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A BRIEF OVERVIEW OF DEEP LEARNING'S POTENTIAL FOR MRI IMAGE BASED ALZHEIMER'S DISEASE PREDICTION

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Abstract: Cognitive capacities gradually deteriorate with the onset of Alzheimer's Disease (AD), an irreversible neurological disease. As the disease progresses, it gradually robs people of their ability to control their movements and other brain functions. Initiating therapeutic measures that can impede the advancement of the disease is made possible by early detection. To detect structural and functional alterations linked to AD, Magnetic Resonance Imaging (MRI) offers high-resolution pictures of the brain. However, owing to typical aging overlap and brain architecture diversity, MRI picture interpretation might be difficult. In order to conduct a longitudinal study, sophisticated analytic methods and highly trained radiologists are required. This problem has been addressed in recent decades with the emergence of Deep Learning (DL) systems that automatically detect and classify AD using MRI scans. DL models are able to learn from complicated patterns and enormous datasets, allowing for early diagnosis and the detection of minor changes in brain structure prior to clinical signs. This study provides a comprehensive analysis of various DL frameworks that have been created for the purpose of AD picture recognition and classification using MRI. A number of AD classification systems built using DL algorithms have been briefly reviewed at the outset. In order to regulate the global morality rates, it is necessary to predict and classify MRI-based AD effectively. A comparative analysis is then performed to analyse the shortcomings of such algorithms and propose a new approach.

Keywords: Alzheimer's Disease, Magnetic Resonance Imaging, Brain Anatomy Variability Deep Learning, Earlier Diagnosis.

I. INTRODUCTION

Brain atrophy and cell death are hallmark symptoms of Alzheimer's disease (AD), a degenerative brain disorder that progresses over time. Eventually, the patient will die as the condition progresses and their bodily functions deteriorate [1]. In most cases, there is a progression of symptoms from early to late stages of Alzheimer's disease [2]. In its early stages, dementia manifests itself mildly, with symptoms such as forgetfulness of recent events, language difficulties, mood swings, and personality changes. Memory loss, confusion, impaired judgment, communication issues, behavioral changes (such as restlessness and agitation), and impaired recognition of loved ones are all part of the middle stage. Severe memory loss, communication difficulties, swallowing problems, loss of physiological functions, and total reliance on caretakers are all symptoms of the late stage [2].

Brain structures in both healthy and AD states are shown in Figure 1. A person's genetic makeup and family history contribute to an increased risk of Alzheimer's disease (AD) after the age of 65. The development of Alzheimer's disease can be accelerated by certain lifestyle factors, such as being inactive, smoking, having poor cardiovascular health, being overweight, or having diabetes [3]. An additional risk factor for the condition in old age is traumatic brain injury. Several medical interventions can alleviate symptoms in the early stages of Alzheimer's disease. Imaging procedures, mental status assessments, neurological and physical examinations, and medical history all play a role in making a diagnosis [4]. Magnetic Resonance Imaging (MRI), Electro-Encephalography (EEG), and genotyping are some of the imaging and computational technologies that will provide the accurate detection. Brain Computed Tomography (CT). These tools have shown signs of brain atrophy and helped neuropsychologists detect early-stage Alzheimer's disease and initiate therapeutic interventions to slow its progression [5].

For the purpose of AD prediction and categorization, Magnetic Resonance Imaging (MRI) is one of several imaging models that offers a degree of flexibility [6]. Using a stack of two-dimensional (2D) slices, an MRI scanner may create a three-dimensional (3D) volumetric data image of the brain. Since magnetic resonance imaging (MRI) does not involve ionizing radiation, it is safe to use repeatedly over an extended period of time [7]

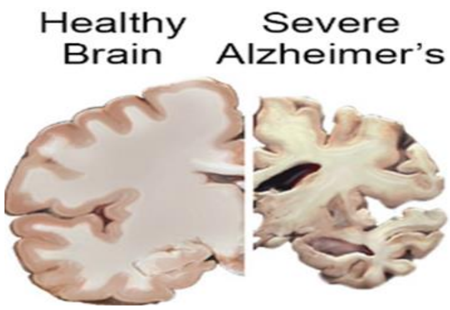

Figure 1. Healthy Brain Structure Vs. AD Brain Structure

. Furthermore, it offers high-resolution pictures of brain structures, which enable accurate assessment of structural alterations such atrophy [8]. Using MRI images, Figure 2 shows the anatomy of the healthy brain and the structure of the AD brain. MRI techniques can be utilized to identify various brain functions for the prediction of AD which are listed below.

