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Machine and deep learning approaches for alzheimer disease detection using magnetic resonance images: An updated review

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ABSTRACT

The most frequent chronic illness affecting the elderly and one with a high incidence rate is Alzheimer's disease (AD). Deep Learning (DL) and Machine Learning (ML) techniques has significant success and gained popularity in medical imaging. It has emerged as the method of choice for examining medical images and has drawn considerable interest in identification of AD. The review paper mainly focus on image pre-processing which contributes on noise removal, illumination and intensity correction in Magnetic Resonance (MR) images, segmentation methods which helps in extracting the region of interest for AD detection, feature extraction which are considered as the inputs for classification and various machine and deep learning algorithms are analysed for detecting AD. The survey focus on papers related with academic year 2013 to 2023. The maximum number of paper considered for the review falls from 2019 with 13 papers, 2021 with 27, 2022 with 18 and 2023 with 22 papers and other papers are related with dataset reference and papers published before 2019. From the survey, deep learning techniques are more robust in detecting AD.

1. Introduction

Globally Neurological disorders affects hundred million peoples. 50 million peoples affected by epilepsy globally [1]. It is estimated as 47.5 million worldwide affected with dementia, and 7.7 million new patients are reported each year. AD is the most frequent cause of dementia and may be to blame for 60 to 70 % of cases. Over 10 % of people globally suffer from migraines. Two crucial illness indicators are morbidity and mortality. The term morbidity refers to the presence of a disease or its symptoms. Mortality is the total number of fatalities or injuries. The rates of morbidity and mortality for some of the most common neuropsychiatric and neurological conditions, including stroke, AD, epilepsy, Parkinson's disease, migraine and multiple sclerosis, are shown in Figures 1 and 2. Stroke, AD, Parkinson's, epilepsy, migraine, and multiple sclerosis morbidity rates are 61 %, 12 %, 1 %, 7 %, 17 %, and 1 %, respectively. Similarly, the death rates for stroke, AD, epilepsy, migraine, Parkinson's and multiple sclerosis are, respectively, 74 %, 22 %, 1 %, 2 %, 0 %, and 0 %.[2].

AD is a clinical illness that is characterized by a steady decline in mental and memory function. It accounts for 60 to 80 percent of all dementia subtypes, making it a rather common condition among the elderly. The prevalence of AD is significant and currently no cure. Mild Cognitive Impairment (MCI) is the term used for patients who are in the starting stages of AD [60]. About 30–40 % of MCI patients will eventually get AD, but not all MCI patients will suffer AD. Before the patient's neurological deterioration starts the AD-related brain changes starts that includes early lateral ventricle expansion and noticeable hippocampal and amygdala atrophy. Some brain areas will started to shrink, according to studies on biomarkers linked to AD [67].

The development of numerous open-source Alzheimer's databases has boosted this area of study. The most popular databases are OASIS (https://www.oasis-brains.org), ADNI (adni.loni.usc.edu). The ADNI database, which contains information from long-term studies conducted in Japan, is a new clinical Alzheimer data source that is open to the public. Additionally, processing MR images is quite labor-intensive. Open-source programmes like Statistical Parametric Mapping (SPM) have been created at the Welcome Centre for Human Neuroimaging to make it easier for users to analyse MR images. Voxel-Based Morphometry (VBM) [76] of MRI data is carried out using SPM. Freesurfer is a very well-liked piece of open-source software that was created for volume-based morphometry and is employed by numerous researchers.

It is typically difficult to identify AD using artificial intelligence

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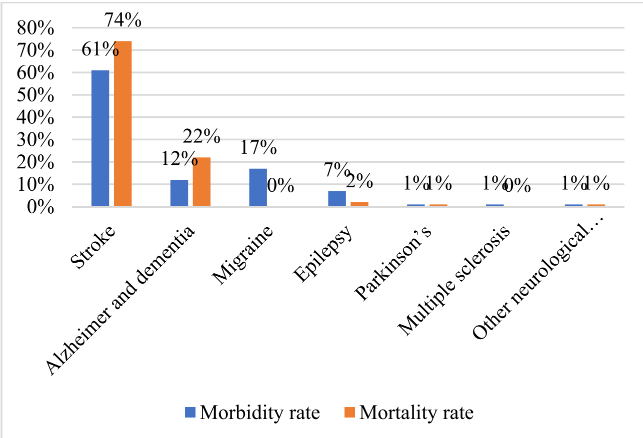

Fig. 1. Morbidity and Mortality rate for various disorder.

because.

- Low quality of medical images, brain segmentation and pre-processing errors.
- Lack of a sizable dataset with a variety of people and biomarkers.
- Low interclass variability throughout AD stages.
- A lack of knowledge, particularly with regard to identifying brain Regions-Of-Interest (ROIs).
- Medical images are more complex than the typical other images.

Computer vision has become more important in the diagnosis of AD due to the quick development of artificial intelligence. The constraints of more conventional methods overcome by a significant subset of ML and DL approches. Recently, the field of imaging has seen advancements in DL and ML technology, which have been applied for extracting information from images [63,64]. Since identifying medical images is a difficult task, computer-aided systems have a significant impact on clinical diagnosis. Positron Emission Tomography (PET), Structural Magnetic Resonance imaging (sMRI), and Computed Tomography (CT) are the most widely used techniques for diagnosing neurodegenerative diseases [61]. This paper reviews various datasets used for analysis, image preprocessing methods, segmentation, machine learning, deep learning approach and their parameters used for predicting the AD [65,74].

2. Dataset

Dataset of Alzheimer are Alzheimer's Disease Neuroimaging Initiative (ADNI) [94]. The dataset are related to ADNI1, ADNI2, ADNI3 and ADNI GO. The dataset are classified as Alzheimer (AD), Normal control (NC), Early Mild Cognitive impairment (EMCI), Late Mild Cognitive impairment (LMCI), Mild Cognitive impairment (MCI). The MR images of ADNI are related to Structural MRI, FLAIR, T2 GRE, DTI, fMRI, ASL, Hippocampal T2. Open Access Series of Imaging Studies (OASIS) [95]. The dataset has OASIS1 belong to Cross-sectional MRI Data with 416 subjects and 434 MR session. OASIS2 belong to longitudinal MRI Data with 150 subjects and 373 MR session. OASIS3 belong to longitudinal multimodal neuroimaging with subjects 1379, MR session 2842, PET session 2157 and CT session 1472. OASIS4 belong to clinical cohort with subjects 663 and MR session 676. Kaggle dataset [96]. The MR images are resized for 128 x 128 and mainly classified into four groups. The dataset has 6400 MR images. The grouping of dataset is given as Mild Demented (MD) with 896 images, Moderate Demented (MoD) with 64 images, Non Demented (ND) with 3200 images and Very Mild Demented (VMD) with 2240 images. Other dataset are Minimal Interval Resonance Imaging in Alzheimer's Disease (MIRIAD) [97], ANSH Database [98].

