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REVIEW ARTICLE

A survey of Alzheimer's disease diagnosis using deep learning approaches

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ABSTRACT

The dementia with the highest prevalence is Alzheimer's Disease (AD), which can cause a nervous brain syndrome that impairs daily functioning as well as causes gradual remembrance loss by harming brain cells. This fatal condition is exceptional in its field. Early identification of AD is important due to the disease's global prevalence and evolving threat. Early detection holds promise because it can help predict the health of many people who may be encountered in the future. Therefore, by evaluating the disease's effects using Magnetic Resonance Imaging (MRI) scans, we may use Artificial Intelligence (AI) technology to categorize AD patients and determine whether or not they will eventually develop the fatal condition. In the area of deep learning methods and analysis, this paper presents essential knowledge and cutting-edge deep learning techniques. The goals of the paper are to advance the knowledge and implementation of medical image processing methods for AD. The paper aims to advance the body of knowledge and promote the creation of efficient and standardised ways in the field by discussing the pertinent techniques and putting recognised recommendations into practise.

Keywords: Alzheimer disease; deep learning; learning methods; survey; accuracy

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1. Introduction

Alzheimer's Disease (AD) is a degenerative nervous condition which results in brain shrinkage as well as the loss of brain cells. The most prevalent kind of dementia, which is characterised by a steady decline in mental, behavioural, and social abilities and impairs a person's capacity for independent functioning, is Alzheimer's disease[1]. The degenerative condition that is most well-known and advances slowly is AD. Age-specific prevalence rates and global interest in dementia-related research have grown over time. There were about 26.6 million AD individuals recorded in 2006[2]. By 2050, it has been expected that 0.1 billion individuals would be influenced by this. Depending on the stage of the ailment, Alzheimer's disease (AD) has different signs and symptoms[3]. Memory loss and other Alzheimer's symptoms might make it difficult for people to recognise their mental condition. **Figure 1** shows the different signs of Alzheimer's Disease.

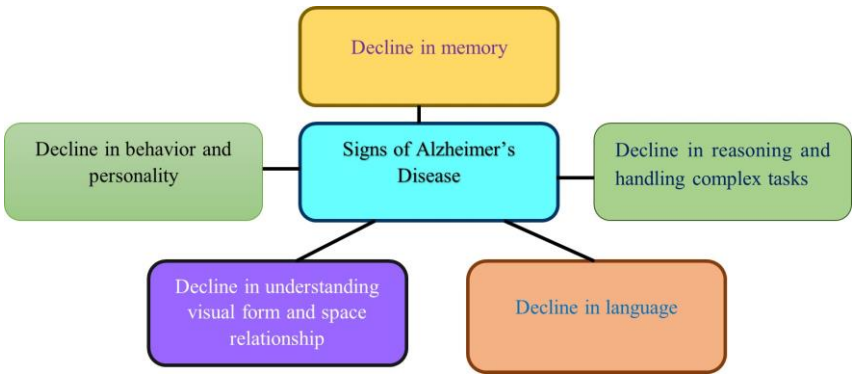

Figure 1. Signs of Alzheimer's disease.

For family members, these symptoms could be more visible. Anyone showing signs of dementia should consult a doctor as soon as possible[4]. People affected by Mild Cognitive Impairment (MCI) include individuals those are having early-stage Alzheimer's Disease. However, not all MCI influenced people will experience AD[5]. A stage between healthy and AD is Mild Cognitive Impairment in which a person experiences subtle deviations in their psychological abilities that are only noticeable to themselves as well as their immediate relatives[6,7]. MCI is a phase from normal to AD, if any person has indirect intellectual abnormalities that are visible to them and to their loved ones but who are capable to carry out daily tasks[8].

MCI affects about 15–20% of adults over the age of 65, and 30–40% of those people go on to acquire AD within five years. The conversion period might be between 6 and 36 months, however it is usually around or MCI non-convertors (MCInc), that the patient may or may not transformed within one and half years. In less than 18 months, MCI victims shall be classified into MCI converters (MCIc) to AD. The correct treatment of AD patients requires early detection before the onset of advanced symptoms, which is still a difficult medical task. Early AD diagnosis may be possible with progression detection, and treatment can be given to stop the disease's progression. The existence of a person's genome contains linked genes and family histories are the two biggest risk factors for AD. The Alzheimer's association society reports that it has been the sixth most prevalent reason of death in the USA. According to a study, there may be 131.5 million dementia sufferers globally, the majority of them will be older than 65 and at a higher risk of developing the condition. The patient's hippocampus section of the brain shrinks and wrinkles, affecting thinking, memory, and reasoning. This is the leading factor causing AD[9]. A thorough clinical evaluation based on the patient's health history, as well as specific neuropsychological examinations such as the Mini-Mental State Examination (MMSE), the neuropsychiatric inventory questionnaire, the clinical dementia rating, and other neurotic surveys, is required for early identification of this syndrome[9].