- **Structural MRI:** It assess brain anatomy and detect structural changes. It identifies two brain malfunctions: brain atrophy, a shrinkage of brain tissue, especially in the hippocampus with entorhinal cortex, and ventricular enlargement, the expansion of the brain's ventricles due to tissue loss.

- **Functional MRI (fMRI):** Variations in blood flow are detected by it as a measure of brain activity. Patterns of brain activity were changed, particularly in areas and networks associated with memory, such as the Default Mode Network (DMN).
- **Diffusion Tensor Imaging (DTI):** It measures the diffusion of water molecules in the brain to evaluate the integrity of white matter tracts. A decrease in white matter integrity is discovered, suggesting that the brain's communication channels have been disrupted.
- **Arterial Spin Labeling (ASL):** It evaluates the Cerebral Blood Flow (CBF). It is common to find the reduced CBF in regions typically affected by AD, such as the parietal and temporal lobes.
- **Magnetic Resonance Spectroscopy (MRS):** It measure the concentration of various brain metabolites. It also finds the altered levels of metabolites such as N-Acetyl-Aspartate (NAA), choline and myo-inositol, which can indicate neuronal loss and glial activation.

MRI can detect early brain changes before significant cognitive symptoms appear, aiding in early diagnosis and intervention. It effectively monitors disease progression for tracking changes in brain structure and function over time, helping to monitor disease progression and the effectiveness of treatments [9, 10]. MRI is widely used in research to study the mechanisms of AD and to evaluate the efficacy of new treatments in clinical trials. But still, MRI resolution is limited, making it difficult to accurately distinguish between healthy and diseased tissues due to its inability to detect subtle brain structure changes. The task of processing large samples for diagnosing various Alzheimer's disease conditions will also be a challenging task.

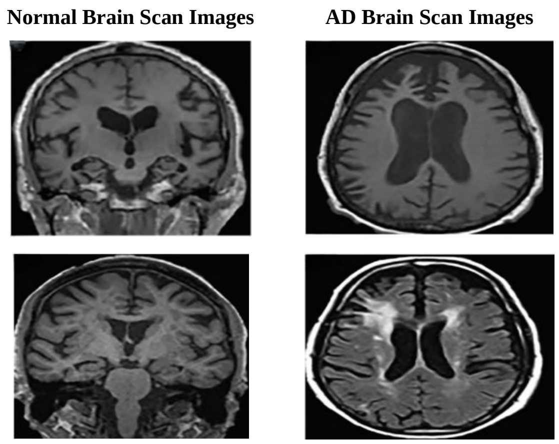

Figure 2. Healthy Brain MRI Image Vs. AD Brain MRI Image

1.1 AD Prediction using Image Processing Techniques

Recent years have seen significant improvements in AD detection skills, thanks to developments in image analysis techniques. Image acquisition, pre-processing, feature extraction, and classification are some of the steps involved in detecting and classifying AD using MRI imaging [11].