The AD Detection can be performed by analysing biomarkers of MR images. The brain MRI helps in analysing brain shrinkage, damages in blood vessels, inflammation etc. Hippocampi region is initially affected first so this can be analysed effectively from MR images for AD detection. MR images can help in analysing the shape and size of brain region for detecting atrophied (brain shrinkage). Atrophied helps in diagnosing AD. Gray and white matter region is considered as biomarkers. When gary region shrinks it leads to decline in cognitive function. When white matter shrinks it leads to problem with memory loss, balance and mobility functions. The sample images that is normal and Alzheimer from Kaggle and ADNI dataset is shown Figure 3a and 3b. The image shows the shrinkage in white and gray matter region

3. Methods

Figure 4 shows the general block diagram of the survey paper which includes image preprocessing methods, image enhancement, image segmentation, image classification using ML and DL techniques [69].

Figure 5 shows the detailed survey of these steps like image preprocessing, image denoising and enhancement. Image enhancement is performed by Histogram equalization, Intensity Normalization, Skull Striping, Thersholding, Discrete wavelet transform, 2D Adaptive consensual filter, Laplacian, Hessian, Contrast Stretching and Curvelet filtering. For image segmentation to extract region of intrest for AD prediction are thersholding, Atlas-based registration, M−Net, Optimization-based segmentation techniques, Bayesian segmentation, Statistical Parametric Mapping, Patch-Based Classifiers, Particle Swarm Optimization, Convolutional Neural Network, SegNet, Autoencoder, K-

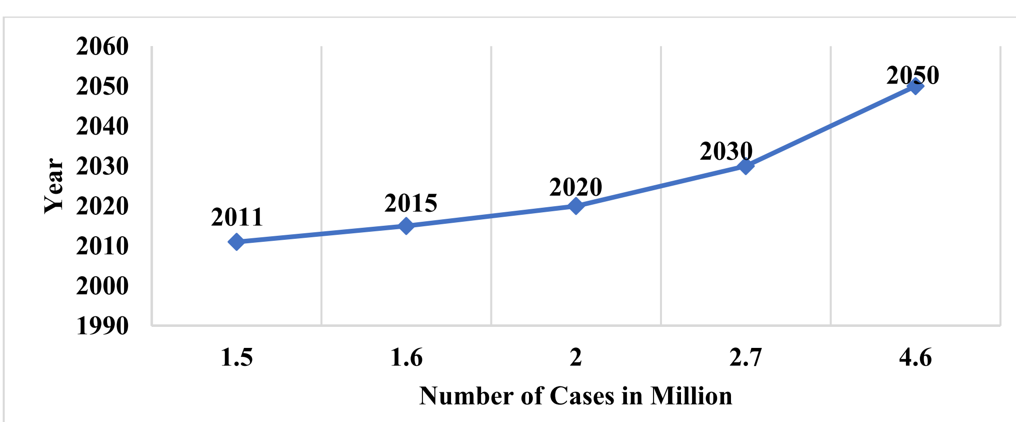

Fig. 2. Number of Cases of Alzheimer Disease.

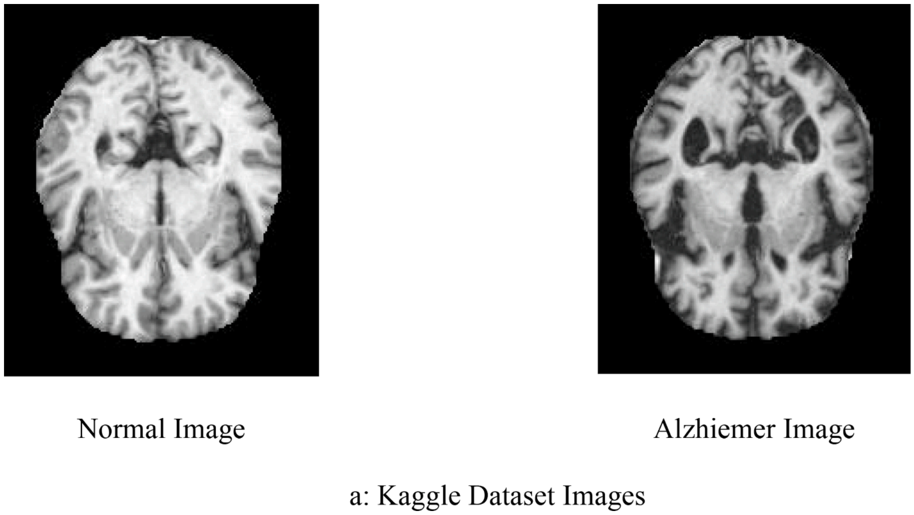

Fig. 3a. Kaggle Dataset Images.

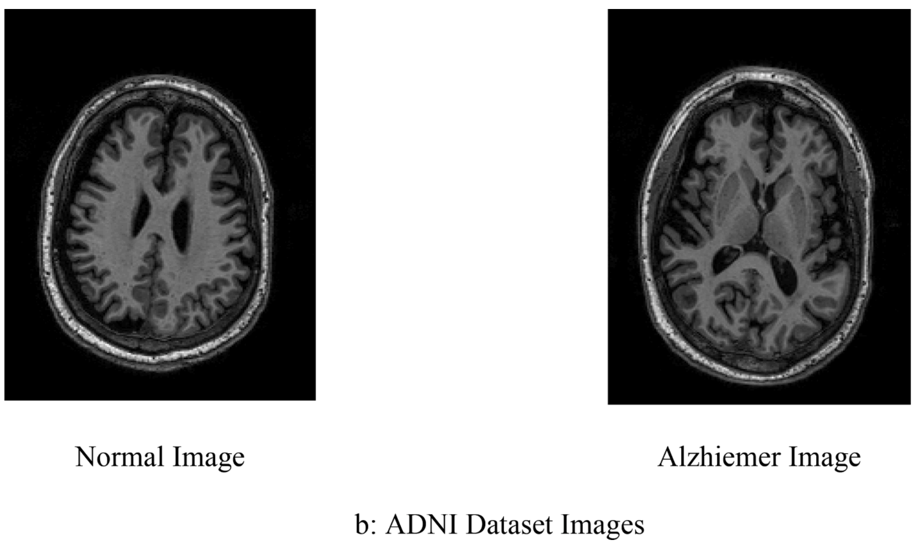

Fig. 3b. ADNI Dataset Images.