The diagnosis of AD is made after a thorough medical assessment of the patient and their family members. Only an autopsy can diagnose AD, which is not clinically beneficial. The study uses a subset of an AD individuals with an autopsy-confirmed diagnosis. Patients require supplementary conditions to authenticate AD in advance. Such condition could further help for our understanding of AD and enable its analysis in patients who are still alive. In recent years, numerous research and contests have presented various methods to address this issue utilising a mixture of markers and biomarkers, for example, using PET or MRI data as load to machine learning (ML) systems[10]. Along with these medical procedures, there are numerous alternate ways that identifies AD, including biomarkers, Cerebrospinal Fluid (CSF) analysis, brain imaging with MRI and PET scans, and blood protein analysis[11].

The disease progresses through seven phases, three of which are the pre-clinical stage of Alzheimer's disease, mild cognitive impairment (MCI), and Alzheimer's disease (AD). Patients at AD stage have noticeable symptoms, and it is challenging for them to go about their regular lives normally accepted manuscript[12]. Recently, an amount of approaches for detecting AD using Magnetic Resonance Imaging (MRI) has been

presented, and we categorised them into three groups. This objective suggests a focus on developing and improving techniques that utilize medical imaging data to aid in the diagnosis, progression monitoring, and understanding of AD. Medical image processing methods can provide valuable insights into the structural and functional changes in the brain associated with AD, allowing for more accurate and early detection of the disease. **Figure 2** represents various AD diagnosis methods using 3D brain MRIs[13].

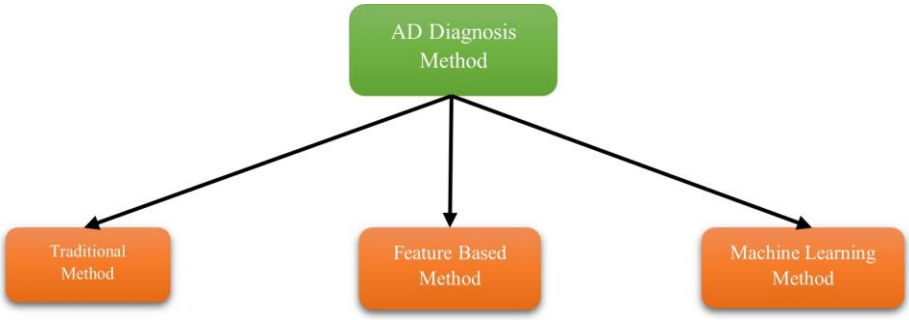

Figure 2. AD Diagnosis methods using 3D brain MRIs.

1.1. Traditional methods

Voxel-based Morphometry (VBM) is a well-known method. VBM compares tissue densities voxel-by-voxel. VBM segments in brain MRI provide data to a variety of tissues, consisting CSF, Grey Matter (GM), White Matter (WM)[14]. Additionally, there are additional techniques in this classification for AD disease diagnosis, like those depending on cortical thickness as a biomarker, measurement or deformation evaluation. On the volume of the MRI, the cortical thickness was assessed.

A normalised viscosity index had been calculated with the help of the subgroup of sections that separated steady MCI from progressive MCI from the resultant cortical width map, which was distributed in the direction of 22 sections[15]. The structural MRI volume of a subject will be nonlinearly registered to a reference template. The registration's deformation field's scalar measurements are then calculated, and cross-volume statistical group operations are carried out. Scalar measures are analysed to look for effects. Asymmetric differomorphic registration was used to measure the space between each pair of matters, and then an embedding procedure and learning strategy for grouping were applied.

1.2. Feature-based methods

To find local features in the input photos, people frequently utilise the scale-invariant feature transform (sift) technique. Since they are linked to important structural points in the loaded picture, they are constant to changes to the translation, rotation, and image's scale[16]. Hence, sift is widely employed as an article filter to diagnose AD[17]. The histogram of oriented gradient (hog) is another local thing that is frequently utilised to diagnose AD. A picture is divided into small, squares cells by hog, which then calculates a graph representing the leaning slope in each cell, normalises the outcome, and then proceeds a description as a result for every cell[18]. The physician typically looks at the brain nerves to learn additional regarding the location, size, and other properties of the brain's modules in addition to the disease's state. To enable doctors to visually diagnose brain-related illnesses, tissue segmentation is performed prior to categorization[19].

1.3. Machine learning methods

An effective classifier for diagnosing the disease from extracted features is the Support Vector Machine (SVM). To detect Alzheimer's disease (AD) from MRI scans, numerous DL-based methods are recently presented[20]. The doctor typically looks at the brain nerves to learn more regarding the location, size, and other properties of the brain's modules in addition to the disease's state. To enable doctors to visually diagnose brain-related illnesses, tissue segmentation is performed prior to classification. The typical approaches for

achieving such a goal typically involve four key steps[21]. **Figure 3** shows the various steps available in machine learning.

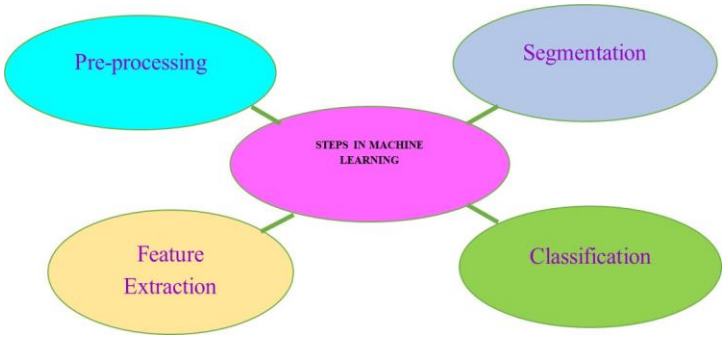

Figure 3. Steps in machine learning.

