Deep Learning: Classification and Automated Detection Earlier of Alzheimer’s Disease Using Brain MRI Images

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Abstract. Alzheimer’s disease (AD) progression can be avoided by conducting diagnosis beforehand. This diagnosis acquired quick preventive care which could be possibly done by specialists. Fast and accurate evaluation at the earliest and most challenging stage were required to detect in the diagnosis of AD. In this paper, previous studies were reviewed into a better approach that recognizes the presence of disease in sagittal magnetic resonance automatically (MRI) images that are unusually used. The MRI brain images were used to identify and distinguish characteristics using a range of characteristics recognition techniques. The review of research papers on Alzheimer’s Disease published in reputable journals from 2017 to 2020 were presented and discussion of various strategies related to the latest tools used in early diagnosis is our main focus in this study, which could enable researchers to understand current algorithms and techniques in this area, and eventually develop new and more effective algorithms.

1. Introduction

Dementia with Alzheimer’s disease (AD) is a significant public health issue in the 21st century, with progressive degenerative disease with a steady deterioration of intellectual function as the most common cause among the elderly of dementia [1]. In the cerebral cortex, a gradual depletion of healthy neurons marks cognitive decline, primarily in the brain’s frontal and medial temporal areas [2]. AD is also a powerful morbidity factor, ranked by the World Health Organization (WHO) as 5th among the causes of death [3]. The development in the brain of amyloid plaques and neurofibrillary tangles is a symptom of this disorder. The risk variables include race, history of head injury, depression, and hypertension, although the cause of AD is misunderstood. AD has also been reported to develop about 20 years earlier in people with Down’s syndrome than in the general population [4]. The progression of the disorder is progressive and typically continues until the age of 65 years or older. The first big innovations involve problems in the short term [5].

Phases in AD include non-dementia, very mild dementia, mild dementia, and moderate dementia, as seen in Figure 1. Symptoms of the non-dementia stage suggest natural ageing, such as forgetfulness and moderate cognitive impairment [6,7]. In very mild dementia, intellectual disability, executive control and memory are more common, sometimes leading to linguistic difficulties [8]. Speech problems become more evident in the case of mild dementia, Reading and writing skills are increasingly diminished and long-term memory is also affected [9,10]. Alzheimer’s patients can develop apathy in the stages of mild dementia, and it is not possible to perform basic tasks independently; the entity affected will gradually become bedridden, and death will inevitably occur [11,12].
2. Deep Learning technique

Deep learning developments, specifically the deep learning sub-field, have developed algorithms that perform diagnostic tasks based on processing digital images with an accuracy close to those of qualified clinicians. These deep learning technologies, despite well-documented accomplishments, are vulnerable to cognitive and technological biases, including bias introduced by using an insufficient amount or a variety of data to train an algorithm [13]. Deep learning algorithms also are distinguished by their ability to extract features and a high-precision classification that provides accurate results in the diagnosis of diseases and others [14] as shown in Figure 2.

3. Analysis of approaches

This section provides the common methods of Alzheimer Disease detection which have been considered and analyzed. Basically, studies on Automated Alzheimer’s Disease Identification Techniques were presented in this paper.

P. Kalavathi et al, 2017

For this paper, a process consisting of two methods was proposed. In the first step, the Contour-based brain segmentation method (CBSM) was used to remove the skull from the image data, and then the Quick Fuzzy C Means (FFCM) clustering technique was used to segment the brain tissue such as White Matter (WM) and Gray Matter (GM). In the second step, by computing similarity measures such as Jaccard and Dice against the normal brain, the segmented WM and GM were analyzed to detect Alzheimer’s Disease in MR brain images [15].
Lauge Sorensen et al. 2018
The use of a support vector machine (SVM) ensemble that combines bagging without substitution and future option was implemented. In multivariate classification of dementia, SVM was the most widely used algorithm, and it was therefore useful to determine the potential value of this type of classifier ensemble [16].