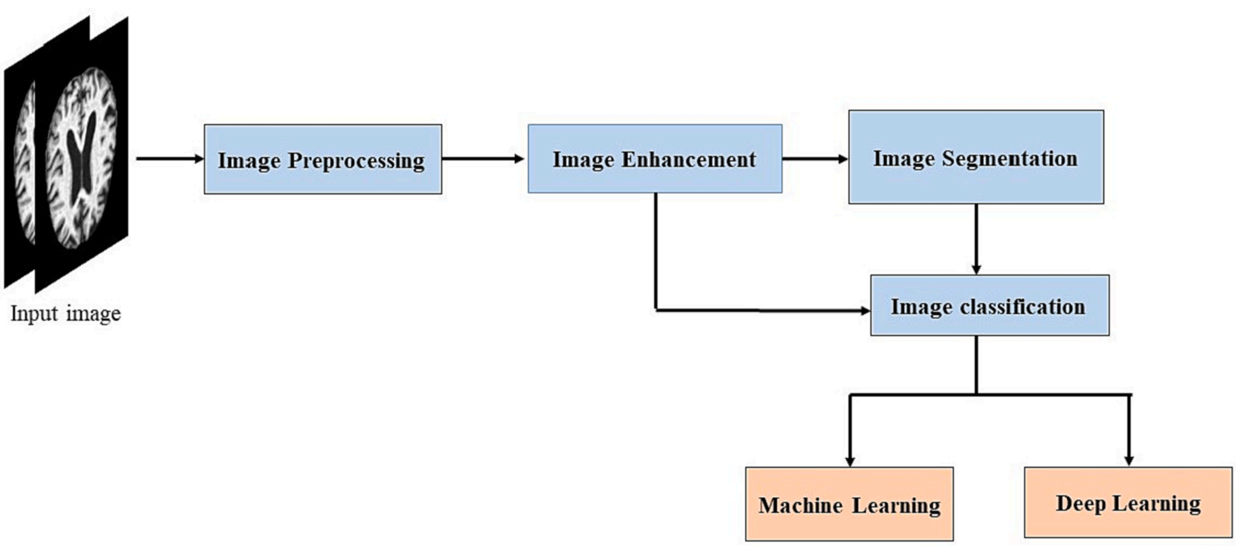

Fig. 4. General block diagram of AD analysis.

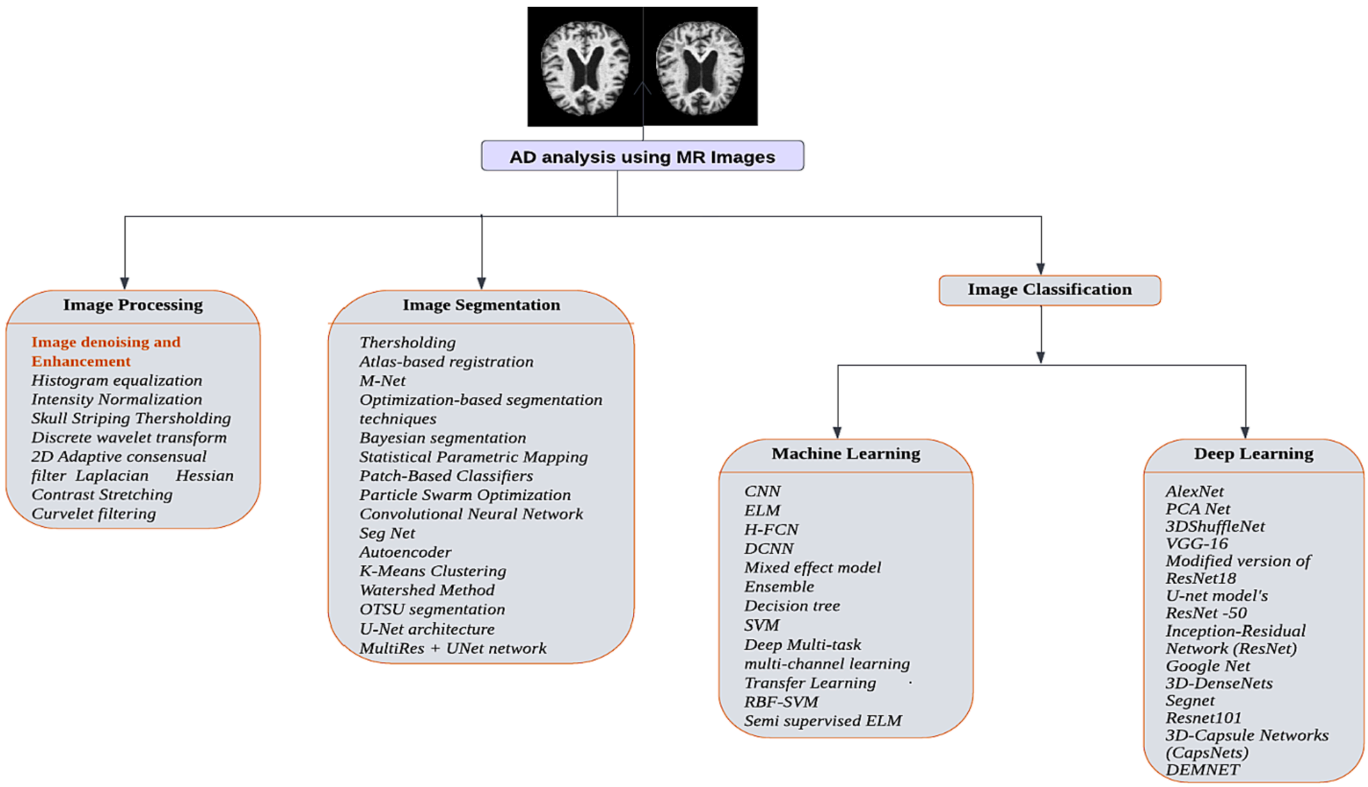

Fig. 5. Algorithms and methods used in AD Analysis.

Means Clustering, Watershed Method, OTSU segmentation, U-Net architecture and MultiRes + U Net network. For image classification ML and DL methods such as CNN, ELM, H-FCN, DCNN, Mixed effect model Ensemble, Decision tree, SVM, Deep Multi-task multi-channel learning, Transfer Learning, RBF-SVM and Semi supervised ELM were used widely [78].

4. Image preprocessing

The operating procedures used by medical staff may differ as image acquisition perfomed by devices made by various manufacturers. The patient's body position will surely change slightly because of the prolonged capturing period. Several preprocessing procedures must be carried out in order to obtain the clear image and the obtained image is used for feature extraction, and classification. Most studies require preprocessing before data analysis, particularly in machine learning. Some investigations might not require preprocessing with the aid of DL. Most of the articles in ML and DL used intensity normalization, skull stripping, registration, tissue segmentation and motion correction as preprocessing methods [79].

