SEMARAK ILMU
PUBLISHING
202103268166(003316878-P)

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

An Overview of Deep Learning Approaches for Alzheimer's Disease Classification: A Review

V. Sanjay[1], P. Swarnalatha[1,*]

[1] School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, Tamil Nadu, India

ARTICLE INFO

Article history:
Received 21 July 2023
Received in revised form 17 September 2023
Accepted 3 October 2023
Available online 17 October 2023

Keywords:
Multi Cognitive Impairment (MCI); Amyloid, Structural MRI (sMRI); Neuro fibrillary; Feature extraction; Long Short Term Memory (LSTM); Artificial Neural Network (ANN)

ABSTRACT

The most impressive organ that has the ability to produce emotion, flexible enough to enthusiastically modify itself, and is more potent than any computer ever created is the human brain. The well-known form of dementia, which is characterized by progressive loss of memory and cognitive function that affects more than 15 million people globally, is termed Alzheimer's Disease (AD). Nevertheless, for neurologists, AD classification is a well-known problem. For the classification of various stages of AD, enormous techniques are wielded recently. Grounded on Deep Learning (DL) approaches, a review was done on AD classification. Feature extraction and selection approaches, Deep neural network center classification, and dataset-centric classification are highlighted, as are new studies focusing on the categorization of AD based on these methods. Finally, regarding performance metrics, the performance of the several approaches wielded for the classification of AD is analogized.

1. Introduction

A multifaceted organ to control thought, memory, emotion, hunger, and all course of action, which controls our body is called the brain [1]. The mind and different organs will quit working if the brain doesn't work appropriately, which prompts the demise of the individual within a couple of moments [2]. A progressive neurologic disorder, which causes the brain to shrink (atrophy) and brain cells to die, is termed Alzheimer's syndrome. The '2' key characteristic features of AD are Amyloid plaques and neurofibrillary tangles [3]. Lack of ability to access new information is the general symptom in which it will be tedious to recall recent events, and many complex daily activities will also be affected [4].

As per World Health Organization (WHO), AD ranked 5th amongst causes of death. Normal, mild, moderate, and severe are the '4' stages of AD [5]. The primary stage of AD is the normal stage where the patients have gentle cognitive complications with loss of memory. The learning and memory impairment of patients is maximized in the mild stage. When a patient reaches the moderate level, their condition has worsened since they no longer have the freedom to perform even the most

* *Corresponding author.*
E-mail address: pswarnalatha@vit.ac.in

https://doi.org/10.37934/araset.33.1.122140

fundamental of everyday tasks. Disorientation to familiar surroundings, as well as a general decline in long-term memory, are possible indications [6]. Emotional instability, irritability, and violent behaviour are the general manifestations. The late stage of AD is the severe stage in which patients rely completely on caregivers [7].

Very careful medical assessments like patient history, a Mini-Mental State Examination (MMSE), and physical and neurobiological exams are essential for diagnosing AD [8]. For the detection and prevention of AD, several methods were adopted. As Magnetic Resonance Imaging (MRI) is capable of producing high-quality 3-Dimensional (3D) images of brain structures by employing magnetic fields and radio waves rather than ionizing radiation or radioactive tracers, Computed Tomography (CT) is mostly replaced by MRI. For the diagnosis, medical imaging methodologies like MRI and Positron Emission Tomography (PET) provide rich and complementary imaging information [10]. MRI is an extremely powerful and safe methodology along with offers more detailed structural information. In the field of biological data mining, image analysis, disease detection, and certain other purposes, machine learning (ML) has been wielded recently [11]. DL approaches are being used for the classification of AD from the MRI data owing to the advancements in technology. In figure 1, the general diagram of the DL-centric classification of AD is depicted.

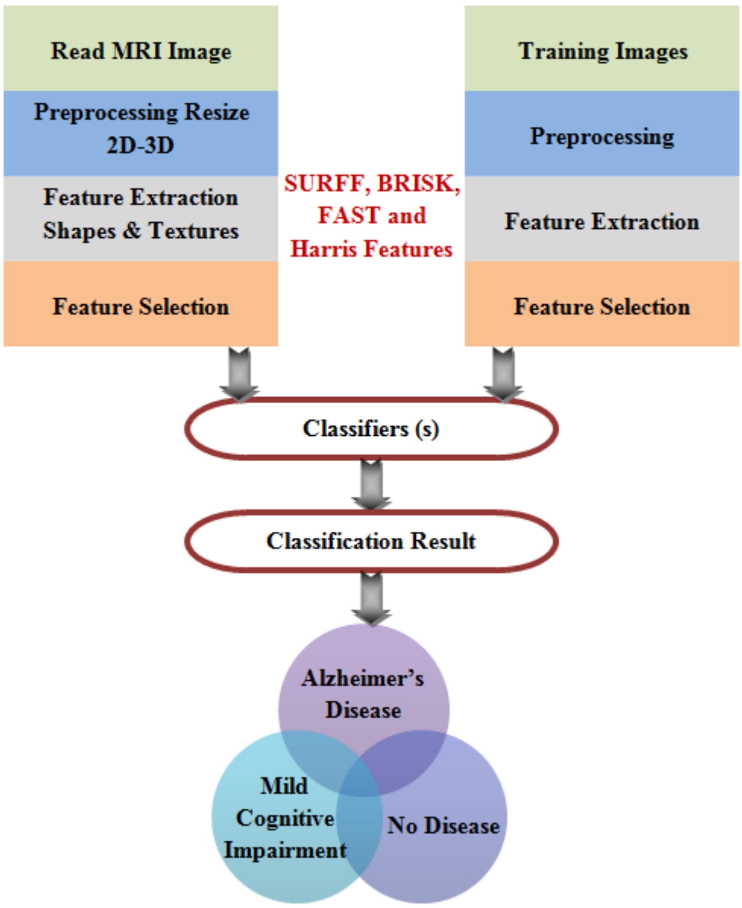

Fig. 1. General diagram for DL-based classification of AD

Since DL performs classifications as well as FE for AD identification, it is a multi-tasking technique [12]. A popular representation of ML methodologies for imitating the functionalities of a human brain to process information and creates patterns, which help in making complex decisions, is termed the DL. DL is made one among the choices by researchers due to the knack to attract information, even from unstructured and unlabeled data [13]. For AD classification, the adapted Neural Network (NN) classifiers require only fewer parameters when weighed against other network architectures.

1.1 Contributions

The contributions of this review paper are depicted below.

- For reducing err, this study analyses the different existing FE and selection-based AD classifications.
- By employing several datasets, this study discusses the AD categorization.
- This study highlights the deep belief network and auto-encoder-based classification of AD.
- In the end, this study highlights different ensemble and DNN-based classifications of AD.

The remaining part is arranged as: all the state-of-art methods were detailed with their upshot and inadequacy in section 2; the review paper is concluded with a suggestion in section 3.

2. Related Works

Here, the deployed techniques for the AD classification are elucidated further.

2.1 Different Feature Extraction and Selection Process in the Classification of AD

Manhua *et al*., [14] developed automatic hippocampus segmentation and AD classification of MRI data by utilizing a multi-model DL-centric Convolutional NN (CNN). By employing multi-task deep CNN, the hippocampus segmentation was conducted. For extracting the features obtained from the hippocampus segmentation, 3D Densely Connected Convolutional Networks (3D Dense Net) were adopted. To classify the stage of AD, the extracted features obtained from the multi-model CNN and Dense Net were combined. For AD classification, the system surpassed various prevailing techniques with an accuracy level of 88.9%. However, for a better understanding of brain abnormalities, the extracted features provided insufficient clinical information.

Luis Javier *et al.,* [15] presented a fresh methodology for the identification and categorization of AD from MRI images. For extracting the features, the Discrete Wavelet Transform (DWT) was deployed. Normalized Mutual Information Feature Selection (NMIFS) was utilized in the Feature Selection (FS). For the classification of AD, a Support Vector Machine (SVM) was wielded. Hence, the system was less sensitive along with capable of working in complex environments with several variables. Nevertheless, the FS process was made more challenging due to dimensionality reduction, which affected the classification accuracy.

Jie Zhang *et al.,* [16] designed a CNN-centric network for the diagnosis and prediction of AD. Pre-processing was conducted subsequent to the FE process. By employing a densely connected NN, FE was carried out. For merging connections amidst various features from diverse layers in which MRI data was mapped into high-level features, a connection-centric attention system was wielded. The low-convergence was solved by the utilization of the input data in the form of MRI patches. But, information redundancy is caused by the information extracted from various layers.

Rachna Jain *et al*., [17] exhibited a transfer learning methodology for the classification of AD by employing brain MRI data. For the transfer learning approach, a pre-trained Visual Geometry Group (VGG16) was deployed as a feature extractor. On top of the VGG network, the fully connected layers were placed. Hence, the over fitting issue was avoided by the adapted dropout regularisation technique. Nevertheless, a huge amount of data is required during the training phase.

