigated in the literature study shed light on the potential of DL to revolutionize the diagnosis of Alzheimer's disease (AD), which includes the construction of hybrid models. There have been a number of methods, such as ensemble learning and hybrid learning, that have shown promising outcomes in terms of classification accuracy, specificity, and sensitivity. This improvement in model performance has also been shown to be significantly aided by the use of efficient data preparation techniques and feature learning approaches. CNN designs have shown the greatest performance in diagnosing Alzheimer's disease, which is an important finding.

F. References

[1] Litjens, G., Kooi, T., Bejnordi, B.E., Setio, A.a.A., Ciompi, F., Ghafoorian, M., Van Der Laak, J., Van Ginneken, B., and Sanchez, C.I. (2017). A survey on deep learning in medical image analysis. Med Image Anal 42, 60-88.

[2] Liu, M., Cheng, D., Yan, W., and , A.S.D.N.I. (2018a). Classification of Alzheimer’s Disease by Combination of Convolutional and Recurrent Neural Networks Using FDG-PET Images. Frontiers in Neuroinformatics 12.

[3] Celik, S.; Onur, O.; Yener, G.; Kessler, J.; Özbek, Y.; Meyer, P.; Frölich, L.; Teichmann, B. Cross-cultural comparison of MMSE and RUDAS in German and Turkish patients with Alzheimer’s disease. Neuropsychology 2022, 36, 195–205.

[4] Taher, K. I., & Abdulazeez, A. M. (2021). Deep learning convolutional neural network for speech recognition: a review. *International Journal of Science and Business*, *5*(3), 1-14.

[5] Hu, K.; Wang, Y.; Chen, K.; Hou, L.; Zhang, X. Multi-scale features extraction from baseline structure MRI for MCI patient classification and AD early diagnosis. Neurocomputing 2016, 175, 132–145.

[6] X. Bi, X. Zhao, H. Huang, D. Chen, and Y. Ma, "Functional brain network classification for Alzheimer’s disease detection with deep features and extreme learning machine," Cognitive Computation, vol. 12, pp. 513-527, 2020.

[7] Yasin, H. M., & Abdulazeez, A. M. (2021). Image compression based on deep learning: A review. *Asian J. Res. Comput. Sci*, *8*(1), 62-76.

[8] Y. Zhang, "Three-Dimensional Eigenbrain for the Detection of Subjects and Brain Regions Related with Alzheimer’s Disease," Journal of Alzheimer's Disease, vol. 50, pp. 1163- 1179, 2016 e0225759, 2019.

[9] L. Li, H. Jiang, G. Wen, P. Cao, M. Xu, X. Liu, et al., "TE-HI-GCN: An ensemble of transfer hierarchical graph convolutional networks for disorder diagnosis," Neuroinformatics, pp. 1-23, 2021.

[10] Stevenson, G.; Dobson, S. Sapphire: Generating Java Runtime Artefacts from OWL Ontologies. In Proceedings of the Advanced Information

Systems Engineering Workshops—CAiSE 2011 International Workshops, London, UK, 20–24 June 2011; pp. 425–436.
[11] F. Hajamohideen *et al.*, "Four-way classification of Alzheimer's disease using deep Siamese convolutional neural network with triplet-loss function," *Brain Inform*, vol. 10, no. 1, Dec. 2023, doi: 10.1186/s40708-023-00184-w.
[12] F. M. J. M. Shamrat *et al.*, "AlzheimerNet: An Effective Deep Learning Based Proposition for Alzheimer's Disease Stages Classification From Functional Brain Changes in Magnetic Resonance Images," *IEEE Access*, vol. 11, pp. 16376–16395, 2023, doi: 10.1109/ACCESS.2023.3244952.
[13] D. Muller, I. Soto-Rey, and F. Kramer, "An Analysis on Ensemble Learning Optimized Medical Image Classification with Deep Convolutional Neural Networks," *IEEE Access*, vol. 10, pp. 66467–66480, 2022, doi: 10.1109/ACCESS.2022.3182399.
[14] Chicho, B. T., Abdulazeez, A. M., Zeebaree, D. Q., et al. (2021). Machine learning classifiers based classification for IRIS recognition. *Qubahan Academic Journal*, *1*(2), 106-118.
[15] Rajan KB et al (2023) Longitudinal changes in blood biomarkers of clinical Alzheimer disease in a biracial population sample. Neurology 100(8):e874–e883
[16] Mirakhori F et al (2022) Diagnosis and treatment methods in Alzheimer's patients based on modern techniques: the orginal article. J Pharm Negat Results 2022:1889–1907.
[17] X. Jiang, L. Chang, and Y.-D. Zhang, "Classification of Alzheimer's disease via Eight-Layer Convolutional Neural Network with Batch Normalization and Dropout Techniques."
[18] Cai, Q.; Xin, Z.; Zuo, L.; Li, F.; Liu, B. Alzheimer's Disease and Rheumatoid Arthritis: A Mendelian Randomization Study. Front. Neurosci. 2018, 12, 627.
[19] Yildirim, M.; Cinar, A. Classification of Alzheimer's Disease MRI Images with CNN Based Hybrid Method. Ingénierie Systèmes d'Inf. 2021, 2020, 413–418.
[20] M. Liu *et al.*, "A multi-model deep convolutional neural network for automatic hippocampus segmentation and classification in Alzheimer's disease," *Neuroimage*, vol. 208, Mar. 2020, doi: 10.1016/j.neuroimage.2019.116459.
[21] M. Nguyen, T. He, L. An, D. C. Alexander, J. Feng, and B. T. T. Yeo, "Predicting Alzheimer's disease progression using deep recurrent neural networks," *Neuroimage*, vol. 222, Nov. 2020, doi: 10.1016/j.neuroimage.2020.117203.
[22] N. An, H. Ding, J. Yang, R. Au, and T. F. A. Ang, "Deep ensemble learning for Alzheimer's disease classification," *J Biomed Inform*, vol. 105, May 2020, doi: 10.1016/j.jbi.2020.103411.
[23] H. S. Suresha and S. S. Parthasarathy, "Alzheimer Disease Detection Based on Deep Neural Network with Rectified Adam Optimization

