Prediction and Feature Extraction Techniques used for Classification of Alzheimer's Disease in its Early Stage using MRI: A Review

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***Abstract*— Most people worldwide are affected by an acute neurological disorder called Alzheimer's disease. Despite the reality that there is no treatment, it can be tapered off if it is detected early enough. 6 million individuals in the United States have Alzheimer's disease, and more than 120,000 people have died as a result of it. This has been designated as the sixth leading cause of death. Early diagnosis of AD can be useful to improve the quality of living of AD patients and will be helpful for their caretakers also. The anatomy of brain is intricate in structure packed with more information which makes it more burdensome to extract the features. This study outlines the machine learning and deep learning techniques utilized in the prediction and categorization of Alzheimer's disease, with an emphasis on the most recent approaches in feature extraction based on texture, voxel, wavelet and graph.**

Keywords: Neurological disorder, early diagnosis, Alzheimer's disease, anatomy of brain, machine learning, deep learning.

I. INTRODUCTION

Alzheimer's disease is a brain ailment that causes memory and cognitive abilities to deteriorate over time. About 100 billion neurons make up a sound adult brain. Between neurons, a microscopic fragment called beta-amyloid builds up, producing clusters or plaques.

Tau, another protein, helps neurons develop thick thread tangles. These plaques and tangles work together to prevent neurons from delivering and receiving impulses. Neurons begin to die as a result of these alterations in the brain, a condition known as Early-stage Alzheimer's.

The first place this occurs is in the parts of the brain where memories are formed. As more neuron begins to die, the brain starts to shrink and this stage is called middle-stage Alzheimer's. As it gets worse over time the brain may shrink to about a third of its normal size, which is Late-stage Alzheimer's. Alzheimer's was first found in the year 1960 by Dr. Alois Alzheimer [1]. Researchers are intensively developing methods that can detect AD accurately from then. Table 1 lists some popular diagnostic methods for AD at clinics.

[7]	Mini-Mental State Examination, Alzheimer Disease Assessment Scale, Clinical Impression of Global Change, Short Blessed Test, Clinical Dementia Rating	Based on the outcome acquired in numbers (Ex: MMSE – 0 to 30 for a normal patient)	No technology is required. Easy to do.	May not obtain the correct result. Takes more time.
[8] [9]	ATN Classification System	The proportion of amyloid, tau, and neurodegeneration.	does not compromise acquaintance to radioactivity	Costlier method

Paper	Diagnostic method	Based on	Merits	Demerits
[2], [3]	Biomarkers	Blood-based	• This blood test is possible to do anywhere around the world. • Cheaper. • Agile process	Studying the numerous molecular component present in the test becomes a hurdle for research.
[4]	Transcranial Magnetic Stimulation(TMS)	Change in the magnetic pulse where an electromagnetic coil will be placed in front of our forehead.	• Blood-less method. Patients can go ahead with their usual tasks.	• Tedious process. Prior to and for the duration of the treatment the patient may feel tense.
[5], [6]	Electrovestibulography (EVestG)	The electrical signal produced by the part of the brain and inner ear during certain contrivances is measured.	• Cheap • No pain Blood-less method	Based on the fitness of the patient.

TABLE 1. List of various diagnostic methods for AD

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II. Various Approaches for Categorization of Brain MRI in Alzheimer's Disease

Several steps must be performed for reliable image classification. Pre-processing, which may include eliminating noise or other artifacts, is the first step in the classification process. Effective feature extraction is then achieved by using the proper approach. Figure 1 depicts a standard procedure for choosing distinguishing characteristics for use in classification.

