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Automatic Alzheimer's Disease Recognition from MRI Data Using Deep Learning Method

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Abstract

Alzheimer's Disease (AD), the most common form of dementia, is an incurable neurological condition that results in a progressive mental deterioration. Although definitive diagnosis of AD is difficult, in practice, AD diagnosis is largely based on clinical history and neuropsychological data including magnetic resource imaging (MRI). Increasing research has been reported on applying machine learning to AD recognition in recent years. This paper presents our latest contribution to the advance. It describes an automatic AD recognition algorithm that is based on deep learning on 3D brain MRI. The algorithm uses a convolutional neural network (CNN) to fulfil AD recognition. It is unique in that the three dimensional topology of brain is considered as a whole in AD recognition, resulting in an accurate recognition. The CNN used in this study consists of three consecutive groups of processing layers, two fully connected layers and a classification layer. In the structure, every one of the three groups is made up of three layers, including a convolutional layer, a pooling layer and a normalization layer. The algorithm was trained and tested using the MRI data from Alzheimer's Disease Neuroimaging Initiative. The data used include the MRI scanning of about 47 AD patients and 34 normal controls. The experiment had shown that the proposed algorithm delivered a high AD recognition accuracy with a sensitivity of 1and a specificity of 0.93.

Keywords

Alzheimer's Disease, AD, Recognition, Magnetic Resource Imaging, MRI, Deep Learning, Convolutional Neural Network, CNN

*Data used in preparation of this article were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (ad-ni.loni.usc.edu). As such, the investigator within the ADNI contributed to the design and implementation of ADNI and/or provided data but did not participate in analysis or writing of this report. A complete listing of ADNI investigators can be found at: http://adni.loni.usc.edu/wp-content/uploads/how_to_apply/ADNI_Acknowledgement_List.pdf.

1. Introduction

Dementia describes a collection of symptoms that are caused by disorders affecting the brain. There are more than 46.8 million people worldwide with dementia today and 131.5 million predicted by 2050 [1]. There are many types of dementia, of which Alzheimer's Disease (AD) is the most common form. Although considerable efforts have been made to unravel the pathophysiologic mechanisms of dementia and develop effective treatments, definitive diagnosis of dementia is mostly difficult. In searching for an effective way of diagnosing AD, some computer-aided systems have been investigated to diagnose AD. These systems are based on machine learning using clinical history information and neuropsychological data including magnetic resource imaging (MRI), structural MRI (sMRI), functional MRI (fMRI), and positron emission tomography (PET).

Deep learning (DL) simulates the hierarchical structure of human brain, processes data from lower levels to higher levels, and gradually composes more and more semantic concepts. As a new machine learning paradigm, deep learning has been increasingly explored in the development of technology for big data and artificial intelligence [2] [3] [4]. Some deep learning based algorithms have been proposed recently to recognise, or detect, AD. [5] presented a deep learning method consisted of sparse autoencoders and 3D convolutional neural networks. It can predict the disease status of a patient based on MRI scan. It achieved 95% accuracy when predicting between AD brains and healthy brains. [6] presented a multimodal neuroimaging feature extraction pipeline for multiclass AD diagnosis. It developed a deep-learning framework using a zero-masking strategy to preserve all possible information encoded in imaging data. It achieved high accuracy of 87%. [7] outlined deep learning-based pipelines employed to distinguish Alzheimer's MRI and fMRI from normal healthy control data for a given age group. It almost perfectly distinguished Alzheimer's patients from healthy normal brains. [8] proposed to predict the AD with a deep 3D convolutional neural network. The network was built upon a 3D convolutional autoencoder, which is pre-trained to capture anatomical shape variations in structural brain MRI scans. Experiments on the adopted MRI dataset with no skull-stripping preprocessing had shown that it outperformed several conventional classifiers by accuracy.