Technique using MRI Analysis," in *Proceedings of 2020 3rd International Conference on Advances in Electronics, Computers and Communications, ICAECC 2020*, Institute of Electrical and Electronics Engineers Inc., Dec. 2020. doi: 10.1109/ICAECC50550.2020.9339504.

[24] A. Mehmood, M. Maqsood, M. Bashir, and Y. Shuyuan, "A deep siamese convolution neural network for multi-class classification of alzheimer disease," *Brain Sci*, vol. 10, no. 2, Feb. 2020, doi: 10.3390/brainsci10020084.

[25] J. Y. Choi and B. Lee, "Combining of Multiple Deep Networks via Ensemble Generalization Loss, Based on MRI Images, for Alzheimer's Disease Classification," *IEEE Signal Process Lett*, vol. 27, pp. 206–210, 2020, doi: 10.1109/LSP.2020.2964161.

[26] S. Ahmed, B. C. Kim, K. H. Lee, and H. Y. Jung, "Ensemble of ROI-based convolutional neural network classifiers for staging the Alzheimer disease spectrum from magnetic resonance imaging," *PLoS One*, vol. 15, no. 12 December, Dec. 2020, doi: 10.1371/journal.pone.0242712.

[27] K. Aderghal, K. Afdel, J. Benois-Pineau, and G. Catheline, "Improving Alzheimer's stage categorization with Convolutional Neural Network using transfer learning and different magnetic resonance imaging modalities," *Heliyon*, vol. 6, no. 12, Dec. 2020, doi: 10.1016/j.heliyon.2020.e05652.

[28] R. C. Suganthe, M. Geetha, G. R. Sreekanth, K. Gowtham, S. Deepakkumar, and R. Elango, "Multiclass Classification of Alzheimer's Disease Using Hybrid Deep Convolutional Neural Network," 2021.

[29] M. Amini, M. M. Pedram, A. R. Moradi, and M. Ouchani, "Diagnosis of Alzheimer's Disease by Time-Dependent Power Spectrum Descriptors and Convolutional Neural Network Using EEG Signal," *Comput Math Methods Med*, vol. 2021, 2021, doi: 10.1155/2021/5511922.

[30] G. Liang, X. Xing, L. Liu, Q. Ying, A.-L. Lin, and N. Jacobs, "Alzheimer's Disease Classification Using 2D Convolutional Neural Networks", doi: 10.1101/2021.05.24.21257554.

[31] Y. AbdulAzeem, W. M. Bahgat, and M. Badawy, "A CNN based framework for classification of Alzheimer's disease," *Neural Comput Appl*, vol. 33, no. 16, pp. 10415–10428, Aug. 2021, doi: 10.1007/s00521-021-05799-w.

[32] R. A. Hazarika, A. Abraham, D. Kandar, and A. K. Maji, "An Improved LeNet-Deep Neural Network Model for Alzheimer's Disease Classification Using Brain Magnetic Resonance Images," *IEEE Access*, vol. 9, pp. 161194–161207, 2021, doi: 10.1109/ACCESS.2021.3131741.

[33] S. Lee, J. Kim, H. Kang, D. Y. Kang, and J. Park, "Genetic algorithm based deep learning neural network structure and hyperparameter optimization," *Applied Sciences (Switzerland)*, vol. 11, no. 2, pp. 1–12, Jan. 2021, doi: 10.3390/app11020744.

[34] R. Logan *et al.*, "Deep Convolutional Neural Networks With Ensemble Learning and Generative Adversarial Networks for Alzheimer's Disease Image Data Classification," *Frontiers in Aging Neuroscience*, vol. 13. Frontiers Media S.A., Aug. 17, 2021. doi: 10.3389/fnagi.2021.720226.