Silvia Basaia *et al.,* [18] developed a DL technique for the detection of AD grounded on single cross-sectional MRI brain data. In the convolutional network, the features were extracted from the incoming input data and were stored in the form of a feature map. To increase the non-linearities, an activation function was implemented. Down-sampling was done subsequent to the AD classification. Hence, by employing this system, the regularization issue was minimized. The technique was backbreaking and prone to inter-and intra-rater variability as feature definition and extraction typically rely on brain structures.

Yousry *et al*., [19] expounded on a CNN-centric technique for AD classification. By employing adaptive thresholding, the incoming data was pre-processed. By utilizing Glorot Uniform Weight Initializer (GUWI), the features were extracted after weight initialization. For performing the optimization, ADAM (ADAptive Momentum Estimation) was wielded. The system's classification accuracy surpassed the other current techniques. However, the effectiveness wasn't good for all the datasets since the outcome was proved just with a small sample size.

Ali Nawaz *et al*., [20] designed a 2-dimensional Deep CNN (2D-DCNN) centered detection of AD. For effectual AD detection, the 3D image was converted into 2D slices. Via a cluster of neurons, a convolution operation was conducted. From the MRI image, the features were extracted. Hence, not just the classification accuracy was improved but also the class imbalance in the multiclass classification issues was elucidated. Nevertheless, for cross-checking, joined usage of the metadata along with the clinical details wasn't possible.

Bijen Khagi and Goo-Rak Kwon [21] examined a 3D CNN for AD classification. For minimizing the over fitting issue, the input image was resized after multiple downsizing. In the FE, a simple encoder-centric CNN was wielded after data classification. Hence, filter redundancy was minimized. However, poor classification performance was caused due to the difficulty in predicting the features.

In table 1, the FE count and the FS method of the existing research work, their outcome, and limitations are elucidated.

Table 1
Analysis of FE and FS methods for the classification of AD

Author	Feature Extraction/ Selection methods	Steps involved	Results	Drawbacks
Emtiaz Hussain *et al.,* [22]	For CNN-based AD classification, 12 features were extracted and selected.	Through image resizing and denoising, Initially, Data pre-processing was done followed by a data labelling procedure. Finally, 12-layer CNN was utilized for AD classification	The CNN classifiers achieved accuracy at the level of 97.75%.	By utilizing this approach, multiclass classification of data was not possible.
Regina Esi Turkson *et al.,* [23]	For extracting features for AD classification, the unsupervised convolutional Spike NN (SNN) approach was used.	Via skull-striping, registration, segmentation, and region of interest outlining, the MRI data were pre-processed. For extracting AD features, the pre-processed images were pre-trained with an unsupervised SNN. For classification, the	The presented methodology achieved a classification accuracy of about 90.15% and was more reliable and error-free.	For the dataset, the dependence of the execution speed on the weight dynamics wasn't good.

		pre-trained spikes were then passed to the deep CNN.		
Shaik Basheera and Satya Sai Ram [24]	By using threshold and morphological operations, features were extracted.	By using Gaussian filters, MRI images were pre-processed. By using hybrid enhanced Independent Component Analysis, the FE was carried out after the classification of the AD.	With less affected by noise and data augmentation, Obtained accuracy at an average of 98%, a sensitivity of about 96%.	From Mild Cognitive Impairment (MCI) and Cognitive Normal (CN), just AD was differentiated; however, it was not tested on neurological disorders.
Kruthika *et al.,* [25]	For extracting unsupervised data, 3 layered Artificial NN (ANN) was used.	After ANN-based FE, the incoming data was pre-processed. For AD classification, 3D-capsule networks together with 3D-autoencoder were wielded.	With (94.06%) accuracy and reduced requirement of data, 3D-CapsNet provided robust dynamic routing.	Because of the random weight selection of the neurons of the layer, The ANN classifier might not perform well.
Ahsan *et al.,* [26]	For the extraction of features from the local brain images, Deep 2D CNN (2D-CNNs) were wielded.	The pre-processed features were passed through Inception version 3 and Xception architectures together with CNN which aids in the automatic learning of the generic features from imaging data for further classification.	Efficient and faster classification accuracy.	For a better understanding of brain abnormalities, no adequate clinical information was obtained.

Swathi *et al*., [27] suggested a DCNN-centric methodology for AD classification by utilizing MRI data. The data was pre-processed in which by employing an element-wise multiplication filter in the CNN classifier, the incoming data was converted into slices subsequent to the FE. Hence, the over fitting issue was avoided. However, in predicting the fresh data, the noise affected the system's capability.

Janghel *et al.,* [28] recommended a DL-centric system for the diagnosis and classification of AD. In the images' resizing phase, the incoming 3D image was converted to a 2D image. For the FE, the VGG-centric technique was wielded. For the AD classification, SVM-centric Linear Discriminate, K means clustering, and Decision tree classifiers were wielded. Hence, for the classification of ADNI-centric MRI images, 99.95% accuracy was attained. Nevertheless, in the datasets with huge images, it can't be wielded.

Amir Ebrahimi *et al*., [29] exhibited sequence-centric DL methodologies for the detection and classification of AD. Via intensity normalization, the incoming data from MRI was pre-processed. For obtaining a fixed-size template, these normalized images were registered. For FE, the CNN was wielded that was then merged with the trained image sequences. For the effectual AD classification, RNN was wielded. By employing just fewer parameters, this system attained accurate classification along with offered with simplified networks. However, there were several vanishing gradient issues.

Mostafa Amin-Naji *et al.,* [30] deployed Siamese CNN (SCNN) for AD classification. In SCNN, ‘3’ CNN branches were included with anchor images fed to one branch; while, positive and negative images were fed to the other two branches. The pair-wise distance betwixt the positive and anchor image as well as the negative and anchor image was recognized. AD was classified grounded on the distance measurement. In low dimensional search space, the dimension of the input image was reduced. Nevertheless, just when the data is less, enhanced outcomes were offered, and the accuracy was affected if the data size was more.

2.2 AD Categorization using a Different Dataset

For the effectual AD classification, several kinds of datasets were deployed; in addition, they are elucidated as follows,

- *OASIS dataset-based AD classification.*

Alejandro Puente-Castro *et al.,* [31] magnified DL-centric AD detection from Sagittal MRI. Details concerning the patient's sex and age were loaded. For FE, the ResNet ANN was wielded. Next, the extracted features were connected to their respective sex and age. For data classification, the SVM was deployed. The data imbalance issue was avoided by parameterization. However, owing to the random weight selection of the neurons, the system may generate less accuracy.

Karim Aderghal *et al.,* [32] developed a cross-model-centric transfer learning approach for the effectual AD classification. On the dataset, the models were pre-trained. To initialize network parameters on Mean Diffusivity data, domain-depended data augmentation was employed. By utilizing DCNN, the features were extracted and classified. Hence, the over-fitting phenomena were minimized; in addition, learning performance was enhanced. But, there was a low convergence issue.

Marcia Hon and Naimul Mefraz Khan [33] utilized ‘2’ well-liked CNN (VGG16 and Inception) architectures for the effectual AD classification. The features are extracted from the input MRI brain image by the convolutional layers in CNN. In the max-pooling layer, the maximal feature response in a local neighbourhood was chosen. By convolutional layers, a non-linear relationship amongst the local features extracted was offered by huge fully connected layers in CNN. The Softmax classifier offered the normalized output. The system attained enhanced performance regarding the smaller training dataset. However, in the datasets with several images, this scheme can’t be deployed.

Rigel Mahmood and Bishad Ghimire [34] incorporated Principal Component Analysis (PCA) cenetred ANN classification of AD. By employing rigid transformation, the incoming MRI brain images were normalized. By deploying the PCA, the normalized images’ dimensions were minimized. Or effectual AD classification, the dimensionality-educed features were inputted into a multi-stage multi-fed NN classifier. Hence, in the datasets with a larger number of images, the system can be wielded. However, since was classified grounded on a particular (hippocampus) section of the brain, this methodology wasn’t effectual.

Bijen Khagi *et al*., [35] presented a CNN-centric classification of AD from MRI brain data. For pre-training of the Alex net, the brain images were gathered along with the network was fine-tuned after the effectual AD classification. By employing this scheme, a smoother, faster along with validation process was attained. Nevertheless, merely when the layers were fine-tuned, enhanced performance was attained.