Images obtained from various modalities like CT, MRI, PET and Single Photon Emission Computed tomography(SPECT) mainly affected by different types of noises. The pre-processing improves the quality of the image by using denoising method and those images are used for image segmentation and image classification. Spatial and frequency domain filters are widely used for denoising the images [3].

Image normalization, a common procedure in image processing, which changes the pixel intensity values. An image in n dimensions that is grayscale is changed via normalization [70].

$$\mathrm{I}: \{x \subseteq r^n\}\{min, \ldots.max\}$$

Values of intensity between (Min, Max)
For new image

$$\mathrm{I}: \{x \subseteq r^n\}\{newmin, \ldots.newmax\}$$

Range of new intensity value is (new Min, new Max).

The N3 nonparametric non-uniform intensity normalization technique is the method most frequently used. Sharpening histogram peaks with the reliable and well-proven algorithm N3 will lessen any intensity non-uniformity [4,5,7].

Image scans are spatially aligned to a reference anatomical space by registration. It is crucial since human brains differ from one another and have complicated structural differences. Image registration helps to standardize neuroimaging techniques in relation to a single fixed-size template [6]. In MR images, measurement of tissue volume in each location is the purpose of tissue segmentation. Early stages of neurodegeneration, especially in the medial temporal lobe, have an impact on Grey Matter (GM). GM probability provide a measurable depiction of the location of this tissue in the brain, with the quantity of local GM indicated by the brightness of each voxel [8].

Skull Stripping is one of the risky preprocessing techniques that could aid in the precise detection of neurological disorder. This eliminates the skull's from images. This can be utilised independently or in conjunction with neck or cerebellar excision. Additionally, Skull Stripping lessens the possibility of incorrect classification of brain tissues during the division of incompatible tissues [75]. Correct brain extraction increases the possibility that many neurological illnesses, including dementia and schizophrenia, will be self-diagnosed. The primary concept behind Skull Stripping is that it solely affects the brain and destroys non-brain tissue-dura substances like the exterior blood vessels. The computational efficiency of many neuroimaging algorithms is improved by these non-brain tissues. Skull Stripping is divided into a number of groups, as manual, semi-automated and automated methods [3] and motion artifacts in the brain image are reduced [67].

In preprocessing noise removal play a major role. Various filters are used for removing noises in the images. Image filtering is the preprocessing steps that aids in the removal of noise and enhances the image quality. There are many imaging modalities including X-rays, CT, ultrasound, MRI [71]. Every modality is affected by the appropriate noises. One important non-invasive medical imaging technique is MRI.

MRI is affected by various types of noises such as Gaussian noise, salt and pepper noise, speckle noise and Rician noise. Rician noise is mostly reflected in the MR image [77]. Rician noise is a type of multiplicative noise, so MR images become challenging to analyses [72]. Denoising techniques are classified into a spatial and frequency domain filtering. In spatial domain mean filter, median filter, gaussian filter and wiener filters used widely. In frequency domain lee filter, cuan filter, frost filter, wavelet filter and curvelet filter are considered [73,76]. Tables 1 and 2 shows the different preprocessing methods and denosing techniques used for AD analysis.

5. Image segmentation

In brain MRI, the affected area is highlighted via image segmentation. In brain MRI, the hippocampus and overall brain volume are the areas that are diagnosed with the help of segmentation process. Alzheimer's disease patients, members of the healthy cohort, and people with mild cognitive impairment are identified using different segmentation methods. Depending upon the area of brain in MR images different methods of segmentation algorithm is used to segment the region of interest. Thersholding, region-based methods, clustering, atlas guide approaches, edge-based methods are widely used methods for image segmentation. Table 3 shows the different segmentation methods used for AD analysis.

6. Feature extraction

Feature extraction is an important step in image classification. The output of segmentation which give the region of interest is considered as input for feature extraction. In machine learning the necessary features are extracted. The deep learning methods extracted features from the layers developed. The tabulation of feature analysis is shown in Table 4.

7. Image classification

For the purpose of early disease prediction and classification, different automated techniques based on ML and DL have recently been developed. Table 5 shows the performance analysis of various ML techniques.

7.1. Machine learning approach for AD classification

In this survey different machine learning algorithm for classification of AD is discussed. Weimingling et al. (2018) developed a learning strategy based on CNN. It is intended to precisely predict the conversion of MCI to AD using MRI data. Features are extracted from the patch images and principal component analysis was used for feature reduction. These features are given to an ELM to predict the AD with accuracy of 81.4 %, specificity of 68 %, sensitivity 89.6 % and Area Under Curve (AUC) of 87.8 %. Samsuddin Ahmed *et al.* (2019) designed CNN network for patch-based classification, left and right hippocampus classification of AD and NC images. Ensemble classifiers achieves the classification accuracy of 90.0 % for the GRAD dataset and 85.55 % for the ADNI dataset. Chunfeng Lian *et al.* (2020) developed a hierarchical classification model by jointly learning and fusing multi-scale feature representations. This network reduces the parameter and increases the classification performance. Classification of AD vs NC achieves the accuracy of 90 %, the sensitivity of 82 %, specificity of 97 %, and AUC of 95 %, Progressive MCI vs MCI achieves 81 % accuracy,53 % of sensitivity, and 85 % of specificity.

Abolbaher *et al.* (2021) proposed a CNN and Deep Neural Network (DNN) model for AD classification from structural MR image. From this method 94.82 % of average weighted classification accuracy and 94.02 % for volumetric feature accuracy for left and right hippocamp was achieved. Additional to this AUC of 92.54 % and 90.62 % for right and left hippocampi was achieved. Jie Zhang (2021) suggested a technique

Table 1
Preprocessing methods for Quality Improvement.

