

Development Of Ultra Convolution Neural Network For Early Alzheimer's Disease Detection For Brain Tumor Patients Using Mr Image Analysis

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Abstract

Alzheimer's disease (AD) is slowly growing intense effect disease and causes brain shrinkage and various neurological disorders. The core cause is the buildup of tau and amyloid protein around the brain cells. As detection of AD is a crucial task as AD takes years to get detected. If untreated and/or not diagnosed early, a person can enter into a mild stage with slight forgetfulness. At this stage, it is clinically considered that the AD initiated 10 years ago. Hence, this paper presents the newly developed algorithm ultraCNN for early detection of AD for patients with a brain tumor using brain MR image dataset BRATS. Neural networks are a powerful means for fast detection of brain anatomical changes in brain dimensions. In the case of radiological image interpretation, there can be a human error. The proposed algorithm gives exact results by de-blurring of MR images. So, the proposed algorithm can be helpful for medical experts to predict and diagnose AD very fast.

Keywords: Alzheimer's disease, CNN, neural network, brain MRI

1. INTRODUCTION

As world-wide outbreak Covid-19 influenced in diverse ways, it shares etiological cofactors with diverse conditions, including Alzheimer's disease (AD). Comprehending the facts of the prevalent bonds amongst COVID-19 as well as AD may control strategizing restorative strategies to prevent both [1]. Alzheimer's disease (AD), among the biggest risks to individual wellbeing, is indicated by dropped cognition as well as modified behavior. Cyclic adenosine monophosphate (cAMP) and cyclic guanosine monophosphate (cGMP) that have an essential part in learning and memory are hydrolyzed by phosphodiesterase (PDEs) [2]. In AD, MRI provides a PPV to the analysis; sound trials have proven that alterations in brain elements can be discovered with structural MRI in aged subjects with moderate intellectual disability (MCI) [3].

Alzheimer's disease (AD) is intensifying brain instability and so the most prevalent of dementia occurs in the later life. AD directs to the death of the nerve system cell and anatomical damage all over the brain, hence lowering the brain volume level in proportions drastically through time frame and impacting many of its function [4]. Recent Alzheimer's disease (AD) analysis is structured on medical examination, imaging as well as neuropsychological assessments that are effective merely at high level phases of the disease. Very early analysis of AD can give definitive possibilities for precautionary medication and advancement of disease-modifying drugs [5]. Artificial intelligence (AI) has viewed incredible improvement in the past decade. As in other areas of medication, there is a significant awareness in using AI for helping supervision of brain disorders. AI approaches consist of supporting medical diagnosis, featuring diagnosis data, and forecasting results to medication [6]. Machine learning gives a strategy for automated classification by learning complicated as well as delicate structures from high-dimensional statistics. In AD analysis, many of these algorithms have been often formulated to execute automated prognosis and forecast the upcoming medical situation at a specific level founded on biomarkers [7].

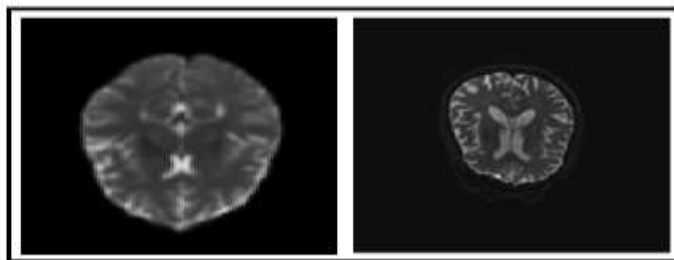


Fig.1: ADNI sample images (Source: Alzheimer's disease Neuroimaging Initiative)

Many researchers have identified that variability powered by site variations, frequently known as site effects, lessens the consistency of produced measurements, and so can create error. Neuroimaging measurements have been consistently demonstrated to be influenced by the scanner model [8]. According to author(s), the etiology of AD is heterogeneous, that directs to excessive variability in disease structures. Additionally, variability stems from multicentric analysis models, transforming accumulation standards, as well as glitches in the pre-processing of magnetic resonance imaging (MRI) tests. The substantial variability creates the difference amongst signal as well as noise hard and may tweaked to over-fitting [9].

