IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 20 June 2023, accepted 6 July 2023, date of publication 13 July 2023, date of current version 19 July 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3294981

SURVEY

A Review on Alzheimer's Disease Through Analysis of MRI Images Using Deep Learning Techniques

BATTULA SRINIVASA RAO AND MUDIYALA APARNA
School of Computer Science and Engineering, VIT-AP University, Amaravati, Andhra Pradesh 522237, India
Corresponding author: Battula Srinivasa Rao (sreenivas.battula@gmail.com)

ABSTRACT The anatomical structure of the brain has been studied with the help of magnetic resonance imaging (MRI), which has been used to analyze numerous neurological diseases and define pathological areas. Early detection of Alzheimer's Disease (AD) patients is critical in order to implement preventative measures. Alzheimer's disease (AD) is the most common chronic disease in the elderly, with a high incidence rate. In recent years, deep learning has seen a lot of success in the medical image analysis. Brain diseases can be more accurately categorized using segmented MRI scans due to in-depth analyses of tissue architecture. Many, complex segmentation approaches have been presented for AD diagnosis. Since deep learning algorithms can yield effective results over a large data collection, they have received interest for use in segmenting the brain's structure and classifying AD. Consequently, the deep learning techniques are currently favored over machine learning techniques. We discuss how convolutional neural network concepts can be used to study brain anatomy in order to detect AD. New techniques, their results on open datasets, and the benefits of brain MRI segmentation for Alzheimer's disease categorization are discussed. In this article, the literature on Alzheimer's disease is briefly reviewed, and the possibility of Deep Learning to improve early diagnosis is discussed.

INDEX TERMS Alzheimer's disease, brain analysis, classification techniques, deep learning techniques, image processing techniques.

I. INTRODUCTION

Cognitive and memorization skills deteriorate over time in the clinical syndrome of Alzheimer's disease. It is estimated that between 60 and 80 percent of all cases of dementia are caused by this illness, making it a major problem for the elderly. It takes a long time for symptoms of AD to develop into a definitive diagnosis. Patients with moderate cognitive impairment (MCI) are at risk for Alzheimer's disease (AD), but only 30%–40% of MCI patients progress to full-blown AD [1]. The brain of an Alzheimer's patient shows signs of the disease long before the start of cognitive deterioration, including early enlargement of the lateral ventricles and apparent degeneration of the hippocampus and amygdala. Biomarker research on Alzheimer's disease reveals that some parts of the brain have started to decline. Thus, it is crucial to identify AD in its earliest stages with high precision. Because of the excellent spatial resolution and contrast it affords in brain tissue, magnetic resonance imaging (MRI) can be used to study the structure of the brain. Computed tomography (CT) and positron emission tomography (PET) are thought to be safer for patients than magnetic resonance imaging (MRI) [2]. Over the past few decades, MRI has become standard equipment for diagnosing brain injuries and studying the structure of the brain. Alzheimer's disease (AD) and multiple sclerosis (MS) are just two of the many brain illnesses that MRI may detect.

Segmenting MRI scans of the brain collected at varying intervals allows researchers to quantify alterations to brain anatomy across time. For diseases like Alzheimer's, a correct

The associate editor coordinating the review of this manuscript and approving it for publication was Tony Thomas.

diagnosis relies on the precise identification and categorization of diseased tissue and the healthy components around it [3]. To make better diagnoses, a lot of data is needed. On the other hand, it may be challenging for physicians to manually analyse vast and complex MRI datasets in order to extract meaningful information [4]. Evaluating a brain MRI manually is a time-consuming process that might lead to mistakes owing to operator variability. For this reason, it is important to create an automated segmentation approach that yields reliable results. Segmentation of brain MRI scans has several clinical uses because of the impact it has on the overall data analysis. Several conventional machine learning-based methods can be used to examine various types of brain tissue, including white-matter (WM), grey-matter (GM), and cerebrospinal-fluid (CSF). Patients with AD benefit from the ability to segment abnormal brain tissues with MRI. However, sophisticated technical methods and professional judgment are needed to obtain the image information necessary for segmentation. Separating the image into groups of similar-looking pixels is the goal of brain MRI segmentation [5]. In our analysis, we focus on how deep learning can be used to isolate these areas in brain scans. In a brain MRI scan, it may be challenging to discern between GM, WM, and cerebrospinal fluid (CSF) due to tissue intensities, non-uniformity (bias), noise abnormalities, and partial volume effects [6]. In order to overcome these problems, researchers have created and investigated a few deep learning methods for brain MRI segmentation. We also examine many deep learning approaches to the early detection of Alzheimer's disease, kind of dementia that can impact cognition, memory, and behaviour [7]. The purpose of this study is to provide an overview of cutting-edge deep learning techniques for determining whether MRI scans contain healthy or diseased brain tissue. Additionally, we investigate the deep learning-based solutions to the problems associated with brain MRI segmentation.

The primary goals of this analysis are to:

1. Summarize the current deep learning strategies for identifying Alzheimer's disease in brain MRIs.
2. Determine the challenges in using MRI segmentation of brain structure for AD diagnosis.
3. Demonstrate how MRI brain structure segmentation can improve AD diagnosis accuracy.

The goal of this study was to look at how CNN has progressed in recent years for use in diagnosing Alzheimer's disease from single and multimodal brain scan data, and to also investigate the model's intrinsic capabilities to extract elements that could enhance its performance.

II. MRI DATASET FOR BRAIN ANALYSIS

Publicly available datasets like those provided by the Open Access Series of Imaging Studies (OASIS)Alzheimer's Disease Neuroimaging Initiative (ADNI) Medical Image Computing and Computer-Assisted Intervention (MICCAI)and the Internet Brain Segmentation Repository (IBSR) are routinely used for the segmentation of brain MRI images and the diagnosis of AD [8], [9], [10]. In Table 1 we show the data set specifications for OASIS, ADNI, MICCAI, and IBSR. After a brief introduction to brain MRI, the article goes on to detail the distinct features of the datasets.

TABLE 1. Overview of OASIS, ADNI, IBSR, MICCAI datasets.

Datasets	Class	No of subjects	Sex		No of MRI Images
			Male	Female	
OASIS	AD	120	40	80	120
	HC	320	146	174	320
ADNI	AD	210	75	135	210
	MCI	408	226	182	408
	HC	248	86	162	248
IBSR	HC	28	10	18	28
MICCAI	HC	38	-	-	38

A. OASIS

The OASIS dataset was developed by the Alzheimer's Disease Research Unit at Washington University and contains significant brain MRI data from both healthy and affected patients. [11]. Different scans were taken at different times for each subject in the longitudinal dataset, while 440 people aged 18-96 were represented in the cross-sectional dataset. It is possible to assess an individual's risk for acquiring AD with the help of diagnostic techniques like the Clinical Dementia Rating (CDR) and the Mini-Mental State Examination (MMSE) [12]. Subjects are classified as having no dementia risk factors (CDR-0), very mild dementia risk factors (CDR-0.5), mild dementia risk factors (CDR- 1), and moderate dementia risk factors (CDR-2) based on an assessment of cognitive and functional abilities.

B. ADNI

Data from 843 MRI scans with 1.5 T to 3 T scanner intensity fields are included in the ADNI dataset, making it suitable for Alzheimer's disease diagnosis. Most people over the age of 65 will get AD [13]. Patients with diminished cognitive abilities, such as memory loss and thinking, are diagnosed with mild cognitive impairment (MCI). They are distinct from AD but are extremely susceptible to developing AD or any other form of dementia.

C. IBSR

Techniques for segmenting brain images are tested and refined using the IBSR dataset. In addition to the MRI data, this dataset also includes the results of a manually guided expert segmentation. This dataset, which comprises of 28 real T1-W MRIs with expert-guided manual segmentation, serves as the "ground truth" for testing automatic segmentation approaches [14], [15], [16], [17], [18]. In addition, there are approximately 60 slices of coronal T1-W data (slice gap between successive slices) measuring 3.1 mm in each MRI volume, and 18 slices of cortical T1-W data (slice gap

between successive slices) measuring 1.5 mm. This dataset subject volumes feature 256 × 256 × 128pixel dimensions and three different voxel spacings:0.84 × 0.84 × 1.5mm3, 0.94 × 0.94 × 1.5mm3 and 1.0 × 1.0 × 1.5mm3. 32 non-cortical structures have also been manually segmented by Massachusetts General Hospital.

D. MICCAI

In order to compile the MICCAI-2012 dataset, Neuromorphic metrics, Inc. of Scotts Valley, California used 38 T1-w MRI volumes in addition to 134 manually segmented structures. It was primarily used for segmenting anatomical structures, tissues, and tumors. [19]. In 2012, the first 80 samples were added to this dataset, which included both real and simulated cases. It has become increasingly difficult to train and test on small datasets [20], [21], [22], [23]. To identify sub-cortical structures, we entered them into the MICCAI 2012 multi-atlas labelling challenge.

E. PRE-PROCESSING OF BRAIN MRI ANALYSIS

In the context of brain MRI segmentation, it depicts a workflow that has been proposed in the literature. The four primary parts of the Architecture are the pre-processing, trained models, segmentation, and classification stages. After acquiring an MRI, a variety of pre-processing steps must be completed before the images are used for brain tissue segmentation.

Images of the eyes, fat, spinal cord, and skull can all be obtained in high resolution during a brain MRI scan. Skull removal is required for voxel classification into brain and non-brain regions [24]. In skull stripping, only the voxels that represent the brain are kept, or the voxels that represent the remainder of the tissue are assigned a value of zero. The brain's grey and white matter, as well as subcortical structures and the cerebellum, are all considered brain voxels, while the scalp, matter, eyes, bones, dura, skin, muscles, and fat are all considered non-brain voxels [25], [26], [27], [28]. Reduce the Rician noise in MRI scans that varies locally with this technique. The significance of this is discounted for deep learning classification applications. Data augmentation or patch-based procedures are used to the input volumes following pre-processing to complete data preparation. After that, we use the input modalities and patch dimensions to perform segmentation or classification, depending on the goal of the analysis. The given results could be better if the largest groups were chosen or the regions were smoothed out [29].

III. REVIEW OF BRAIN SEGMENTATION AND DIAGNOSIS

Here, we present systematic literature review about structural segmentation and classification of brain MRI data with the aim of identifying AD. We also briefly cover CNN architecture, then proceed on to discussing how deep learning can be used to segment brain structures, and finally classify Alzheimer's disease. Finally, we discuss about how MRI segmentation improves the accuracy of AD classification.

