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Alzheimer Disease: A Survey on its Prediction Techniques

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***Abstract*: Alzheimer is the most relevant form of dementia that causes problem such as memory, communication and language, ability to focus and pay attention, Prior research have shown that symptoms develop gradually over time and get worse, becoming severe enough to interfere with daily tasks. Microscopic changes in the brain begin long before the first signs of memory loss There are numerous techniques that have been proposed to rectify Alzheimer's disease at an early age. Several neuroimaging studies have aimed at classification and predicting conversion from mild cognitive impairment to Alzheimer disease. A couple of test for examining Alzheimer disease at an early stage are Alzheimer's Disease Assessment Scale, the Mini Mental State Examination(MMSE) and anatomically partitioned artificial neural network (APANN) model.**

***Keywords*: Alzheimer disease, APANN, dementia, MMSE, neuro imaging.**

1. Introduction

Alzheimer's disease is the most common form of dementia and according to prior research, approximately 47 million people are living with dementia worldwide and Alzheimer's disease accounts for 60 percent to 80 percent of dementia cases. Alzheimer Disease is a neurological disease that mostly affects older people and is characterized by a progressive dementia. It causes a degeneration of specific nerve cells and the presence of neurotic plaques. Alzheimer's has no current cure, but treatments for symptoms are available and research continues. Although current Alzheimer's treatments cannot stop Alzheimer's from progressing, they can temporarily slow the worsening of dementia symptoms and improve quality of life for those with Alzheimer's. The most common early symptom of Alzheimer's is difficulty remembering newly learned information because Alzheimer's changes typically begin in the part of the brain that affects learning. As Alzheimer's advances through the brain it leads to increasingly severe symptoms, including disorientation, mood and behavior changes; deepening confusion about events, time and place.

There are different techniques used for identifying Alzheimer's disease and Alzheimer's disease assessment scale is one among them. So let us have a quick look on this technique. Alzheimer disease assessment scale consists of cognitive and non-cognitive sections. Cognitive test includes test of language, comprehension, memory, orientation. It also include test of visual spatial ability such as drawing geometric figures, physical tasks such as folding papers into envelope. Patient will be given score of 0 to 70 wherein higher score signifies poorer performance. Advantage of this test is that it is easy and can be conducted by an untrained person. Disadvantage of this method is that exact stage is not predictable.

Another technique used for examining Alzheimer disease is MMSE. Mini mental state examination is 30-point questionnaire that is used extensively in clinical and research setting to measure cognitive impairment. The series of test include attention, calculation, recall, language, ability to follow simple command, orientation and so on. The advantage of this test is that it requires no specialized training or equipment and also it has validity and reliability for diagnosis. The disadvantage of this method is that it is affected by demographic factor such as age. This method also lacks in sensitivity to mild cognitive impairment.

Anatomically partitioned artificial neural network (APANN) model deals with the prediction of clinical score using MRI (magnetic resonance imaging) data. In this method, the model combined input from two neurodegenerative patterns observed in Alzheimer disease that is hippocampal segmentations and cortical thickness. The performance of this method was conducted in three experiments using cohorts from Alzheimer's Disease Neuroimaging Initiative (ADNI).

2. Related work

Three experiments were conducted in [1] ADNI 1 cohort, ADNI 2 cohort, ADNI1+2 cohort, as described below.

A. Experiment 1: ADNI1 cohort

The combined hippocampal + cortical thickness input provided the best results for ADAS-13 prediction (r = 0.60, RMSE = 7.11). We observed similar trends for MMSE prediction with the combined hippocampal + cortical thickness input (r = 0.52, RMSE = 2.25). The hippocampal input alone yielded findings of r = 0.53, RMSE = 7.56 for ADAS-13 score prediction and r = 0.40, RMSE = 2.41 for MMSE. The cortical thickness input alone yielded findings of r = 0.51, RMSE = 7.67 for ADAS-13 score prediction and r = 0.50, RMSE = 2.29 for MMSE.

B. *Experiment 2: ADNI2 cohort*

Similar to experiment 1, the combined hippocampal + cortical thickness input provided the best results for ADAS-13 prediction (r = 0.68, RMSE = 7.17). We observed similar trends for MMSE prediction with the combined hippocampal + cortical thickness input (r = 0.55, RMSE = 2.25). The hippocampal input alone yielded findings of r = 0.52, RMSE = 8.32 for ADAS-13 score prediction and r = 0.40, RMSE = 2.51 for MMSE. The cortical thickness input alone yielded findings of r = 0.63, RMSE = 7.58 for ADAS-13 score prediction and r = 0.52, RMSE = 2.31 for MMSE.