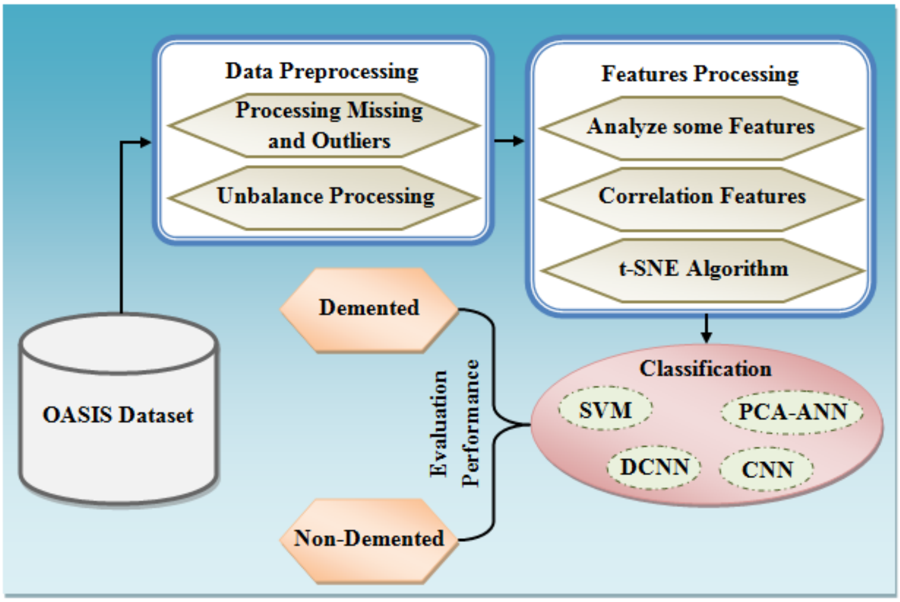

Fig. 2. OASIS dataset based classification of AD

Previtali *et al.*, [36] targeted an automatic methodology for AD classification from MRI brain images. For acquiring a noise-free image, the incoming MRI brain image was pre-processed. To extract features, which were deployed for task classification, Oriented Fast (OF) and Rotated Brief (RB) were deployed. Those features with spatial position information were processed along with inputted into the SVM. By taking only less than a second, the system exhibited enhanced performance. Nevertheless, owing to its supervised nature, this methodology failed that is, it detected just brain diseases.

Babak A. Ardekani *et al*., [37] recommended AD classification centered on the shape of the Corpus Callosum (CC). By utilizing a fresh system, the incoming MRI brain image was normalized along with the brains' mid-Sagittal region was segmented. The segmented region was fed into the scheme. The AD's stage was grounded on the CC's circularity. This system is made apt for clinical usage due to its lower requirements, improved precision, and pace. The deployed statistical test was insufficiently power-driven for perceiving the true difference since it classified AD grounded on sample size and measurement errors.

➢ *ADNI dataset-based AD classification.*

In table 2, the classification of AD deploying several methodologies on the ADNI is elucidated.

Table 2
Evaluation of various approaches involved in AD classification on the ADNI dataset

Researcher Name	Techniques	Dataset used	Accuracy	Merits	Limitations
Lulu Yue *et al.,* [38]	DCNN-based automatic AD classification	ADNI	96.91%	To classify AD patients based on the stages, The model explores the efficient accuracy rate.	The prediction accuracy might be affected by the random nature of the test data.
Tooba Altaf *et al.,* [39]	Hybrid texture-based automatic	ADNI	98.4%	By demonstrating multifaceted	The standard format of the approach is

	AD classification using MR images			information in a simpler form, FE espoused the minimized burden on resources like memory and computational power.	affected by the pre-processing based on weighted sequences.
Jin Liu *et al.*, [40]	weighted Multiple Kernel Learning (wMKL) technique.	ADNI	95.24%	Various classification issues were solved by the linear transformation of original vectors in high dimensional space.	with only edge features, classification performance was obtained.
Dolph *et al.,* [41]	New texture features for multiclass classification of AD-MCI-CN	ADNI	58%	For the classification of AD with higher True Positive Fraction (TPF), the method was used in the medical field.	The irregular nature of the real-life signals was not effectively handled.
Rémi Cuingnet *et al.,* [42]	SVM-based classification of AD.	ADNI	81.5%	Enhanced outcomes are attained by SVM-based classification and were more applicable to be used in the high dimensional databases.	Over fitting of data is caused due to an increase in the classification functions due to the FS step.
Amir Ebrahimighahnavieh *et al.,* [43]	Region Of Interest (ROI) based on AD classification.	ADNI	90.3%	Due to the particulate selection of features, Overlapping data features were avoided.	In pre-processing and brain segmentation, Lower acquisition of MRI image quality and errors might arise.

The process of classification of AD using the ADNI dataset is illustrated in figure 3.

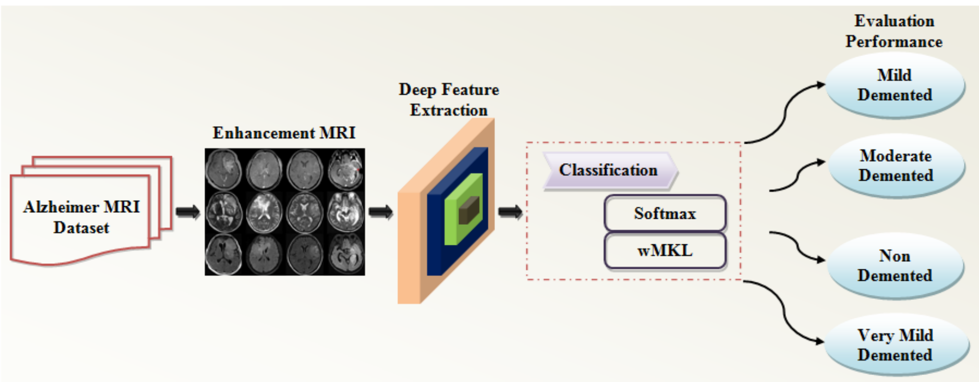

Fig. 3. ADNI dataset-based classification of AD

2.3 Deep Neural Network (DNN) and Auto-Encoder (AE) based classification of AD.

Various DNN and AE-based techniques encompassed in AD classifications are elucidated further. Ratna Mufidah *et al.,* [44] offered a Voxel-Based Morphometric (VBM) for AD detection by deploying structural MRI (sMRI). By utilizing the VBM, the data was pre-processed. By employing the mask generated from VBM, the features were extracted. For effectual classification, the extracted raw features were inputted into DBN. Thus, in higher-dimensional data classification, the DBN was enhanced. Nevertheless, the disadvantage was the dependence of the classification results on the number of nodes.

Nianyin Zeng *et al*., [45] targeted a fresh Deep Belief Network (DBN) grounded in multi-task learning for AD classification. To eradicate the noise available in the input MRI image, data pre-processing was done. To choose the suitable features for classification, PCA was wielded for the extraction of features subsequent to Multiple Task FS (MTFS). Hence, via dropout methodology, the generalization ability was developed. But, due to the presence of outliers, the novelty was damaged.

Shaimaa Abed Al-Majeed *et al.,* [46] presented an automated classification of AD grounded on DBN. For pre-processing the MRI brain data, a k-means smoothing filter was deployed. By employing the seed filling methodology, the brain parts were segmented subsequent to FE. For extraction of certain features, texture features were wielded after the normalized feature vectors' DBN-centric classification. Hence, the histogram was enhanced by the contrast enhancement usage in pre-processing. Nevertheless, the performance hugely relayed on the node initialization.

Ahmad *et al*., [47] examined the DBN-centric pipeline for the classification of various stages of AD by employing brain MRI images. For offering Grey Matter (GM) images, the MRI images were pre-processed. To extract features, the achieved GM was then fed to the NN after FS. By employing the DBN, the chosen features were classified. Efficient multi-class classification of AD was offered initially. But, in maintaining the network structure, the utilization of the factorization layer in retaining the network depth acted as an extra burden.

Ruoxuan *et al.,* [48] projected a DL-centric longitudinal evaluation for the AD classification. For extracting the MRI images' spatial features, CNN was deployed. To attain longitudinal features for effective classification, the RNN with cascaded '3' Bidirectional Gated Recurrent Units (BGRU) was placed at the CNN output point. 91.33% of classification accuracy was achieved. However, useful information might be lost due to the necessity of longitudinal images.

Farheen Ramzan *et al*., [49] developed Resting-State Functional MRI (RS-fMRI) grounded RNN for the automatic detection and classification of AD. For removing the noise, data were pre-processed by employing RS-fMRI. Via the intensity histogram-based threshold estimation, the non-brain tissues were extracted. For the FS, the motion correction was deployed after AD classification. Hence, the accuracy degradation was avoided. Nevertheless, the layers were maximized due to the difficulty in training the deeper networks.

Sumit Sharma *et al*., [50] intended the healthcare framework for the classification of AD by utilizing an IoT-centric DL approach. To predict AD patients, the MRI brain data were inputted into the RNN. For tracking the individual's effectual abnormality, an ensemble-centric system was adopted. Via IoT-centric methodology, the AD-affected patient was offered help. Hence, the AD-affected patient's quality of life index was enhanced. But, decision tree reconstruction might be caused due to the existence of exceptional data values.

Fan Li *et al*., [51] recommended a hybrid CNN Recurrent NN (RNN) for the effective analysis of MRIs in AD. Via segmentation, a binary mask was produced; in addition, to the cropped 3D image patch on the centre of the mask. The intensity and shape features of the hippocampus were attained since the 3D image patch was then partitioned into internal and external hippocampus regions. For acquiring high-level correlation features, an RNN was cascaded with the features from the left and right hippocampus subsequent to a fully connected layer for AD classification. When analogized to the prevailing techniques, this system attained 91% accuracy. However, the segmentation error might be maximized by the irregularity in the shape and blurred edges.

Mostafa *et al.,* [52] expounded on the LSTM-centric RNN for AD classification. To tackle the missing values, a generalized training rule was adapted via a batch gradient descent algorithm. Regarding biomarker prediction and subsequent diagnostic classification, this system surpassed several other techniques. Nevertheless, the missing values are maximized by the longitudinal measurement; hence, the time interval was maximized.