A. INTRODUCTION TO THE STRUCTURE OF CNNs

Deep learning, in the field of computer vision, is the process of extracting a hierarchy of features from raw input images using a neural network with multiple layers (typically more than five) [30]. Deep learning improves on the accuracy of traditional machine learning algorithms by automatically extracting complicated, high-level characteristics from images and training on massive amounts of data. Due to advancements in GPU processing power, large quantities of imaging data may now be used for training, resulting in improved accuracy despite cosmetic alterations when employing deep learning methods. Deep learning is essential to numerous fields and technologies, such as image segmentation, genotype/phenotype detection, disease categorization, object detection, and speech recognition [31], [32], [33], [34]. The terms ''deep Boltzmann machines,'' ''convolutional neural networks,'' ''stacked auto-encoders,'' and ''deep neural networks'' all refer to popular deep learning approaches.

In image segmentation and classification, deep neural networks (DNNs) are frequently used. A lot of people started paying attention to convolutional neural networks (CNNs) after seeing their outstanding results in the 2012 ImageNet Competition, even though CNNs have been around since 1989. On a dataset of millions of images with 1000 possible classifications, CNN reportedly produces results with a half-error rate compared to the prior best computing methodologies [35]. CNN architecture is becoming increasingly computationally complex due to the increasing number of layers, the use of neurons with millions of weights, and the large number of connections between the neurons. The CNN architecture consists of several basic parts, such as convolution layers, pooling layers, and fully connected layers. Multiple convolutional layers are used in this architecture, followed by a pooling layer and then one or more fully connected layers [36]. Forward propagation refers to the step in which these layers transform input data into output.

Convolution, pooling, activation function, and fully linked layers are shown in Figure 2 as the primary components of a CNN. In order to create feature maps from the input images, the convolutional layer convolves over the kernel. Rather than passing along individual convolutional layer results, the final layer receives the maximum or average of all previous results [37]. Two of the most common activation functions are the rectified linear unit (ReLU) and its leaky variant, the Rectified Leaky ReLU. The ReLU performs a nonlinear transformation on data by transmitting only the positive values of the input and clipping the negative values to zero. For input prediction, the final CNN layer's output is related to a loss function (cross-entropy loss, for instance, converts scores to a multinomial distribution over labels) [38], [39], [40], [41] The regularization constraints are then utilized to construct network parameters via minimizing the loss function between the prediction labels and the ground truth labels. In addition, backpropagation is used to change the network's weights at each iteration (for instance, by stochastic gradient descent) until convergence is reached.

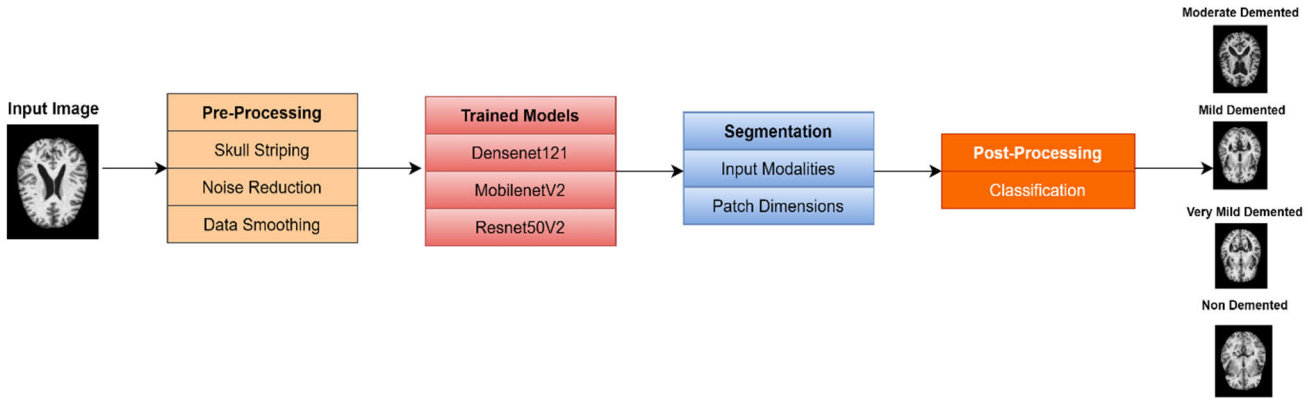

FIGURE 1. General flowchart for brain MRI image analysis.

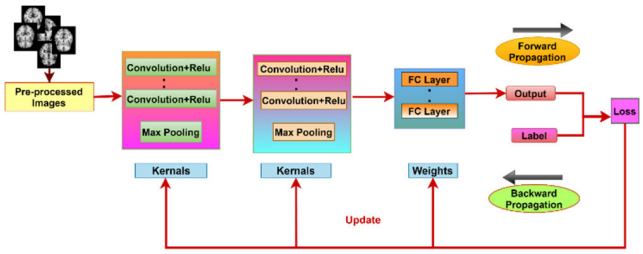

FIGURE 2. Basic architecture of convolution neural network.

B. DEEP LEARNING-BASED BRAIN MRI SEGMENTATION AND CLASSIFICATION CHALLENGES

1) DEEP LEARNING USED IN BIG DATA ANALYTICS

Finding an adequate dataset to train the model on and increase its accuracy is a major challenge. As a result of its enormous amount (high dimensional decision space and many objectives), variety (modeling with different data sets and sharing insights across difficulties), durability and veracity, big data presents challenges for deep learning [42]. In order to address this issue, the author proposes several optimization strategies, such as global optimization, that make use of previously learned insights from the study of massive volumes of high-dimensional, heterogeneous, noisy data. Complex optimization techniques offer effective responses by developing novel perspectives and methodology for optimization issues that make the most of deep learning approaches to large data challenges. The conventional machine learning methods do better with less data [43]. While the performance of traditional machine learning methods tends to level after a certain threshold of data, that of deep learning methods improves with additional data. Using deep learning architectures like deep neural networks, deep belief networks, and recurrent neural networks, researchers have been able to match or surpass the performance of human specialists in a wide range of subjects.

2) SCALABILITY OF DEEP LEARNING APPROACHES

It is important to examine not only the accuracy but also various other metrics related to computational resources when assessing the scalability of deep learning. For deep learning to succeed, scalability is essential. The traditional enterprise-grade servers and storage systems are struggling to keep up with the data explosion in terms of volume, velocity, veracity, and variety [44]. A high-performance computing (HPC) system (supercomputing, clustering, often referred to as cloud holds enormous promise for data-intensive commercial computing and can be used to scale up deep learning techniques. data generation capability, which is useful in situations where training data is unavailable.

3) MULTI-TASK, TRANSFER LEARNING OR MULTI-MODULE LEARNING

One of the major obstacles in deep learning is learning from multiple domains or models at the same time. The biggest problem with learning transfer right now is the possibility of adverse transfer [45]. For transfer learning to be successful, there must be substantial overlap between the training set and the target problem. If the model's initial training is too dissimilar from subsequent training, it may perform inferior than if it had never been trained [46], [47], [48]. There is a lack of agreed-upon criteria for determining whether forms of learning and training are sufficiently related. Table 2 demonstrates the CNN architecture's scalability by showcasing a variety of classification and segmentation methodologies, including single-modality, multi-modality, semantic, patch and cascaded approaches.

The term single-modality is used to describe the use of one information modality that may be adapted to many contexts. Multi-modality approaches, like positron emission tomography, stress pathognomonic alterations and metabolic activity of the target tissue by integrating data from multiple sources to determine their precise location. When approaching images in a semantic way, we assign a label to every individual pixel. Segmentation labels are applied to the input image to decrease the loss function. This allows for the creation of segmentation maps for images of any size [69]. This method has a much lower computational complexity than other methods. Most current methods employ this segmentation principle. The patch-wise method uses fragments

TABLE 2. The brain structure classification and segmentation methods based on deep learning.

Sno	Author	Year	Strategies/Content	Image Type	Key-Method	Data Set
1	Lian et al. [49]	2020	Brain	MRI Images	FCN	ADNI (820)
2	Shi et al. [50]	2020	Brain	MRI+PET+CSF Images	Machine- Learning	ADNI (201)
3	Feng et al. [51]	2020	Brain	MRI+PET	CNN	ADNI (354)
4	Mefraz et al. [52]	2019	Brain	MRI Images	Transfer Learning	ADNI (52)
5	Lee et al. [53]	2019	Brain	MRI Images	CNN	ADNI (846) OASIS (414)
6	Aderghal et al. [54]	2018	Hippocampus	MRI+DTI Images	CNN	ADNI (817)
7	Jyoti et al. [55]	2018	Brain	MRI Images	CNN	OASIS (418)
8	Wang et al. [56]	2017	Brain	MRI Images	CNN	ADNI (824)
9	Qiao et al. [57]	2017	Brain	MRI+PET Images	Auto Encoder	ADNI (209)
10	Andres et al. [58]	2016	Grey-Matter	MRI+PET Images	Deep-belief Network	ADNI (820)
11	Yang et al. [59]	2022	patch-wise	MRI Images	CNN	ADNI (274)
12	Liu et al. [60]	2022	Brain	MRI+PET Images	CNN	ADNI (354)
13	Pengcheng et al. [61]	2020	Semantic based	3D/4D Images	Fuzzy C-Mean	BLSA
14	Bernal et al. [62]	2019	patch-wise	2D/3D Images	FCNN	IBSR/MICCAI2012&iseg2017
15	Wachinger et al. [63]	2018	patch-wise	3D Images	CNN	MICCAI 2012
16	Mehta et al. [64]	2017	Semantic-based	2D/3D Images	CNN	IBSR/MICCAI2012
17	Bao et al. [65]	2016	Patch-wise	2D Images	CNN	IBSR/LPBA40
18	Shakeri et al. [66]	2016	Semantic-based	2D Images	FCNN	IBSR data
19	Syed et al. [67]	2021	Semantic-based	2D Images	CNN	ADNI(275)
20	Patil et al.[68]	2022	patch-wise	2D Images	CNN	ADNI(418)

of larger higher-resolution images. To be more precise, the system is trained by segmenting the input images into a collection of local patches. Predicting the data for a single patch can lead to more accurate local knowledge. The model can be trained with local information using patch-wise procedures, however this method increases computing complexity [70]. First, one CNN does the initial classification, and then another CNN uses the results of the first CNN's classification (as input) to provide even more accurate results. When compared to other CNN approaches, cascaded CNN produces comparable results. Deep learning's segmentation performance has been successful, but there are a few drawbacks and limitations.

