Alzheimer's disease diagnosis from structural MRI using Siamese convolutional neural network

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***Abstract*—Deep learning (DL) methods have been recently utilized in medical imaging diagnosis and prognosis, which have significantly improved the performance of algorithms. As Alzheimer's Disease (AD) is one of the most financial costly diseases, many researchers have concentrated on introducing a high accuracy automated algorithm for classifying the AD and the Normal Control (NC) cases. In this paper we proposed a new deep learning based automated method for Alzheimer's disease diagnosis. Among the DL networks, the Siamese Convolutional Neural Network (SCNN) is implemented with three branches of ResNet-34 to discriminate between the AD and NC from the Structural Magnetic Resonance Imaging (sMRI). We selected 235 subjects from OASIS dataset. The proposed method achieved the accuracy of 98.72%. The proposed method has the best performance compared with the previous state of the art methods.**

Keywords— Alzheimer's Disease, Deep Learning, Siamese Convolutional Neural Network, Structural MRI

I. INTRODUCTION

Alzheimer's Disease (AD) is the most common cause of dementia which accounts for about 60~80 percent of patients with dementia. Although AD was first described in 1906, it was recognized as a common cause of dementia about 70 years later [1]. Between the years of 2000 and 2015, the deaths from Alzheimer's disease have increased about 123%. Scientists estimate that there will be one person with AD in every 85 people by 2050 [2]. The accurate and early AD diagnosis can save up to 7.9 trillion dollars in the costs of the care and medical.

There are many effective ways for AD diagnosis, which includes computer-aided systems. These systems used the various pattern recognition and machine learning approaches with neuropsychological data such as functional MRI (fMRI), structural MRI (sMRI), and positron emission tomography (PET) [3]. The sMRI prepare the measures of brain gray matter and white matter which helps to measure cortical thickness, volumes, and different brain regions for AD classifying. Hence, many researchers have used sMRI for AD diagnosis, especially detection of AD from the Normal Control (NC) [3]–[10].

There are many methods for detection of AD and NC that most of them could be categorized as the pattern recognition and deep learning based methods [3–11].

Shen et al. [12] presented some of the latest developments in the application of machine learning algorithms to AD diagnosis and prognosis. Zhou et al. [13] combined the MRI data with a neuropsychological test, for the classification of AD and its prodromal stages. They also showed that at different stages of AD, there may be hemisphere-dependent atrophy dominance. Bron et al. [14] proposed method based on support vector machine weights with a significance map. Liu et al. [15] proposed the method based on multi-view learning and support vector machine for Alzheimer's Disease Diagnosis with Multi-template Feature Representation. Demirhan et al. [16] investigated measures from fractional anisotropy maps of diffusion tensor imaging and used SVM for classification of the Alzheimer patients. Gorji and Haddadnia [17] proposed the method based on Zernike moment for early diagnosis of Alzheimer disease from the axial view of sMRI of ADNI dataset. After it, Shams-Baboli and Ezoji [18] extend the Zernike moments based method for three views of axial, coronal, and sagittal of sMRI from OASIS dataset. Yu et al. [5] combined the feature selection with the additional correlation information, and they modeled it by the connectivity of an undirected graph. Ramaniharan et al. [19] proposed a method based on Laplace Beltrami eigenvalue which is used Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and Naive Bayes (NB) for the classification task. Lizarraga et al. [10] provided a web platform which uses SVM for diagnosing the Alzheimer disease. Previtalia et al. [3] introduced a feature extraction method based on Rotated BRIEF and Oriented FAST and giving them as input to SVM for AD classification.

Recently deep learning has reached great achievements in image processing, computer vision, and medical imaging applications, and therefore the convolution neural networks are utilized in Alzheimer's disease diagnosis [6, 7, 21–26]. Hosseini-Asl et al. [6] introduced deep 3D convolutional neural network to predict the Alzheimer's disease. Gunawardena et al. [25] introduced a simple convolution neural network for Alzheimer's disease prediction. Payan and Montana [8] proposed 3D convolutional neural networks for Alzheimer's disease prediction. Islam and Zheng [4, 26] introduced two

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methods based on ensemble of convolution neural networks for Alzheimer's disease diagnosis.