Process	Remarks	Method	Author and year
Skull-stripping	Gray and white mater are separated from non brain,	FreeSurfer	Fan, Z [30], 2021
		–	Weimingling [8], 2018
		FMRIB's Brain Extraction Tool	Shaji [33], 2021
		–	Jain [19], 2019
		CAT12 with SPM12 software	Sun, H. [35], 2021
		–	Oktavian [24], 2022
		–	Liu M [26], 2019
		Brain Extraction Tool (FSL-BET)	Hongfei Wang [36], 2019
		–	Buvaneswari, P.R [44], 2021
Intensity normalization and Intensity correction (contrast, Brightness)	(i) handle the illumination correction in image (ii) improve contrast and brightness (iii) normalize uneven light distribution where linear contrast stretching helps in enhancing the image quality (iv) affine alignment of brain images are performed to remove the linear global differences	Performed by histogram deformation	Weimingling [8], 2018
		–	Samsuddin Ahmed [9], 2019
		Non-parametric and non-uniform bias correction algorithm	Jie Zhang [13], 2021
		Adaptive thresholding	AbdulAzeem, Y [15], 2021
		Statistical Parametric Mapping (SPM)	Vaithinathan K [18], 2019
		–	Jain [19], 2019
		Edge-Preservation Coherence Improvement (EP-CI) algorithm	T.V.Ramana, [21],2021
		Adaptive Histogram Adjustment (AHA) algorithm	V. Sathiyamoorthi [22], 2021
		Histogram Equalization	Ahmed s. Musallam [40], 2022
		VBM-DARTEL, and DPABI	Yu Wang [27], 2021
		CAT12 toolkit	N. Deepa [28], 2022
		FreeSurfer	Fan, Z [30],2021
		FMRIB's Brain Extraction Tool	Shaji [33],2021
		linear contrast stretching algorithm	Jayanthi Venkatraman [34], 2022
		CAT12 with SPM12 software	Sun, H. [35], 2021
		Brain Extraction Tool (FSL-BET)	Hongfei Wang [36], 2019
		nnU-Net	K.R. Kruthika [49], 2019
		Octagon histogram equalization with black and white Stretching.	Menagadevi [45], 2023
Hippocampus localization	Left and right hippocampus regions are detected better and considered as Region of interest	–	Samsuddin Ahmed [9],2019
sMRI image sampling	Improve spatial resolution	–	Chunfeng Lian [10],2020

Table 2
Preprocessing Methods for Image Denoising.

Filter	Noises and distortion	Author and year
Median Filter	Salt and pepper noise	Muhammad Assam [80], 2021
	Scalp and skull	Nayak, M.M [86], 2023
	–	Allada [92], 2023
	Rician noise	Saladi, S [93], 2023
	–	Kaur [90], 2023
2D-Adaptive Consensual Filter	Salt and pepper noise Gaussian noise,Speckle and random noise	T.V.Ramana [21], 2021
Non-local mean algorithm (NLM)	–	Ahmed s. Musallam [40], 2022
3-D Log-Gabor Filters	–	Katia M. Poloni [81], 2021
Gaussian Filter	Geometric distortion and noise	Shaik Basheera [82], 2019
Adaptive Bilateral Filter	Speckle noise,Binary noise and random noise	V. Sathiyamoorthi [22], 2021
Rolling Guidance Filter	–	Vanitha, K [87], 2023
Spacial Domain Filters	–	Archana Gopinadhan [88], 2022
Wiener filter	Rician noise, Gaussian noise, andRayleigh noise	Alabdali, R. N [89], 2023
Anisotropic diffusion filtering method	Interference noise and blurred edge	Bin Yan [83], 2022
3D median modified Wiener filter (MMWF)	Rician noise	Dohwa Lee [85], 2023
SGLSA algorithm	Static speckle noise	Ximeng Feng [91], 2023
Modified optimal curvelet	Rician noise	M.Menagadevi [45]
Transform-based multi-sensor denoising methods	–	Vishwakarma, A[66], 2022

that eliminated the white spaces from the brain image.3D CNN method was developed with an accuracy of 97.35 %, sensitivity of 97.10 %, specificity of 97.95 %, AUC of 99.70 % to classify AD. AbdulAzeem, Y *et al.* (2021) proposed a CNN based end to end structure to classify AD from MR images The framework achieved 97.5 % accuracy for ADNI dataset during multi-classification testing.

Amir Ebrahimi *et al.* (2021) proposed a 2D and 3D CNNs and Recurrent Neural Networks (RNN). 96.88 % accuracy, 100 % sensitivity, and 94.12 % specificity are achieved. Vaithinathan K (2019) proposed random forest, KNN and linear SVM for classification. The 812 images from ADNI database are used for validation. For AD/NC classification, the sensitivity of 89.58 % and specificity of 85.82 % was achieved. Jain *et al.* (2019) proposed a CNN architecture, for feature extractor VGG-16 was used and for the classification problem the mathematical model called PFSECTL which is based on transfer learning. V. Sathiyamoorthi *et al.* (2021) proposed a new methodology called the computer aided design process, which employs different algorithms to detect AD. The developed method is used to categorise the images and its symptoms based on a selection of parameters.98 % accuracy is achieved to detect AD disease.

Oktavian *et al.* (2022) proposed a CNN approach using the Residual Network 18 Layer (ResNet-18) architecture. The model shows the accuracy of 88.3 %. Liu M *et al.* (2019) used both MR imaging data and demographic data. They proposed deep multi task and channel learning framework for simultaneous AD categorization and clinical score regression. The algorithm shows the accuracy of 93.7 %, specificity 93.2 %, sensitivity of 94.6 %, and area under curve of 98.6 % for AD vs CN images. C.Kavitha *et al.* (2022) proposed a ML model for the early detection of AD disease. They used OASIS and kaggle dataset of AD detection. The correlation coefficient, information gain, chi square feature is used for classification. The classification was achieved using decision tree, random forest, SVM, and XG boost voting with an

Table 3
Segmentation methods for AD analysis.

Segmentation Techniques	Segmentation region	Author and year
Efficient Fuzzy C Means Adaptive Thresholding	Alzheimer region	T.V.Ramana [21], 2021
Adaptive Mean Shift Modified Expectation Maximization	Alzheimer region	V. Sathiyamoorthi [22], 2021
DBSegment	Small deep brain structures	K.R. Kruthika [49], 2019
DeepBrain library	Alzheimer region	Oktavian [24], 2022
Multiatlas label propagation and expectation maximization based refinement segmentation	138 anatomical morphometry image region	Saidjalol Toshkhujaev [41],2020
Thersholding	Hippocampus region	Balasundaram, A [47], 2023
SCF intensity probability distribution with bias regularization	Gray and white matter region	Raza, N. [48], 2023
Whale optimization algorithm and gray wolf optimization		Chitradevi [51],2023
SPM with CAT12 toolbox	Brain tissue segmentation andWhite and gray region smoothing	Chitradevi Dhakhinamoorthy [53], 2023
SynthSeg	Alzheimer region,Not effected by changes in contrast and resolution.	Benjamin Billot [52],2023
Seg Net	Detect Alzheimer region pertinent brain parts	Buvaneswari, [44], 2021
Multi scale pooling Residual autoencoder architecture	White matter extraction	Menagadevi [45], 2023
K-Means Clustering and Watershed Method	Segmentation of hippocampus region	D Holilah [46], 2018
Modified Fuzzy C-means, pixel power segmentation	orchestrated location, white and gray region	Balaji, P [54],2023
OTSU segmentation	Alzheimer region	Alhassan, A.M [56],2019
U-Net architecture	Left and right hippocampus region	Helaly, H.A [57],2022
MultiRes + UNet network	White and gray region	Li M [58],2022

accuracy of 83 %.