Particularly in the initial stage of skull stripping or brain segmentation, pre-processing is essential for 3D brain MRI tissue segmentation. By eliminating the non-brain tissues from the MRI scans, the target brain areas may currently be perceived obviously. The division of the brain pictures into various tissues or areas, such as Cerebrospinal Fluid (CSF), Grey Matter (GM), White Matter (WM), or particular structures like the hippocampus, is known as segmentation[22]. Researchers can examine and predict the state or characteristics of the brain by locating and isolating these unique regions.

Several strategies are utilised for feature extraction after the brain tissues have been segmented. Principal Component Analysis (PCA)[23] is a widely used method that minimises the dimension of the data by finding the primary components that best represent the differences between the segmented tissues. This aids in the removal of valuable characters that may be useful to additional analysis. Machine learning (ML) techniques can be used for classification after feature extraction. Support Vector Machine (SVM) is one popular ML algorithm[24]. A supervised learning model called SVM can evaluate and categorise extracted features according to their patterns and correlations. The organisation or classification of the brain tissues can be accomplished by training the SVM with labelled data.

Brain segmentation or skull stripping is used in the 3D brain MRI tissue segmentation pre-processing stage to remove non-brain tissues. The next step is segmentation, which identifies certain brain regions or tissues. To extract useful traits from the segmented tissues, feature extraction methods like PCA and Gray-Level Invariant Feature Modules are applied. Finally, classification based on the collected features can be achieved using ML techniques like SVM. In terms of medical study and diagnosis, these activities aid in the general analysis and comprehension of the architecture and conditions of the brain[25].

Contemporary techniques are used to increase sensitivity and specificity in diagnosing cognitive loss caused by Alzheimer's disease, newer cognitive tests have been created, such as the Alzheimer's Disease Assessment Scale-Cognitive (ADAS-Cog). These modern evaluations seek to diagnose patients more precisely by capturing tiny changes in cognition. Traditional approaches for brain imaging include two most popular imaging methods for detecting structural abnormalities in the brain are Magnetic Resonance Imaging (MRI) and computed tomography (CT) scans[26]. They can aid in excluding other probable reasons for cognitive decline and assist spot patterns connected to more advanced Alzheimer's disease, like brain atrophy.

The use of radiotracers like F-FDG and C-PiB in Positron Emission Tomography (PET) scans can provide important information about the metabolism of the brain and the buildup of amyloid plaques, which are a hallmark of Alzheimer's disease[27]. Additionally, more recent PET tracers, including flutemetamol and florbetapir, selectively target amyloid-beta, making it possible to detect amyloid plaques with greater accuracy.

The cerebrospinal fluid that surrounds the brain and spinal cord is collected using a lumbar puncture. The quantities of amyloid-beta, tau proteins, and other indicators linked to Alzheimer's disease can be determined

by analysing the CSF. The lumbar puncture method is invasive, so it might not be appropriate for regular diagnostic needs.

2. Deep learning

In a rather short period of time, clinical data, all DL presentations, associated artificial intelligence (AI) simulations and image analysis might possess greatest ability to have a positive, long-lasting impact on people's lives[28]. Image generation, image analysis, image retrieval and image-based visualisation are all part of the system handling and study of clinical pictures. Vision mining, computer image, pattern appreciation, and machine learning had all become increasingly common in medical image processing[29].

Deep learning uses neural networks made up of several convolutional nodes of artificial neurons to learn patterns in data structures[30]. A sort of functional cell called an artificial neuron that functions similarly to a biological neuron in that it accepts multiple inputs, essentially performs a calculation, and outputs the outcome. Deep learning's growth roots can be found in the work of Walter Pitts and Warren McCulloch (1943). Along with the development of AlexNet (2010), ImageNet (2008), the back propagation model (1961), the long short-term memory (LSTM) (1978) and Convolutional Neural Network (CNN) framework (1996)[31].

In 2014, Google launched GoogleNet, a search engine that won the ILSVRC 2013 issue and had start-up modules, which significantly decreased CNN's computing requirements. The concept of start-up modules was incorporated into GoogleNet, which was released in 2014 and won the ILSVRC 2014 challenge. This significantly reduced CNN's processing complexity. The CNN architecture has multiple layers and changes the input volume into the output volume using a differentiable function (for example, holding the class scores)[32].

2.1. Deep learning architectures

In the past 20 years, DL models have been developed, greatly expanding the types and quantities of issues that may be tackled by networks of neurons[33]. Deep learning is not a single technique but a group of computations and geographic patterns that can be used to solve a variety of problems. Structures with connections have been around for more than 70 years, but contemporary architectures and GPUs have moved them to the forefront of Artificial Intelligence (AI)[34]. Using DL is not an innovative concept, however, they are advancing exponentially due to of the combination of extensively Convolutional Neural Networks (CNN) with layers as well as usage of GPUs to speed up their carrying out. In this article, various deep learning model architectures are compared[35].