- **Image Acquisition:** The first step is to gather magnetic resonance imaging (MRI) scans from different institutions, online sources, or picture databases. After that, the pictures were saved to a program and shown in grayscale. The image database may store MRI-scans in a variety of formats, including the widely used JPEG and PNG formats.
- **Image pre-processing:** Pre-processing of magnetic resonance imaging (MRI) pictures is done to improve picture quality, reduce artefacts, and eliminate extraneous features. This method improves the image by minimizing blueness and light fluctuation, improving lines, boundaries, and textures, and erasing undesired portions. This facilitates the separation of relevant picture data from irrelevant data, leading to improved imaging accuracy and efficiency. Many researchers employ various filtering strategies to eliminate noise from images. These techniques vary depending on the type of noise, but some examples include spatial domain, linear (Wiener or Mean filter), non-linear (median filter), and transform domain (wavelet transform). Furthermore, there are a number of enhancement methods that improve the quality of the image's pixels, such as the Wiener Filter, Fast Fourier Transform, Gabor Filer, and so on [12].
- **Image Segmentation:** Objects can be better identified and distinguished by the process of segmentation, which involves separating an image into segments. It makes a mask for every object in the picture, pixel by pixel. It can detect healthy brain tissue and Alzheimer's disease (AD) brain tissue by learning picture features in MRI images and then removing artifacts. The region of interest (ROI) in Alzheimer's disease (AD) diagnosis is the area that is afflicted, while the undesired area is just that—unwanted. The first is region-based segmentation, which uses techniques like thresholding, region-growing, and clustering in feature space; the second is edge-based segmentation, which uses techniques like zero crossing detection and gradient algorithms [13].
- **Feature Extraction:** The most important part of image processing algorithms is feature extraction, which finds and separates the different characteristics or slices that are desired. It is possible to precisely detect brain nodules caused by cancer when segmentation of the affected area has been finished, characteristics have been extracted from it, and an analysis rule has been computed. Using this method, the quantitative measurements on the nodules' shape, texture, and intensity may be extracted from the CT scans. You can tell benign nodules from cancerous ones by looking for these characteristics. There are three main categories of features used in image processing: structural, texture, and spectral. An important set of features includes: Gabor, Local Binary Pattern (LBP), texture descriptor, color and edge descriptors, Hu moments, edge histogram descriptor, shape characteristics, orientation, dimension, bounding box, autocorrelation, Scale-Invariant Feature Transform (SIFT), and Speeded-Up Robust Feature (SURF). It is no longer necessary to manually extract features because Convolutional Neural Networks (CNN) can learn and capture them automatically [14].
- **Classification:** Classification is the fundamental procedure in image processing. Following feature extraction from photos, early, medium, and late phases of AD can be identified. After radiologists or doctors have identified the AD stage, they can decide

on the best course of treatment depending on the severity of the condition. Training and testing are the two parts of the classification process. Images are acquired, pre-processed, feature-extracted, and classified during the training phase of an image processing pipeline. In contrast, the captured image is tested during the testing phase by repeating the steps of the training pipeline, which include test image pre-processing, classification, and feature extraction. By and large, ML and DL are useful for medical system decisions, early identification, and treatment planning since they represent the AI subsets that can automatically predict and categorize AD [15]. The MDL module that uses image processing techniques to identify AD in MRI images is shown in figure 3.