7.2. Deep learning approach for AD classification

A batch normalisation layer and modified pre-trained AlexNet using brain images were proposed by Lu, Siyuan et al. in 2021. The chaotic bat method was employed to enhance the ELM's classification performance. The sensitivity, specificity and overall accuracy of the BN-AlexNet is better compared to other networks. Yu Wang *et al.* (2021) proposed a multimodal diagnosis approach for AD based on principal component analysis network and three-dimensional shufflenet. For AD versus NC, accuracy, sensitivity, specificity, precision, recall, f1 score and AUC is 85.2 %,69 %,96 %,93.3 %,69 %,79 % and 86.9 %. For AD versus MCI accuracy, sensitivity, specificity, precision, recall, f1 score and AUC is 84 %, 84 %, 84 %, 84.9 %,84 %,84.1 % and 91.9 %. For MCI versus NC accuracy, sensitivity, specificity, precision, recall, f1 score and AUC 64.8 %,43 %,79.3 %,60.2 %,43 %,48 % and 67.3 %.

N. Deepa *et al.* (2022) proposed the classification of AD, an improved VGG-16 network using the arithmetic optimization algorithm. An improved VGG-16 with arithmetic optimization algorithm successfully distinguishes between the several AD classes, including normal, early dementia and late dementia. Odusami *et al.* (2021) applies a modified version of ResNet18, which does binary classification of AD to detect different stages of AD. The 99.99 % of accuracy for EMCI vs. AD, 99.95 % for LMCI vs. AD and 99.95 % MCI vs. EMCI was obtained. Fan, Z *et al.* (2021) used the U-net model's characteristics for the purpose of diagnosing AD. Accuracy of 95.71 ± 1.36 % for AD versus NC, 90.14 ± 3.66

Table 4
Feature Extraction for AD diagnosis.

Features	Method	Author and year
Deep (low and high level) features and multi-level features	Convolution Neural Network	Samsuddin Ahmed et.al [9], 2019 Jie Zhang et.al [13],2021 Ahmed s. Musallam et. al[40],2022 N. Deepa et.al[28], 2022 S. Murugan et.al [16],2021
	Two dimensional ShuffleNet	Yu Wang et.al [27],2021
	U-net with skip connection	Fan, Z et.al[30],2021 Zhonghao Fan et.al [30],2021
	Base model	Jain et.al[19],2019
	Deep Convolution Neural Network	Naz, S. et.al[32],2022
	Deep ResNet learning	Sun, H. et.al[35],2021
	DenseNet	Hongfei Wang et.al [36], 2019
	SegNet	Buvaneswari, P.R et.al [44],2021
Patch, region, Structural and subject level feature	Hierarchical fully convolutional network	Chunfeng Lian et.al [10],2020
	FreeSurfer	Weimingling et.al [8],2018
	Fusion scheme with multiple grading maps	Hett K et.al[23],2018
	landmark-based feature extraction	Zhang J [60], 2017
Texture		Vaithinathan K et.al [18], 2019
Gray Level Co-Occurrence Matrix		V. Sathiyamoorthi et.al [22],2021
Features of Ventricles and Hippocampi	Mixed effects models	Samaneh Abolpour Mofrad[12],2021
	Convolution Neural Network	Samsuddin Ahmed et.al [9],2019
Cortical thickness and subcortical volumes	MALPEM toolbox	Saidjalol Toshkhujaev et.al[41],2020
Jacobian domain features	DLB framework	S. Qasim Abbas[55], 2023

% for EMCI versus LMCI 90.05 ± 2.63 % for AD versus LMCI, and 87.98 ± 4.54 % for NC versus EMCI, was obtained.

Heta Acharya *et al.* (2021) proposed VGG16, modified AlexNet and ResNet −50 to classify AD vs MCI, mild Alzheimer, moderate Alzheimer and severe impairment. Modified AlexNet shows improved result compared to other models. Naz, S. *et al.* (2022) developed the CNN architectures to classify binary and ternary data using freeze characteristics that were taken from the original data set ImageNet. It achieves an accuracy of 99.27 % for MCI/AD, 98.89 % for AD/CN, and 97.06 % for MCI/CN.

Jayanthi Venkatraman Shanmugam *et al.* (2022) proposed transfer learning to identify early signs of AD and different phases of cognitive impairment. The total success rates in identifying AD using GoogleNet, AlexNet, and ResNet-18 are 96.39 %, 94.08 %, and 97.51 %, respectively. Hongfei Wang (2019) developed an ensemble of 3D densely connected convolutional networks for the diagnosis of AD and MCI. Accuracy, recall and precision for classification of MCI/AD are 93.61 %,92.45 % and 94.59 %. for MCI/NC 98.42 %,98.34 % and 98.37 %, for AD/NC are 98.83,98.70 and 98.70 %. Sunday Adeola Ajagbe *et al.* (2022) used magnetic resonance imaging to increase the classification of AD images using deep CNN, CNN, and transfer learning (VGG16 and VGG19). VGG 19 shows better accuracy. Buvaneswari, P.R *et al.* (2021) proposed deep learning-based segmenting strategy uses SegNet to identify brain regions relevant to AD from sMRI and ResNet-101 to reliably categorise AD and dementia conditions. Sensitivity of 96 % and

Table 5
Performance Analysis of Various Machine Learning Techniques.

Author name/Year	Methodology	Dataset	Performance metrics
Weimingling *et al.* /2018 [18]	CNN, ELM	ADNI	Accuracy = 81.4 % Sensitivity = 89.6 % Specificity = 68 %
Samsuddin Ahmed *et al.* / 2019[9]	ELM	GRAD ADNI	Accuracy ADNI dataset = 85.55 % GRAD dataset = 90.05 %
Chunfeng Lian *et al.* /2020[10]	H-FCN	ADNI	AD vs NC Accuracy = 90.3 % Sensitivity = 82.4 % Specificity = 96.5 % Progressive MCI Vs MCI Accuracy = 80.9 % Sensitivity = 52.6 % Specificity = 85.4 %
A. Basher *et al.* /2021[11]	DCNN	ADNI OASIS	Accuracy Left hippocampi = 94.82 % Right hippocampi = 94.02 %
Samaneh Abolpour Mofrad *et al.* /2021[12]	Mixed effect model	ADNI	MCI Accuracy = 69 % Precision = 73 % Recall = 60 % AD Accuracy = 75 % Precision = 74 % Recall = 77 %
Jie Zhang *et al.* /2021[13]	CAM-CNN	ADNI	Accuracy = 97.35 % Sensitivity = 97.10 % Specificity = 97.95 %
Salunkhe, S *et al.* /2021 [14]	Ensemble Decision tree, SVM		Accuracy Ensemble = 90.2 % Decision tree = 88.5 % SVM = 87.2 %
AbdulAzeem, Y *et al.* /2021 [15]	CNN	ADNI	Accuracy = 97.5 %
Amir Ebrahimi *et al.* /2021 [17]	CNN, RNN	ADNI	Accuracy = 96.88 % Sensitivity = 100 % Specificity = 94.12 %
Vaithinathan K *et al.* /2019 [18]	RROI-GM + WMkNN (Fisher)	ADNI	Sensitivity = 89.58 % Specificity = 85.82 %
Jain *et al.* /2019[19]	$P_FS_EC_{TL}$CNN	ADNI	AD Precision = 100 %