Juha R. Koikkalainen et al. 2019
A collection of volume test methods and voxel-based morphometric image biomarkers were obtained from T1-weighted and FLAIR images. For predict Scale of visual ranking a regression model was developed using values from a variety of biomarkers for imaging. Three scales for visual ratings were studied: medial temporal atrophy lobe (MTA), global cortical atrophy (GCA), and Faze-as-scale measured white matter hyper intensities (WMHs). To build the models and cross-validate them, photographs and visual ratings from the Amsterdam Dementia Cohort (ADC) (N = 513) were used. For independent validation to assess generalizability, the Predict ND (N = 672) and ADNI (N = 752) cohorts were used [17].

Ales Bartos et al. 2019
In 75 participants, three-dimensional brain MPRAGE MRI at 3 T was segmented into 44 regions using 3-dimensional brain MRI using Free Surfer v6. The nation's size was measured in absolute volumes between 39 AD patients and 36 regular (NC) controls matching age, education and sex and proportional proportions to the overall brain volume [18].

H. Choi et al. 2019
The Ranking for Abnormality was described based on a type of unsupervised learning, using variational autoencoder, how far a mostly to image is from data samples. The model was used to determine behavioral disturbances and seizures using FDG PET data for Alzheimer's disease (AD) and mild cognitive impairment (MCI) and FDG PET data from clinical habits. Accuracy was calculated using the receiver-operating-characteristic (ROC) curve region under curve (AUC). Deep learning was investigated in order to see whether it has additional advantages for recognizing irregular patterns with the visual understanding of experts or vice versa [19].

Hanane Allioui et al. 2019
By maximizing capital, our job targets AD. The 3D image has to be cut into a 2.5D image, for that. While in many works, the 2.5D framework was previously used, to explore and define the emerging possibilities of integration between brain images in 2D and 3D. In this work, the 2.5D A sub-volume of proportions was used to illustrate (x x y z= 3) where the dimensions of the MRI slice are x, y, and z. There are many 2.5D scans in each 3D image, which cover the whole area studied. The use of depth information (z-direction) in MRI images was useful to promote the implementation of our method [20].

U. Rajendra Acharya et al. 2019
Filtering, extraction of features, collection of features were based on Student t-test, and classification was based on k-Nearest Neighbor (KNN). Furthermore, by applying other function extraction methods, a comparative study is carried out [21].

A. YİĞİT and Z. İŞIK 2019
The predictive models based on structural magnetic resonance (MR) brain images were included in this work. Via several preprocessing methods for three different projections, T1 weighted volumetric MR images were reduced to two-dimensional space [22].

Garam Lee et al. 2019
For the study of the sequence of words and time series results, RNN is commonly used. The benefit of applying RNN is that it is possible to process variable-length sequences to take
advantage of temporal patterns concealed in the sequence in question. Electronic Health Records (EHRs) Sequence RNN takes time in the sentiment analysis task using a 12 to 18-month window for observation. In these instances, where it is appropriate to address the variable-length input, RNN is a suitable candidate to be used. An RNN processes and updates one part of an input sequence at a time and its memory state, which implicitly includes background information for all of the sequence’s past elements [23].

Yupeng Li et al, 2019
In this study a support vector machine (SVM) was used to assess the capacity of the radiomic characteristics to identify patients with HCs, MCI and AD. In a cohort of 422 people from the Alzheimer’s Disease Neuroimaging Initiative (ADNI) and 44 individuals from Huashan Hospital, Shanghai, China, 18F-FDG PET and clinical evaluations were obtained [24].

Alejandro P. Castro et al, 2020
This proposes a system using sagittal MRI images and DL techniques to detect AD. Using the ANN Res-Net function with the SVM classifier extractor, the TL technique was used. The model was evaluated in reference data sets, demonstrating its quality-of-fit through previously accepted assessment methods and metrics [25].

In order to obtain more detailed outcomes, experiments were performed using Transfer Learning (TL) technique. This research has two main results to draw from: first, in sagittal MRI, the damage associated with AD and its stages can be differentiated. Secondly, the findings of sagittal MRI DL models are similar to the state-of-the-art MRI horizontal plane.