The hidden layer is the network's secret weapons. They are capable of modelling intricate information due to their nodes and neurons. They are unknown since the training dataset doesn't contain information about their nodes' true values[36]. In actuality, all we can see are the input and output. Any neural network has at least one unknown level. Law does not mandate that the quantity of input images be divided by N.

The appropriate hidden layer count could very well be lower than the input layer count[37]. Layers of coupled neurons make up a neural network. It has three hidden layers: an input layer for data intake, an output layer for prediction-making, and hidden layers for processing and feature extraction. The connections, weights, and activation factors that let information flow and non-linear transformations determine the network's topology. The over-all structure of neural networks is represented in **Figure 4**.

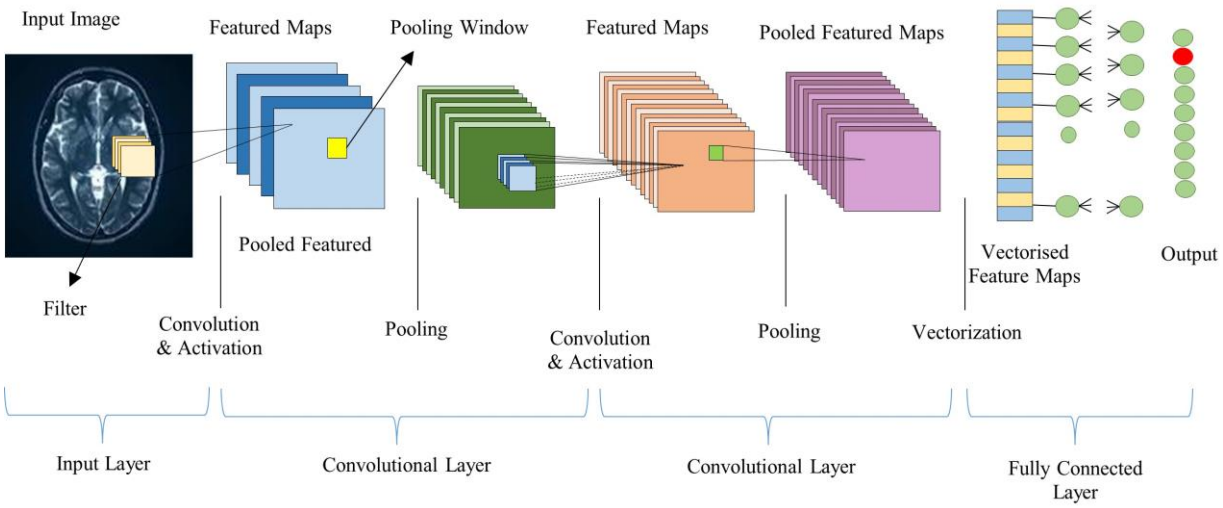

Figure 4. Overall structure of neural network.

2.1.1. Deep neural network (DNN)

As a minimum two of the layers in this architecture support nonlinear complexity. Here, regression and classification are both possible. Because of its excellent accuracy, this model has a tendency to be employed. The disadvantage is the working out procedure would be challenging because the fault is sent to the preceding level and furthermore diminishes. Aside from that, the model's learning act comes too late[38].

2.1.2. Convolutional neural network (CNN)

Convolutional Neural Networks (CNN) are the subset of Deep Neural Networks (DNN) that take their cues from the brain's visual cortex. They have been developed to utilise the spatial information by using input from pictures in 2D and 3D and getting structures by arranging numerous convolutional layers. The end outcome is an arrangement of ever additional intellectual structures. The most effective deep model for image analysis is them[39]. The fundamental principle of CNNs is the integration of feature extraction and classification, which is also a key advantage. According to their reasoning, training a classifier without first going through the feature derivation step can result in subpar learning performance, probably because the retrieved features and the classifier are heterogeneous[40].

For pictures, the operational data among adjacent voxels or pixels is moreover crucial[41]. Although most of the inputs to the deep frameworks that we are investigating are trajectory, vectorization necessarily removes structural information from images. Additionally, compared to DNNs, the number of factors is considerably lower with CNNs because of pooling layers and shared weights[42].

LeCun and colleagues first introduced CNNs in 1989. Regardless of the first victory, they were not generally used till lately, while a variety of new techniques for effectively training Deep Neural Networks (DNN) appeared, and computer schemes advanced. CNNs expected a great deal of focus following deep in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) contests, CNNs excelled when intended for recognizing 1000 different classes of images in a data collection of around a million images[43].

2.1.3. Recurrent neural network (RNN)

RNNs are capable to identify the sequences. The neuron weights are distributed across all measurements. There are numerous versions, including such LSTM, BLSTM (Bi-directional LSTM), MDLSTM (Multi-dimensional LSTM), and HLSTM (Heterogeneous LSTM). This includes contemporary accuracy issues with Speech recognition, character recognition, and a few other problems with NLP (Natural Language Processing)[44]. The drawback of this strategy is that gradient vanishing causes more problems, and this design requires large datasets[45]. RNNs incorporate a temporal dependency known as "memory to model" when

solving problems in time series, such as those in video uses. This approach computes the outcome of the recently input sequentially by taking into account both the recent input data and all prior loaded data. Former data is purposely kept in unknown units known as state vectors[46].