Minh Nguyen *et al*., [53] offered DRNN for the diagnosis and classification of AD. For recognizing the missing data, it was trained to interpolate and extrapolate the data. Effective classification of AD was done by updating the back-propagated gradient error values. However, the disadvantages were the necessity of larger features and completely trained data with fixed time intervals.

Minh Nguyen *et al.,* [54] introduced AD classification via minimal RNN. '3' stages were encompassed in which pre-processing was conducted via forward filling or linear filling. During training and testing, the minimized RNN was deployed for filling the missing data. By the under fitting issue, the system was affected. This system was reliable as the AD classification was grounded on assumption.

Amir Ebrahimi *et al*., [55] exhibited Transfer Learning (TL) centered on CNN and LSTM classification of AD from MRI brain images. To train the network, the TL was deployed along with fine-tuned by retraining. To extract the features, the pre-trained CNN was espoused after classification by utilizing LSTM offered with spatial dependent information. Hence, by employing this scheme, the overall cognition and disease-related pathologies were found effectively. Nevertheless, the stability was affected owing to the complex network structure and the inability to make decisions alone.

2.4 Ensemble and Neural Network-based classification of AD.

The deployed various ensemble and NN-based approaches for AD classifications are elucidated further.

Ning An *et al.,* [63] developed a deep ensemble-centric framework for AD classification. For learning about the features, '2' sparse AE was trained in the voting layer. To rank the baseline classifiers at the stacking layer, a non-linear feature-weighted approach was deployed. For optimization, over-sampling and threshold moving methodologies were wielded after NN-centric classification. The easier distinguishing of features is maximized due to the addition of the feature transformation. But significant information might be lost owing to the reduction in the dimension of the features in transformed spaces.

Wenjie Kang *et al.,* [64] deployed multi-model and multi-slice EL-centric classification of AD. After FS, the incoming MRI brain image was pre-processed. With the selected features, the discriminator was trained. For achieving that feature, multi-scale ensemble learning was wielded. When weighed against the prevailing systems, this one attained enhanced classification outcomes. Nevertheless, the classification accuracy was affected due to training with the selected number of features.

Emimal Jabason *et al.,* [65] recommended an ensemble of hybrid deep CNNs classification of AD. With pre-trained ImageNet weights, the CNN was initialized. With the bottleneck features, which were extracted from the baseline CNN, a small fully-connected model was fine-tuned. For extracting features, the utilization of ResNet and Dense Net in the CNN architectures strengthened feature propagation along with solved the vanishing gradient issue. However, completely distinguishing every class without training was tedious.

Table 3
Classifications of AD based on DNN and AE

Researcher	Method used	purpose	Result	Limitation
Solale Tabarestani *et al.*, [56]	RNN-based longitudinal AD classification.	Mini-Mental State Examination (MMSE) score-centric AD classification.	In regression and classification, the Utilization of the FE process ahead of RNNs led to superior performance.	For training, the presence of a larger number of variables and weights in RNN required huge samples.
Ruoxuan Cui *et al.,* [57]	Multi-Layer Perceptron (MLP) NN along with RNN-centric AD classification	Spatial and longitudinal features of variable length obtained from the MRI brain data at multiple time points were used for classification	For the classification of AD, 89.7% accuracy was attained.	In the testing database, some main attributes were missed; so, prediction accuracy was reduced.
Yanbei Liu *et al*., [58]	Auto-Encoder-centric Multi-View missing data Completion (AEMVC)	To sustain the structural information, Graph regularization and Hilbert-Schmidt Independence Criterion (HSIC) centered constraints were wielded. For the representation of certain acquisitions, a kernel-based multi-view was deployed.	The harmonizing information was exploited by Co-regularising the clustering premises within the spectral clustering framework.	During the completion process, Correlation between the image views was not considered.
Rohollah Hedayati *et al.,* [59]	DL-centric-Ensemble Convolutional Auto-Encoders (DL-ECAE).	For producing image features from a 3D input image, an ensemble of features extracted through a pre-trained auto encoder was deployed after AD classification.	For accuracy, specificity, and sensitivity, the AD attained 95%, 93.8%, and 92%.	In the absence of information and supervision, it was tedious to uphold the alignment of the completed matrix and the true value.
Tien-Duong Vu *et al.,* [60]	CNN-based Auto Encoder for AD classification(CNN-AE)	In the CNN, pre-trained weights utilized from auto-encoder network improved the classification practice.	The accuracy (94.48%) was maximized by the reduction of noises in the white matter.	the quality of AD classification was affected by the Extra images obtained while capturing the image might.
Ricardo Mendoza-Léon *et al*., [61]	Patch-based Supervised Switching Auto encoder (PSSA)	On test data, the binary class prediction was performed at the patch level; hence, by employing the ensemble of patch predictions, AD was classified.	Indicative and consistent associated regions were obtained with better accuracy and sensitivity.	The classification performance was affected since low-dimensional information was not considered.
Wan-Ting Hsieh *et al.,* [62]	AD classification based on Behavior Score-embedded Encoder Network (BSEN)	BSEN was grounded on a 3D convolutional auto-encoder structure with contrastive loss jointly optimized by deploying behaviour scores from Mini-Mental State Examination (MMSE) along with Clinical Dementia Rating (CDR).	In AD classification, the recognition accuracy of about 59.44% was achieved.	However, the presented approach was suitable for the datasets with a lower number of samples.

Xiuli Bi *et al.,* [66] imagined an unsupervised DL-centric methodology for AD classification. For attaining features from MRI images, an unsupervised CNN was deployed. In classification, an unsupervised classification grounded on k-means clustering was deployed. Hence, enhanced classification of AD was attained. Nevertheless, it was challenging to fine-tune the system; in addition, the prediction accuracy was affected.

Chihyun Park *et al.,* [67] aggrandized the DL-centric classification of AD by employing gene expression and DNA methylation data. From the MRI brain data, the gene expression and methylation data were achieved. By utilizing the ReLu activation function, it was normalized in the softmax regression layer. Hence, by employing minimized features, the performance was enhanced. But, it was tedious to incorporate the actual MRI brain data with the high dimensional low sample size data.

Buvaneswari and Gayathri [68] targeted DL-centric segmentation for AD classification. To detect AD pertinent brain parts features from MRI images, SegNet was deployed. Via extracted features, ResNet architecture was trained from SegNet for classification. In AD classification, the system attained 95% and 96% for classification accuracy and sensitivity. However, insignificant accuracy loss maximized the requirement of storing the maximum feature value of the encoder.

Shui-Hua Wang *et al.,* [69] deployed ‘8’ layered CNN with Leaky Rectified Linear Unit (LRLU) and Max Pooling for AD classification. Every brain image was pre-processed. By employing Brain Extraction Tool (BET), the brain areas were extracted. By Gaussian kernel, the extracted features were normalized. After softmax layer-based classification, histogram stretching was wielded. This system surpassed the current techniques. Nevertheless, the classification accuracy was affected by the intrusion of hyper parameters.

Table 4
Ensemble and NN-based classification of AD

Author	Techniques involved	Process	Advantage	Drawbacks
Jyoti Islam *et al.,* [70]	Ensemble-based DCNN	By employing patch normalization, the pre-processed data was regularized. By utilizing the ReLu activation function, the weights were adjusted after the AD classification in the pooling layer.	The vanishing gradient problem was avoided. Hence, for a smaller dataset, enhanced feature propagation and classification result was obtained.	Over fitting problem is caused due to the requirement of a huge number of training data.
Santos Bringas *et al.,* [71]	AD classification based on CNN	In the convolutional layer, features were extracted using trainable kernels via a sliding window approach. In the pooling layer, the dimension of the normalized data was reduced. In the end, based on the features, the feed-forward networks are classified as AD.	For accuracy and F1 score, the CNN-centric technique achieved 90.91% and 0.897.	However, the presented algorithm was suitable only for a smaller sample size.
Heung-Il Suk *et al.,* [72]	Deep Ensemble Sparse Regression Network (DESRN).	With different regularization parameters, which were fed as input to CNN for further classification of AD, multiple	Regarding statistical significance, the presented approach outperformed other approaches and	The classification accuracy was affected by a Pre-defined number of

		sparse regularisation approaches were deployed.	rejected the null hypothesis.	regularisation control parameters.
Mengya Yang *et al.,* [73]	Joint and Deep ensemble-based classification of AD.	For selecting the features, the brain image was pre-processed after correntropy regularization of joint features. By employing the deep polynomial network, the chosen features were encoded. Via support vector regression, the AD was classified.	the presented method accurately explained the relationship betwixt MRI data and scores.	The classification accuracy was affected by the presence of outliers and missing values during training.
Ammarah Farooq *et al.,* [74]	DCNN-based multi-class classification of AD.	To produce feature maps, the input image was convolved. For further classification, it was passed through ReLu and pooling layers, and fed into the fully connected layers.	Reliable and error-free classification of AD is offered by the usage of deep networks for learning the distinct features from the MRI data.	By the local optimum problem, Performance was affected.
Ahmad Waleed Salehi *et al.,* [75]	CNN-based detection and classification of AD.	By employing Kernelized ReLu, the relationship between the image and features was obtained. For effective classification, the non-linearised features were fed into the classifier.	Accuracy along with percentage loss is 0.99% and 0.0571 respectively.	In the training database, some main attributes were missing; thus, the result was not reliable.