In this paper, we proposed a different deep learning based method for Alzheimer's disease diagnosis from structural MRI using Siamese convolutional neural network. The axial view of sMRI images of OASIS dataset is selected for training and testing for the proposed method. The achieved accuracy of the proposed method is the better than the previous state of the art methods.

In section II, the proposed method is explained. In section III, the experiment and discussion are presented. Finally, the conclusions of this paper are written in section IV.

II. The Proposed Method

In this section, the proposed method is described in details. In the first part, the Siamese Convolutional Neural Networks is explained and the proposed network architecture is explained in the second part.

A. Siamese Convolutional Neural Network

A Siamese Convolutional Neural Network (CNN) contains more than two branches of CNNs which they are often identical. Each branch includes series of convolutional, ReLU, pooling, and fully connected layers [22]. These multi branches of CNNs are trained simultaneously on multi subjects of images and they create the same dimension feature vectors. The similarity of the input images is achieved by calculating the similarity and distance of the output feature vectors. There are many Siamese models such as Siamese, Pseudo-Siamese, and 2-channel [28]. Siamese CNNs have many applications in image processing and computer vision such as face recognition and One-shot image recognition [28-30].

B. The proposed network architecture

The proposed network architecture of this paper is depicted in Fig. 1. This network contains three CNN braches, which each branch is for one type of image. Actually, the proposed network considers an anchor image for feeding to one CNN branch of network that is selected randomly from AD or NC training dataset. Then, the positive and negative images are fed to the two other CNN branches of the network. The positive image is the randomly selected image from the same label of anchor image. In the same way, the negative image is the randomly selected image from the opposite label of anchor image. In this network, we used ResNet-34 [31] for each three branches of this architecture that is shown in Fig. 2. At the end of each CNN branch of this network, there is an embedding vector of size 128. Then, the pair-wise distance between the anchor and the positive image ($dist_p$) and the pair-wise distance between the anchor image and the negative image ($dist_n$) are calculated. The proposed network is trained with the loss function of triple loss (L) as below:

$$L(anch, pos, neg) = \max(\|f(anch) - f(pos)\|^2 - \|f(anch) - f(neg)\|^2 + \alpha, 0) \quad (1)$$

which *anch*, *pos*, and *neg* are anchor image, positive image, and negative image, respectively. The f(.) is the extracted feature vector from each branch of Siamese CNN that are known as embedding vector. Value of α is a margin that is set to 0.2 in this paper.