RNNs may struggle to remember long-term input data because they neither as intense as DNNs nor CNNs according to the measure of levels[47]. It continues to want bigger datasets. Fortunately, the memory issue can be greatly reduced by replacing the straightforward perceptron hidden units with more intricate ones that serve as memory cells, like LSTM (Long Short-Term Memory) or GRU (Gated Recurrent Unit)[48]. Compared to conventional RNN, the LSTM has a more complex configuration with a memory cell unit and three gate units, but it is still capable of efficiently capturing important data in an order. GRU is a less complex LSTM variant with marginally improved performance[49].

2.1.4. Deep convolutional extreme learning machine (DC-ELM)

DC-ELM, also known as Deep Convolutional Extreme Learning Machine, merges the ELM training's speed with the power of CNN. To successfully obtain high level characteristics based on input images, it makes use of numerous alternative convolution layers and pooling layers[50]. An ELM classifier is then given the abstracted features, improving generalisation performance and speeding up learning. Additionally, DC-ELM adds randomised pooling to the final covert layer to drastically decrease feature dimensionality and conserve practise period and computational resources. We carefully assessed DC-performance ELMs on the MNIST and USPS data sets with handwritten digits. Investigational outcomes show that our approach performed improved in terms of analysis precision than DL methods and other ELM approaches while requiring significantly less training time[51].

In contrast to LRFELM, it uses a variety of different convolution stratums and pooling levels to produce additional theoretical as well as significant representation of features[52]. In contrast to CNN, the regionally relevant weights are created at random deprived of tweaking, and the resulting weights are determined critically. So as to lower the feature vector's dimension and conserve computer memory and training complexity, the last hidden layer uses stochastic pooling[53].

2.1.5. Deep Boltzmann Machine (DBM)

A deep generative model with three levels is known as a DBM (Deep Boltzmann Machine). A deep belief network-like layout of DBM, but with bottom layers that provide bidirectional connections[54]. Equation (1) illustrates its energetic extensional characteristics of the RBM's function of energy.

$$E = (\sum_{i<j} W_{ij} s_i S_j + \sum_i \theta_i s_i) \tag{1}$$

DBM has N hidden layers. All hidden levels are connected in a single direction. Ambiguous outcomes are integrated through top-down input for more precise inference. For a large dataset, parameter optimization is challenging[55].

2.1.6. Deep Belief Network (DBN)

Deep Belief Networks are nothing but a fundamentally generative visual representation which may construct all the possible attributes for the given situation. With neural networks and AI, it combines measurements and likelihood[56]. Deep belief networks are made up of a few layers containing values. The layers are related, but the qualities are not. The main objective is to help the machine classify the input into many categories. The disadvantage of this architecture is that the initialization step increases the cost of training[57].

2.1.7. Deep autoencoder (DAN)

This could be useful for feature mining and bulk depletion in the unsupervised learning process. Here, a

measure of the inputs and outputs are equal[58]. The model's benefit is that it doesn't require tagged data. For robustness, many auto encoder types, including denoising, sparse, and conventional auto encoders, are required. Here, it must provide a previously training step, but the preparation may not be effective[59].

2.1.8. Deep Stacking Networks (DSN)

The fundamental architecture is a Deep Stacking Network (DSN), often known as a Deep Convex Network. Despite having a deep network, a Deep Stacking Network (DSN) is distinct than traditional Deep Learning (DL) methods due to it was actually a complex gathering of different linkages, every by using their own secret levels[60].

This architecture approach addresses one of the problems with deep learning[61]. Every layer in a DL design greatly increases the complexity of preparation, hence the DSN views preparation as a series of distinct preparation challenges rather than as a single problem[62].

2.1.9. Long short-term memory/gated recurrent unit networks (LSTM/GRU)

Hoch Reiter and Schimdhuber created the unit network of gated recurrent in 1997. Nonetheless, it has rapidly increased acceptance as a Recurrent Neural Network (RNN) model for a diverse application. The Long Short-Term Memory abandoned conventional neural association models based on neurons in favour of including the potential of a memory cell[63].

For some applications, the GRU executes similarly to the LSTM, but because it uses simpler approaches, it executes more quickly and with less loads[64–66]. An updated doorway and new entryway are joined by the GRU. The updated entrance displays the amount of previous cell substance that needs to be maintained[67]. Simply setting the update doorway to 0 and the reset entryway to 1, a GRU can display a regular Recurrent Neural Network (RNN)[68].

2.2. Development methodologies

It has been easy for creating these Deep Learning (DL) structures, but then doing so from scratch and allowing them to refine and mature would take some time[69]. Fortunately, deep learning algorithms may be implemented more quickly using a variety of open-source platforms. These frameworks support the Python, C/C++, Java and other programming languages[70].

Deeplearning4j—A popular deep learning system called Deeplearning4j emphasises Java programming yet also has relevance encoding boundaries for Python, Scala, and Clojure. The stage, which is provided based on the Apache licence, provides assistance for RNN, RBMs, CNNs, and DBNs[71].

Additionally, Deeplearning4j offers distributed the same variations (massively preparing frameworks for information) that function with Apache Hadoop and Spark. The financial sector fraud detection, recommendation systems, cyber security, and picture recognition (finding network intrusions) are only a few of the problems it has been used for. The solution combines CUDA for GPU optimization and might be spread using Hadoop and OpenMP[72–74].