This paper introduces an automatic AD recognition algorithm that is based on deep learning on 3D brain MRI. In Section 2, we describe the algorithm in detail, including its major steps. In Section 3, we describe the results of the experiments of applying the proposed algorithm on real MRI data, and the related performance discussion. Finally, in Section 4, we conclude by summarising the approach and pointing out possible future pursuits in the area.

2. Method

The proposed AD recognition system can be completed in two processes including system training and practical testing. The training mainly builds the

system based on designing and training data. The test will give recognition result based on current input data. In particular, the recognition algorithm starts from using MRI data as input, pre-processes the data to increase recognition accuracy, then completes the recognition using convolutional neural networks. The following subsections describe these steps.

2.1. Data Collecting and Pre-Processing

The proposed system is built and tested with the MRI data acquired from Alzheimer's Disease Neuroimaging Initiative (ADNI) database [9]. The primary goal of ADNI has been to test whether serial MRI, PET, other biological markers, and clinical and neuropsychological assessment can be combined to measure the progression of mild cognitive impairment and early AD.

The data used include the MRI scans of about 47 AD patients and 34 normal controls (NC) from ADNI1. They are all from different subjects, making the recognition performance test more reliable. The scans are T1-weighted, acquired according to the ADNI acquisition protocol. They are 3D magnetization-prepared rapid gradient echo (MP-RAGE) sequence. The sequence was undergone a series of pre-processing including Gradwarp, B1 non-uniformity, N3, and scale.

Gradwarp is a system specific correction of image geometry distortion due to gradient non-linearity. B1 non-uniformity correction employs B1 calibration scans to correct the image intensity non-uniformity that results when RF transmission is performed with a more uniform body coil while reception is performed with a less uniform head coil. N3 is a histogram peak sharpening algorithm which is applied to all images. It is applied after grad warp and after B1 correction. N3 will reduce intensity non-uniformity due to the wave or the dielectric effect. In scaling, the image is scaled based on the spatial scale factors that are collected from a local phantom.

2.2. CNN Network Structure

The algorithm uses a convolutional neural network (CNN) to fulfil AD recognition. The CNN architecture used in this study consists of three convolutional layers, of each is followed by normalization and spatial max-pooling [10]. The final layers of the network consist of fully connected layers and a classification layer. The network architecture was given in **Figure 1**. The size of filter was 5 × 5 in each convolutional layer. Max-pooling of size 2 × 2 was applied after the convolutional layers, halving the feature map sizes after the operations. Max-

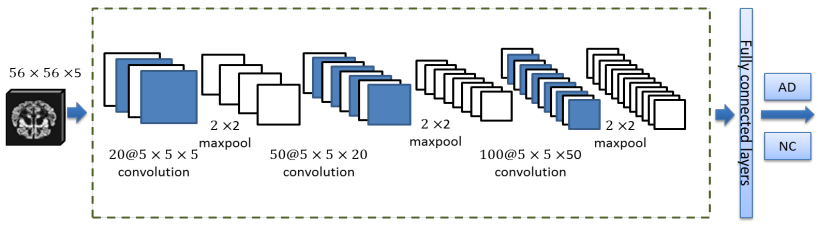

Figure 1. The architecture of the proposed CNN.

pooling reduces the number of free parameters and introduces small spatial invariance in the network. The fully connected layers followed by a sigmoid logistic regression which outputs a score ranging between 0 and 1, indicating the probability of the slice to be AD. All network parameters are randomly initialized according to a normal distribution with variance 0.02. The network was trained using stochastic gradient descent with learning rate0.001. The cost function was defined as follows:

$$C(l,s) = -\sum_{i=1}^{B} l_i \log\log s_i + (1-l_i)\log\log(1-s_i) \quad (1)$$

where s is the assigned pixel probability score, l is the reference pixel label and $B$is the size of mini-batch.