2.5 Comparative Analysis of Different Methods of AD Classification

Several techniques wielded for AD classification are evaluated here. For AD classification, prevailing Deep Ensemble based NNs (DENN) [63], Transfer Learning based VGG (TL-VGC) [17], BGRU [48], and Residual sMRI [49] deploy ADNI. In Figures 4 and 5, the performance analysis of the prevailing methodologies regarding the accuracy, precision, recall, f-measure, sensitivity, and specificity is depicted.

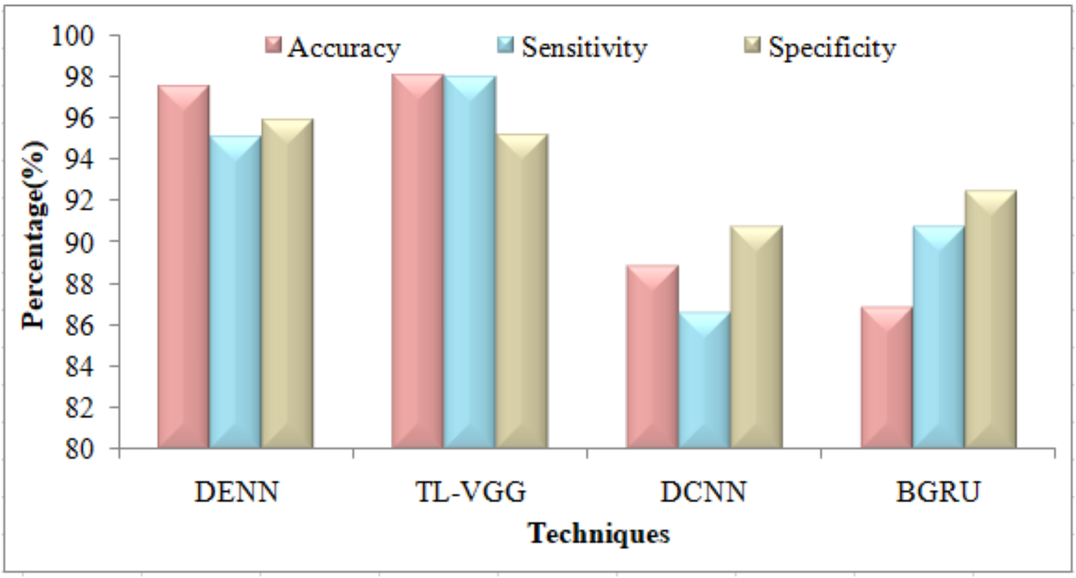

Fig. 4. Comparative analysis of various methods based on accuracy, sensitivity, and specificity

Regarding accuracy, sensitivity, and specificity, the comparative analysis of several techniques deployed in AD classification is depicted in figure 4. For accuracy, sensitivity, and specificity, the TL-VGG achieves an enhanced accuracy of 98.14%, 98.01%, and 95.21%; whereas the BGRU attains low performance of 86.87%, 90.8%, and 92.55%. Likewise, other prevailing methodologies' performance metrics are also evaluated. When weighed against other techniques, the TL-VGG exhibited enhanced performance.

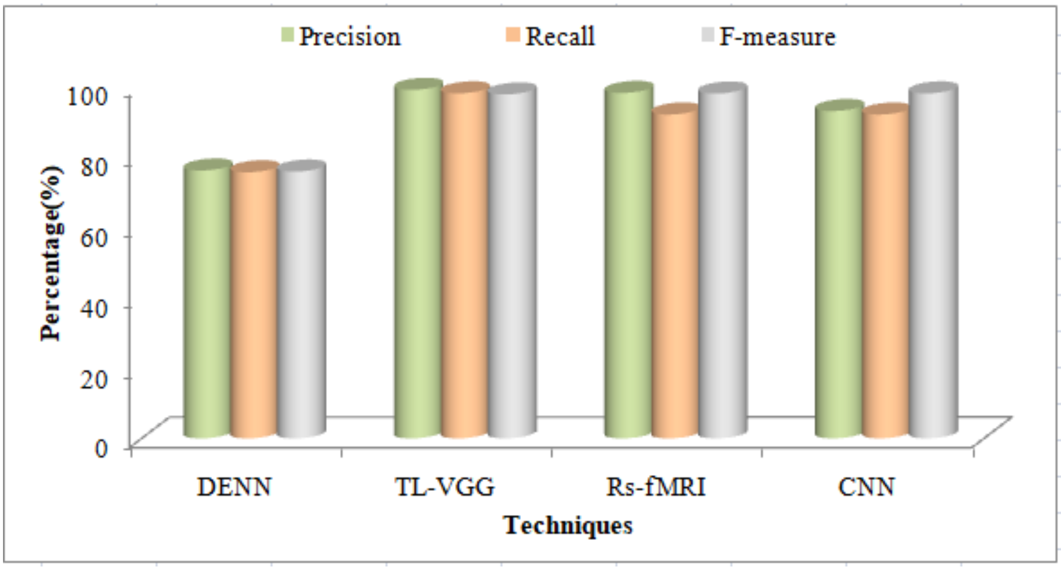

Fig. 5. Performance analysis of various methods based on precision, f-measure, and recall

Grounded on precision, f-measure, and recall, the performance of the several techniques wielded in AD classification is depicted in figure 5. When analogized to other methodologies, the TL-VGG attained enhanced outcomes regarding all metrics. For precision, f-measure, and recall, the TL-VGG attained 99%, 97.7%, and 98.01%; while, the prevailing DENN attained the lowest 76.1%, 75.8%, and 75.6% whilst the CNN is much better than DENN with a recall of 92% and 98% f-measure. Thus, when weighed against other techniques, the TL-VGG-centric system achieves superior classification.

2.6 Performance determination based on AUC

In figure 6, regarding Area under Curve (AUC), the performance of the current [14], CNN [75], BGRU [48], and ANN [39] are analogized by employing the ADNI dataset.

The prevailing technique's performance analysis grounded on AUC is depicted in figure 6. The performance will be enhanced if the AUC is high. 99.7% is the AUC of the DCNN, which depicts the AD's enhanced classification. 97.5%, 93.22%, and 92.99% are the AUC of prevailing CNN, BGRU, and ANN.

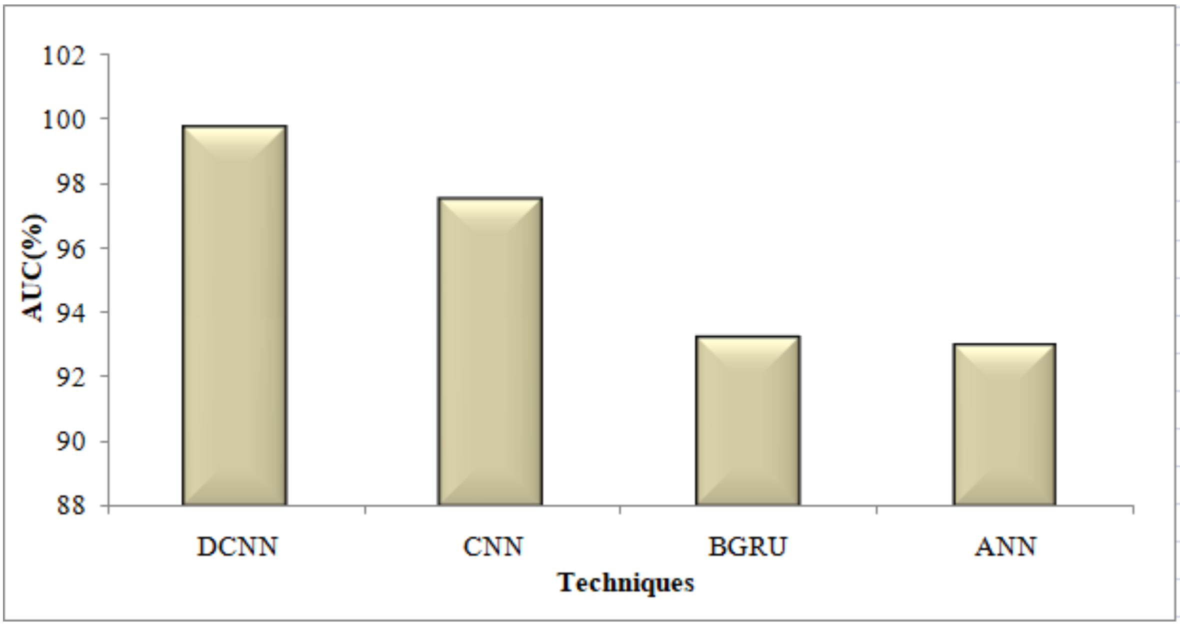

Fig. 6. Performance analysis based on AUC of various approaches for AD classification.