2. LITERATURE REVIEW

According to author(s), machine learning models are ensuring substitutions for calculating the innate risk of late-onset AD (LOAD). Organized machine learning model decision likewise give the prospect to determine new innate markers possibly linked by way of the disease [10]. Author(s) presented an analysis of articles from 2005 to 2019 applying numerous feature extraction as well as machine learning methods. The machine learning approaches are targeted within three main groups: support vector machine (SVM), artificial neural network (ANN), and deep learning (DL) and ensemble methods. Author(s) proclaimed a comprehensive analysis of all these three methods for Alzheimer's with conceivable future guidelines [11]. Author(s) portrayed that a support vector machine (SVM) is a monitored machine learning model that incorporates classification methods for two-group classification complications. Support vector machine is a swift and reliable classification protocol that works fairly well with a modest quantity of data to evaluate [12].

In the latest years, deep learning has received major popularity in resolving intricate challenges from plenty of areas; therapeutic image evaluation is among them. Author(s) suggested a K-Nearest Neighbor as well as a Deep Neural Network bundled model intended for the rapid analysis of Alzheimer's disease [13]. In real life challenges, discrepancy in data samples creates main concern for the classification difficulty as the data samples of a specified class are major. Challenges like error as well as disease recognition entail disproportion data and consequently require focus to prevent the prejudice toward an individual class [14]. Author(s) formulated a technique of diagnosis and classification of AD via Brain MR images, applying numerous image processing approaches, feature extraction methods as well as machine learning deviser's is suggested. Classification criteria are modelled by the common k-Nearest Neighbor classification formula to boost the accuracy of classification as well as functionality of the suggested technique. It is noticed that the classification accuracy of the suggested model is 93.18% equipped with positive specificity and sensitivity [15]. Deep models have been testified to be even more accurate for AD diagnosis compared to standard machine learning methods. On the other hand, AD diagnosis is still difficult, and so for classification, it needs an extremely discriminative characteristic manifestation to divide equivalent brain patterns [16].

3. RESEARCH METHODOLOGY

As numerous researches done for AD analysis, there is rare research on brain tumor patients with AD possibility. Hence, the proposed research uses BRATS dataset of MR images for the classification of brain anatomy.

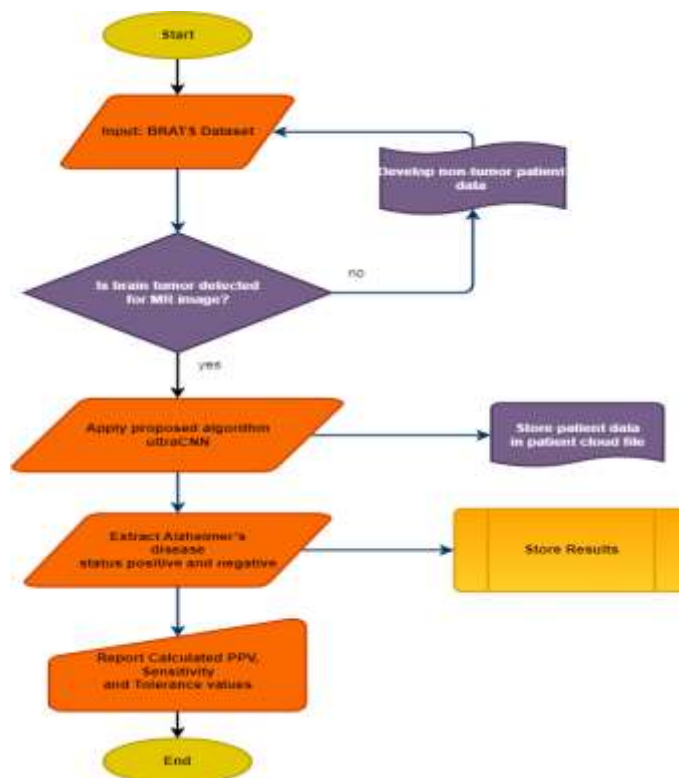


Fig. 2: Proposed Methodology

The newly developed ultraCNN algorithm will analyze the brain dimensions with a comparison of two images of the same patient for the duration of 12 months. This will give the status of AD positivity or negativity for a brain tumor patient. Obviously, if brain shrinking is detected, then AD is positive and vice versa. Further to that, the classification of brain tumor will be done. The core research query is scan the brain tumor also shrinks with AD positive status? Following Fig.2 shows the proposed methodology.