IV. DIAGNOSING ALZHEIMER'S DISEASE FROM A BRAIN MRI USING DEEP LEARNING

Brain MRI segmentation is carried out to remove noise from the final processed images and find important characteristics. Brain illnesses like Alzheimer's disease can be more accurately classified after careful examination of the tissue architecture revealed by the segmented MRI. As a form of dementia, AD is relatively common, especially among the elderly. Patients with Alzheimer's disease gradually lose mental capacity as the disease progresses. Patients in advanced cases have difficulty performing day-to-day activities, which eventually leads to an inability to take care of themselves. The human brain's nerve cells and tissues are affected by this disease. At first, this could influence the parts of the brain responsible for planning, thinking, and memory formation, including the hippocampus. Alzheimer's disease is becoming more prevalent among the elderly, but it is not necessarily associated with getting older. By 2050, more than 90 million people will have Alzheimer's, according to a recent study [71]. Many studies have been conducted to stop or delay the advancement of AD, but so far there have not been any promising findings.

A. SEGMENTATION OF BRAIN MRI USING DEEP LEARNING

For quantitative study of brain tissues and a complete assessment of intracranial volume, MRI needs accurate auto-segmentation of brain components including GM, WM, and CSF. Segmenting brain tissue is typically accomplished using atlas-based methodologies or pattern recognition software.

1) ATLAS-BASED METHODS

Atlas-based methods do this by comparing the intensity levels of two images. Although they are widely used to segment the human brain, map and registry-based approaches often fail to accurately segment small, highly variable regions such as the hippocampus due to registration limitations and differences in the underlying data of the real world.

2) PATTERN RECOGNITION

Classifying brain tissues using a set of local intensity features is a common use of pattern recognition methods. Recent

evidence indicates that hippocampal atrophy is a potential biomarker for Alzheimer's disease. The hippocampus resides within the limbic system of brain and is encircled by various other brain regions [72]. Patients with Alzheimer's disease have been demonstrated in multiple studies to have a smaller hippocampus volume. Accordingly, MRI hippocampal segmentation may find use in the clinic. The hippocampus is notoriously difficult to segment using magnetic resonance imaging (MRI) due to its tiny size, partial volume impact, anatomical heterogeneity, low contrast, low signal-to-noise ratio, and imprecise borders. along with proximity to the amygdaloid structure. Additionally, expert analysis takes time for manual segmentation. According to a recent study, conventional approaches like thresholding, region growing, and segmenting the hippocampus do not yield satisfactory results. In Table 3 summarized some papers with key features and methodologies.

3) CHALLENGES IN BRAIN MRI SEGMENTATION

There are numerous different physical structures in the brain, and these differences emerge across a wide range of phenotypes, ages, sexes, and diseases. It is challenging to generalize a single phenotypic segmentation technique to all phenotypes in order to produce valid performance

- Tissues with gyral folds, deep sulci, thin architecture, and smooth borders are particularly challenging to digest.This may lead to ambiguous classifications of different types of tissues. Experts on the human species have often found this as a challenge.
- Segmenting a brain MRI by hand is labor-intensive and prone to human error. In addition, an in-depth understanding of the brain and how it works is required. Due to this, gathering enough ground truth data to construct a segmentation model is difficult.
- When segmenting an ordinary image, the noisy background makes it difficult to accurately label each pixel or voxel using learned features.
- The hippocampal region offered several difficulties for segmentation due to its small size and volume, morphological diversity, partial volume effects, low contrast, low signal-to-noise ratio, ambiguous borders, and proximity to amygdaloid structures.

4) CHALLENGES IN THE DIAGNOSIS OF AD

The main problem with AD is that it is difficult to track and examine the patient's pathology over an extended period. As a result, it is difficult to follow the change in AD status. Only 152 transitions out of a total of 2731 MRIs are included in the ADNI dataset. Since MRIs do not record the changing AD state, the model is likely to overfit without producing generalizable distinctions between the various stages of AD.

- Multimodal data collection for the diagnosis of AD
  a) Due to heterogeneity, a prediction model built only from multimodality data will be inaccurate, as data from neuroimaging (i.e., MRI or PET) and genetics (single nucleotide polymorphism) have different data distributions, feature numbers, and levels of discriminative ability to AD diagnosis [90]. It has been discovered, for example, that raw SNP data is of limited value in the case of Alzheimer's disease.
  b) Issue with high dimensionality: Millions of voxels often make up a neuroimage scan, while hundreds of SNPs associated with AD might be found in a subject's genetic information.
- Due to the anatomical structure's low contrast in MRI, the automatic classification of AD is rather it is difficult. If MRI scans contain noisy or outlier pixels as a result of various scanning conditions, the classification accuracy may also suffer.

Alzheimer's disease impairs one's ability to make rational decisions and judgements in everyday situations. Multitasking is especially difficult. Routine activities that necessitate the completion of steps become difficult. There are many limitations in 2D/3D MRI image analysis. To address these issues in Alzheimer's patients, we suggested MRI and fMRI images (2D/3D images) for analysis. The majority of the researchers used deep learning techniques. These techniques are useful for recognizing the Alzheimer's disease classification and segmentation of MRI images. It provides the most accurate results.

B. BRAIN MRI SEGMENTATION IMPROVES IN CLASSIFICATION OF ALZHEIMER'S DISEASE

Alzheimer's disease is widely recognized as the most common form of dementia among Caucasians. Diffuse brain atrophy, which manifests in a few different ways, is a hallmark of Alzheimer's disease. a diminished cerebral cortex, enlarged ventricles, and atrophy of the hippocampus and other parts of the medial temporal lobes (MTL). The GM and WM tissues have been linked to AD pathology, and it has been found that anomalies in these tissues have a strong correlation with cognitive decline. It is therefore required to analyze neuropsychological and anatomical data from the patient at various transitional stages of the disease in order to have an overall understanding of the course of AD. MCI patients have a high possibility of developing AD as their medical condition. According to the results, converting from MCI to AD carries a much higher risk than it does for healthy individuals. The amnesic variety of MCIs, also known as aMCIs,is known for affecting most people. The highest yearly conversion rate from aMCI to AD supports the hypothesis that MCI represents the preclinical stage of Alzheimer's disease. As the disease progresses, the hippocampus, amygdala, entorhinal, and Para hippocampal cortices all atrophy, as was found in prior studies. There has been a lot of study into using hippocampal segmentation to derive brain size or shape. It has also been shown that cortical thickness and GM tissue maps are strongly predictive in the diagnosis of AD.Voxel-, deformation-, and tensor-based morphometry were also studied for their potential to provide light on variations across groups (TBM). Voxel-based morphometry (VBM) is a spatially specific and objective technique for

TABLE 3. A summary of studies that employ deep learning methods for brain MRI labelling and segmentation.

Sno	Authors	Methodologies	Applications: Key features
1	Aderghal et al. [73]	CNN Models	AD/HC Classification: several CNN base classifiers, each trained on its own layer of MRI brain data, to create a single CNN ensemble
2	Claude et al. [74]	CNN Models	AD/HC Classification: transfer-learning-based diffusion tensor imaging as an extension of magnetic resonance imaging
3	Liu et al. [75]	CNN Models	AD/MCI/HC Classification: Training a Convolutional Neural Network on a variety of MRI and PET brain image modalities
4	R. H. Blank et al. [76]	CNN Models	AD/MCI/HC Classification: Neuroimaging methods that use a convolutional neural network to express latent hierarchical features from retrieved patches.
5	Ahmed et al. [77]	CNN Models	AD/HC Classification: classification ensembles based on patch features for Alzheimer's disease detection
6	Mefraz et al. [52]	Transfer Learning	AD/MCI/HC Classification: Predicting AD and CNN using transfer learning with intelligent training data selection using a network trained with the VGG architecture.
7	Andres et al. [58]	Deep belief Network Models	AD/HC Classification: Brain region labels are automatically generated for use in developing deep learning architecture-based categorization methods.
8	Jyoti et al. [55]	CNN Models	AD/HC Classification: deep Convolutional Neural Network model for correcting a dataset imbalance for AD diagnosis and stage recognition
9	Logan et al. [78]	CNN Models	AD/HC Classification: fMRI data-adapted Lenet-5 architecture
10	Maryam et al. [79]	CNN Models	AD/HC Classification: Using a combination of multiscale and multimodal deep neural networks, early detection of Alzheimer's disease is possible.
11	Tan et al. [80]	CNN Models	AD/HC Classification: a multi-instance learning framework based on landmarks for diagnosing neurological disorders
12	Prakash et al. [81]	Machine Learning Models	AD/HC Classification: Multimodal data, including MRI, PET, and cerebrospinal fluid (CSF), are employed. modelling and learning an informative feature projection from the various modalities using a linked metric ensemble and coupled boosting technique.
13	Payan et al. [82]	CNN Models	AD/HC Classification: Pre-trained 3D convolutional neural networks using sparse auto-encoders
14	I. Vatanabe et al. [83]	CNN Models	AD/HC Classification: Scheme for data permutation in deep CNN Alzheimer's disease MRI classification.
15	Feng et al. [51]	CNN Models	AD/HC Classification: using a deep convolutional neural network (CNN) cluster powered by multimodal imaging to detect Alzheimer's disease
16	Shi et al. [50]	Auto-encoder	AD/HC Classification: Using a stacked deep polynomial network and a support vector machine classifier on the top layer, we can analyse MRI and PET scans.
17	Siqi et al. [84]	Auto-encoder	AD/HC Classification: A softmax regression layer and sparse auto-encoders are part of the deep learning architecture used to categorise AD.
18	Wachinger et al. [63]	CNN Models	Anatomical Segmentation: use of a deep convolutional neural network to segregate neuroanatomy from T1-W MRI scans.
19	Milletari et al. [33]	Hough-CNN Models	Anatomical Segmentation: Utilizing Hough voting, we may get a mapping from CNN features to comprehensive patch segmentations.
20	Syed et al. [67]	CNN Models	Tissue Segmentation: ensemble learning using a late fusion approach for several sensory modalities.