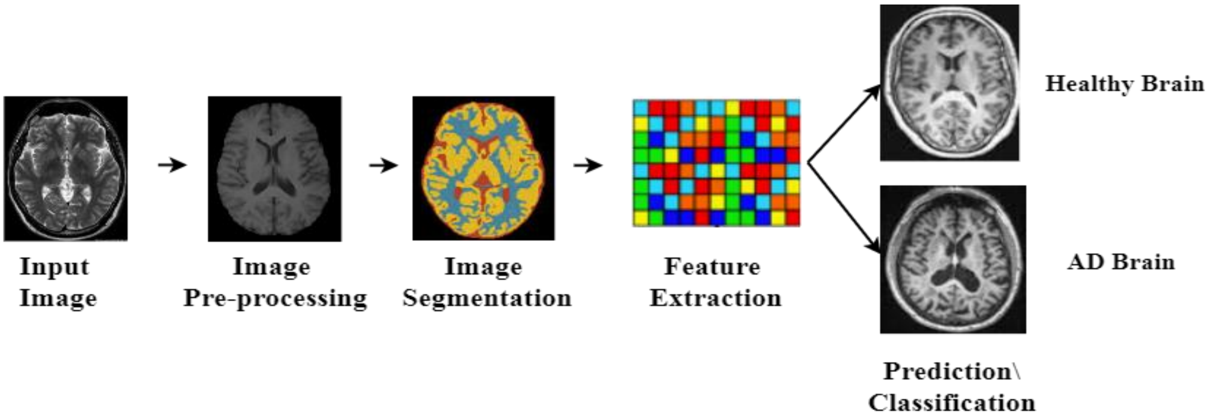

Figure 3. Pipeline of image processing techniques for AD detection

The performance of DL models on AD stages classification is more efficient than that of ML frameworks. By controlling variability, DL systems reduce effort and address neurologist shortages in low-resource settings. They are cost-effective, efficient, and less subjective than manual techniques [16]. Neural Networks (RNNs), Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTMs), Deep Belief Networks (DBNs), etc. are all examples of DL models. By using important and distinct characteristics found in pertinent medical data, these models aid clinicians in making an unbiased and trustworthy diagnosis of the condition [17]. DL helps with a number of tasks related to magnetic resonance imaging (MRI) (e.g., normalizing picture intensity, extracting non-brain tissues via skull stripping, aligning images to a standard template, and providing adjustments to improve model robustness) [18].

Recent years have seen the development of multiple DL frameworks that use MRI scans to forecast and categorize different types of AD. This paper takes a look at how several DL models have been used to categorize and predict AD using MRI scans. Using MRI image classification, it reviews current research that have used DL for AD detection, pointing out the pros and cons. Discovering the obstacles encountered by current AD prediction models is another goal, along with identifying research gaps and proposing future routes to enhance classification accuracy. While Section III offers a comparative examination of these models, Section II analyzes DL-based AD prediction models that use MRI images. The full study is summarized in Section IV, which also provides suggestions for the future scope.

II. LITERATURE SURVEY

AlSaeed & Omar [19] proposed ResNet-50 model for Alzheimer's disease detection with MRI of the brain. To do this, the pictures were first processed with FWHM Gaussian filter smoothing methods to lessen pixelation and noise. Among ResNet-50's components are convolutional blocks, pooling layers, and an FC layer. The feature extraction process makes use of convolutional and pooling layers, whilst the picture classification process makes use of FC layers. To optimize the AD classification process, the FC layers can be substituted with SVM\RF, which calculates the output for every input MRI picture.

Liu et al. [20] developed a 3D Deep Convolutional Neural Network (DCNN) model to reliably differentiate between mild cognitive impairment, cognitively normal persons, and mild Alzheimer's disease (AD) using structural MRI. Using the Unified Segmentation approach, the pictures were pre-processed by correcting for bias and normalizing spatial dimensions. Next, examples of moderate cognitive impairment and normal cognition were utilized to classify the stages of Alzheimer's disease using 3D convolutional neural networks (CNNs) that included instance normalization, ReLU, max-pooling layers, and convolutional layers.

Savaş [21] developed EfficientNet B6 model for the AD prediction using MRI images. Data scaling and resizing method were employed to pre-process the images. The rotation and flipping were used to augment the pre-processed images. The convolutional and pooling layers EfficientNet B6 were used to extract the features. The softmax layer of EfficientNet B6 were employed to classify the AD.

Helaly et al. [22] developed a DL model that can use MRI scans to detect Alzheimer's disease early on. Images were pre-processed with oversampling and undersampling techniques to eliminate noise in this procedure. After four stages of the Alzheimer's disease spectrum were multi-classified, binary medical image classifications were performed between each pair of stages. Medical picture classification and AD detection made use of two approaches. The first one analyzes 2D and 3D structural brain scans with a CNN model, and the second one employs transfer learning to classify AD using pre-trained models like the VGG19 model.

El-Latif et al. [23] devised a Lightweight DL model for AD prediction using MRI data. In this method, specific augmentation techniques were applied to improve the image pixel quality. Then, the images were processed through Conv2D and MaxPooling2D to extract features from the augmented images. Two dense layers were performed for feature transformations. Finally, the softmax layer was employed for AD prediction.

Wang et al. [24] developed a reliable approach to classifying AD phases using functional magnetic resonance imaging (fMRI). To prepare fMRI data for constructively extracting functional connectivity matrices, our approach used the Joint Human Connectome Project Multi-Modal Parcellation (J-HCPMMP). After that, the best features were chosen using the MRMR selection algorithm in conjunction with DGT. The last step was to distinguish between AD-related brain areas using a support vector machine (SVM) model.