Proposed Algorithm: ultra CNN

Input: BRATS dataset

1. Select hyper-parameter 'ultraCNN_task'=(enhance | edema | necrotic)

If ultraCNN_task==enhance

else if ultraCNN_task==edema

else ultraCNN_task== necrotic

2.Create ultra_algo_batch_0 (M , N): ultra_algo_batch_n (M, N) + M_{cl} # Creating the first batch

Where, $M = 0$

3.ultra_algo_batch_n = (Incr_algo_0 (M, N) + ConcatLayer) # Run the training using ConcatLayer to identify dice loss, Sensitivity etc.

Where, $M_{cl} \neq 0$

4. while ($M_{cl} \neq 0$) do

5. Add Concat Layer

ultra_algo_batch_n = M_{cl} + ultra_algo_batch_n(M, N) – losses# connects all layers and removes losses for prediction

6. If tumor exists

7. Go to step 3

8. else store non-tumor MR image ID back to BRATS

9. if previous MR image == New MR image print 'No Alzheimer's disease detected'

10. else print 'Alzheimer's disease detected'

11. Calculate PPV, Sensitivity and Tolerance

12. End

The algorithm discussed above provides positive prediction value (PPV), sensitivity and tolerance. Next section 4 shows the actual results of execution of algorithm.

4. RESULT AND DISCUSSIONS

As discussed previously, the MR image analysis for BRATS dataset of MRI gives very quick results with Epoch size 150 with GPU execution. The PPV values show the AD existence and Sensitivity values depict that de-blur of images done so that medical professionals can visualize the MR image clearly. Refer following Fig. 3.

dsc	ppv	sensitivity	tolerance
epoch 0			
0.9195		0.64	75.06
0.9195		0.64	75.44
0.9195		0.66	75.3
0.9195		0.79	75.15
0.9195		0.33	75.71
0.9195		0	86
0.9195		0.81	90
0.9195		0.9	333.33
0.9195		0.2	444.4
0.9195		0.88	460
0.9195		0.9	455.77
0.9195		0.82	213.67
0.9195		0.74	215.42
0.9195		0.83	208
0.9195		0.71	204
0.9189	0.7374	0.7949	0.584
0.9182	0.8259	0.7869	0.7
0.9179	0.89	0.7886	0.8
0.9192	0.761	0.7859	0.6142
0.9275	0	0.7943	0

Fig.3: Results of proposed research

The tolerance values are within acceptable limits so, errors in readings are negligible. Hence, the proposed ultraCNN provides a good prediction of AD.

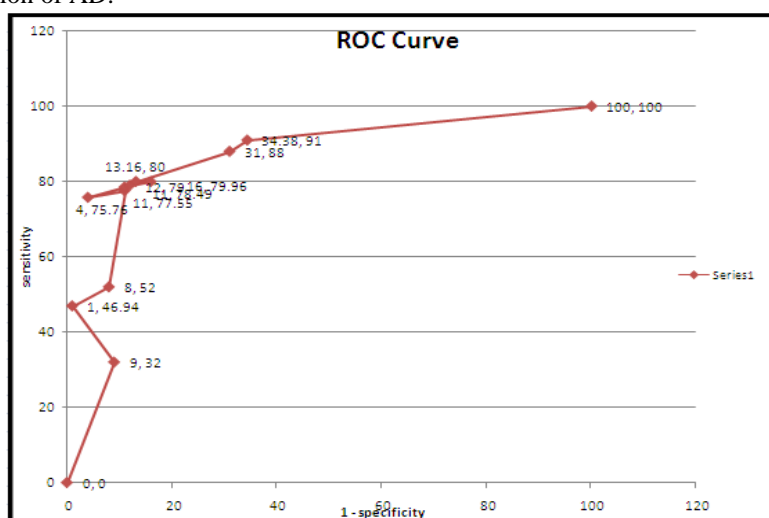


Fig.4: Region of interest for the proposed algorithm

Fig.4 above shows the Region of Interest (ROI) for brain tumor and in case of AD, tumor size remains the same, though brain shrinkage is noted.