analyzing MRI scans, since it provides a voxel-scale representation of regional gray and white matter (gm and wm) volume. Reflecting GM irregularity patterns matched to the clinical stage of disease, this technique has been applied to the treatment of both AD and MCI, and it is predict the probability of MCI progressing to AD. To evaluate the occurrence of microscopic tissue degradation in AD, different MRI techniques are commonly used because difficulty in determining the presence and extent of WM atrophy. The updated diagnostic criteria for MCI and AD emphasize the use of CSF and structural imaging markers. Hippocampal and lateral ventricle volumes, as well as CSF Markers (Ab42, t-tau, and p-tau), can be utilized to differentiate between HC and MCI. The combination can also be helpful in identifying moderate cognitive impairment and Alzheimer's disease in the elderly. Recently, advancements in deep learning technologies have allowed for more accurate automatic hippocampal segmentation and classification in Alzheimer's disease [91]. To solve the classification problem, we build a deep CNN model to study hippocampal segmentation data and learn the characteristics of the 3D patches we extracted. Hippocampal segmentation and clinical score regression using an MRI-based multi-tasking deep learning (MDL) approach are shown. Using PET, researchers have shown that biomarkers

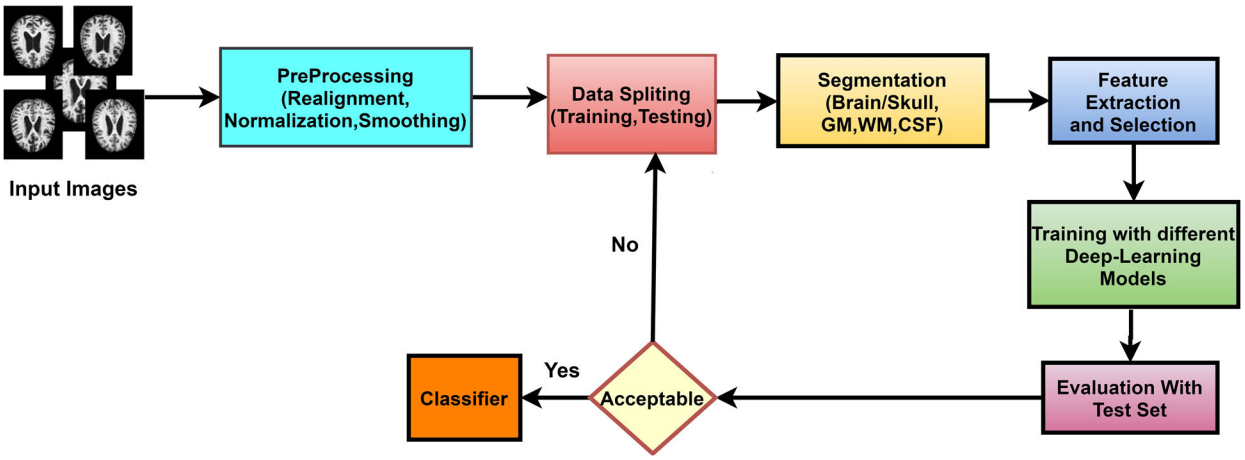

FIGURE 3. General block diagram of AD diagnosis.

based on deep CNNs have a robust correlation with cognitive decline in the road.

The above diagram depicts a schematic representation of the typical steps taken in a conventional approach to diagnosing Alzheimer's disease. To begin, MRI slices must be obtained. The next step is data preparation via pre-processing, wherein extraneous information is discarded and the data are reorganized for better readability. Data from brain MRI scans is pre-processed, and then deep learning segmentation employed to extract the useful features. The patient's body size, for example, is a crucial factor. The classifier makes use of a deep learning architecture to create a prediction about the output based on the input parameters, which include the mean intensity, the standard deviation, and the location of the center of mass.

V. EVALUATION CRITERIA FOR BRAIN MRI SEGMENTATION

When analyzing medical images,comparing the results of various segmentation methods can be difficult. A comparison of segmented output against ground truth data is necessary for validation. The amount of ground truth data available for evaluating gathered data in humans is inadequate in a real-world setting. As a result, following the MRI acquisition, specialists manually produce ground truth data of patients. Manual segmentation is error-prone, extremely subjective, and difficult to recreate, thus this validation must be carefully addressed even though it is to validate the genuine patient's MRI data (even by the same expert). Many software simulations and phantom-based alternative validation approaches have been offered to get over these restrictions. Software simulations produce fabricated image that is meant to represent the method of actual acquisition. Also, imaging artifacts can be regulated and analyzed apart from the various acquisition parameters, and the ground truth is known. This validation method is more flexible and straightforward to implement [92], [93], [94], [95]. The simulated images can only be approximations of the real ones because the software simulation approach does not take into account all the aspects that could affect genuine picture collection.To generate more realistic phantom images it can be achieved with software models, MRI scanners are used. Phantom images, however, are rigid and cannot be adjusted. In addition to this conducting software simulations and obtaining phantom imaging findings takes a lot of time and money. Several measures of similarity were employed to compare the accuracy of the predicted brain MRI to the actual image [96], [97], [98]. In the works that were published, researchers used a wide variety of metrics to assess the efficacy of their methods. Most of these metrics were derived from a comparison of automatic segmentation results to ground truth, and they were primarily computed using four fundamental concepts.

- TP (True Positive). An outcome for which the model correctly predicted a positive class is a true positive.
- TN (True Negative). A true negative is an outcome for which the negative class is correctly predicted by the model.
- FP (False Positive). A false positive is an outcome in which the positive class is predicted incorrectly by the model.
- FN (False Negative). A false negative is an outcome in which the negative class is predicted incorrectly by the model.

A. SOME OF THE EVALUATION METRICS ARE

1) DICE COEFFICIENT

The Dice coefficient measures how well a projected segmentation matches up with the corresponding ground truth at the pixel level. Dice coefficient can be determined by dividing the sum of pixels in both images by square root of the overlap area plus one. The formula is given by

$$\text{Dice}(X, Y) = \frac{2 * |X \cap Y|}{|X| + |Y|} \tag{1}$$

where X is the predicted set of pixels, Y is the ground truth. When both X and Y are empty, the Dice coefficient is said to be 1.

2) JACCARD INDEX

When comparing the statistical similarity of two samples, the Jaccard index (also known as the Jaccard similarity coefficient) is used. Across finite sample sets, similarities are highlighted by the formal definition of the measurement as the size of the intersection divided by the size of the sample set union. The Mathematical formula can be represented as:

$$J(X, Y) = \frac{|X \cap Y|}{|X| + |Y| - |X \cap Y|} \tag{2}$$

3) POSITIVE PREDICTED VALUE

The ratio of correctly identified (True Positive) positive samples to the total number of correctly or erroneously classified positive samples is known as the positive predicted value, or PPV. It is another name for ''Precision.''. It is expressed as

$$PPV = \frac{TP}{TP + FP} \tag{3}$$

where TP -True Positive, FP-False Positive

4) TRUE POSITIVE RATE

The recall is determined as the proportion of Positive samples that were correctly identified as Positive to all Positive samples. The recall evaluates the model's capacity to recognize positive samples. It is also called as Recall.

$$TPR = \frac{TP}{TP + FN} \tag{4}$$

5) LESION TRUE POSITIVE RATE

The LTPR is calculated by dividing the number of positive lesions by the sum of the positive and negative lesions.

$$LTPR = \frac{TP}{TP + FN} \tag{5}$$

6) LESION FALSE POSITIVE RATE

For every particular lesion, the LFPR measures the proportion of false positives relative to the total number of false positives and true negatives.

$$LFPR = \frac{FP}{FP + TN} \tag{6}$$

7) ABSOLUTE VOLUME DIFFERENCE (AVD)

Absolute volume difference (AVD) measures the gap in dimensions between two areas relative to a common reference volume.

$$AVD(G, S) = \frac{|V_s - V_g|}{V_g} \tag{7}$$

where V_s is the volume of segmentation results and V_g represents the volume of ground truth.

TABLE 4. Description of mathematical equations for evaluation metrics.

Metrics of Segmentation	Mathematical Description
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$
Negative Predictive Rate	$\frac{TN}{TN + FN}$
Dice Similarity Coefficient	$\frac{2\,TP}{2\,TP + FP + FN}$
Volume Difference Rate	$\frac{\lvert FP - FN \rvert}{TP + FN}$
Lesion True Positive Rate	$\frac{TP}{TP + FN}$
Lesion False Positive rate	$\frac{FP}{FP + TN}$
Specificity	$\frac{TN}{TN + FP}$
F1 Score	$\frac{2\,TP}{2\,TP + FP + FN}$
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
Balanced Accuracy	$\frac{(Sensitivity + Specificity)}{2}$

Average Symmetric Surface Distance: The sum of all the distances from points on the machine segmented region's boundary to the ground truth's boundary and vice versa is called the ASSD. Table 4 provides a summary of the formulas for determining the TP, FP, and FN rates at the voxel and lesion levels, and the validation metrics for brain segmentation.

VI. DISCUSSIONS AND FUTURE DIRECTIONS

The relative performance of the various architectures is shown in Table 5. A high level of generalisation can be attained using trained hyper-parameters and architecture layers that have been optimized for performance. The results of the evaluated paper's DSC and JI values for segmenting brain structure using deep learning algorithms are summarized in this section. Wachinger et al Dice Similarity Coefficient (DSC) performs better on the MICCAI dataset compared to the other contenders, as shown in Table 5. This is due to the use of Cartesian and spectral coordinates to provide precise location information within the brain, which significantly increased the classifier's ability to distinguish between classes. [101] Dolz et al. successfully used a 3D fully convolution network design to map sub-cortical regions in brain MRI, outperforming state-of-the-art DSC methods on IBSR datasets. However, it was observed that valid comparisons of these results could not be made due to the diverse datasets and experimental circumstances employed in these investigations. In order to make reliable comparisons, it was essential to have a universal architecture that faithfully represented the underlying input image without resorting to excessive overfitting. Extraction of imaging characteristics, development of classification models, and pre-determination of ROIs were the three mainstays of MRI-based computer-aided diagnosis

TABLE 5. Summary of the results for brain structure segmentation utilising the current methodologies using deep learning algorithms. Unit: % (y: DSC, ∗: JI).