3. Conclusion

By employing MRI brain data, the development in computational intelligence, DL, and computer-aided detection has fascinated AD classification greatly in medical imaging. For AD classification, several techniques are wielded. For classifying AD, enormous methodologies are deployed by the recent study. Several techniques grounded systems like FE and FS techniques of AD classification, AD categorization using diverse datasets, DNN and auto-encoder-centric classification of AD, and ensemble base NN-centric AD classification are highlighted by this study. Regarding accuracy, precision, recall, f-measure, sensitivity, specificity, and AUC, the performance of various techniques is evaluated. When analogized to other systems, the DNN-centric disease classification acquires enhanced performance; in addition, the altered version of the DNN also achieves superior performance. The review article recommends that cardiovascular disease prediction with the improved version of DNN will acquire enhanced classification outcomes in the future.

References

[1] Brand, Lodewijk, Kai Nichols, Hua Wang, Li Shen, and Heng Huang. "Joint multi-modal longitudinal regression and classification for alzheimer's disease prediction." *IEEE transactions on medical imaging* 39, no. 6 (2019): 1845-1855. https://doi.org/10.1109/TMI.2019.2958943

[2] Yamanakkanavar, Nagaraj, Jae Young Choi, and Bumshik Lee. "MRI segmentation and classification of human brain using deep learning for diagnosis of Alzheimer's disease: a survey." *Sensors* 20, no. 11 (2020): 3243. https://doi.org/10.3390/s20113243

[3] Shahbaz, Muhammad, Shahzad Ali, Aziz Guergachi, Aneeta Niazi, and Amina Umer. "Classification of Alzheimer's Disease using Machine Learning Techniques." In *Data*, pp. 296-303. 2019. https://doi.org/10.5220/0007949902960303

[4] Feng, Chiyu, Ahmed Elazab, Peng Yang, Tianfu Wang, Feng Zhou, Huoyou Hu, Xiaohua Xiao, and Baiying Lei. "Deep learning framework for Alzheimer's disease diagnosis via 3D-CNN and FSBi-LSTM." *IEEE Access* 7 (2019): 63605-63618. https://doi.org/10.1109/ACCESS.2019.2913847

[5] Acharya, U. Rajendra, Steven Lawrence Fernandes, Joel En WeiKoh, Edward J. Ciaccio, Mohd Kamil Mohd Fabell, U. John Tanik, Venkatesan Rajinikanth, and Chai Hong Yeong. "Automated detection of Alzheimer's disease using brain MRI images–a study with various feature extraction techniques." *Journal of Medical Systems* 43 (2019): 1-14. https://doi.org/10.1007/s10916-019-1428-9

[6] Naik, Binny, Ashir Mehta, and Manan Shah. "Denouements of machine learning and multimodal diagnostic classification of Alzheimer's disease." *Visual Computing for Industry, Biomedicine, and Art* 3 (2020): 1-18. https://doi.org/10.1186/s42492-020-00062-w

[7] Vaithinathan, Krishnakumar, Latha Parthiban, and Alzheimer's Disease Neuroimaging Initiative. "A novel texture extraction technique with T1 weighted MRI for the classification of Alzheimer's disease." *Journal of neuroscience methods* 318 (2019): 84-99. https://doi.org/10.1016/j.jneumeth.2019.01.011

[8] Ferri, Raffaele, Claudio Babiloni, Vania Karami, Antonio Ivano Triggiani, Filippo Carducci, Giuseppe Noce, Roberta Lizio et al. "Stacked autoencoders as new models for an accurate Alzheimer's disease classification support using resting-state EEG and MRI measurements." *Clinical Neurophysiology* 132, no. 1 (2021): 232-245. https://doi.org/10.1016/j.clinph.2020.09.015

[9] Fan, Zhonghao, Johann Li, Liang Zhang, Guangming Zhu, Ping Li, Xiaoyuan Lu, Peiyi Shen et al. "U-net based analysis of MRI for Alzheimer's disease diagnosis." *Neural Computing and Applications* 33 (2021): 13587-13599. https://doi.org/10.1007/s00521-021-05983-y

[10] Bron, Esther E., Stefan Klein, Janne M. Papma, Lize C. Jiskoot, Vikram Venkatraghavan, Jara Linders, Pauline Aalten et al. "Cross-cohort generalizability of deep and conventional machine learning for MRI-based diagnosis and prediction of Alzheimer's disease." *NeuroImage: Clinical* 31 (2021): 102712. https://doi.org/10.1016/j.nicl.2021.102712

[11] Noor, Manan Binth Taj, Nusrat Zerin Zenia, M. Shamim Kaiser, Shamim Al Mamun, and Mufti Mahmud. "Application of deep learning in detecting neurological disorders from magnetic resonance images: a survey on the detection of Alzheimer's disease, Parkinson's disease and schizophrenia." *Brain informatics* 7 (2020): 1-21. https://doi.org/10.1186/s40708-020-00112-2

[12] Shao, Wei, Yao Peng, Chen Zu, Mingliang Wang, Daoqiang Zhang, and Alzheimer's Disease Neuroimaging Initiative. "Hypergraph based multi-task feature selection for multimodal classification of Alzheimer's disease." *Computerized Medical Imaging and Graphics* 80 (2020): 101663. https://doi.org/10.1016/j.compmedimag.2019.101663

[13] Fan, Zhao, Fanyu Xu, Xuedan Qi, Cai Li, and Lili Yao. "Classification of Alzheimer's disease based on brain MRI and machine learning." *Neural Computing and Applications* 32 (2020): 1927-1936. https://doi.org/10.1007/s00521-019-04495-0

[14] Liu, Manhua, Fan Li, Hao Yan, Kundong Wang, Yixin Ma, Li Shen, Mingqing Xu, and Alzheimer's Disease Neuroimaging Initiative. "A multi-model deep convolutional neural network for automatic hippocampus segmentation and classification in Alzheimer's disease." *Neuroimage* 208 (2020): 116459. https://doi.org/10.1016/j.neuroimage.2019.116459

[15] Herrera, Luis Javier, Ignacio Rojas, Héctor Pomares, Alberto Guillén, Olga Valenzuela, and Oresti Baños. "Classification of MRI images for Alzheimer's disease detection." In *2013 international conference on social computing*, pp. 846-851. IEEE, 2013. https://doi.org/10.1109/SocialCom.2013.127

[16] Zhang, Jie, Bowen Zheng, Ang Gao, Xin Feng, Dong Liang, and Xiaojing Long. "A 3D densely connected convolution neural network with connection-wise attention mechanism for Alzheimer's disease classification." *Magnetic Resonance Imaging* 78 (2021): 119-126. https://doi.org/10.1016/j.mri.2021.02.001

[17] Jain, Rachna, Nikita Jain, Akshay Aggarwal, and D. Jude Hemanth. "Convolutional neural network based Alzheimer's disease classification from magnetic resonance brain images." *Cognitive Systems Research* 57 (2019): 147-159. https://doi.org/10.1016/j.cogsys.2018.12.015

[18] Basaia, Silvia, Federica Agosta, Luca Wagner, Elisa Canu, Giuseppe Magnani, Roberto Santangelo, Massimo Filippi, and Alzheimer's Disease Neuroimaging Initiative. "Automated classification of Alzheimer's disease and mild cognitive impairment using a single MRI and deep neural networks." *NeuroImage: Clinical* 21 (2019): 101645. https://doi.org/10.1016/j.nicl.2018.101645

[19] AbdulAzeem, Yousry, Waleed M. Bahgat, and Mahmoud Badawy. "A CNN based framework for classification of Alzheimer's disease." *Neural Computing and Applications* 33 (2021): 10415-10428. https://doi.org/10.1007/s00521-021-05799-w

[20] Nawaz, Ali, Syed Muhammad Anwar, Rehan Liaqat, Javid Iqbal, Ulas Bagci, and Muhammad Majid. "Deep convolutional neural network based classification of Alzheimer's disease using MRI data." In *2020 IEEE 23rd International Multitopic Conference (INMIC)*, pp. 1-6. IEEE, 2020. https://doi.org/10.1109/INMIC50486.2020.9318172

[21] Khagi, Bijen, and Goo-Rak Kwon. "3D CNN design for the classification of Alzheimer's disease using brain MRI and PET." *IEEE Access* 8 (2020): 217830-217847. https://doi.org/10.1109/ACCESS.2020.3040486

[22] Hussain, Emtiaz, Mahmudul Hasan, Syed Zafrul Hassan, Tanzina Hassan Azmi, Md Anisur Rahman, and Mohammad Zavid Parvez. "Deep learning based binary classification for alzheimer's disease detection using brain mri images."