2.3. CNN Network Training

2.3.1. Patch Extraction

The original MRI data had different sizes: $256\times256\times166$ and $192\times192\times160$. To standardized the data, we reform all data into $56\times56\times56$. The MRI data consists of many slices. The starting and ending slices do not contain brain tissues. Therefore, we only extracted middle cross-section for AD detection [7]. The patch size we selected was $56\times56\times5$, which means we merged five neighboured slice as one patch. For each MRI data, seven sections centred at number 25 to 31 respectively were extracted as patches.

2.3.3. Data Augmentation

The MRI data do not have rotational invariance. Therefore, randomly rotation and mirror cannot be used for data augmentation. We generate additional training data using random zooming in and out and cropping. This is especially important as there are too few examples in the training set, and unbalanced number of AD and NC cases.

2.3.3. Training

We randomly selected 66% data for training and 33% for testing. Details were given in **Table 1**. Training is stopped when the accuracy on the validation dataset does not improve after three epochs. Both the training loss and validation loss started to drop after about 20 epochs and reached minimum and stable after about 40 epochs. The training loss reached zero and the validation loss converged at 0.02.

2.4. CNN Network Testing

When testing the proposed CNN, we also extracted seven middle cross-sections as patches. Since not all patches are abnormal in AD cases, only when all seven patches were classified as NC, we considered the data as NC. If one or more than one of the patches was/were classified as AD, we considered the data as AD.

2.5. Evaluation Metrics

Two performance metrics were measured: sensitivity and specificity. Let TP, TN,

Table 1. Statistics on training and validation data.

Data	Number of data		Number of Patch	
	Training	Validation	Training	Validation
AD	33	16	2300	1000
NC	20	10	2300	1000

FP and FN represents true positive, true negative, false positive and false negative respectively. Sensitivity is defined as

$$sensitivity = \frac{TP}{TP + FN}$$

Specificity is defined as

$$specificity = \frac{TN}{TN + FP}$$

According to the definition, the sensitivity reflects how many AD cases were detected accurately. Higher the sensitivity, less AD cases were missing. The specificity reflects how many NC cases were detected accurately. Higher the specificity, less normal cases were misrecognized as AD. Using these two metrics together, the performance of the proposed method can be evaluated comprehensively.

3. Experimental Results

The AD recognition performance of the proposed method was tested on ADNI1 data. The testing data consist of 17 AD cases and 16 NC cases. 119 and 112 patches were extracted for AD and NC cases, respectively. 37 AD patches were classified as NC and 2 NC patches were classified as AD. The sensitivity at patch level is 0.69 and specificity is 0.98. When using the AD detection rule which were mentioned in testing section, the case level sensitivity is 1 and specificity is 0.93. The details were given in **Table 2** and **Table 3** respectively, where GT means ground truth.

4. Conclusions

This paper describes an automatic AD recognition algorithm that is based on deep learning on 3D brain MRI. The algorithm uses a convolutional neural network (CNN) to fulfil AD recognition. It is unique in that the 3D topology of brain is considered as a whole in AD recognition, resulting in an accurate recognition. The CNN used in this study consists of three consecutive groups of processing layers, two fully connected layers and a classification layer. In the structure, every one of the three groups is made up of three layers, including a convolutional layer, a pooling layer and a normalization layer. The algorithm was trained and tested using the MRI data from Alzheimer's Disease Neuroimaging Initiative. The data used include the MRI scanning of about 47 AD patients and 34 normal controls. The experiment had shown that the proposed algorithm

Table 2. The experiment result at patch level.

	Number of patches	Number of patches	Sensitivity	Specificity
AD (GT)	82	37	0.69	0.98
NC (GT)	6	96		
	AD (CNN)	NC (CNN)		

Table 3. The experiment result at case level.

	Number of patches	Number of patches	Sensitivity	Specificity
AD (GT)	17	0	1	0.93
NC (GT)	3	13		
	AD (CNN)	NC (CNN)		

delivered a high AD recognition accuracy with a sensitivity of 1and a specificity of 0.93. Future study will include searching for more efficient data processing and CNN structure, and testing on more cases.

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