S.No.	Authors	MICCAI			OASIS			Clinical/IBSR		
		DSC&JI			DSC &JI			DSC&JI		
		csf	gm	wm	csf	gm	wm	csf	gm	wm
1	Wachinger et al. [63]	**90.6**	**90.6**	**90.6**	-	-	-	-	-	-
2	Milletari et al. [33]	-	-	-	-	-	-	**77.0**	**77.0**	**77.0**
3	Shakeri et al. [66]	-	-	-	-	-	-	**82.4**	**82.4**	**82.4**
4	Alotaibi et al. [99]	-	-	-	-	-	-	**94.3**	**90.2**	**91.4**
5	Bao et al. [65]	-	-	-	-	-	-	**82.2**	**85.0**	**82.2**
6	Patil et al.[68]	**72.5**	**72.5**	**72.5**	-	-	-	-	-	-
7	Zhang et al. [18]	-	-	-	-	-	-	**83.5**	**85.2**	**86.4**
8	Moeskops et al. [28]	**73.5**	**73.5**	**73.5**	-	-	-	-	-	-
9	Syed et al. [67]	-	-	-	**72.5**	**72.5**	**72.5**	-	-	-
10	Khagi et al. [91]	-	-	-	**72.2**	**73.0**	**74.6**	-	-	-
11	Perri et al. [100]	**74.3**	**74.3**	**74.3**	-	-	-	**84.4**	**84.4**	**84.4**
12	Dolz et al. [86]	-	-	-	-	-	-	**90.0**	**90.0**	**90.0**
13	Cheng et al. [5]	-	-	-	-	-	-	**93.6**	**94.8**	**97.5**
14	Korolev et al. [94]	-	-	-	**71.6**	**71.6**	**71.6**	-	-	-
15	Siqi et al. [84]	-	-	-	-	-	-	**81.4**	**82.1**	**81.6**
16	Hosseini et al. [93]	**70.5**	**70.5**	**70.5**	-	-	-	-	-	-
17	Shi et al. [50]	-	-	-	-	-	-	**75.3**	**75.3**	**75.3**
18	Pulkit et al. [89]	-	-	-	-	-	-	**82.4**	**81.3**	**80.6**
19	Ruoxuan et al. [104]	-	-	-	**72.5**	**72.5**	**72.2**	-	-	-
20	Khvostikov et al. [105]	-	-	-	-	-	-	**84.3**	**82.3**	**82.3**

approaches used in earlier the research on the identification of AD-related brain diseases. Depending on the size of the pre-defined regions of interest (ROIs) in MR images, these feature extraction and classifier construction methods can be further classified as voxel-level, region-level, or patch-level morphological pattern analysis [102]. In order to classify Alzheimer's disease, voxel-based approaches look for microstructures inside individual voxels that are linked to the disease. However, the region-based techniques use quantitative information extracted from previously segmented brain areas to build classifiers that can distinguish between patients and healthy controls [103] The statistical statements are summarized to encourage readers and researchers to use current deep learning methodologies to analyze brain structure. The fact that these studies used various datasets and experimental setups means that these results cannot be accurately compared.

To improve their ability to detect subtle changes in the brain, patch-based techniques use MRI feature representations on a scale in between the voxel-level and the region-level to train classifiers that are sensitive to localised areas of change. The below Table 6 shows an overview of the current best practices for using MRI data to diagnose Alzheimer's disease (AD vs. HC) and forecasts whether someone with MCI will worsen into severe dementia (pMCI vs. sMCI). Lian et al. compared studies that solely used ADNI-1 MRI datasets with those who have tried out the procedure on bigger cohorts, in this case 1,457 people taken from both the ADNI-1 and ADNI-2 studies. The success rate of the authors in forecasting pMCI conversions to sMCI is equivalent to that of the field since they use a more stringent evaluation technique (i.e., separate training and testing sets). The ADNI datasets were used to train a three-stacked 3D convolutional autoencoder network, Improved generality of features capturing the AD biomarkers allows our results on AD vs. HC classification to outperform state-of-the-art methods. A 3D convolutional neural network(CNN) deeper layers use the recovered features as biomarkers for AD. The authors of a paper with similar findings recommended combining AlexNet with data permutation to make better use of the spatial correlation information provided by CNN's localized convolution kernels and AlexNet's more informative slice selection during training. This approach outperformed the competition in AD classification. An overview of the current best practices for using MRI data to diagnose Alzheimer's disease (AD vs. HC) and forecast whether someone with MCI will progress to severe dementia (pMCI vs. sMCI). The top outcomes for each statistic are displayed in bold.

One of the recommended techniques of practice is to evaluate the model using a variety of datasets. Multiple public

TABLE 6. An overview of the current best practises for using MRI data to diagnose Alzheimer's disease (AD vs. HC) and forecast whether someone with MCI will progress to severe dementia (pMCI vs. sMCI). The top outcomes for each statistic are displayed in bold.

S.No.	Authors	Subjects	AD vs HC				pMCI vs sMCI			
			ACC	SEN	SPE	AUC	ACC	SEN	SPE	AUC
1	Feng et al. [51]	398 subjects(AD,MCI,HC)	0.93	0.98	0.93	0.97	-	-	-	-
2	Lee et al. [53]	842 subjects(AD,MCI,HC)	0.99	0.97	0.98	-	-	-	-	-
3	Payan et al. [82]	757 Subjects(AD,MCI,HC)	0.96	-	-	-	-	-	-	-
4	Pulkit et al. [89]	361HC+409sMCI+217pMCI	-	-	-	-	0.76	0.74	0.78	-
5	Andres et al. [58]	69HC+70AD	0.92	0.87	0.95	0.96	-	-	-	-
6	Lian et al. [49]	430HC+465sMCI+205pMCI +358AD	0.91	0.83	0.98	0.96	0.82	0.54	0.86	0.79
7	Korolev et al. [94]	62HC+77sMCI+43pMCI+50 AD	0.82	-	-	0.88	0.53	-	-	0.54
8	Siqi et al. [84]	207HC+180AD	0.78	0.82	0.88	0.79	-	-	-	-
9	Ruoxuan et al. [104]	814 subjects(AD,MCI,HC)	0.91	0.85	0.91	0.93	0.74	0.68	0.74	0.75
10	Liu et al. [75]	399 subjects(AD,MCI,HC)	0.94	0.91	0.94	0.96	-	-	-	-
11	Hosseini et al. [93]	72HC+71AD	0.98	-	0.97	-	-	-	-	-
12	Shi et al. [50]	54NC+56 sMCI+43pMCI+51AD	0.94	0.93	0.95	0.94	0.73	0.62	0.86	0.71
13	L. Vermunt et al. [98]	227HC+188AD	0.84	0.83	0.86	-	-	-	-	-
15	Khvostikov et al. [105]	59HC+48AD	0.84	0.87	0.92	-	-	-	-	-
16	Liu et al. [60]	102HC+128sMCI+76pMCI+ 93AD	0.93	0.94	0.96	0.98	0.73	0.38	0.92	0.74
17	Pengcheng et al. [61]	757 Subjects(AD,MCI,HC)	0.87	0.90	0.91	-	-	-	-	-
18	Moeskops et al. [28]	455 subjects(AD,MCI,HC)	0.84	0.87	0.91	0.89	0.75	0.68	0.85	0.81
19	Dubois et al. [85]	230HC+168AD	0.87	0.82	0.84	-	-	-	-	-
20	Jiong et al. [87]	789 subjects(AD,MCI,HC)	0.94	0.86	0.91	0.92	0.85	0.89	0.89	0.91

datasets have been used to validate the models in several recent publications. These methods can be applied to data collected from a wide range of imaging devices, including MRI scanners, in order to fortify the model [106]. Training deep CNNs with low-resolution MRI is challenging because of the time pressure associated with making accurate predictions. Developing a method with faster convolution makes training such networks viable. However, while FFT algorithms and rapid matrix multiplication techniques have helped raise the processing speed of CNNs, versions of SGD and their parallelized implementations can help improve the efficiency of deep CNN training procedures. New algorithms that need few or no hyper-parameters are becoming available, which should boost the performance of deep CNNs using this high optimization strategy.The wide availability of GPU has been an important factor in deep learning's sudden rise. Graphics processing units (GPUs) are capable of parallel computation and perform with more concurrent execution threads (CPUs). It's common knowledge at this point that graphics processing units (GPUs) can do deep learning workloads 10-30 times faster than regular computers. Open-source software has also played a role in deep learning's spectacular rise to fame.

Current research has proven that deep learning offers a viable alternative to traditional approaches to analysing brain MRI by overcoming limitations of previous state-of-the-art machine learning methods. Computer-aided interpretation of brain MRIs has proven challenging for several reasons. Some of these issues include the scans' convoluted composition and inconsistent appearance, unstable image capture, non-standardized MR scales, varying imaging methodologies, and the presence of disease. Therefore, it is preferable to use more generic approaches based on deep learning to manage these risks. Although there is much to be gained from using deep learning techniques for analyzing brain MRIs, there are still significant limitations. Comparable results are not produced on small datasets, but on large datasets, it outperforms ImageNet. Numerous analyses showed that when training datasets grow, performance improvements are seen across the board with most approaches. There has been a rise in the need for massive datasets on which deep learning models can be trained. Large-scale brain MRI data collection

is complicated by concerns over patient privacy and security. Therefore, it is essential to create a deep learning strategy utilizing numerous brain MRI datasets. One approach to this issue is to supplement the dataset with additional information. To do this, deep learning algorithms require a process known as data augmentation, which includes randomly changing the original data through operations including translation, flipping, deformation, and rotation. A few studies have demonstrated the usefulness of data augmentation for reducing overfitting by adding random variation to the original data. Further, supervised learning methods build prediction models by analysing a large set of training instances, where each example is labeled with information about the actual outcome of the experiment. While the state-of-the-art has advanced significantly, the high cost of data labelling makes it difficult to collect robust supervisory information such as fully ground truth labels in many applications. When large datasets labelled with ground truth are unavailable for brain MRI, weakly supervised deep learning methods can be used to train on small dummy datasets. Deep weakly-supervised learning models, which do not require a large number of ground truth annotations, can be used to identify diseases in brain MRIs. Brain MRI scans can be quickly and accurately classified using these models. This is accomplished by generating pixel-wise localization scores that are used to pinpoint specific regions of interest (ROIs). Using transfer learning, researchers in the field of brain imaging can share successful deep learning models that have been trained on both normal and abnormal MRI scans of the brain. This would allow for less laborious improvements to these models' generalisation across datasets.