Goenka et al. [25] created a regularized volumetric ConvNet model for Alzheimer's disease identification using T1-weighted magnetic resonance imaging (MRI) scans. This approach applies pre-processing methods to MRI scans in order to extract high-level characteristics for both normal and AD pictures. These methods include N4 bias, correction, skull-stripping, and rigid registration. The accuracy of the models was further enhanced by applying augmentation techniques such as rotation and rescaling. Lastly, the characteristics needed for AD categorization were extracted and detected using a ConvNet model.

Hazarika et al. [26] proposed a novel Deep Neural Network (DNN) that combines LeNet and AlexNet to classify Alzheimer's disease (AD) from magnetic resonance imaging (MRI) of the brain. In this approach, the brain MRI images were segmented using K-Means Clustering (KMC), Histogram Thresholding (HT), and Fuzzy C Means (FCM). After that, features were extracted using LeNet and AD stages were classified using AlexNet.

Stripelis et al. [27] devised a Federated Learning (FL) 3D CNN for AD detection and classification using multi - cohort brain MRI images. In this method, the collected images were augmented to enhance the diversity of the images. Then, federated learning structure which was applied to train a 3D CNN to detect AD from T1-weighted brain MRI data. The convolutional and pooling layers in FL 3D-CNN used to extract the features while the FC and softmax for the different stages classification in AD.

Ghosh et al. [28] created a reliable distributed DL model for AD image detection using MRI data. In this method, conventional data augmentation methods were used to flip, rotate and zoom and contrast the images for the collected MRI images. Three various orientations like sagittal, coronal and transverse were performed on the MRI images. Then, MobileNet architecture with its initial weights used for feature extraction. The last layer, the dense layer uses two neurons and a sigmoid for activation for classification of normal and AD images.

Shukla et al. [29] employed a convolutional neural network (CNN) model to diagnose Alzheimer's disease (AD) using magnetic resonance imaging (MRI). To improve the quality of the image pixels, the acquired data was first pre-processed with selective clipping, grayscale image conversion, and histogram equalization. To extract and select the features, Principal Components Analysis (PCA) was used. After that, the pictures were classified as normal or AD using XGBoost, Random Forest (RF), and CNN.

Mohammad & Al Ahmadi [30] proposed using the VGG19 and Whale Optimization Algorithm (WOA) models for AD prediction feature extraction and parameter optimization. In this approach, the features were extracted from the MRI scans using the VGG19 FC-7 and FC-8 layers. Incorporating two feature spaces into one vector that highlights the maximum value allowed for the integration of the extracted features. Lastly, a fused feature map was optimized using WOA, leading to a reduced dimensionality map and the elimination of feature redundancy. Lastly, the classification of AD phases was performed using the last FC layer in the VGG19 model.

Chakraborty et al. [31] constructed a 3D-CNN model for the purpose of neuroimaging genetics-based AD prediction utilizing MRI data. Using volumetric 3D sagittal magnetization, this technique produced T1-weighted MRI pictures. Various resolutions of Rapid Gradient Echo Imaging (MPRAGE) were prepared. The following models were employed for the purpose of pre-processing the images: Gradwrap, B1 non-uniformity correction, and N3 correction. The useful brain pictures were extracted using Brain Extraction Tools (BET). Images were segmented using the FMRIB Automated Segmentation Tool (FAST). The AD phases were classified using the characteristics extracted using 3DCNN.

Marwa et al. [32] developed a DL method for precise AD detection using MRI data. Using picture normalization, this technique reduced impulsive noise and adjusted the intensity values of the image's pixels. Next, 2D T1-weighted MR brain images and shallow convolutional neural networks (CNNs) were employed for both the global and local categorization of AD and mild cognitive impairment (MCI), respectively.

Kim & Lee [33] constructed an ECNN utilizing Line Segment Feature Analysis (LFA) for the purpose of AD classification using a patient's brain shape as input. It all started with using the VGGnet model to pull global biomarkers out of raw MRI data. The next step was to extract important morphological features of the brain's anatomy from MRI scans using the LFA algorithm. A 1D convolutional neural network (CNN) model was employed to improve the accuracy of Alzheimer's disease diagnosis by extracting minute local biomarkers. Image data was transformed into vector signals by the integration of LFA and 1DCNN. To make an accurate AD prediction, more structured or time-series data was required.