Distributed Deep Learning—The Deep learning's jet engine is Tensor Flow, and IBM Distributed Deep Learning (DDL) is a collection which that communicates by it. DDL can be used to speed up deep learning calculations over a large number of workers and GPUs[75].

3. Related works

AD recognition has been extensively explored and is fraught with problems. Payan et al.[76] utilized 3D convolutional neural networks in addition to a sparse auto encoder. They created an algorithm that is used to determine a person's illness state by using Magnetic Resonance Imaging (MRI) of the cerebrum. The usage of Three-Dimensional convolutions, that performed superior than 2D convolutions, was the main innovation[77].

The convolutional layer had not remained fine-tuned, but it had previous training using an auto-encoder. With fine-tuning, performance is anticipated to increase.

In the study by Sarraf et al.[78], the researchers used brain pictures to identify between people with Alzheimer's disease (AD) and healthy control participants using the LeNet-5 architecture, a well-known convolutional neural network (CNN) model. The goal was to conduct a binary classification test using a CNN that has been trained to distinguish between AD patients and healthy people. It was demonstrated that an equivalent performance was possible by Korolev et al.[79] When the simple 3D CNN designs and residual network were used on 3D operational MRI brain scans, the outputs revealed but the complexity and viscosity of the two networks were extremely high. They did not perform as well as they should have.

Khagi et al.[80] proposed a narrow adjustment of a previously accomplished structure like Alex net, Google Net, and ResNet50. The primary goal is to obtain the effect of each layer part on the classification of natural and medical images. Wang et al.[81] published a unique CNN model depending on a multimodal MRI systematic technique by utilizing DTI or fMRI (functional Magnetic Resonance Imaging) data. Patients with AD, NC, and amnestic mild cognitive impairment (aMCI) were categorised by the framework. Although it had a high degree of grouping accurateness, it was predicted that 3D convolution would perform better than 2D convolution.

The goal of Liu et al.'s study[82] was to develop a method for using voice data to identify Alzheimer's disease (AD). They deliberately collected voice data from elderly people and used the spectrogram—A visual representation of the frequencies and intensities contained in the voice signal—To extract pertinent parameters. Machine learning techniques were used to analyse the gathered data and categorise the individuals. In order to create predictions or categorise data, machine learning algorithms are able to extract patterns and relationships from the data. The researchers in this study probably trained a machine learning model on the extracted spectrogram data to discover the patterns connected to AD.

Impedovo et al.[83] included a methodology that sought to develop a "cognitive model" by analysing the connection between cognitive functions and handwriting. Both healthy volunteers and those with cognitive impairment, including those suffering from neurodegenerative dementia, participated in the study (**Table 1**).

Table 1. An overview of earlier studies on identifying and classifying Alzheimer's disease.

Literature author	Year of publication	Technology used	Training model	Dataset	Image classes	Accuracy rate
Francisco J. Martinez-Murcia	2020	Deep learning	Deep convolutional autoencoders (CAE)	2182 T1-weighted MRI images from 479 subjects from the Alzheimer's disease neuroimaging initiative (ADNI)	Standard TPM template using the SPM12 software	84%
Wei Feng	2020	Deep learning	3D-CNN-support vector machine (SVM)	3127 MRI samples contains 3T T1-weighted images	Grey matter (GM), white matter (WM) and Cerebro spinal fluid (CSF)	95.74%
M. Raza	2019	Deep learning	AlexNet	1259 MRI scans of AD patients from (ADNI 1 1.5T) and OASIS	Longitudinal and cross-sectional images	95%

Table 1. (*Continued*).

Literature author	Year of publication	Technology used	Training model	Dataset	Image classes	Accuracy rate
Garam Lee	2019	Deep learning	Gated recurrent unit(GRU)	1618 MRI scans of AD patients from Alzheimer's disease neuroimaging initiative	baseline, single modal image classes	81%
Huanhuan J	2019	Convolutinal neural network (CNN)	ConvNets	615 MRI scans of AD patients from ADNI	AD, MCI, NC in NifTI format	97.65%
Jyoti Islam	2017	Deep convolutinal neural network (CNN)	Inception-v4 model pre-trained with imagenet database	516 subjects and for each of them, 3 or 4 T1-weighted MRI scans taken from OASIS	Sagittal view and top view of MRI scan images	73.75%
Saman Sarraf	2016	Convolutinal neural network (CNN)	LeNet-5	fMRI scans of 43 AD patients from Alzheimer's disease neuroimaging initiative (ADNI)	fMRI 4D data in NifTI format	96.85%

4. Brain imaging methods for Alzheimer's disease (AD)

Techniques for non-invasively observing the architecture, function, or pharmacology of the brain. The two primary categories of imaging methods are structural imaging and functional imaging. Structural imaging provides details about the structure of the brain, including its neurons, synapses, glial cells, etc. Functional imaging is used to learn more about how the brain works[84]. The brain visioning techniques for Alzheimer's disease (AD) are shown in **Figure 5**.