Anna Damulina et al 2020
3-T MRI was performed on all participants, corrected mapping with $R_2^*$ for macroscopic B0 field inhomogeneities. In the neocortex and cortical lobes, basal ganglia (BG), hippocampi, and thalami, the anatomical structures were segmented and median $R_2^*$ values were measured. To research the difference between groups in levels of $R_2^*$ and the association between longitudinal shifts in values of $R_2^*$ and cognition in the AD group, multivariable linear regression analysis was applied [26].

D. Chitradevi, S. Prabha 2020
In this paper, four distinct optimization algorithms, such as the Genetic Algorithm (GA), Particle Swarm Optimization Algorithm (PSO), Grey Wolf Optimization (GWO) and Cuckoo Search (CS), Brain sub-regions were considered to diagnose ADD. Among these methods of optimization, even with the right collection of the Optimum global solution for global, GWO shows promising results. The segmented regions were categorized using a Classifier of deep learning and tested with images of Ground Truth (GT) [27].

B. Richhariya, M. Tanveer 2020
In order to integrate prior data distribution information into the recursive feature elimination process, a new technique for selecting characteristics was suggested. Our approach is called the elimination of recursive features based on universal support vector machines (USVM-RFE). The proposed method offers global feature selection was compared to the local approach in SVM-RFE knowledge about data in the RFE phase. The use of algorithms for feature selection and classification for both voxel-based and volume-based structural MRI image morphometry analysis (ADNI database) were also presented [28].

Joel En Wei Koh et al, 2020
The brain’s magnetic resonance images (MRI) were pre-processed using an adaptive histogram and decomposed into four IMFS using bidirectional empirical mode decomposition (BEMD) for this analysis, a computational intelligence (CIT) tool for AD diagnosis. Local binary (LBP) patterns are then measured and concatenated with IMF histograms [29].
Then a newly suggested, updated Residual Network (ResNet) and an ACNN network were installed. Based on another 469 separate 3D MRI image sets, inference or checking of the diagnostic accuracy of the two models was performed. Compared to the conventional ACNN network, the new ResNet is much better, as it demonstrated improved accuracy with statistical significance and had less fulfilling-positive outcomes [30].

4. Comparative analysis

Comparison on accuracy of the different methods published in the papers in recent years are summarized in Table 1, in addition to the advantage, and disadvantages of these methods.

Table 1: Comparative analysis of Classification Alzheimer's disease methods.

| Authors                  | Techniques                  | Characteristics                                                                 | Published Year |
|--------------------------|-----------------------------|---------------------------------------------------------------------------------|-----------------|
| P. Kalavathi et al.      | CBSM+FFCM                   | segment the Brain tissue into White Matter (WM) and Gray Matter (GM), segmented WM and GM are analyzed to detect Alzheimer's disease in MR brain images by calculating similarity measures against normal brain such as Jaccard and Dice. | 2017           |
| Lauge Sorensen et al.    | SVM                         | In multivariate classification of dementia, SVM is the most commonly used algorithm, and Therefore, evaluating the potential advantage of this form of classifier ensemble was useful. | 2018           |
| Juha R. Koikkalainen et al. | WM measured + Fazekas       | Three visual rating scales were studied: atrophy of the medial temporal lobe (MTA), global cortical atrophy (GCA), and hyperintensity of white matter (WMHs) on the Fazekas scale. | 2019           |
| Ales Bartos et al.       | Freesurfer v6               | With Freesurfer v6, The three-dimensional brain MRI was divided into 44 regions at 3 T. The scale of the area was contrasted in actual amounts and quantitative proportions to the entire volume of the brain. | 2019           |
| H. Choi et al.           | variational autoencoder     | Using variational autoencoder FDG + PET Scan. The model was used to determine behavioural disturbances and seizures using FDG PET data for Alzheimer's disease (AD) and mild cognitive disability (MCI) and clinical routine FDG PET data. The accuracy was | 2019           |