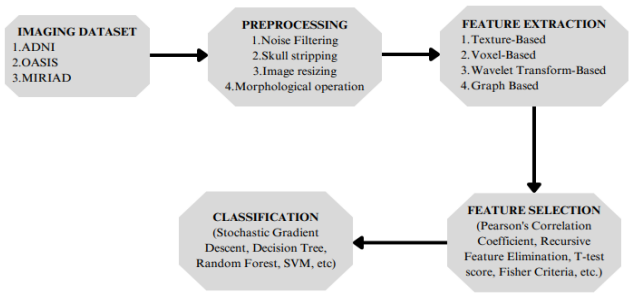

FIGURE 1. Standard procedure used for classification of Brain MRI

A. Different imaging data used for prediction

In research, imaging gives us a perception of the consequences of AD. There are various types of images used for the prediction of AD. In the beginning, CT scans were used. Later MRI eliminated the CT scan as it was very good at capturing the brain images. Apart from these, there are also sMRI, fMRI, T1 weighted, and PET[10]. *ADNI* (Alzheimer's Disease Neuroimaging Initiative)[11], *OASIS* (Open Access Series of Imaging Studies)[12], and *MIRIAD* (Minimal Interval Resonance Imaging in Alzheimer's Disease)[13] are the publicly available data. ADNI dataset has 229 patients who are Cognitively Normal(CN) people, 398 patients who have Mild Cognitive Impairment(MCI), and 192 patients who have Alzheimer's Disease(AD).

Dataset	No of the patients subjected to	Technology
ADNI[11]	819 patients (CN – 229, MCI – 398, AD – 192)	MRI Scan
OASIS[12]	416 patients (18 years to 96 years)	T1-weighted MRI Scan
MIRIAD [13]	69 patients	T1-Weighted MRI Scan

TABLE 2. AD datasets

B. Preprocessing

Before starting the computation, we need to extract the information from an image for the algorithm to work efficiently[14]. While extracting the information, the edges have to be preserved, when the smoothing of an image is done[15]. Some general preprocessing steps in an image are noise filtering, skull stripping, image resizing, morphological operations, etc[16][17]. Various software and toolboxes are also available for preprocessing a neuroimage.

C. Feature extraction

In [18], feature extraction is an important step as it converts the original data into a feature vector. FE is the process of extracting the fundamental features that are useful for classifying an item from existing ones and creating novel features from them[19]. Texture, color, and shape are some useful features in a medical image. Independent Component Analysis (ICA), t-distributed Stochastic Neighbor Embedding, Principle Components Analysis (PCA), Locally Linear Embedding (LLE), etc are the approaches that are used commonly for feature extraction [20].

D. Feature Selection

The procedure of eradicating undesirable features and considering only the relevant features is feature selection [21]. It is important to do feature selection because sometimes the undesirable feature will be extracted and hence it will lead to force a model to learn wrongly. Feature selection using the supervised method compares the independent and the dependent variables and eradicates the irrelevant features. The correlation concept is used in the unsupervised method. It neglects the target variable and removes the unused features [22]. The most often employed techniques in medical image processing are wrapper, filter, and intrinsic/embedded among all supervised methods for feature selection. Initially, a metric is used for measuring the performance of the and later on an appropriate algorithm is used to produce a variety of models having distinct input features. The most useful attribute that helps uncover the top-performing model is chosen as the conclusive step [23]. The Recursive Feature Elimination (RFE) method is the method used generally among the wrapper methods [24].

In the filter technique, the optimal variables to measure are determined by a score based on an estimate of the relationship between the independent and the dependent variables[25]. In the embedded approach, from a large dataset, a model is being trained and automatically most correlated features are nominated[21]. Selection operator and Least Absolute Shrinkage are the most commonly used approaches in embedded feature selection.

E. Classification

Image classification is defined as the task of identifying and trying to label pixels or vectors inside an image using predetermined rules. Classification methods are classified as supervised and unsupervised classification[26]. In supervised classification, the machine learning model is initially selected, then data is assigned to prior identified categories and finally, statistical data are optimized to deploy around every bit of the image[27]. Whereas there is no training data in unsupervised classification and some suitable algorithm is used to judge the properties of an image[28]. Logistic Regression, Stochastic Gradient Descent, Naïve Bayes , K-Nearest Neighbours, Decision Tree, Random Forest, Support Vector Machine, etc are some commonly used image classification techniques[20].