VII. CONCLUSION

The majority of people believe that Alzheimer's disease (AD) is a degenerative condition that gradually destroys neurons in the brain. The medical industry has recently experienced great success with a Deep Learning strategy for the categorization of AD, which does not require any manual feature extraction techniques, in contrast to the conventional machine learning approach. Despite the widespread use of deep learning techniques, current research is lack of reliable and a generalized approach for quantitatively analysing brain MRI scans. In this study, we look at research on the use of MRI to categorise brain anatomy and identify AD. We also discussed about the advantages of segmenting the brain structurally for AD classification. Segmentation of brain MRI scans helps in their interpretation and categorization for diseases like Alzheimer's. Segmenting brain MRIs is difficult because of the images low contrast, partial volume effect, noisy backgrounds and ranging in complexity, have been offered as potential solutions to these problems. In the last few decades, these strategies have produced increasingly reliable outcomes. The ability of deep learning algorithms to automatically learn and make judgments has devoted interest in their application to brain anatomical segmentation and AD classification.

REFERENCES

[1] Z. Huang, X. Zhu, M. Ding, and X. Zhang, "Medical image classification using a light-weighted hybrid neural network based on PCANet and DenseNet," *IEEE Access*, vol. 8, pp. 24697–24712, 2020.

[2] R. K. Mishra, S. Urolagin, J. A. A. Jothi, A. S. Neogi, and N. Nawaz, "Deep learning-based sentiment analysis and topic modeling on tourism during COVID-19 pandemic," *Frontiers Comput. Sci.*, vol. 3, pp. 1–10, Nov. 2021.

[3] Z. Pei, Y. Gou, M. Ma, M. Guo, C. Leng, Y. Chen, and J. Li, "Alzheimer's disease diagnosis based on long-range dependency mechanism using convolutional neural network," *Multimedia Tools Appl.*, vol. 81, no. 25, pp. 36053–36068, Oct. 2022.

[4] R. Gautam and M. Sharma, "Prevalence and diagnosis of neurological disorders using different deep learning techniques: A meta-analysis," *J. Med. Syst.*, vol. 44, no. 2, pp. 1–24, Feb. 2020, doi: 10.1007/s10916-019-1519-7.

[5] J.-Z. Cheng, D. Ni, Y.-H. Chou, J. Qin, C.-M. Tiu, Y.-C. Chang, C.-S. Huang, D. Shen, and C.-M. Chen, "Computer-aided diagnosis with deep learning architecture: Applications to breast lesions in U.S. images and pulmonary nodules in CT scans," *Sci. Rep.*, vol. 6, no. 1, p. 2445, Apr. 2016.

[6] U. R. Acharya, S. L. Fernandes, J. E. WeiKoh, E. J. Ciaccio, M. K. M. Fabell, U. J. Tanik, V. Rajinikanth, and C. H. Yeong, "Automated detection of Alzheimer's disease using brain MRI images—A study with various feature extraction techniques," *J. Med. Syst.*, vol. 43, no. 9, pp. 1–10, Aug. 2019, doi: 10.1007/s10916-019-1428-9.

[7] D. S. Marcus, T. H. Wang, J. Parker, J. G. Csernansky, J. C. Morris, and R. L. Buckner, "Open access series of imaging studies (OASIS): Cross-sectional MRI data in young, middle aged, nondemented, and demented older adults," *J. Cognit. Neurosci.*, vol. 19, no. 9, pp. 1498–1507, Sep. 2007.

[8] C. R. Jack, M. A. Bernstein, N. C. Fox, P. Thompson, G. Alexander, D. Harvey, and B. Borowski, "The Alzheimer's disease neuroimaging initiative (ADNI): MRI methods," *J. Magn. Reson. Imag.*, vol. 27, pp. 685–691, Jan. 2008.

[9] M. S. N. Raju and B. S. Rao, "Colorectal multi-class image classification using deep learning models," *Bull. Electr. Eng. Informat.*, vol. 11, no. 1, pp. 195–200, Feb. 2022, doi: 10.11591/eei.v11i1.3299.

[10] M. Aparna and B. Srinivasa Rao, "Xception-FractalNet: Hybrid deep learning based multi-class classification of Alzheimer's disease," *Comput., Mater. Continua*, vol. 74, no. 3, pp. 6909–6932, 2023.

[11] N. An, H. Ding, J. Yang, R. Au, and T. F. A. Ang, "Deep ensemble learning for Alzheimer's disease classification," *J. Biomed. Informat.*, vol. 105, May 2020, Art. no. 103411, doi: 10.1016/j.jbi.2020.103411.

[12] E. H. Rubin, M. Storandt, J. P. Miller, D. A. Kinscherf, E. A. Grant, J. C. Morris, and L. Berg, "A prospective study of cognitive function and onset of dementia in cognitively healthy elders," *Arch. Neurol.*, vol. 55, pp. 395–401, Jan. 1998.

[13] N. Duta and M. Sonka, "Segmentation and interpretation of MR brain images. An improved active shape model," *IEEE Trans. Med. Imag.*, vol. 17, no. 6, pp. 1049–1062, Dec. 1998.

[14] J. Rogowska, "Overview and fundamentals of medical image segmentation," in *Handbook of Medical Imaging, Processing and Analysis*. Amsterdam, The Netherlands: Elsevier, 2000.

[15] U. Vovk, F. Pernus, and B. Likar, "A review of methods for correction of intensity inhomogeneity in MRI," *IEEE Trans. Med. Imag.*, vol. 26, no. 3, pp. 405–421, Mar. 2007.

[16] P. Coupe, P. Yger, S. Prima, P. Hellier, C. Kervrann, and C. Barillot, "An optimized blockwise nonlocal means denoising filter for 3-D magnetic resonance images," *IEEE Trans. Med. Imag.*, vol. 27, no. 4, pp. 425–441, Apr. 2008.

[17] K. Arno, J. Andersson, B. A. Ardekani, J. Ashburner, B. Avants, M.-C. Chiang, and G. E. Christensen, "Evaluation of 14 nonlinear deformation algorithms applied to human brain MRI registration," *Neuroimage*, vol. 46, pp. 786–802, Jan. 2009.

[18] Y. Zhang, Z. Dong, L. Wu, and S. Wang, "A hybrid method for MRI brain image classification," *Expert Syst. Appl.*, vol. 38, no. 8, pp. 10049–10053, Aug. 2011.

[19] S. Neffati, K. B. Abdellafou, I. Jaffel, O. Taouali, and K. Bouzrara, "An improved machine learning technique based on downsized KPCA for Alzheimer's disease classification," *Int. J. Imag. Syst. Technol.*, vol. 29, no. 2, pp. 121–131, Jun. 2019.

[20] S. Saraswathi, B. S. Mahanand, A. Kloczkowski, S. Suresh, and N. Sundararajan, "Detection of onset of Alzheimer's disease from MRI images using a GA-ELM-PSO classifier," in *Proc. 4th Int. Workshop Comput. Intell. Med. Imag. (CIMI)*, Apr. 2013, pp. 42–48.

[21] Y. Ding, C. Zhang, T. Lan, Z. Qin, X. Zhang, and W. Wang, "Classification of Alzheimer's disease based on the combination of morphometric feature and texture feature," in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, Washington, DC, USA, Nov. 2015, pp. 409–412.

[22] D. Jha, J.-I. Kim, and G.-R. Kwon, "Diagnosis of Alzheimer's disease using dual-tree complex wavelet transform, PCA, and feed-forward neural network," *J. Healthcare Eng.*, vol. 2017, pp. 1–13, Jan. 2017.

[23] Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel, "Backpropagation applied to handwritten zip code recognition," *Neural Comput.*, vol. 1, no. 4, pp. 541–551, Dec. 1989.

[24] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, "ImageNet: A large-scale hierarchical image database," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Miami, FL, USA, Jun. 2009, pp. 248–255.

[25] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in *Proc. Adv. Neural Inf. Process. Syst.*, Stateline, NV, USA, Dec. 2012, pp. 1097–1105.

[26] W. Zhang, R. Li, H. Deng, L. Wang, W. Lin, S. Ji, and D. Shen, "Deep convolutional neural networks for multi-modality isointense infant brain image segmentation," *NeuroImage*, vol. 108, pp. 214–224, Mar. 2015.

[27] R. Brookmeyer, E. Johnson, K. Ziegler-Graham, and H. M. Arrighi, "Forecasting the global burden of Alzheimer's disease," *Alzheimer's Dementia*, vol. 3, pp. 186–191, Jan. 2007.

[28] P. Moeskops, M. J. N. L. Benders, S. M. Chiţă, K. J. Kersbergen, F. Groenendaal, L. S. de Vries, M. A. Viergever, and I. Išgum, "Automatic segmentation of MR brain images of preterm infants using supervised classification," *NeuroImage*, vol. 118, pp. 628–641, Sep. 2015.

[29] P. Janjal, S. Shinde, G. Pawar, R. Rashinkar, and S. Rokade, "Health care diagnosis using transfer learning," *Health Care*, vol. 7, no. 19, pp. 1–10, 2020.

[30] T. Brosch, L. Y. W. Tang, Y. Yoo, D. K. B. Li, A. Traboulsee, and R. Tam, "Deep 3D convolutional encoder networks with shortcuts for multiscale feature integration applied to multiple sclerosis lesion segmentation," *IEEE Trans. Med. Imag.*, vol. 35, no. 5, pp. 1229–1239, May 2016.

[31] R. Mendoza-Léon, J. Puentes, L. F. Uriza, and M. H. Hoyos, "Single-slice Alzheimer's disease classification and disease regional analysis with supervised switching autoencoders," *Comput. Biol. Med.*, vol. 116, Jan. 2020, Art. no. 103527, doi: 10.1016/j.compbiomed.2019.103527.

[32] Z. Kong, J. Luo, S. Xu, and T. Li, "Automatical and accurate segmentation of cerebral tissues in fMRI dataset with combination of age processing and deep learning," *Proc. SPIE*, vol. 10485, pp. 24–30, Jan. 2018.

[33] F. Milletari, S.-A. Ahmadi, C. Kroll, A. Plate, V. Rozanski, J. Maiostre, J. Levin, O. Dietrich, B. Ertl-Wagner, K. Bötzel, and N. Navab, "Hough-CNN: Deep learning for segmentation of deep brain regions in MRI and ultrasound," *Comput. Vis. Image Understand.*, vol. 164, pp. 92–102, Nov. 2017.