C. *Experiment 3: ADNI1 + 2 cohort*

Similar to experiments 1 and 2, the combined hippocampal + cortical thickness input provided the best results for ADAS13 prediction (r = 0.63, RMSE = 7.32). We observed similar trends for MMSE prediction with the combined hippocampal + cortical thickness input (r = 0.55, RMSE = 2.25). The hippocampal input alone yielded findings of r = 0.54, RMSE = 7.99 for ADAS-13 score prediction and r = 0.45, RMSE = 2.42 for MMSE. The cortical thickness input alone yielded findings of r = 0.57, RMSE = 7.79 for ADAS-13 score prediction and r = 0.50, RMSE = 2.37 for MMSE.

3. Tables

Table 1
Prediction performance for ADAS-13 scores

	Hippocampal input		Cortical thickness input		Combined hippocampal and cortical thickness input	
Model	*r*	RMSE	*r*	RMSE	*r*	RMSE
ADNI1						
Linear regression with lasso	0.22 ± 0.11	8.72 ± 0.81	0.56 ± 0.08	7.44 ± 0.72	0.56 ± 0.08	7.42 ± 0.74
Support vector regression	0.23 ± 0.11	8.70 ± 0.85	0.52 ± 0.08	7.68 ± 0.76	0.53 ± 0.08	7.62 ± 0.78
Random forest regression	0.15 ± 0.10	9.27 ± 0.80	0.54 ± 0.08	7.55 ± 0.76	0.54 ± 0.08	7.51 ± 0.77
APANN	0.53 ± 0.09	7.56 ± 0.76	0.51 ± 0.10	7.67 ± 0.76	0.60 ± 0.08	7.11 ± 0.72
ADNI2						
Linear regression with lasso	0.14 ± 0.11	9.69 ± 0.70	0.61 ± 0.07	7.77 ± 0.71	0.61 ± 0.07	7.78 ± 0.71
Support vector regression	0.21 ± 0.10	9.75 ± 0.79	0.63 ± 0.07	7.65 ± 0.68	0.63 ± 0.07	7.66 ± 0.70
Random forest regression	0.24 ± 0.09	9.77 ± 0.76	0.58 ± 0.07	7.97 ± 0.65	0.58 ± 0.08	7.97 ± 0.67
APANN	0.52 ± 0.07	8.32 ± 0.79	0.63 ± 0.07	7.58 ± 0.71	0.68 ± 0.06	7.17 ± 0.71
ADNI1 + 2						
Linear regression with lasso	0.12 ± 0.08	9.37 ± 0.50	0.58 ± 0.06	7.71 ± 0.48	0.58 ± 0.06	7.71 ± 0.48
Support vector regression	0.18 ± 0.07	9.39 ± 0.54	0.59 ± 0.05	7.65 ± 0.42	0.59 ± 0.05	7.65 ± 0.42
Random forest regression	0.18 ± 0.09	9.63 ± 0.61	0.57 ± 0.05	7.76 ± 0.46	0.57 ± 0.05	7.75 ± 0.46
APANN	0.54 ± 0.06	7.99 ± 0.59	0.57 ± 0.05	7.79 ± 0.51	0.63 ± 0.05	7.32 ± 0.53

APANN = anatomically partitioned artificial neural network; RMSE = root mean squared error; SD = standard deviation.
*Findings are presented as mean ± SD.