III. Related work on AD Prediction

In [29], the author created a model using MRI images to identify Alzheimer's disease at different phases. The innovative models are used in conjunction with the BLS approach. InceptionNet and several PCA-SVM methods are used to compare the results. The convolution module will be tuned in order to further improve the model. In classifying images, [30] makes use of transfer learning techniques by fine-tuning a pre-trained Alexnet convolution network. The testing data was used to validate the retrained CNN, which produced cumulative accuracy results for binary and multiclass classification of 89.6% and 96.8%, respectively.

Lulu Yue et al. used Deep Convolutional Neural Networks in [31], to extract structural MRI features. Each volume is re-sliced for phase categorization in Alzheimer's disease, a process that occurs before the images are taken. Nearly 97.16 percent accuracy was achieved by the LMCI and AD groups, and nearly the same percentage was achieved by the EMCI and AD groups. The proposed method, however, is only helpful in the very first phases of MCI.

Finding patterns across MRI image slices using a recurrent neural network is proposed as a solution to problems with image series in [32]. CNNs' accuracy has often been boosted with the introduction of a recurrent neural network. Stochastic images could not be quantified using this technique.

To maximize feature extraction from the images in the Minimal Interval Resonance Imaging dataset, Iago R. R. Silva et al. designed a three-layer Convolutional neural network architecture. The random forest, SVM, and K-NN algorithms had accuracy rates of 88.32%, 96.07%, and 87%, respectively [33]. Only positive or negative categories are available for the illness. The suggested design does not take minor cognitive impairment into account.

Using MRI images Naimul et al. recommended utilizing a transfer learning-based strategy in [34] to recognize Alzheimer's. The hypothesis was evaluated using a large number of trials on the ADNI dataset by them and discovered that it was 95.19 percent accurate. In this case, there don't seem to be any predicted image measurements. In [35], Ahsan Bin Tufail evaluated his custom-built CNN model with separable convolution layers on three datasets. The method does not take into consideration the complexity of classifying Alzheimer's disease, which includes control subjects, those with MCI, and those with a high CDR rating. Additionally, it disregards imaging techniques like DTI and functional MRI.

A P-type Fourier descriptor was employed by Hiroki Fuse et al. in their investigation to define the data's form [36]. A Support Vector Machine was used to classify the data, and it was 87.5 percent accurate. The traits cannot be categorized or understood by a thorough analysis of them. Hina Nawaz et al. [37] use the Alexnet transfer learning architecture to extract deep characteristics that are then applied to categorize AD phases. The Multiclass classification used for diagnosing Alzheimer's disease in its early stages is ignored in the designs. Using ML methods such as RF and SVM classifiers, a classification of MRI data with neuropathological AD was given in [38], achieving an accuracy of 77%. Along with a graph (Figure 2.), Table 3. displays the approaches used and the accuracy attained by them.

Paper	Method	Accuracy
[24]	Alexnet	89.6%
[25]	Deep Conv. Neural network	97.81%
[27]	Random forest	88.32%
[27]	SVM	96.07%
[27]	K-NN algorithms	87%
[29]	Transfer learning	95.19%
[32]	RF and SVM	77%