III. COMPARATIVE ANALYSIS

The advantages and disadvantages of the previously mentioned models developed for AD prediction using MRI images are compared in this section, and the results are shown in table 1 below.

Table I. Comparison of different AD classification models for MRI images

Ref No.	Techniques	Merits	Demerits	Datasets	Performance Evaluation
[19]	FWHM Gaussian filter method, ResNet-50 SVM\RF	Flexible to extracts meaningful dependencies within the each image pattern	Models parameter needs to be optimized for training large data	ADNI, MIRIAD datasets	Accuracy (ADNI) = 99%; Accuracy (MIRIAD) = 96%;
[20]	Unified Segmentation procedure. 3D DCNN	Works well on larger database	High convergence difficulties and runtime errors	ADNI, NACC	Area-Under-the-Curve (AUC) = 85.12%

[21]	EfficientNet B6	Lower computational cost and time.	Requires large data for models training	ADNI dataset	Accuracy = 92.98%; Precision = 92.08%
[22]	oversampling and undersampling, methods CNN, VGG19	Reduced memory requirements, overfitting, and provide manageable time.	Hyper-parameter needs to be fine-tuned for processing larger dataset	ADNI dataset	Accuracy (CNN) = 94.39%; Accuracy (VGG19) = 97
[23]	Conv2D and MaxPooling2D, dense layers	Lower computational complexity and processing time	Tested on smaller dataset and lower generazability due to infinite settings	Alzheimer's Dataset from Kaggle images	Accuracy = 95.93%; Precision = 95.93%; Recall = 95.88%; F1-score = 95.90%
[24]	J-HCPMMP MRMR, DGT, SVM	Better convergence rate	Certainly, it results with uncertainty issues	ADNI	Accuracy = 89.19%
[25]	N4 bias, skull-stripping, rigid Rotation and rescaling methods, ConvNet	Eliminates, overfitting and additional learnable parameters and data redundancy	In adequate complexity in the feature extraction module	(MIRIAD)	Accuracy = 97%' AUC = 94
[26]	KMC, HT, FCM LeNet, AlexNet	Reduced noises and irrelevant signals from the training data	High computational complexity and memory usage	Alzheimer's Disease Neurological Initiative (ADNI) Dataset	Accuracy = 93.58%
[27]	3D CNN	Efficient performance on both small and large database	High convergence difficulties and runtime errors	ADNI dataset	Accuracy = 97.67; Precision = 98.68%; Recall = 95.41%; F1-score = 96.9%
[28]	MobileNet architecture	Well versed augmentation model to perform on large dataset	Easy prone noisy images and generazability error was high	OASIS, ADNI	Accuracy (OASIS) = 92.86%; Accuracy (ADNI) 77.78%;
[29]	PCA, XGBoost, RF, CNN	Better convergence rate	Certainly, it results with uncertainty issues	ADNI	Accuracy (CNN)= 96.43%;
[30]	FC-7 and FC-8 layers of VGG19 WOA VGG19 model	Better convergence and eliminates the uncertainty issues	Limited number of training images for models training	ADNI	Accuracy = 98%; Precision = 99%; Recall = 99%; F1-Score 99%
[31]	MPRAGE Gradwrap, BET, 3DCNN	It effectively extracts the complex features from the large training data	High presence of artifacts, decreased reliability of certain shape features	ADNI	AUC = 96
[32]	S-CNN and 2D T1-weighted brain MRI images	Eliminates additional learnable parameters and data redundancy	In adequate complexity in the feature extraction module	Open Access Series of Imaging Studies (OASIS)	Accuracy = 99.68%; Sensitivity = 100%; Specificity = 1005
[33]	VGGNet, ECNN, LFA,	Captures strong features reducing misclassification error	Overfitting and bias training lowers the models stable training efficacy.	Open-source Kaggle platform with 6,400 MRI images	Accuracy = 98%; Precision = 99%; Recall = 99%; F1-Score = 99%

IV. RESULT AND DISCUSSION

The performance review of the exiting DL methods listed in Table 1 to showcase the accuracy of overall prediction and classification of AD prediction. Most of the papers utilized Alzheimer's Disease Neurological Initiative (ADNI) dataset [34]. Afterwards, further algorithms used the benchmark dataset to forecast AD using MRI scans. Using the ADNI and other benchmark datasets, this section assesses the efficacy of various DL-based AD prediction models. The effectiveness of these algorithms in detecting and classifying AD from MRI images is illustrated graphically.