Table 2
Prediction performance for MMSE scores

	Hippocampal input		Cortical thickness input		Combined hippocampal and cortical thickness input	
Model	*r*	RMSE	*r*	RMSE	*r*	RMSE
ADNI1						
Linear regression with lasso	0.23 ± 0.12	2.54 ± 0.18	0.49 ± 0.08	2.28 ± 0.17	0.50 ± 0.08	2.27 ± 0.17
Support vector regression	0.25 ± 0.12	2.59 ± 0.19	0.48 ± 0.07	2.31 ± 0.16	0.50 ± 0.07	2.28 ± 0.16
Random forest regression	0.22 ± 0.11	2.63 ± 0.21	0.48 ± 0.08	2.30 ± 0.17	0.49 ± 0.08	2.28 ± 0.17
APANN	0.40 ± 0.09	2.41 ± 0.15	0.50 ± 0.09	2.29 ± 0.20	0.52 ± 0.08	2.23 ± 0.17
ADNI2						
Linear regression with lasso	0.19 ± 0.12	2.64 ± 0.19	0.46 ± 0.08	2.39 ± 0.19	0.47 ± 0.08	2.39 ± 0.19
Support vector regression	0.28 ± 0.14	2.72 ± 0.24	0.52 ± 0.07	2.32 ± 0.18	0.54 ± 0.07	2.30 ± 0.18
Random forest regression	0.25 ± 0.12	2.67 ± 0.24	0.50 ± 0.09	2.33 ± 0.17	0.51 ± 0.08	2.31 ± 0.17
APANN	0.40 ± 0.09	2.51 ± 0.21	0.52 ± 0.12	2.31 ± 0.25	0.55 ± 0.10	2.25 ± 0.21
ADNI1 + 2						
Linear regression with lasso	0.15 ± 0.08	2.64 ± 0.12	0.50 ± 0.07	2.31 ± 0.13	0.50 ± 0.07	2.31 ± 0.13
Support vector regression	0.22 ± 0.07	2.71 ± 0.13	0.52 ± 0.07	2.31 ± 0.13	0.52 ± 0.07	2.30 ± 0.13
Random forest regression	0.17 ± 0.08	2.74 ± 0.14	0.50 ± 0.07	2.31 ± 0.14	0.50 ± 0.07	2.31 ± 0.14
APANN	0.45 ± 0.06	2.42 ± 0.14	0.50 ± 0.07	2.37 ± 0.15	0.55 ± 0.06	2.25 ± 0.12

APANN = anatomically partitioned artificial neural network; RMSE = root mean squared error; SD = standard deviation.
*Findings are presented as mean ± SD.

4. Figures

The mean correlation (r) and RMSE performance values for all 3 experiments with 3 input modality configurations are summarized in Figure 1, Table 1 and Table 2.

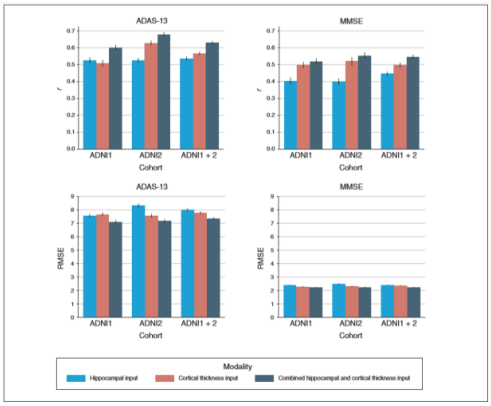

Fig. 1. Performance of anatomically partitioned artificial neural network subject to individual and combined input modalities

5. Conclusion

We have presented the review of different ways of prediction and detection of Alzhemier disease. the clear understanding of Alzheimer disease assessment scale, mini mental state examination and anatomically partitioned artificial neural network model along with advantages and disadvantages are

Table 3
Various models proposed for Alzheimer's disease from different papers from [1] to [4]

S. No.	Title	Author	Proposed technique
1	Fully Automatic Hippocampus Segmentation and Classification in Alzheimer's Disease and Mild Cognitive Impairment Applied on Data from ADNI	Marie Chupin1,2, Emilie Gérardin1,2, Rémi Cuingnet1,2,3, Claire Boutet1,2,5,6, Louis Lemieux4, Stéphane Lehéricy1,2,5,6, Habib Benali3, Line Garnero1,2, Olivier Colliot1,2	They proposed a fully automatic method using probabilistic and anatomical priors for hippocampus segmentation.
2	Automatic classification of patients with Alzheimer's disease from structural MRI: a comparison of ten methods using the ADNI database	Rémi Cuingnet, Emilie Gerardin, Jérôme Tessieras, Guillaume Auzias, Stéphane Lehéricy, Marie-Odile Habert, Marie Chupin, Habib Benali, Olivier Colliot	The goal of this paper was to compare different methods for the classification of patients with AD based on anatomical MRI, using the same study population. To that purpose, we used the Alzheimer's Disease Neuroimaging Initiative (ADNI) database.
3	The MINWii Project: Renarcissization of Patients Suffering from Alzheimer's Disease Through Video Game-Based Music Therapy	Samuel Benveniste1, Pierre Jouvelot1, and Renaud P´equignot2	MINWii, a new serious video game targeting Alzheimer and demented patients, is a simple Music Therapy tool usable by untrained care givers.
4	Predicting Alzheimer's disease: a neuroimaging study with 3D convolutional neural networks	Adrien Payan1 and Giovanni Montana∗1,2	they use deep learning methods, and in particular sparse autoencoders and 3D convolutional neural networks, to build an algorithm that can predict the disease status of a patient, based on an MRI scan of the brain.

surveyed in this paper. In spite of huge research, there is no universally accepted diagnosis method for the Alzheimer disease. Thus, all methods are equally good for prediction but diagnosis still remains a challenge.

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