TABLE 3. Methods and accuracy obtained from it

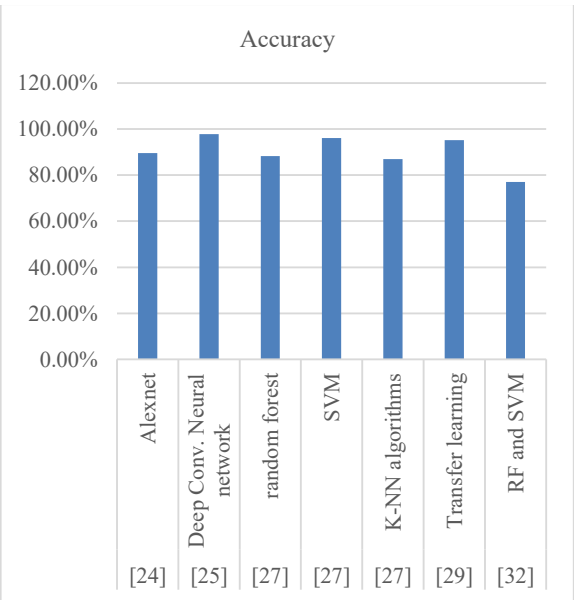

FIGURE 2. Methods used and its accuracy obtained – Summary

IV. Related work on Feature Extraction used for different AD Classification

The classification of neurological disorders like Alzheimer's disease, MCI, and others is facilitated by the detection of distinct features in brain imaging [39]. The authors of the papers [40] and [41] proposed a feature extraction method for AD classification that makes use of GLCM. The GLCM and the Gabor filter are combined in [40]. After collecting a large number of features, the authors employed the Recursive Feature Elimination method to zero down on the most relevant ones.

Clinical features such as the Functional Activities Questionnaire (FAQ), Neuropsychiatric Inventory (NPI), and Geriatric Depression Scale (GDS) are extracted using the GLCM method from the segmented grey matter (GM), white matter (WM), and cerebrospinal fluid (CSF) regions. In the literature, complete MR images are mined for texture elements such edge information, colour, and boundary information, among others [41].

In order to classify AD, Krishnakumar Vaithinathana et al. [42] suggested a classification framework that relies on the extraction of texture information. Multiple textures are picked once the RoI(Region of Interest) voxels are mined, integrated, and merged. To reduce the number of features to only those most important, the authors used a mixture of the elastic net regularisation, the recursive feature elimination technique of the support vector machine, and the Fisher score. The authors employed a random forest, a linear support vector machine, and the k-Nearest Neighbor method to classify the data.

G. Wiselin et al. [43] offered a new approach to Alzheimer's disease diagnosis based on alterations to brain structural integrity and hippocampal shape. To extract the characteristics, the authors identified the busy texture information. Textures that frequently change in strength from one pixel to their neighbor are said to be busy textures. In space, intensity fluctuations occur very frequently. Thus, the commercial significance of a texture is established by excluding the contracting feature from the data describing about the rate of change in intensity. Categorization was accomplished by the authors using SVM.

In [44], the authors proposed the earliest application of the voxel-wise statistical test to the field of medical image processing. The model generates a total of 3816 characteristics for each subject using all of the pre-processed SPECT images as input. Using the collected characteristics, the authors were able to correctly identify AD cases using the SVM classifier.

The authors of [45], a method for classifying Alzheimer's disease based on Voxel-based morphometry-based feature extraction, set out to pinpoint exactly where in the brain grey matter volumes had significantly dropped. Once all the images have been processed, the voxel values are extracted from raw-feature vectors using a 3D mask.

According to [46], a Voxel-based morphometry analysis-based classification method was developed to differentiate between AD and CN patients using structural MRI data. Image enhancement and correction were performed using Statistical Parametric Mapping, Voxel-based morphometry and, Diffeomorphic Anatomical Registration using The Exponentiated Lie algebra (DARTEL) toolboxes. Using Gaussian smoothing kernel the grey matter data were smoothed spatially by the authors. Voxel-based technique also helped to observe the grey matter volume changes. The results of Voxel-based morphometry and DARTEL methods are used to extract a 3D mask of the Volume of Interests from the thinning regions.

A classification strategy based on structural MR images that can distinguish between CN and AD participants has been explored in the literature [47]. Researchers used Brain-Visa software to remove eddy current artefacts from Diffusion Tensor Imaging (DTI) scans. Maps of the apparent diffusion coefficient and fractional anisotropy are obtained following the computation of the diffusion tensors. Segmentation, performed with the use of the Statistical Parametric Mapping software suite, divides the structural pictures into three groups: grey matter, white matter, and cerebrospinal fluid. The apparent diffusion coefficient maps separate cerebrospinal fluid from other types of fluid. The representations of fractional anisotropy are also divisible. There are two main categories of brain maps: white matter and grey matter.