In *2020 15th IEEE Conference on Industrial Electronics and Applications (ICIEA)*, pp. 1115-1120. IEEE, 2020. https://doi.org/10.1109/ICIEA48937.2020.9248213

[23] Turkson, Regina Esi, Hong Qu, Cobbinah Bernard Mawuli, and Moses J. Eghan. "Classification of Alzheimer's disease using deep convolutional spiking neural network." *Neural Processing Letters* 53 (2021): 2649-2663. https://doi.org/10.1007/s11063-021-10514-w

[24] Basheera, Shaik, and M. Satya Sai Ram. "A novel CNN based Alzheimer's disease classification using hybrid enhanced ICA segmented gray matter of MRI." *Computerized Medical Imaging and Graphics* 81 (2020): 101713. https://doi.org/10.1016/j.compmedimag.2020.101713

[25] Kruthika, K. R., H. D. Maheshappa, and Alzheimer's Disease Neuroimaging Initiative. "CBIR system using Capsule Networks and 3D CNN for Alzheimer's disease diagnosis." *Informatics in Medicine Unlocked* 14 (2019): 59-68. https://doi.org/10.1016/j.imu.2018.12.001

[26] Tufail, Ahsan Bin, Yong-Kui Ma, and Qiu-Na Zhang. "Binary classification of Alzheimer's disease using sMRI imaging modality and deep learning." *Journal of digital imaging* 33 (2020): 1073-1090. https://doi.org/10.1007/s10278-019-00265-5

[27] Kundaram, Swathi S., and Ketki C. Pathak. "Deep learning-based Alzheimer disease detection." In *Proceedings of the Fourth International Conference on Microelectronics, Computing and Communication Systems: MCCS 2019*, pp. 587-597. Springer Singapore, 2021. https://doi.org/10.1007/978-981-15-5546-6_50

[28] Janghel, R. R., and Y. K. Rathore. "Deep convolution neural network based system for early diagnosis of Alzheimer's disease." *Irbm* 42, no. 4 (2021): 258-267. https://doi.org/10.1016/j.irbm.2020.06.006

[29] Ebrahimi, Amir, Suhuai Luo, Raymond Chiong, and Alzheimer's Disease Neuroimaging Initiative. "Deep sequence modelling for Alzheimer's disease detection using MRI." *Computers in Biology and Medicine* 134 (2021): 104537. https://doi.org/10.1016/j.compbiomed.2021.104537

[30] Amin-Naji, Mostafa, Hami Mahdavinataj, and Ali Aghagolzadeh. "Alzheimer's disease diagnosis from structural MRI using Siamese convolutional neural network." In *2019 4th international conference on pattern recognition and image analysis (IPRIA)*, pp. 75-79. IEEE, 2019. https://doi.org/10.1109/PRIA.2019.8786031

[31] Puente-Castro, Alejandro, Enrique Fernandez-Blanco, Alejandro Pazos, and Cristian R. Munteanu. "Automatic assessment of Alzheimer's disease diagnosis based on deep learning techniques." *Computers in biology and medicine* 120 (2020): 103764. https://doi.org/10.1016/j.compbiomed.2020.103764

[32] Aderghal, Karim, Alexander Khvostikov, Andrei Krylov, Jenny Benois-Pineau, Karim Afdel, and Gwenaelle Catheline. "Classification of Alzheimer disease on imaging modalities with deep CNNs using cross-modal transfer learning." In *2018 IEEE 31st international symposium on computer-based medical systems (CBMS)*, pp. 345-350. IEEE, 2018. https://doi.org/10.1109/CBMS.2018.00067

[33] Hon, Marcia, and Naimul Mefraz Khan. "Towards Alzheimer's disease classification through transfer learning." In *2017 IEEE International conference on bioinformatics and biomedicine (BIBM)*, pp. 1166-1169. IEEE, 2017. https://doi.org/10.1109/BIBM.2017.8217822

[34] Mahmood, Rigel, and Bishad Ghimire. "Automatic detection and classification of Alzheimer's Disease from MRI scans using principal component analysis and artificial neural networks." In *2013 20th International Conference on Systems, Signals and Image Processing (IWSSIP)*, pp. 133-137. IEEE, 2013. https://doi.org/10.1109/IWSSIP.2013.6623471

[35] Khagi, Bijen, Bumshik Lee, Jae-Young Pyun, and Goo-Rak Kwon. "CNN Models Performance Analysis on MRI images of OASIS dataset for distinction between Healthy and Alzheimer's patient." In *2019 International Conference on Electronics, Information, and Communication (ICEIC)*, pp. 1-4. IEEE, 2019. https://doi.org/10.23919/ELINFOCOM.2019.8706339

[36] Previtali, Fabio, Paola Bertolazzi, Giovanni Felici, and Emanuel Weitschek. "A novel method and software for automatically classifying Alzheimer's disease patients by magnetic resonance imaging analysis." *Computer methods and programs in biomedicine* 143 (2017): 89-95. https://doi.org/10.1016/j.cmpb.2017.03.006

[37] Ardekani, Babak A., Alvin H. Bachman, Khadija Figarsky, and John J. Sidtis. "Corpus callosum shape changes in early Alzheimer's disease: an MRI study using the OASIS brain database." *Brain Structure and Function* 219 (2014): 343-352. https://doi.org/10.1007/s00429-013-0503-0

[38] Yue, Lulu, Xiaoliang Gong, Kaibo Chen, Mingze Mao, Jie Li, Asoke K. Nandi, and Maozhen Li. "Auto-detection of Alzheimer's disease using deep convolutional neural networks." In *2018 14th international conference on natural computation, fuzzy systems and knowledge discovery (ICNC-FSKD)*, pp. 228-234. IEEE, 2018. https://doi.org/10.1109/FSKD.2018.8687207

[39] Altaf, Tooba, Syed Muhammad Anwar, Nadia Gul, Muhammad Nadeem Majeed, and Muhammad Majid. "Multi-class Alzheimer's disease classification using image and clinical features." *Biomedical Signal Processing and Control* 43 (2018): 64-74. https://doi.org/10.1016/j.bspc.2018.02.019

[40] Liu, Jin, Jianxin Wang, Zhenjun Tang, Bin Hu, Fang-Xiang Wu, and Yi Pan. "Improving Alzheimer's disease classification by combining multiple measures." *IEEE/ACM transactions on computational biology and bioinformatics* 15, no. 5 (2017): 1649-1659. https://doi.org/10.1109/TCBB.2017.2731849
[41] Dolph, Chester V., Mahbubul Alam, Z. Shboul, Manar D. Samad, and Khan M. Iftekharuddin. "Deep learning of texture and structural features for multiclass Alzheimer's disease classification." In *2017 International Joint Conference on Neural Networks (IJCNN)*, pp. 2259-2266. IEEE, 2017. https://doi.org/10.1109/IJCNN.2017.7966129
[42] Cuingnet, Rémi, Emilie Gerardin, Jérôme Tessieras, Guillaume Auzias, Stéphane Lehéricy, Marie-Odile Habert, Marie Chupin, Habib Benali, Olivier Colliot, and Alzheimer's Disease Neuroimaging Initiative. "Automatic classification of patients with Alzheimer's disease from structural MRI: a comparison of ten methods using the ADNI database." *neuroimage* 56, no. 2 (2011): 766-781. https://doi.org/10.1016/j.neuroimage.2010.06.013
[43] Ebrahimighahnavieh, Mr Amir, Suhuai Luo, and Raymond Chiong. "Deep learning to detect Alzheimer's disease from neuroimaging: A systematic literature review." *Computer methods and programs in biomedicine* 187 (2020): 105242. https://doi.org/10.1016/j.cmpb.2019.105242
[44] Faturrahman, Moh, Ito Wasito, Nurul Hanifah, and Ratna Mufidah. "Structural MRI classification for Alzheimer's disease detection using deep belief network." In *2017 11th International Conference on Information & Communication Technology and System (ICTS)*, pp. 37-42. IEEE, 2017. https://doi.org/10.1109/ICTS.2017.8265643
[45] Zeng, Nianyin, Han Li, and Yonghong Peng. "A new deep belief network-based multi-task learning for diagnosis of Alzheimer's disease." *Neural Computing and Applications* 35, no. 16 (2023): 11599-11610. https://doi.org/10.1007/s00521-021-06149-6
[46] Al-Majeed, Shaimaa Abed, and Mohammed Sabbih Hamoud Al-Tamimi. "MR Images Classification of Alzheimer's Disease Based on Deep Belief Network Method." *Int. J. Adv. Sci. Technol* 29 (2020): 3078-3088.
[47] Salehi, Ahmad Waleed, Preety Baglat, and Gaurav Gupta. "Alzheimer's disease diagnosis using deep learning techniques." *Int. J. Eng. Adv. Technol* 9, no. 3 (2020): 874-880. https://doi.org/10.35940/ijeat.C5345.029320
[48] Cui, Ruoxuan, Manhua Liu, and Alzheimer's Disease Neuroimaging Initiative. "RNN-based longitudinal analysis for diagnosis of Alzheimer's disease." *Computerized Medical Imaging and Graphics* 73 (2019): 1-10. https://doi.org/10.1016/j.compmedimag.2019.01.005
[49] Ramzan, Farheen, Muhammad Usman Ghani Khan, Asim Rehmat, Sajid Iqbal, Tanzila Saba, Amjad Rehman, and Zahid Mehmood. "A deep learning approach for automated diagnosis and multi-class classification of Alzheimer's disease stages using resting-state fMRI and residual neural networks." *Journal of medical systems* 44 (2020): 1-16. https://doi.org/10.1007/s10916-019-1475-2
[50] Sharma, Sumit, Rajan Kumar Dudeja, Gagangeet Singh Aujla, Rasmeet Singh Bali, and Neeraj Kumar. "DeTrAs: deep learning-based healthcare framework for IoT-based assistance of Alzheimer patients." *Neural Computing and Applications* (2020): 1-13. https://doi.org/10.1007/s00521-020-05327-2
[51] Li, Fan, Manhua Liu, and Alzheimer's Disease Neuroimaging Initiative. "A hybrid convolutional and recurrent neural network for hippocampus analysis in Alzheimer's disease." *Journal of neuroscience methods* 323 (2019): 108-118. https://doi.org/10.1016/j.jneumeth.2019.05.006
[52] Ghazi, Mostafa Mehdipour, Mads Nielsen, Akshay Pai, M. Jorge Cardoso, Marc Modat, Sébastien Ourselin, Lauge Sørensen, and Alzheimer's Disease Neuroimaging Initiative. "Training recurrent neural networks robust to incomplete data: Application to Alzheimer's disease progression modeling." *Medical image analysis* 53 (2019): 39-46. https://doi.org/10.1016/j.media.2019.01.004
[53] Nguyen, Minh, Nanbo Sun, Daniel C. Alexander, Jiashi Feng, and BT Thomas Yeo. "Modeling Alzheimer's disease progression using deep recurrent neural networks." In *2018 International Workshop on Pattern Recognition in Neuroimaging (PRNI)*, pp. 1-4. IEEE, 2018. https://doi.org/10.1109/PRNI.2018.8423955
[54] Nguyen, Minh, Tong He, Lijun An, Daniel C. Alexander, Jiashi Feng, BT Thomas Yeo, and Alzheimer's Disease Neuroimaging Initiative. "Predicting Alzheimer's disease progression using deep recurrent neural networks." *NeuroImage* 222 (2020): 117203. https://doi.org/10.1016/j.neuroimage.2020.117203
[55] Ebrahimi-Ghahnavieh, Amir, Suhuai Luo, and Raymond Chiong. "Transfer learning for Alzheimer's disease detection on MRI images." In *2019 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT)*, pp. 133-138. IEEE, 2019. https://doi.org/10.1109/ICIAICT.2019.8784845
[56] Tabarestani, Solale, Maryamossadat Aghili, Mehdi Shojaie, Christian Freytes, Mercedes Cabrerizo, Armando Barreto, Naphtali Rishe et al. "Longitudinal prediction modeling of alzheimer disease using recurrent neural networks." In *2019 IEEE EMBS international conference on Biomedical & Health Informatics (BHI)*, pp. 1-4. IEEE, 2019. https://doi.org/10.1109/BHI.2019.8834556
[57] Cui, Ruoxuan, Manhua Liu, and Gang Li. "Longitudinal analysis for Alzheimer's disease diagnosis using RNN." In *2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*, pp. 1398-1401. IEEE, 2018. https://doi.org/10.1109/ISBI.2018.8363833