| Author(s) | Architecture/Network | Methodology | Year |
|----------|----------------------|-------------|------|
| Hanane Allioui et al. | U-Net Architecture 2.5D | The technique is to transform the image from 3D to a 2.5D view. While the 2.5D definition has been previously used it in several works to explore and describe the new possibilities of integration between 2D and 3D brain pictures. | 2019 |
| A. YİĞİT, Z. İŞIK | CNN | As an input to the predictive model, structural magnetic resonance (sMRI) brain images were used. For three separate simulations, T1 weighted volumetric MR images are reduced to two-dimensional space by means of many preprocessing methods. | 2019 |
| Garam Lee et al. | RNN | One element of an input sequence is processed at a time by an RNN and changes its memory state, which indirectly includes historical information for all of the sequence's past elements. | 2019 |
| Yupeng Li et al, 2019 | SVM | In this analysis, (SVM) was used to Assess the capacity of radiomic properties to identify HCs, MCI, and AD patients. | 2019 |
| Alejandro P. Castro et al. | SVM | The TL technique was used; with the SVM classifier, using the ANN ResNet feature extractor. In sagittal MRI, the damage associated with AD and its phases can be separated, the findings the horizontal MRI it is similar to the technology obtained DL models & sagittal MRI. | 2020 |
| Anna Damulina et al. | 3-T MRI, R2* mapping | To investigate the discrepancy between the levels of R2* and the association between the longitudinal changes in the values of R2* and the cognition of the AD class, Multivariate linear regression analysis was used. | 2020 |
| D. Chitradevi, S. Prabha | GWO + deep learning | GWO is exhibiting positive results attributable to the careful evaluation of the best global solution. The areas that are segmented were categorized | 2020 |
using a Classifier for deep learning and tested with Ground Truth (GT) images.

B. Richhariya, M. Tanveer  
**USVM-RFE**  
The method offers global knowledge on data in the RFE framework relative to the local approach to the collection of features in the SVM-RFE.

Joel En Wei Koh et al.  
**CIT**  
For AD diagnosis, a Computational Intelligence Platform (CIT). Using an adaptive histogram, MRIs are pre-processed and decomposed into four IMFS for this study using bidirectional empirical mode decomposition (BEMD).

Shuyang Bian  
**ResNet**  
Then a revised, newly proposed Residual Network (ResNet) and an ACNN network have been built. The latest ResNet is better because it displayed increased accuracy with statistical significance compared to the traditional ACNN network and had less satisfying positive results.

| Methods                              | Maximum Detection Accuracy (%) | Specificity (%) |
|--------------------------------------|-------------------------------|-----------------|
| CBSM+FFCM                            | 55.83%                        | 51.11%          |
| six-layer (CNN) model                | 73%                           | -               |
| SVM                                  | 86.05%                        | 97.72%          |
| SVM                                  | 91.5%                         | -               |
| WM measured + Fazekas                | 79%                           | -               |
| Freesurfer v6                        | 74%                           | 78%             |
| variational autoencoder FDG + PET    | 90%                           | -               |
| U-Net Architecture 2.5D              | 92.71%                        | 91.59%          |
| CNN                                  | 82%                           | 81%             |
| PNN+KNN                              | 85%                           | 88%             |
| 3-T MRI, R2* mapping                 | 81%                           | 70%             |
| GWO + deep learning                  | 95%                           | 94%             |

The precision of Alzheimer's disease identification processes has also been summarized in Table 2.

Table 2: Accuracy of diagnosis for multiple tests used in Alzheimer's disease classification.
5. Conclusion
In this paper, introduction to Alzheimer's disease was presented and explained at first, and then importance of detecting diagnosis for MRI images was given. Explanation of the various categories of Alzheimer's disease and different types of techniques were successfully described as well. This paper was basically intended to present the research on all recent 2017 to 2020 studies MRI methods on Alzheimer's diagnosis comparative analysis. The complete review on all recent techniques was discussed in Sections II and III and contrasted wise with accuracy. Finally, in section IV, the study weaknesses and problems were illustrated. For future work, it is suggested to focus on addressing current research problems, since that the previous studies depended on features extracted by deep learning algorithms, which provided less accuracy. Clinical diagnosis was perceived to be one of the most major factors in the prevention of brain diseases, but early clinical diagnosis of Alzheimer's disease is difficult because changes in brain images are subtle and thus cannot be easily detected. Depending on extraction algorithms, the method of feature extraction from MRI images provides more reliable diagnostic results.

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