5. CONCLUSION

The proposed ultraCNN algorithm has been developed and is proved to be a fast prediction algorithm after the training and validation on BRATS dataset. It is also noted that the brain tumor size remains the same in case of patient is with AD. The convolution neural network with the proposed algorithm execution gives de-blurred results of MRI, which is helpful for medical experts to analyze visually. The pre-and postsurgical analysis for brain tumor surgery can be done in future for patients with AD.

REFERENCES:

1. Rahman, Mohammad Azizur, et al. "Neurobiochemical cross-talk between COVID-19 and Alzheimer's disease." *Molecular Neurobiology* 58 (2021): 1017-1023.
2. Xi, Meiyang, et al. "Therapeutic potential of phosphodiesterase inhibitors for cognitive amelioration in Alzheimer's disease." *European Journal of Medicinal Chemistry* (2022): 114170.
3. Lazli, Lilia, Mounir Boukadoum, and Otmame Ait Mohamed. "A survey on computer-aided diagnosis of brain disorders through MRI based on machine learning and data mining methodologies with an emphasis on Alzheimer disease diagnosis and the contribution of the multimodal fusion." *Applied Sciences* 10.5 (2020): 1894.

4. Bi, Xiuli, et al. "Computer aided Alzheimer's disease diagnosis by an unsupervised deep learning technology." *Neurocomputing* 392 (2020): 296-304.
5. Ryzhikova, Elena, et al. "Raman spectroscopy and machine learning for biomedical applications: Alzheimer's disease diagnosis based on the analysis of cerebrospinal fluid." *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy* 248 (2021): 119188.
6. Burgos, Ninon, and Olivier Colliot. "Machine learning for classification and prediction of brain diseases: recent advances and upcoming challenges." *Current Opinion in Neurology* 33.4 (2020): 439-450.
7. Bron, Esther E., et al. "Cross-cohort generalizability of deep and conventional machine learning for MRI-based diagnosis and prediction of Alzheimer's disease." *NeuroImage: Clinical* 31 (2021): 102712.
8. Chen, Andrew A., et al. "Mitigating site effects in covariance for machine learning in neuroimaging data." *Human brain mapping* 43.4 (2022): 1179-1195.
9. Bloch, Louise, Christoph M. Friedrich, and Alzheimer's Disease Neuroimaging Initiative. "Data analysis with Shapley values for automatic subject selection in Alzheimer's disease data sets using interpretable machine learning." *Alzheimer's Research & Therapy*, Springer, 13 (2021): 1-30.
10. De Velasco Oriol, Javier, et al. "Benchmarking machine learning models for late-onset alzheimer's disease prediction from genomic data." *BMC bioinformatics* 20.1 (2019): 1-17.
11. Tanveer, Muhammad, et al. "Machine learning techniques for the diagnosis of Alzheimer's disease: A review." *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)* 16.1s (2020): 1-35.
12. Bari Antor, Morshedul, et al. "A comparative analysis of machine learning algorithms to predict alzheimer's disease." *Journal of Healthcare Engineering* 2021 (2021).
13. Benyoussef, El Mehdi, AbdeltifElbyed, and Hind El Hadiri. "3D MRI classification using KNN and deep neural network for Alzheimer's disease diagnosis." *Advanced Intelligent Systems for Sustainable Development (AI2SD'2018) Vol 4: Advanced Intelligent Systems Applied to Health*. Springer International Publishing, 2019.
14. Ganaie, M. A., Mohammad Tanveer, and Alzheimer's Disease Neuroimaging Initiative. "KNN weighted reduced universum twin SVM for class imbalance learning." *Knowledge-Based Systems* 245 (2022): 108578.
15. Aruchamy, Srinivasan, VeeramachaneniMounya, and Ankit Verma. "Alzheimer's disease classification in brain MRI using modified kNN algorithm." *2020 IEEE International Symposium on Sustainable Energy, Signal Processing and Cyber Security (iSSSC)*. IEEE, 2020.
16. Ebrahimighahnavieh, Mr Amir, Suhuai Luo, and Raymond Chiong. "Deep learning to detect Alzheimer's disease from neuroimaging: A systematic literature review." *Computer methods and programs in biomedicine* 187 (2020): 105242.