DTI-grey matter maps are calculated as the union of CSF-free and white matter-free DTI maps. The final grey matter diagram is a combination of the DTI-grey matter map and the structural grey matter map. As a starting point, the authors propose determining the mean small brain volume. The normalized images are intersected with a binary mask. Automatic Anatomical Labeling (AAL) is then mapped to a standard binary mask in order to preserve the Region of Interests (RoIs). When all is said and done, the AAL has been applied to 73 out of the total 90 ROIs. The ROIs are used to calculate the mean diffusivity (mean ADC), and then the apparent diffusion coefficient and grey matter concentration ratio are used to generate the voxel-wise multimodal characteristics.

The wavelet transform (WT) is a method of analyzing signals that can be applied to the study of object-specific details. WT can be written as a function of two spatial variables (v, t)(WT), since it can be defined in terms of both spatial frequency (v) and spatial position (t) [48].

With the help of the Contourlet Transform, features are extracted from processed brain MRIs in [49]. (CoT). For this study, the authors compared the performance of the Discrete Wavelet Transform, Complex Wavelet Transform, Curvelet Transform, Empirical Wavelet Transform, Shearlet Transform, and Dual-Tree Complex Wavelet Transform on the same set of pre-processed brain MRIs (ST). The most preferred characteristics are determined using the student's t-test.

In [50], Alzheimer’s disease was classified using a twin SVM-based classification, which makes use of Linear Discriminant Analysis and complex dual-tree wavelet

principal coefficients (LDA). Using features at the highest attainable resolution, the authors proposed a method to derive 5-level Dual-Tree Complex Wavelet Transform coefficients from the entire collection of input MRI images. Second, Principal Component Analysis is fed the chosen coefficients to translate the characteristics into a lower dimensional space (PCA). The most informative features can be extracted by mapping PCA coefficients onto a linear discriminant analysis (LDA) projection axis.

The literature discusses a unique approach to dementia classification based on brain MRI [51]. The bag level classifier is trained with an approach termed graph-based multiple instances learning. The proposed method necessitates the generation of a unique graph for each image. There are nodes, which represent patches, and edges, which represent connections between nodes, in this network model. Displaying patch appearances and denying correlations between patches obtained from the same subject are possible using the graphs. There are Alzheimer's disease (AD) patient patches, as well as patches from people with cognitive neuropathy, progressive mild cognitive impairment (MCI), and stable mild cognitive impairment (SMCI) (CN). Each topic cluster should have a distinct graph as a result.

CONCLUSION

In the United States and other industrialized nations, Alzheimer's disease is among the top ten causes of death. Alzheimer's disease is spreading rapidly over the world. Manual diagnosis by neurologists for Alzheimer's disease is laborious and not always reliable. Brain imaging research into Alzheimer's disease subtype identification has shown promising results and requires less effort. Researchers have been working hard to develop a brain imaging-based classification system that can reduce the amount of time spent on analysis. Features extraction is a crucial step in using brain scans for Alzheimer's disease diagnosis. In this study, we discuss and report on the results of a wide range of AD classification approaches based on brain scans, all of which employ different feature extraction algorithms. One of the biggest challenges in Alzheimer's disease treatment is identifying reliable biomarkers. Similar alterations in brain structure may be caused by several different neurological disorders, thus including them in training or testing sets could mislead researchers into thinking the model is flawless even if it's not. It is a significant problem to identify reliable biomarkers in brain research that is particular to AD. Extracting information from brain imaging is challenging for many reasons, one of which is scalability. Constructing a feature extraction approach that can efficiently handle all of the qualities that brain scans include is difficult.

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