(continued on next page)

Table 5 (*continued*)

Author name/Year	Methodology	Dataset	Performance metrics
			Recall = 95 % F1 score = 91 % CN Precision = 99 % Recall = 98 % F1 score = 97 % MCI Precision = 90 % Recall = 94 % F1 score = 100 %
Shailendra Kumar Mishra and V. Hima Deepthi/ 2021 [20]	SVM	ADNI	Accuracy = 98 %
T.V.Ramana, S M Nandhagopal/ 2021 [21]	CNN	FLAIR	Accuracy = 98 %
V. Sathiyamoorthi *et al.* /2021 [22]	CNN	ADNI, OASIS	Accuracy = 98 %
Oktavian *et al.* /2022 [24]	CNN	ADNI	Accuracy = 90.1 % Precision = 93 %
Xu-Dong Li *et al.* /2022 [25]	Probability distributions Biogeography-based Optimization (PDBO)	ADNI	Accuracy = 99.32 % Sensitivity = 95 % Specificity = 98.33 % Precision = 97.26 % F1 score = 96.58 %
Hett K *et al.* /2018 [23]	Texture-based grading method	ADNI	CN Vs AD Accuracy = 94.6 % Sensitivity = 94.2 % Specificity = 86.86 % CN Vs pMCI Accuracy = 92 % Sensitivity = 92.5 % Specificity = 81.2 % ADVs sMCI Accuracy = 82.6 % Sensitivity = 77.6 % Specificity = 72.6 % sMCI Vs pMCI Accuracy = 76.1 % Sensitivity = 74.9 % Specificity = 70.2 %
Liu M *et al.* /2019 [26]	Deep Multi-task multi-channel learning	ADNI MIRIAD	Accuracy = 93.7 % Sensitivity = 94.6 % Specificity = 93.2 %
W. Li, Y *et al.* /2019 [38]	Transfer Learning	ADNI Tongji	Accuracy = 84.6 % Sensitivity = 92 %

Table 5 (*continued*)

Author name/Year	Methodology	Dataset	Performance metrics
			Specificity = 79 %
Y. Lei *et al.* /2019 [39]	Semi supervised ELM	G50C COIL20B USPST USPST (B)	Accuracy = 0.87
SaidjalolToshkhujaev *et al.* /2020 [41]	RBF-SVM principal component analysis	ADNI ARWIBONACC	Accuracy: NACC = 94.74 ARWIBO = 94.87 ADNI = 87.50 Sensitivity: NACC = 92.56 ARWIBO = 88.89 ADNI = 77.78 Specificity: NACC = 100 ARWIBO = 92.75 ADNI = 100
C. Kavitha *et al.* /2022 [42]	Decision Tree Random Forest	OASIS Kaggle	Accuracy = 83 %

an accuracy of 95 % was achieved over 240 ADNI sMRI that were not used for training.

Zhonghao Fan *et al.* (2021) used 3D T1-weighted MRI, a U-net type model for AD diagnosis. The model was evaluated for classification of AD vs. NC vs. EMCI vs. LMCI in addition to these binary-classification tasks and it performs accuracy is 96 %. K.R. Kruthika (2019) presented a system for the early detection of Alzheimer's that uses 3D Capsule Network, 3D-CNN, and pre-trained 3D-autoencoder technology. The model could classify AD with up to 98.42 % accuracy. Suriya Murugan *et al.* (2021) proposed Dementia Network architecture to diagnose Alzheimer and dementia disorder. The model produced an accuracy of 95.23 %, 97 % of the area under curve and 93 % of cohens kappa value for ADNI and Kaggle dataset. Table 6 shows the performance metrics of various DL techniques. Figure 6 shows the accuracy of different DL techniques.

8. Limitation of learning techniques

There are various machine and deep learning techniques are mentioned and discussed. Both the techniques have their own limitations. The limitation of machine learning techniques includes limited number of dataset for validation [8,22,29,30,38], less accuracy [9], fixed input patches, complicated pruning strategy, nonlinear registration increased the computational complexity [10], less explainable model [12] computational time to train parameters [13,18], multi-classification not possible [15,24,33,35,37,39,44,59], not applicable for larger dataset [17,21,23], computational complexity [19,20,27,28,30–32,36,43], input images should be increased [25], performance degradation due to different dataset [26], redundant and irrelevant features are used [42], structure complexity [34].

The accuracy of various machine and deep learning techniques are shown in figure 6 and 7.

9. Conclusion

Major causes of death in developed nations after stroke is AD. Due to the difficulty of early AD detection in hospitals, the integration of computer-based methods with medical professionals has much to recommend it for early AD detection. ML and DL has established a lot of attention recently for this task. The study describes how the development of AD detection systems has been made possible by machine learning and deep learning. This paper is about image dataset available

Table 6
Performance analysis of Various DL Techniques.

