ADV MATH SCI JOURNAL
Advances in Mathematics: Scientific Journal **9** (2020), no.6, 3941–3946
ISSN: 1857-8365 (printed); 1857-8438 (electronic)
https://doi.org/10.37418/amsj.9.6.74 Spec Issiue on ICAML-2020

ALZHEIMER'S DISEASE DETECTION TECHNIQUES: A REVIEW

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ABSTRACT. Alzheimer's Disease (AD) is a neurological disease that leads to death of brain cells and hence causes memory loss. Age is a prominant risk factor. Memory loss is gradual and eventually the individual loses the ability to respond to his environment. This paper reviews various works in Computer Aided Alzheimer's Disease Detection (CAADD).

1. INTRODUCTION

Alzheimer's Disease (AD) is a type of dementia that leads to abnormal behaviour of memory. It affects mostly people above 65 years. It is a progressive disease, where symptoms gradually worsen over age. Mini Mental State examination (MMSE) (Folstein, 1975, [12]) and Clinical Dementia Rating (CDR) (Morris, 1993, [8]) are two of the most commonly used neuropsychological tests for ADD. MRI, PET, and SPECT are the imaging modalities used with MMSE and CDR for accurate and detailed ADD. Due to its high contrast and better resolution MRI is the standard. Some well-known publicly available datasets for AD are ADNI (Alzheimer's Disease Neuroimaging Initiative) and OASIS (Open Access Series of Imaging Studies). Commonly used assessment metrics for ADD are Sensitivity, Precision, Specificity and Accuracy. Most of ADD techniques are based on SVM eg (Beheshti et al., 2016, [3]), (Ortiztoro et al., 2019, [18]), (Tu et al., 2018, [19]), (Zhang et al., 2016, [20]), Nearest Neighbour (Acharya et al., 2019, [1]) and Deep learning (Islam et al., 2017, [7]).

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2010 *Mathematics Subject Classification.* 94A16.
Key words and phrases. classification, Alzheimer's, MRI.

2. Literature review

Leandrou et al., 2018 [9] reviewed five AD detection techniques:

(i) Voxel-based Morphometry (VBM)
(ii) ROI Volume measurement
(iii) Cortical thickness measurements
(iv) Shape analysis
(v) Texture analysis

and claimed that early stages of the disease are more pronounced in the Medial Temporal Lobe (MTL) whereas entorhinal cortex and hippocampus offer more discrimination as the disease progresses.

Li et al., 2015 [10] exploited Mid-level visual element to cluster image patches and used them for pattern mining using Convolutional Neural Networks (CNNs) with Association Rule Mining.

Perez et al., 2017 [16] explored data augmentation techniques in image classification and found cropping, rotating, and flipping to be useful. They made a NN to learn from augmentations which improved the classification accuracy.

Hira et al., 2015 [6] summarised various dimensionality reduction techniques on high-dimensional microarray data.

Table 1: Summary of literature

Reference	Technique	Dataset	Metrics	Remarks
Mahmood et al., 2013, [14]	ANN	OASIS	Accuracy	Using PCA, Accuracy=89.92% is achieved
Ahmed et al., 2015, [2]	Bag of words, Harmonic Functions	ADNI, Bordeaux	Accuracy, Specificity, Senstivity	accuracy= 87%
Islam and Zhang, 2017, [7]	Data Augmentation, DL	OASIS	Accuracy	Accuracy=73.75% is achieved
Tanchi et al., 2012, [17]	Mathematical morphology	ADNI	Brain volume, accuracy	87% accuracy is achieved
Zhang et al., 2015, [21]	Eigenbrain and ML	OASIS	Accuracy, sensitivity, specificity, precision	Accuracy=92.36%

Padovese et al., 2016, [15]	Rank based unsupervised Distance Learning	ADNI, OASIS	Gain by FCTH, SPyCEDD, SColor	NIL
Tu et al., 2018, [19]	Surface based features	AD-135 NC-248	Accuracy, Senstivity	Accuracy of 81.82% is achieved
Beheshti et al, 2016, [3]	Structural MRI based technique	ADNI	Accuracy, sensitivity, specificity, AUC	Accuracy=83.58% is achieved
Toro et al, 2019, [18]	Radiomics textural features based technique	ADNI	Accuracy, Sensitivity, Specificity	Accuracy=93% is achieved
Magnin et al., 2009, [13]	SVM	AD-16 NC-22	Accuracy	Accuracy=94.5% is achieved
Zhang et al., 2016, [20]	Landmark feature based technique	ADNI	Accuracy, Sensitivity, Specificity	Accuracy=83% is achieved
Acharaya et al., 2019, [1],	Comparative analysis of features	AD-11 NC-22	Accuracy, Precision, Sensitivity, Specificity	Accuracy=95% is achieved
Bucks et al., 2000, [4]	PCA, LDA, linguistic features	AD-8 NC-16	Accuracy	88% accuracy is achieved.
Fraser et al., 2016, [5]	BOW, LR, voice features	AD-167 NC-97	Accuracy	82% accuracy is achieved.
Lopez et al., 2013, [11]	SVM, FT	AD-20 NC-50	Accuracy	Accuracy=94% is achieved

3. Research gaps

- Mostly researchers used VBM or cortical thickness based methods. Texture based features haven't being explored well.

- Not many researchers applied image enhancement to improve the quality of image, which is an essential step to be followed as it leads to better results.
- Further classification can be done on the basis of stage of disease progression, i.e. stage 1, 2, 3 etc.
- Accuracy is improved with DL methods but being "data hungry" is a big drawback. Not much data is available for brain MRI because most of the people do not like to disclose their personal information in public domain. Another major constraint for DL based methods is requirement of high computational hardware to compute massive image data which is not feasible always.

4. Challenges

- Brain MRI data is very complex and brain structure varies with each patient. Region boundaries are usually unclear and irregular, posing great challenge for ADD.
- Brain MRI data obtained from clinical scans is usually very unstructured as devices and protocols used for acquisition vary and hence impose intensity biases.
- Brain MRI data is voluminous and hence involves complex computations. Thus, Memory is also a challenge.
- Medical images are often degraded by noise and low contrast and hence need enhancement. There is no standard image enhancement algorithm to remove noise and improve contrast without compromising on accuracy.
- Several state-of-the-art techniques are available for ADD, however a robust method is still a need of the hour.

5. Conclusion

MRIs can be mined efficiently for ADD. Different types of features can be extracted. After their correlation is assessed with the target class, features can be filtered to produce optimal classification by using a suitable Machine Learning algorithm. Early detection of AD improves the responses of AD patients to drug therapy and their quality of life.

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