Using ADNI datasets, DL-based AD prediction is shown in Figure 5. Model ResNet-50 [19] yields effective results in AD prediction and classification, according to this analysis. For feature extraction and picture classification in MRI images, the ResNet-50 was employed, as described in [19], and it consisted of Convolutional blocks, pooling layers, and the FC layer. It is possible to optimize AD classification jobs by replacing the FC layers with a softmax layer, which calculates the output for each input MRI picture. In addition, the model's adaptability allowed it to improve feature extraction and classification by identifying significant dependencies inside each picture pattern.

Using additional benchmark datasets, DL-based AD prediction is shown in Figure 6. This investigation shows that the S-CNN [32] and ECNN-LFA [33] models efficiently predict and classify AD. Due to S-CNN's high computational cost caused by its feature extraction module's adequate complexity, ECNN-LFA offers more efficient model performance. There is an increase in the misclassification error when it comes to AD classification using S-CNN because it does not capture strong features. By first using the VGGnet model to extract global biomarkers from MRI image data, and then the LFA algorithm to determine brain shape morphological properties, ECNN-LFA overcomes the shortcomings of S-CNN. An Alzheimer's disease diagnostic tool—local biomarkers—was retrieved using a 1D CNN model. For AD prediction, extra structured or time-series data was needed for the integration of LFA and 1DCNN. In order to classify AD with minimal data loss and mistake in misclassification, ECNN-LFA effectively recovers robust features and gives precise information.

In the below two analyses, it is concluded that ResNet-50 [19] performs better on ADNI datasets and ECNN-LFA [33] models work efficiently on Open-source Kaggle platform dataset. However, ResNet-50 model fails to optimize the models parameter while training on large samples. ECNN-LFA results in overfitting and bias training lowers the models stable training efficacy. Also, ECNN-LFA was efficient to train single dataset (ADNI), but lacks the performances to train on other validated datasets for AD detection.

The limitations of these model will be resolved in the future proposed models by introducing the models adaptable to train on various AD detection dataset, providing advanced classification models to eliminate the overfitting, optimize models parameter and reduce computational complexity. Moreover, the future model will be intending to train by combining MRI images from ADNI and other benchmark AD dataset. By training on all sort of dataset, the future model enhances the real-time application by identifying specific AD characteristics and guiding personalized treatment plans. It can analyse large medical image datasets, providing researchers with new insights into nature, progression and treatment strategies of AD.