[35] P. Zhang, S. Lin, J. Qiao, and Y. Tu, "Diagnosis of alzheimer's disease with ensemble learning classifier and 3D convolutional neural network," *Sensors*, vol. 21, no. 22, Nov. 2021, doi: 10.3390/s21227634.

[36] A. Basher, B. C. Kim, K. H. Lee, and H. Y. Jung, "Volumetric Feature-Based Alzheimer's Disease Diagnosis from sMRI Data Using a Convolutional Neural Network and a Deep Neural Network," *IEEE Access*, vol. 9, pp. 29870–29882, 2021, doi: 10.1109/ACCESS.2021.3059658.

[37] N. Mahendran, P. M. D. R. Vincent, K. Srinivasan, and C. Y. Chang, "Improving the Classification of Alzheimer's Disease Using Hybrid Gene Selection Pipeline and Deep Learning," *Front Genet*, vol. 12, Nov. 2021, doi: 10.3389/fgene.2021.784814.

[38] V. Patil, M. Madgi, and A. Kiran, "Early prediction of Alzheimer's disease using convolutional neural network: a review," *Egyptian Journal of Neurology, Psychiatry and Neurosurgery*, vol. 58, no. 1. Springer Science and Business Media Deutschland GmbH, Dec. 01, 2022. doi: 10.1186/s41983-022-00571-w.

[39] S. Sharma, K. Guleria, S. Tiwari, and S. Kumar, "A deep learning based convolutional neural network model with VGG16 feature extractor for the detection of Alzheimer Disease using MRI scans," *Measurement: Sensors*, vol. 24, Dec. 2022, doi: 10.1016/j.measen.2022.100506.

[40] I. Yousaf, F. Anwar, S. Imtiaz, A. S. Almadhor, F. Ishmanov, and S. W. Kim, "An Optimized Hyperparameter of Convolutional Neural Network Algorithm for Bug Severity Prediction in Alzheimer's-Based IoT System," *Comput Intell Neurosci*, vol. 2022, 2022, doi: 10.1155/2022/7210928.

[41] K. T. Chui, B. B. Gupta, W. Alhalabi, and F. S. Alzahrani, "An MRI Scans-Based Alzheimer's Disease Detection via Convolutional Neural Network and Transfer Learning," *Diagnostics*, vol. 12, no. 7, Jul. 2022, doi: 10.3390/diagnostics12071531.

[42] S. Fouladi, A. A. Safaei, N. Mammone, F. Ghaderi, and M. J. Ebadi, "Efficient Deep Neural Networks for Classification of Alzheimer's Disease and Mild Cognitive Impairment from Scalp EEG Recordings," *Cognit Comput*, vol. 14, no. 4, pp. 1247–1268, Jul. 2022, doi: 10.1007/s12559-022-10033-3.

[43] A. A, P. M, M. Hamdi, S. Bourouis, K. Rastislav, and F. Mohmed, "Evaluation of Neuro Images for the Diagnosis of Alzheimer's Disease Using Deep Learning Neural Network," *Front Public Health*, vol. 10, p. 834032, 2022, doi: 10.3389/fpubh.2022.834032.

[44] G. Ahmed *et al.*, "DAD-Net: Classification of Alzheimer's Disease Using ADASYN Oversampling Technique and Optimized Neural Network," *Molecules*, vol. 27, no. 20, Oct. 2022, doi: 10.3390/molecules27207085.

[45] Y. F. Khan, B. Kaushik, M. K. I. Rahmani, and M. E. Ahmed, "Stacked Deep Dense Neural Network Model to Predict Alzheimer's Dementia Using Audio Transcript Data," *IEEE Access*, vol. 10, pp. 32750–32765, 2022, doi: 10.1109/ACCESS.2022.3161749.

[46] G. Mohi ud din dar *et al.*, "A Novel Framework for Classification of Different Alzheimer's Disease Stages Using CNN Model," *Electronics (Switzerland)*, vol. 12, no. 2, Jan. 2023, doi: 10.3390/electronics12020469.

[47] F. Hajamohideen *et al.*, “Four-way classification of Alzheimer’s disease using deep Siamese convolutional neural network with triplet-loss function,” *Brain Inform*, vol. 10, no. 1, Dec. 2023, doi: 10.1186/s40708-023-00184-w.
[48] B. S. Rao and M. Aparna, “A Review on Alzheimer’s Disease Through Analysis of MRI Images Using Deep Learning Techniques,” *IEEE Access*, vol. 11, pp. 71542–71556, 2023, doi: 10.1109/ACCESS.2023.3294981.
[49] R. A. Hazarika *et al.*, “An Approach for Classification of Alzheimer’s Disease Using Deep Neural Network and Brain Magnetic Resonance Imaging (MRI),” *Electronics (Switzerland)*, vol. 12, no. 3, Feb. 2023, doi: 10.3390/electronics12030676.