[34] M. Aparna and B. S. Rao, "A novel automated deep learning approach for Alzheimer's disease classification," *IAES Int. J. Artif. Intell. (IJ-AI*, vol. 12, no. 1, p. 451, Mar. 2023.

[35] K. Kamnitsas, C. Ledig, V. F. J. Newcombe, J. P. Simpson, A. D. Kane, D. K. Menon, D. Rueckert, and B. Glocker, "Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation," *Med. Image Anal.*, vol. 36, pp. 61–78, Feb. 2017.

[36] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain tumor segmentation using convolutional neural networks in MRI images," *IEEE Trans. Med. Imag.*, vol. 35, no. 5, pp. 1240–1251, May 2016.

[37] M. Havaei, A. Davy, D. Warde-Farley, A. Biard, A. Courville, Y. Bengio, C. Pal, P.-M. Jodoin, and H. Larochelle, "Brain tumor segmentation with deep neural networks," *Med. Image Anal.*, vol. 35, pp. 18–31, Jan. 2017.

[38] Q. Dou, H. Chen, L. Yu, L. Zhao, J. Qin, D. Wang, V. C. Mok, L. Shi, and P. Heng, "Automatic detection of cerebral microbleeds from MR images via 3D convolutional neural networks," *IEEE Trans. Med. Imag.*, vol. 35, no. 5, pp. 1182–1195, May 2016.

[39] H. Chen, Q. Dou, L. Yu, J. Qin, and P.-A. Heng, "VoxResNet: Deep voxelwise residual networks for brain segmentation from 3D MR images," *NeuroImage*, vol. 170, pp. 446–455, Apr. 2018.

[40] M. Lyksborg, O. Puonti, M. Agn, and R. Larsen, "An ensemble of 2D convolutional neural networks for tumor segmentation," in *Proc. Scand. Conf. Image Anal.* vol. 9127, 2015, pp. 201–211.

[41] X. Chen and X. Lin, "Big data deep learning: Challenges and perspectives," *IEEE Access*, vol. 2, pp. 514–525, 2014.

[42] M. Z. Alom, T. M. Taha, C. Yakopcic, S. Westberg, P. Sidike, M. S. Nasrin, M. Hasan, B. C. Van Essen, A. A. S. Awwal, and V. K. Asari, "A state-of-the-art survey on deep learning theory and architectures," *Electronics*, vol. 8, no. 3, p. 292, Mar. 2019.

[43] V. Srhoj-Egekher, M. J. N. L. Benders, M. A. Viergever, and I. Išgum, "Automatic neonatal brain tissue segmentation with MRI," *Proc. SPIE*, vol. 8669, Jan. 2013, Art. no. 86691K.

[44] P. Anbeek, I. Išgum, B. J. M. van Kooij, C. P. Mol, K. J. Kersbergen, F. Groenendaal, M. A. Viergever, L. S. de Vries, and M. J. N. L. Benders, "Automatic segmentation of eight tissue classes in neonatal brain MRI," *PLoS ONE*, vol. 8, no. 12, Dec. 2013, Art. no. e81895.

[45] H. Vrooman, F. Van der Lijn, and W. Niessen, "Auto-kNN: Brain tissue segmentation using automatically trained k-nearest-neighbor classification," *MIDAS J.*, vol. 37, pp. 71–81, Oct. 2013.

[46] A. Makropoulos, I. S. Gousias, C. Ledig, P. Aljabar, A. Serag, J. V. Hajnal, A. D. Edwards, S. J. Counsell, and D. Rueckert, "Automatic whole brain MRI segmentation of the developing neonatal brain," *IEEE Trans. Med. Imag.*, vol. 33, no. 9, pp. 1818–1831, Sep. 2014.

[47] G. E. Christensen, R. D. Rabbitt, and M. I. Miller, "Deformable templates using large deformation kinematics," *IEEE Trans. Image Process.*, vol. 5, no. 10, pp. 1435–1447, Oct. 1996.

[48] C. Davatzikos and J. L. Prince, "Brain image registration based on curve mapping," in *Proc. IEEE Workshop Biomed. Image Anal.*, Seattle, WA, USA, Jun. 1994, pp. 245–254.

[49] C. Lian, M. Liu, J. Zhang, and D. Shen, "Hierarchical fully convolutional network for joint atrophy localization and Alzheimer's disease diagnosis using structural MRI," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 42, no. 4, pp. 880–893, Apr. 2020.

[50] J. Shi, X. Zheng, Y. Li, Q. Zhang, and S. Ying, "Multimodal neuroimaging feature learning with multimodal stacked deep polynomial networks for diagnosis of Alzheimer's disease," *IEEE J. Biomed. Health Informat.*, vol. 22, no. 1, pp. 173–183, Jan. 2018.

[51] C. Feng, A. Elazab, P. Yang, T. Wang, F. Zhou, H. Hu, X. Xiao, and B. Lei, "Deep learning framework for Alzheimer's disease diagnosis via 3D-CNN and FSBi-LSTM," *IEEE Access*, vol. 7, pp. 63605–63618, 2019.

[52] Y. Shi, H. Suk, Y. Gao, S. Lee, and D. Shen, "Leveraging coupled interaction for multimodal Alzheimer's disease diagnosis," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 1, pp. 186–200, Jan. 2020.

[53] N. M. Khan, N. Abraham, and M. Hon, "Transfer learning with intelligent training data selection for prediction of Alzheimer's disease," *IEEE Access*, vol. 7, pp. 72726–72735, 2019.

[54] K. Aderghal, J. Benois-Pineau, K. Afdel, and C. Gwenaëlle, "FuseMe: Classification of sMRI images by fusion of deep CNNs in 2D+ε projections," in *Proc. 15th Int. Workshop Content-Based Multimedia Indexing*, Florence, Italy, Jun. 2017, pp. 19–21.

[55] J. Islam and Y. Zhang, "Brain MRI analysis for Alzheimer's disease diagnosis using an ensemble system of deep convolutional neural networks," *Brain Informat.*, vol. 5, no. 2, pp. 1–12, Dec. 2018.

[56] L. Wang, Y. Gao, F. Shi, G. Li, J. H. Gilmore, W. Lin, and D. Shen, "LINKS: Learning-based multi-source integration framework for segmentation of infant brain images," *Neuro Image*, vol. 108, pp. 734–746, Jan. 2014.

[57] J. Qiao, Y. Lv, C. Cao, Z. Wang, and A. Li, "Multivariate deep learning classification of Alzheimer's disease based on hierarchical partner matching independent component analysis," *Frontiers Aging Neurosci.*, vol. 10, pp. 1–10, Dec. 2018, doi: 10.3389/fnagi.2018.00417.

[58] A. Ortiz, J. Munilla, J. M. Górriz, and J. Ramírez, "Ensembles of deep learning architectures for the early diagnosis of the Alzheimer's disease," *Int. J. Neural Syst.*, vol. 26, no. 7, Nov. 2016, Art. no. 1650025.

[59] Q. Yang, X. Li, X. Ding, F. Xu, and Z. Ling, "Deep learning-based speech analysis for Alzheimer's disease detection: A literature review," *Alzheimer's Res. Therapy*, vol. 14, no. 1, pp. 1–16, 2022.

[60] S. Liu, A. V. Masurkar, H. Rusinek, J. Chen, B. Zhang, W. Zhu, C. Fernandez-Granda, and N. Razavian, "Generalizable deep learning model for early Alzheimer's disease detection from structural MRIs," *Sci. Rep.*, vol. 12, no. 1, p. 17106, Oct. 2022.

[61] P. Li, Y. Zhao, Y. Liu, Q. Chen, F. Liu, and C. Gao, "Temporally consistent segmentation of brain tissue from longitudinal MR data," *IEEE Access*, vol. 8, pp. 3285–3293, 2020.

[62] J. Bernal, K. Kushibar, M. Cabezas, S. Valverde, A. Oliver, and X. Lladó, "Quantitative analysis of patch-based fully convolutional neural networks for tissue segmentation on brain magnetic resonance imaging," *IEEE Access*, vol. 7, pp. 89986–90002, 2019.

[63] C. Wachinger, M. Reuter, and T. Klein, "DeepNAT: Deep convolutional neural network for segmenting neuroanatomy," *NeuroImage*, vol. 170, pp. 434–445, Apr. 2018.

[64] R. Mehta, A. Majumdar, and J. Sivaswamy, "BrainSegNet: A convolutional neural network architecture for automated segmentation of human brain structures," *J. Med. Imag.*, vol. 4, no. 2, Apr. 2017, Art. no. 024003.

[65] S. Bao and A. Chung, "Multi-scale structured CNN with label consistency for brain MR image segmentation," *Comput. Methods Biomechanics Biomed. Eng., Imag. Vis.*, vol. 6, pp. 1–5, Jan. 2016.

[66] M. Shakeri, S. Tsogkas, E. Ferrante, S. Lippe, S. Kadoury, N. Paragios, and I. Kokkinos, "Sub-cortical brain structure segmentation using F-CNN's," in *Proc. IEEE 13th Int. Symp. Biomed. Imag. (ISBI)*, Prague, Czech Republic, Apr. 2016, pp. 13–16.

[67] Z. S. Syed, M. S. S. Syed, M. Lech, and E. Pirogova, "Automated recognition of Alzheimer's dementia using bag-of-deep-features and model ensembling," *IEEE Access*, vol. 9, pp. 88377–88390, 2021, doi: 10.1109/ACCESS.2021.3090321.

[68] V. Patil, M. Madgi, and A. Kiran, "Early prediction of Alzheimer's disease using convolutional neural network: A review," *Egyptian J. Neurol., Psychiatry Neurosurgery*, vol. 58, no. 1, pp. 1–10, 2022.

[69] O. T. Carmichael, H. A. Aizenstein, S. W. Davis, J. T. Becker, P. M. Thompson, C. C. Meltzer, and Y. Liu, "Atlas-based hippocampus segmentation in Alzheimer's disease and mild cognitive impairment," *Neuro Image*, vol. 27, pp. 979–990, Jan. 2005.

[70] S. M. Chiţă, M. Sabina, M. Benders, P. Moeskops, K. J. Kersbergen, M. A. Viergever, and I. Išgum, "Automatic segmentation of the preterm neonatal brain with MRI using supervised classification," *Proc. SPIE*, vol. 8669, Mar. 2013, Art. no. 086693.