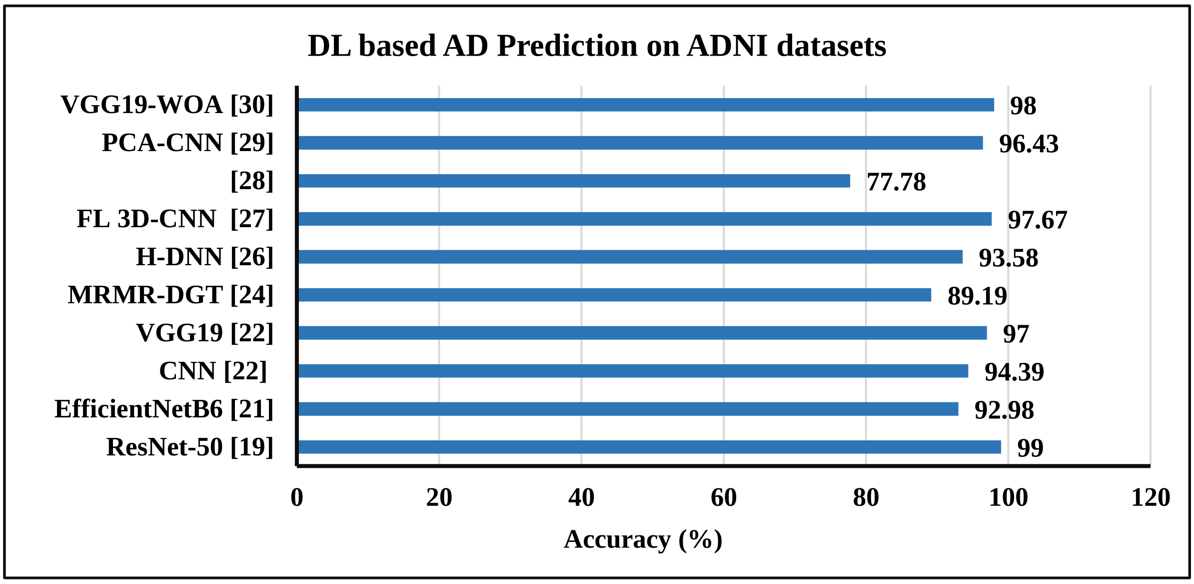

Figure 4. DL based AD Prediction using ADNI dataset

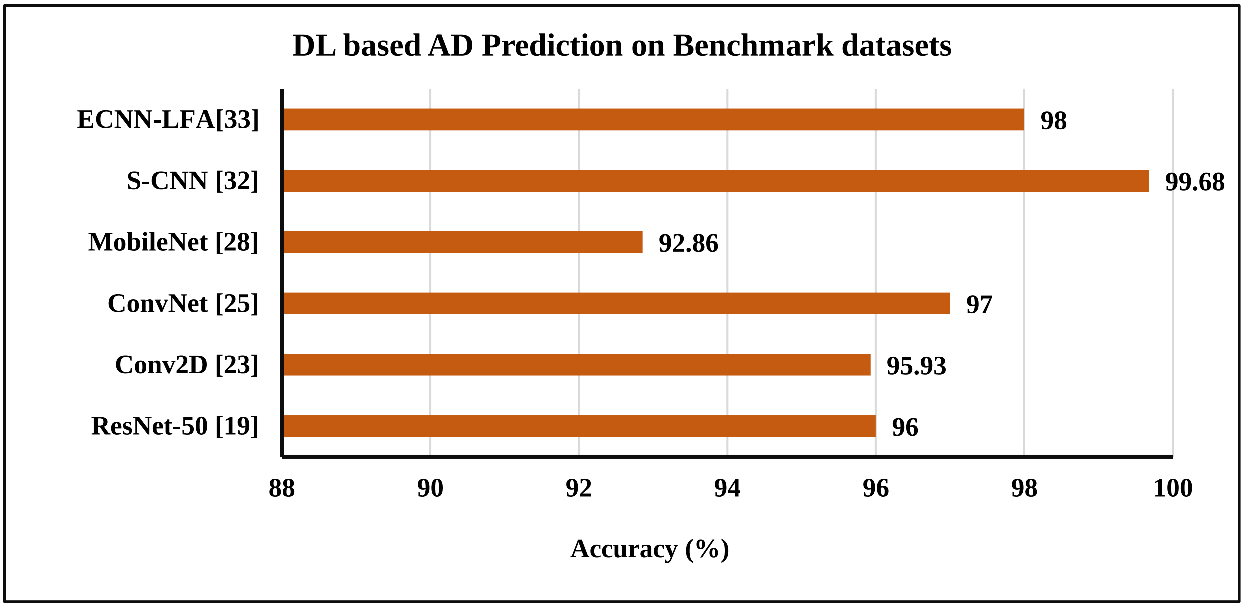

Figure 5. DL based AD Prediction on other benchmark datasets

V. Conclusion

In this paper, a detailed review was presented to discuss the different AI models implemented in the AD detection, classification and diagnosis systems using MRI images to support neuropsychologists in identifying high-risk AD patients and choosing a proper decision for an effective diagnosis. A summary of the models was also provided, broken down by their advantages, disadvantages, and performance metrics. This included both machine learning and deep learning algorithms. From this analysis, it was observed that although some scholars concentrated on AD detection, classification, prediction and diagnosis models using different MRI variational images. Many negatives were noticed that impact the efficiency of AD classification and diagnosis. This study provides insights for researchers to create functional models that improve AD prediction and diagnosis, ultimately leading to personalized treatments. Future work focuses on developing advanced DL models to overcome the limitations of ooverfitting, bias training lowers and learn complex patterns from large datasets for efficient prediction and classification of AD.

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