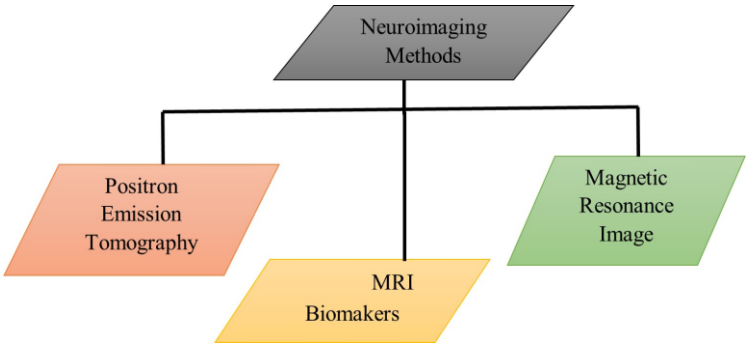

Figure 5. Brain imaging techniques for AD.

4.1. Magnetic resonance image (MRI)

These visualizing method uses radio frequencies and magnetic fields for creating high-quality, high-tenacity 2D/3D descriptions of the brain's structural components. MCI-related brain abnormalities can be seen with MRI, which can also be used to identify MCI patients who may eventually acquire Alzheimer's disease[85]. No radioactive tracers or hazardous X-ray radiation is produced. The structural MRI, that analyses brain capacities internally to sense brain deterioration, is the type of MRI most frequently utilised for AD cases (loss of neurons, cells, tissue, etc.). Alzheimer's disease (AD) is accompanied by gradual brain deterioration. **Figure 6** shows a sample of Structural Magnetic Resonance Imaging (sMRI)[86].

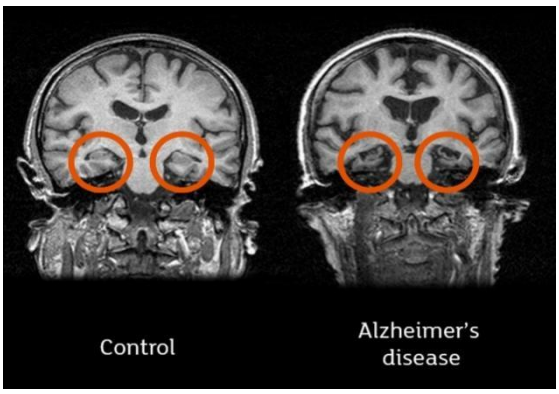

Figure 6. Sample of structural magnetic resonance imaging (sMRI).

The primary visual cortex of humans is measured using the Functional magnetic resonance imaging (fMRI), which are also used for determining the topography of the brain. fMRI offers valuable information and statistics on the activity of the human brain, or functioning of the brain[80]. fMRI methods, like brain visioning depending on major Blood Oxygenation Level Dependent (BOLD) differences and Arterial spin-labelling (ASL), are complex to cerebral metabolic ratio of oxygen ingestion and brainy blood flow[87]. **Figure 7** shows an example of Functional Magnetic Resonance Imaging (fMRI).

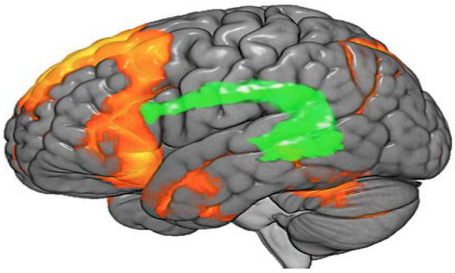

Figure 7. Illustration of functional magnetic resonance imaging (fMRI).

Single-Photon Emission Computed Tomography (SPECT) is extra affordable unlike other methods, but this is more delicate when used to check for changes in cerebral blood flow for the first time[88]. However, when it comes to analysing cerebral functions, this method continues to be one of the most widely employed methods. Numerous experiments have demonstrated that SPECT can accurately assess patients' cerebral perfusion while performing AD examinations[89].

4.2. Positron emission tomography (PET)

In this technique, radiotracers are used to analyse the brain's activity as radiation emitting spheres. **Figure 8** displays the application of amyloid and fluorodeoxyglucose, the most commonly used trackers, for AD detection[90].

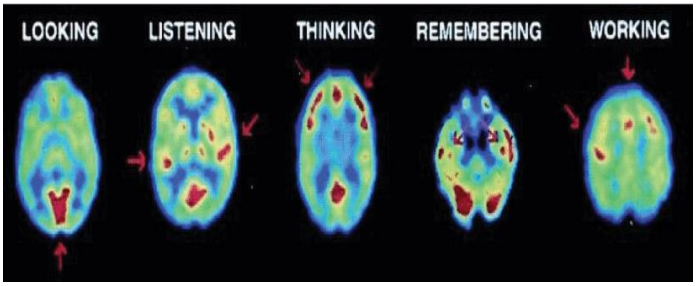

Figure 8. PET scan of a brain in systematic situation.

This study suggests that the temporal lobes of the AD affected individuals have shrunk. Patients with MCI experienced the same decrease, which finally led to AD[91]. Further classifications were made for the AD

and neurodegenerative dementia patients. Because the subjects with AD demonstrated developments in comparison to the issues with frontotemporal lobar degeneration (FTLD) and Parkinson's disease Pittsburgh substance C-PIB, which is an A-beta amyloid-specific ligand, was used (PD).