Author name/Year	Methodology	Dataset	Performance metrics
Lu, Siyuan *et al.* /2021[37]	AlexNet ELM optimized by chaotic bat algorithm	ATLAS	Sensitivity = 97.14 % Specificity = 95.71 % Accuracy = 96.43 %,Precision = 96.17 % F1 score = 96.50 %
Yu Wang *et al.* /2021 [27]	PCA Net 3D ShuffleNet	ADNI	AD versus NC Accuracy = 85.2 %, Sensitivity = 69 % Specificity = 96 %, Precision = 93.3 % F1 score = 69 %, Recall = 79 % AD versus MCI Accuracy = 84 %, Sensitivity = 84 % Specificity = 84 %, Precision = 84 % F1 score = 84.9 %, Recall = 84.1 % MCI versus NC Accuracy = 85.2 %, Sensitivity = 69 % Specificity = 96 %, Precision = 93.3 % F1 score = 69 %, Recall = 79 %
N. Deepa *et al.* /2022 [28]	VGG-16	ADNI OASIS	Accuracy = 97 %
Odusami *et al.* /2021 [29]	Modified version of ResNet18	ADNI	Accuracy EMCI vs. AD = 99.99 % LMCI vs.AD = 99.95 % MCI vs. EMCI = 99.95 %
Fan, Z *et al.* / 2021 [30]	U-net model's	ADNI, AIBL	Accuracy AD versus NC = 95.71 ± 1.36 % EMCI versus LMCI = 90.14 ± 3.66 % AD versus LMCI = 90.05 ± 2.63 % NC versus EMCI = 87.98 ± 4.54 %
Heta Acharya *et al.* /2021[31]	VGG16, ResNet −50 and modified AlexNet	ADNI	VGG16 Accuracy = 84 %, Precision = 84 % F1 score = 84.9 %, Recall = 84.1 % ResNet-50 Accuracy = 75.25 %,Precision = 56.56 % F1 score = 79.41 %, Recall = 43.78 % AlexNet Accuracy = 95.70 %,Precision = 91.90 % F1 score = 94.70 %, Recall = 92.30 %
Naz, S. *et al.*/2022 [32]	VGG	ADNI	Accuracy MCI/AD-99.27 %, AD/CN-98.89 % MCI/CN-97.06 %
Shaji *et al.*/2021[33]	Inception-Residual Network (ResNet)	ADNI	Precision = 69 %, Recall = 69 %
Jayanthi Venkatraman Shanmugam *et al.* /2022[34]	Google Net, Alex Net, ResNet-18	ADNI	Accuracy GoogleNet = 96.39 %,AlexNet = 94.08 % ResNet-18 = 97.51 %
Sun, H. *et al.* /2021 [35]	ResNet	ADNI	Accuracy = 97.1 %, Precision = 95.5 % F1 score = 95.4 %, Recall = 95.3 %
Hongfei Wang *et al.*/ 2019[36]	3D-DenseNets	ADNI	MCI/AD Accuracy = 93.61 %,Precision = 92.45 % Recall = 94.59 % MCI/NC Accuracy = 98.42 %,Precision = 98.34 % Recall = 98.37 % AD/NC Accuracy = 98.83 %,Precision = 98.70 % Recall = 98.70 %
Sunday Adeola Ajagbe *et al.*/2022 [43]	DL CNN VGG-16,19	Kaggle	Accuracy CNN = 0.7102 VGG-16 = 0.7704 VGG-19 = 0.7766 Precision CNN = 0.54 VGG-16 = 0.5708 VGG-19 = 0.5848 F1 score CNN = 0.52 VGG-16 = 0.4617 VGG-19 = 0.4505 Recall CNN = 0.5004 VGG-16 = 0.3878 VGG-19 = 0.3667
Buvaneswari, P.R *et al.*/2021 [44]	Segnet Resnet101	ADNI	Accuracy = 95 %, Sensitivity = 96 %
Zhonghao Fan *et al.*/ 2021[30]	U-net	ADNI, AIBL	Accuracy AD vs NC = 95.71 %, EMCI vs LMCI = 90.14 % AD vs LMCI = 90.5 % NC vs EMCI = 87.98 %
K.R. Kruthika *et al.* /2019[49]	3D-Capsule Networks (CapsNets)	ADNI	Accuracy = 98.42 %
S. Murugan *et al.* /2021[16]	DEMNET	ADNI, Kaggle	Accuracy = 95.23 %
Mujahid, M *et.al* / 2023 [84]	Efficient ensemble approach of VGG16 and Efficient-Net-B2	ADNI	Accuracy = 97.35 %
Ibrahim, R *et.al* / 2023 [50]	Particle Swarm Optimization with CNNs	ADNI	Accuracy = 98.50 %
Marwa EL *et.al* / 2023 [59]	Shallow Convolutional Neural Network	OASIS	Accuracy = 99.68 %.
Rana *et.al* / 2023 [68]	Hybrid Deep Learning Model	kaggle	Accuracy = 97.31 %
Rana *et.al* / 2023 [62]	Sub-grouping analysisby manifold learning	ADNI	Accuracy = 97.14 %

for AD analysis, image pre-processing techniques for image denoising and enhancement, image segmentation techniques to segment the region of interest and image classification using machine learning and deep learning techniques. Classification accuracy of AD is better in DL compare to ML models.

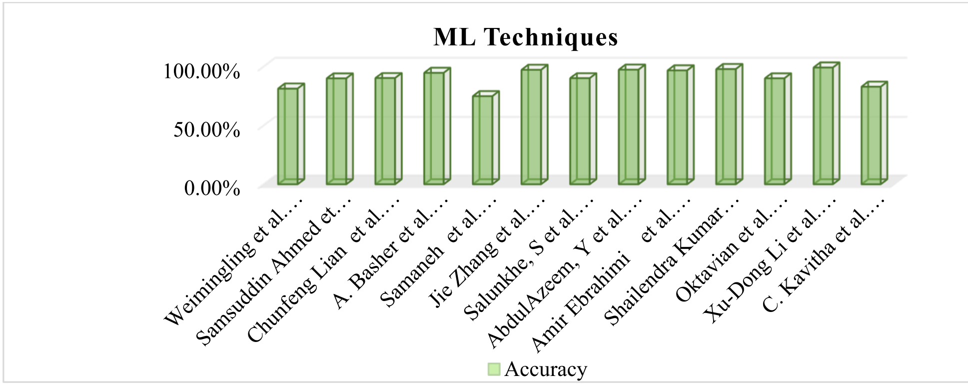

Fig. 6. Accuracy of different ML techniques.

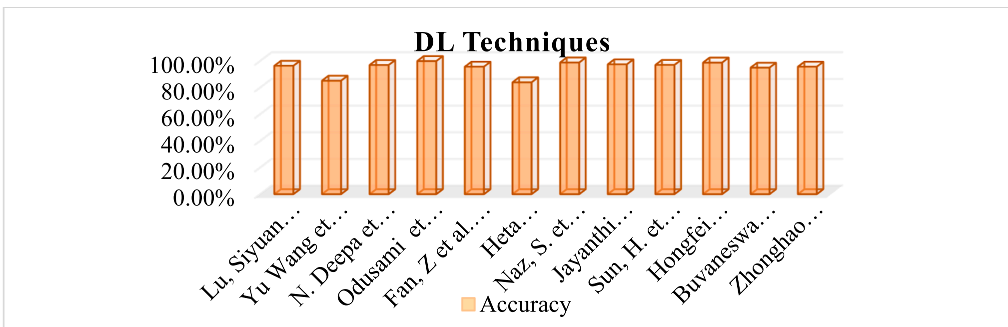

Fig. 7. Accuracy of different DL techniques.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Review Paper

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