[58] Liu, Yanbei, Lianxi Fan, Changning Zhang, Tao Zhou, Zhitao Xiao, Lei Geng, and Dinggang Shen. "Incomplete multi-modal representation learning for Alzheimer's disease diagnosis." *Medical Image Analysis* 69 (2021): 101953. https://doi.org/10.1016/j.media.2020.101953
[59] Hedayati, Rohollah, Mohammad Khedmati, and Mehran Taghipour-Gorjikolaie. "Deep feature extraction method based on ensemble of convolutional auto encoders: Application to Alzheimer's disease diagnosis." *Biomedical Signal Processing and Control* 66 (2021): 102397. https://doi.org/10.1016/j.bspc.2020.102397
[60] Vu, Tien-Duong, Ngoc-Huynh Ho, Hyung-Jeong Yang, Jahae Kim, and Ho-Chun Song. "Non-white matter tissue extraction and deep convolutional neural network for Alzheimer's disease detection." *Soft Computing* 22 (2018): 6825-6833. https://doi.org/10.1007/s00500-018-3421-5
[61] Mendoza-Léon, Ricardo, John Puentes, Luis Felipe Uriza, and Marcela Hernández Hoyos. "Single-slice Alzheimer's disease classification and disease regional analysis with Supervised Switching Autoencoders." *Computers in biology and medicine* 116 (2020): 103527. https://doi.org/10.1016/j.compbiomed.2019.103527
[62] Hsieh, Wan-Ting, Jeremy Lefort-Besnard, Hao-Chun Yang, Li-Wei Kuo, and Chi-Chun Lee. "Behavior score-embedded brain encoder network for improved classification of Alzheimer disease using resting state fMRI." In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pp. 5486-5489. IEEE, 2020. https://doi.org/10.1109/EMBC44109.2020.9175312
[63] An, Ning, Huitong Ding, Jiaoyun Yang, Rhoda Au, and Ting FA Ang. "Deep ensemble learning for Alzheimer's disease classification." *Journal of biomedical informatics* 105 (2020): 103411. https://doi.org/10.1016/j.jbi.2020.103411
[64] Kang, Wenjie, Lan Lin, Baiwen Zhang, Xiaoqi Shen, Shuicai Wu, and Alzheimer's Disease Neuroimaging Initiative. "Multi-model and multi-slice ensemble learning architecture based on 2D convolutional neural networks for Alzheimer's disease diagnosis." *Computers in Biology and Medicine* 136 (2021): 104678. https://doi.org/10.1016/j.compbiomed.2021.104678
[65] Jabason, Emimal, M. Omair Ahmad, and M. N. S. Swamy. "Classification of Alzheimer's disease from MRI data using an ensemble of hybrid deep convolutional neural networks." In *2019 IEEE 62nd international Midwest symposium on circuits and systems (MWSCAS)*, pp. 481-484. IEEE, 2019. https://doi.org/10.1109/MWSCAS.2019.8884939
[66] Bi, Xiuli, Shutong Li, Bin Xiao, Yu Li, Guoyin Wang, and Xu Ma. "Computer aided Alzheimer's disease diagnosis by an unsupervised deep learning technology." *Neurocomputing* 392 (2020): 296-304. https://doi.org/10.1016/j.neucom.2018.11.111
[67] Park, Chihyun, Jihwan Ha, and Sanghyun Park. "Prediction of Alzheimer's disease based on deep neural network by integrating gene expression and DNA methylation dataset." *Expert Systems with Applications* 140 (2020): 112873. https://doi.org/10.1016/j.eswa.2019.112873
[68] Buvaneswari, P. R., and R. Gayathri. "Deep learning-based segmentation in classification of Alzheimer's disease." *Arabian Journal for Science and Engineering* 46 (2021): 5373-5383. https://doi.org/10.1007/s13369-020-05193-z
[69] Wang, Shui-Hua, Preetha Phillips, Yuxiu Sui, Bin Liu, Ming Yang, and Hong Cheng. "Classification of Alzheimer's disease based on eight-layer convolutional neural network with leaky rectified linear unit and max pooling." *Journal of medical systems* 42 (2018): 1-11. https://doi.org/10.1007/s10916-018-0932-7
[70] Islam, Jyoti, and Yanqing Zhang. "Brain MRI analysis for Alzheimer's disease diagnosis using an ensemble system of deep convolutional neural networks." *Brain informatics* 5 (2018): 1-14. https://doi.org/10.1186/s40708-018-0080-3
[71] Bringas, Santos, Sergio Salomón, Rafael Duque, Carmen Lage, and José Luis Montaña. "Alzheimer's disease stage identification using deep learning models." *Journal of Biomedical Informatics* 109 (2020): 103514. https://doi.org/10.1016/j.jbi.2020.103514
[72] Suk, Heung-Il, Seong-Whan Lee, Dinggang Shen, and Alzheimer's Disease Neuroimaging Initiative. "Deep ensemble learning of sparse regression models for brain disease diagnosis." *Medical image analysis* 37 (2017): 101-113. https://doi.org/10.1016/j.media.2017.01.008
[73] Yang, Mengya, Peng Yang, Ahmed Elazab, Wen Hou, Xia Li, Tianfu Wang, Wenbin Zou, and Baiying Lei. "Join and deep ensemble regression of clinical scores for alzheimer's disease using longitudinal and incomplete data." In *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 1254-1257. IEEE, 2018. https://doi.org/10.1109/EMBC.2018.8512549
[74] Farooq, Ammarah, SyedMuhammad Anwar, Muhammad Awais, and Saad Rehman. "A deep CNN based multi-class classification of Alzheimer's disease using MRI." In *2017 IEEE International Conference on Imaging systems and techniques (IST)*, pp. 1-6. IEEE, 2017. https://doi.org/10.1109/IST.2017.8261460
[75] Salehi, Ahmad Waleed, Preety Baglat, Brij Bhushan Sharma, Gaurav Gupta, and Ankita Upadhya. "A CNN model: earlier diagnosis and classification of Alzheimer disease using MRI." In *2020 International Conference on Smart Electronics and Communication (ICOSEC)*, pp. 156-161. IEEE, 2020. https://doi.org/10.1109/ICOSEC49089.2020.9215402