Most AD participants had a temporoparietal hypo perfusion impression on the PET scan. The usage of and FP-CIT SPECT are further beneficial and suitable since they allow scholars to view disparities in the nigrostriatal dopaminergic nerves[92]. False-positive results, which have no significance for MRI, make SPECT inconvenient for clinical purposes. An imaging technique used in water diffusion studies is called FP-CIT SPECT. The location, orientation, and symmetry of the brain's White Matter (WM) can be determined using this technique. With this strategy, the differences in the micro-structural structure of water particles are the main subject. Although a lot of study has been done to determine amyloid levels and CSF-tau biomarkers, diffusion tensor imaging (DTI) has excluded as a credible approach for examining CSF biomarkers due to the absence of a consensus[87].

4.3. MRI biomarkers of AD

The clinical signals (i.e., the outward appearances of patients' health conditions) which may be carefully assessed are known as biomarkers. There are numerous definitions for biomarkers[93]. For instance, the International Program on Chemical Safety (IPCS) describes a biomarker as a body part, a structure, or a process that may be quantified and used to infer the presence of a problem. **Figure 9** shows an example of MRI Biomarkers of AD.

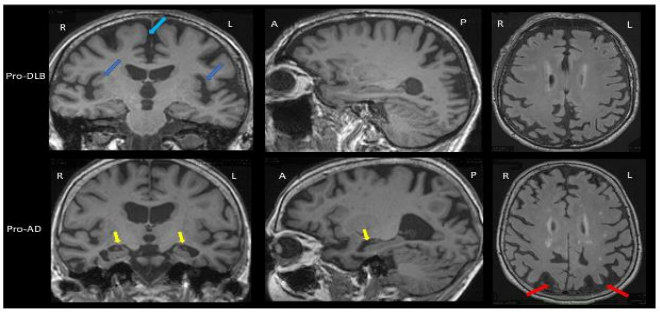

Figure 9. MRI biomarkers of AD.

AD biomarkers have the following properties:

- Ability to recognise the fundamental neuropathology of AD
- Possible to certify AD cases with neuropathological confirmation
- Effective, able to recognise the initial phases of AD, and able to differentiate AD from other types of dementias
- Dependable, non-intrusive, simple to use, and inexpensive[94–96].

Due to their huge potential in the identification of AD, MRI biomarkers are taken into consideration. Atrophic changes that impact the entorhinal cortex and the hippocampus at the beginning of MCI, that might progress to the temporal and parietal lobes in AD, and which may affect the frontal lobes at the end stages of AD, can be seen in structural pictures from MRI. Using functional MRI and DTI, it is possible to identify AD and neurons that are still functionally intact[97]. These two techniques can establish structural and functional connection, and they give biomarkers for AD additional power and resources. However, they still need regulation and authorization to confirm their medical value. These facts suggest that structural MRI, particularly when the hippocampal bulk is involved, is the most effective and often utilized MRI biomarker for AD[98].

5. Results and discussion

Identifying MCI patients at an early stage and foreseeing the changeover from MCI to AD are more important for AD diagnosis. Traditional machine learning is less effective than deep learning[99,100]. The effectiveness of the AD detection technology is highly hooked on the neuroimaging's quality[101–103]. The human visual system serves as the basis for convolutional neural networks (CNN)[104]. A small amount of neurons in the visual system are sensitive to a certain field, meaning that some of these neurons in the brain only responded when edges with a specific orientation were present[105]. Such CNN explains how the surgery is done[103]. Convolution layer functions by employing multiplication of elements with a mesh along the whole picture to take features maps by design from the loaded images as an input[106]. With the aim of avoiding over-fitting, or when the network memorises the data instead of generalising, the pooling layer is typically used. Neurons are triggered via Rectified Linear Unit (ReLU) activation, which is also utilized to control the output of neural networks[107,108]. Combining several of these ConvReLU-Pool processes yields the ultimate only or several completely interlinked layers, which are feature maps[109].

6. Conclusion

The task of early AD detection has always been difficult, and relevant computer experts are continually investigating. This work primarily introduces the AD-linked biomarkers, the article abstraction approach, the pre-processing methodology, and the use of complexity models in AD detection. When it comes to classification techniques, CNN is often utilised and performs improved than other deep models in this area. The over fitting issue with the data set still has to be resolved, though. Unsupervised and self-monitoring methodologies are developing study arenas in medicinal imagery as a result of the dearth of medical data. Initiating an effective treatment for Alzheimer's disease (AD) requires a thorough and precise diagnosis. Early AD diagnosis in particular is crucial for the development of successful treatments and, ultimately, for the care of patients. In this analysis, we conducted a thorough detection of DL methods based on data of brain images for the detection of Alzheimer's disease (AD). We examined 13 publications from 2016 to 2022 and categorised them using deep learning algorithms and several forms of neuroimaging. Additionally, it was discovered that Rectified Linear Unit has the best performance. For the grouping of AD, deep learning techniques have produced efficiency levels of up to 98.57%.

Author contributions

Conceptualization, SS and SPA; methodology, SS; software, SPA; validation, FDS and BK; formal analysis, BK; investigation, RK and UA; resources, SS; data curation, FDS; writing—original draft preparation, SPA; writing—review and editing, SS; visualization, BK; supervision, RK; project administration, UA. All authors have read and agreed to the published version of the manuscript.

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Data availability

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflict of interest

The authors declare no conflict of interest.

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