[71] R. Cuingnet, E. Gerardin, J. Tessieras, G. Auzias, S. Lehéricy, M.-O. Habert, M. Chupin, H. Benali, and O. Colliot, "Automatic classification of patients with Alzheimer's disease from structural MRI: A comparison of ten methods using the ADNI database," *NeuroImage*, vol. 56, no. 2, pp. 766–781, May 2011.

[72] R. Wolz, V. Julkunen, J. Koikkalainen, E. Niskanen, D. P. Zhang, D. Rueckert, H. Soininen, and J. Lötjönen, "Multi-method analysis of MRI images in early diagnostics of Alzheimer's disease," *PLoS ONE*, vol. 11, no. 6, 2011, Art. no. e25446.

[73] K. Aderghal, A. Khvostikov, A. Krylov, J. Benois-Pineau, K. Afdel, and G. Catheline, "Classification of Alzheimer disease on imaging modalities with deep CNNs using cross-modal transfer learning," in *Proc. IEEE 31st Int. Symp. Computer-Based Med. Syst. (CBMS)*, Karlstad, Sweden, Jun. 2018, pp. 345–350.

[74] I. Claude, J.-L. Daire, and G. Sebag, "Fetal brain MRI: Segmentation and biometric analysis of the posterior fossa," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 4, pp. 617–626, Apr. 2004.

[75] M. Cheng, D. Wang, and K. Wang, "Multi-modality cascaded convolutional neural networks for Alzheimer's disease diagnosis," *Neuroinformatics*, vol. 16, pp. 295–308, Jan. 2018.

[76] R. H. Blank, "End-of-life decision making for Alzheimer's disease across cultures," in *Social & Public Policy of Alzheimer's Disease in the United States*. USA: PubMed Central, 2019, pp. 121–136.

[77] S. Ahmed, K. Y. Choi, J. J. Lee, B. C. Kim, G. Kwon, K. H. Lee, and H. Y. Jung, "Ensembles of patch-based classifiers for diagnosis of Alzheimer diseases," *IEEE Access*, vol. 7, pp. 73373–73383, 2019.

[78] R. Logan, B. G. Williams, M. F. da Silva, A. Indani, N. Schcolnicov, A. Ganguly, and S. J. Miller, "Deep convolutional neural networks with ensemble learning and generative adversarial networks for Alzheimer's disease image data classification," *Frontiers Aging Neurosci.*, vol. 13, pp. 1–11, Aug. 2021.

[79] H. Maryam, B. Bagherinakhjavanlo, J. Dehmeshki, and T. Ellis, "Segmentation of the hippocampus for detection of Alzheimer's disease," in *Advances in Visual Computing*. Berlin, Germany: Springer, 2012, pp. 42–50.

[80] P. Tan, "Hippocampus region segmentation for Alzheimer's disease detection," Dept. Biomed. Sci., Technische Universiteit Eindhoven, Eindhoven, The Netherlands, 2009.

[81] D. Prakash, N. Madusanka, S. Bhattacharjee, C.-H. Kim, H.-G. Park, and H.-K. Choi, "Diagnosing Alzheimer's disease based on multiclass MRI scans using transfer learning techniques," *Current Med. Imag. Formerly Current Med. Imag. Rev.*, vol. 17, no. 12, pp. 1460–1472, Dec. 2021.

[82] A. Payan and G. Montana, "Predicting Alzheimer's disease: A neuroimaging study with 3D convolutional neural networks," in *Proc. 4th Int. Conf. Pattern Recognit. Appl. Methods*, Lisbon, Portugal, Jan. 2015, p. 12.

[83] I. P. Vatanabe, P. R. Manzine, and M. R. Cominetti, "Historic concepts of dementia and Alzheimer's disease: From ancient times to the present," *Revue Neurologique*, vol. 176, no. 3, pp. 140–147, Mar. 2020.

[84] S. Liu, S. Liu, W. Cai, S. Pujol, R. Kikinis, and D. Feng, "Early diagnosis of Alzheimer's disease with deep learning," in *Proc. IEEE 11th Int. Symp. Biomed. Imag. (ISBI)*, Apr. 2014, pp. 1015–1018.

[85] B. Dubois, H. H. Feldman, C. Jacova, S. T. DeKosky, P. Barberger-Gateau, J. Cummings, and A. Delacourte, "Research criteria for the diagnosis of Alzheimer's disease: Revising the NINCDS-ADRDA criteria," *Lancet Neurol.*, vol. 6, pp. 734–746, Jan. 2007.

[86] J. Dolz, C. Desrosiers, and I. B. Ayed, "3D fully convolutional networks for subcortical segmentation in MRI: A large-scale study," *NeuroImage*, vol. 170, pp. 456–470, Apr. 2018.

[87] J. Wu, Y. Zhang, K. Wang, and X. Tang, "Skip connection U-Net for white matter hyperintensities segmentation from MRI," *IEEE Access*, vol. 7, pp. 155194–155202, 2019.

[88] H. Nawaz, M. Maqsood, S. Afzal, F. Aadil, I. Mehmood, and S. Rho, "A deep feature-based real-time system for Alzheimer disease stage detection," *Multimedia Tools Appl.*, vol. 80, nos. 28–29, pp. 35789–35807, Nov. 2021, doi: 10.1007/s11042-020-09087-y.

[89] P. Kumar, P. Nagar, C. Arora, and A. Gupta, "U-SegNet: Fully convolutional neural network based automated brain tissue segmentation tool," in *Proc. 25th IEEE Int. Conf. Image Process. (ICIP)*, Oct. 2018, pp. 3503–3507.

[90] Y. Wang, Y. Zhu, W. Gao, Y. Fu, and Z. Lin, "The measurement of the volume of stereotaxtic MRI hippocampal formation applying the region growth algorithm based on seeds," in *Proc. IEEE/ICME Int. Conf. Complex Med. Eng.*, Harbin, China, May 2011, pp. 22–25.

[91] B. Khagi, G. Kwon, and R. Lama, "Comparative analysis of Alzheimer's disease classification by CDR level using CNN, feature selection, and machine-learning techniques," *Int. J. Imag. Syst. Technol.*, vol. 29, no. 3, pp. 297–310, Sep. 2019.

[92] M. S. N. Raju and B. S. Rao, "Colorectal cancer disease classification and segmentation using a novel deep learning approach," *Int. J. Intell. Eng. Syst.*, vol. 15, no. 4, pp. 227–236, 2022.

[93] E. Hosseini-Asl, G. Gimel'Farb, and A. El-Baz, "Alzheimer's disease diagnostics by a deeply supervised adaptable 3D convolutional network," 2016, *arXiv:1607.00556*.

[94] S. Korolev, A. Safiullin, M. Belyaev, and Y. Dodonova, "Residual and plain convolutional neural networks for 3D brain MRI classification," in *Proc. IEEE 14th Int. Symp. Biomed. Imag. (ISBI)*, Apr. 2017, pp. 835–838.

[95] J. H. Morra, Z. Tu, L. G. Apostolova, A. E. Green, A. W. Toga, and P. M. Thompson, "Comparison of AdaBoost and support vector machines for detecting Alzheimer's disease through automated hippocampal segmentation," *IEEE Trans. Med. Imag.*, vol. 29, no. 1, pp. 30–43, Jan. 2010.

[96] D. Lu, K. Popuri, G. W. Ding, R. Balachandar, and M. F. Beg, "Multimodal and multiscale deep neural networks for the early diagnosis of Alzheimer's disease using structural MR and FDG-PET images," *Sci. Rep.*, vol. 8, pp. 1–13, Jan. 2017.

[97] T. Kam, H. Zhang, Z. Jiao, and D. Shen, "Deep learning of static and dynamic brain functional networks for early MCI detection," *IEEE Trans. Med. Imag.*, vol. 39, no. 2, pp. 478–487, Feb. 2020.

[98] L. Vermunt, A. J. L. van Paasen, C. E. Teunissen, P. Scheltens, P. J. Visser, and B. M. Tijms, "Alzheimer disease biomarkers may aid in the prognosis of MCI cases initially reverted to normal," *Neurology*, vol. 92, no. 23, pp. e2699–e2705, Jun. 2019.

[99] B. Alotaibi and M. Alotaibi, "A hybrid deep ResNet and inception model for hyperspectral image classification," *PFG-J. Photogramm., Remote Sens. Geoinf. Sci.*, vol. 88, no. 6, pp. 463–476, Dec. 2020.

[100] R. Perri, L. Serra, G. Carlesimo, and C. Caltagirone, "Preclinical dementia: An Italian multicentre study on amnestic mild cognitive impairment," *Dementia Geriatric Cogn. Disorders*, vol. 23, pp. 289–300, Jan. 2007.
[101] 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, 2021.
[102] P. Nagabushanam, S. T. George, and S. Radha, "EEG signal classification using LSTM and improved neural network algorithms," *Soft Comput.*, vol. 24, no. 13, pp. 9981–10003, Jul. 2020, doi: 10.1007/s00500-019-04515-0.
[103] A. Puente-Castro, E. Fernandez-Blanco, A. Pazos, and C. R. Munteanu, "Automatic assessment of Alzheimer's disease diagnosis based on deep learning techniques," *Comput. Biol. Med.*, vol. 120, May 2020, Art. no. 103764, doi: 10.1016/j.compbiomed.2020.103764.
[104] R. Cui and M. Liu, "Hippocampus analysis by combination of 3-D DenseNet and shapes for Alzheimer's disease diagnosis," *IEEE J. Biomed. Health Informat.*, vol. 23, no. 5, pp. 2099–2107, Sep. 2019.
[105] A. Khvostikov, K. Aderghal, J. Benois-Pineau, A. Krylov, and G. Catheline, "33D CNN-based classification using sMRI and MD-DTI images for Alzheimer disease studies," *arXiv:1801.05968*, 2018.
[106] S. B. Rao, "A hybrid Siamese-LSTM (long short-term memory) for classification of Alzheimer's disease," *Int. J. Softw. Innov.*, vol. 10, no. 1, pp. 1–14, Oct. 2022.

BATTULA SRINIVASA RAO is currently an Associate Professor with the School of Computer Science and Engineering, Vellore Institute of Technology, VIT-AP University. His current research interests include soft computing, image processing, machine learning, and deep learning.

MUDIYALA APARNA is currently a Research Scholar with the School of Computer Science and Engineering, Vellore Institute of Technology, VIT-AP University. Her current research interests include image processing, medical image analysis, and deep learning.