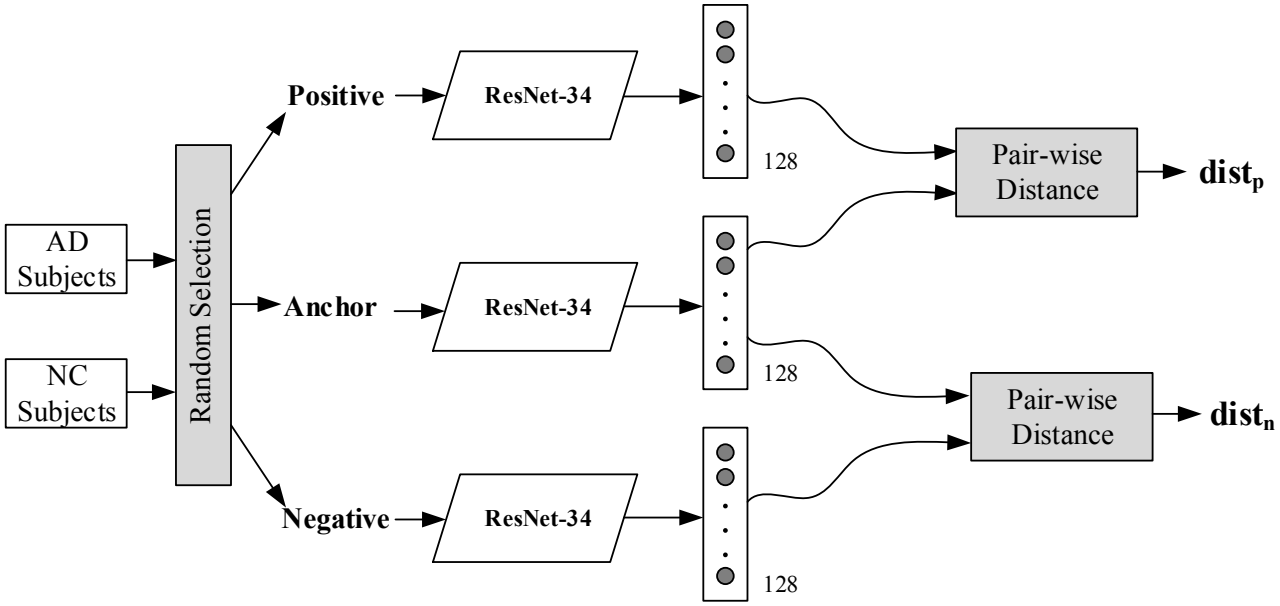

Fig. 1. Architecture of the proposed network

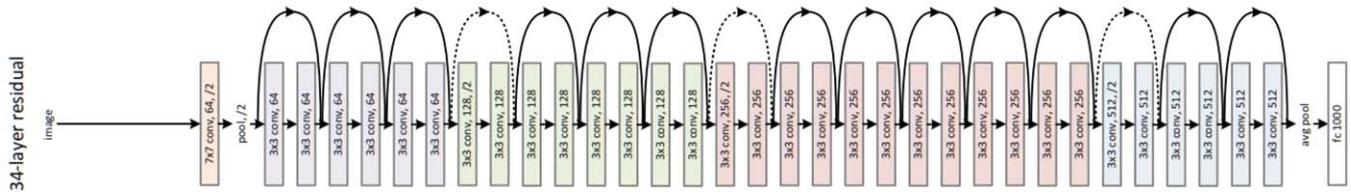

Fig. 2. ResNet-34 network architecture [30]

C. Dataset

Data used in this paper were obtained from the Open Access Series of Imaging Studies (OASIS[1]) dataset [27]. OASIS dataset consists of a cross-sectional collection of 416 subjects between the ages of 18 and 96. There are one hundred patients with AD who are older than sixty. We selected 235 subjects from the dataset which includes 100 AD subjects and 135 NC subjects. The demographic information of the selected subjects is demonstrated according to values of Clinical Dementia Rating (CDR) in Table I. The CDR=0 represents no dementia which is known as Normal Control (NC). The values of CDR of 0.5, 1, and 2 represent very mild, mild, and moderate dementia, respectively, which they are known as AD [26]. Five sample slices of axial view for each AD and NC subjects are shown in Fig. 3.

TABLE I. DEMOGRAPHIC STATUS OF THE INCLUDED SUBJECTS IN THIS STUDY

	AD (CDR=0.5/1/2)	NC (CDR=0)
No. of subjects	100 (70/28/2)	135
Gender (F/M)	59/41	97/38
Age (mean±SD)	76.76±7.08	69.07±13.82

D. Alzheimer's disease diagnosis with the proposed network

We selected five axial slices (82, 85, 88, 91 and 94) for each subject individually. Therefore, there is 1645 slice of sMRI for 235 subjects. The samples of selected five slices for the AD and NC subjects are depicted in Fig. 2. In this paper, we used 70% and 30% of these images for training and testing dataset, respectively. The proposed network is trained with the training dataset and triple loss function of (1). After training the network, two samples from AD and NC training sets are selected in order to calculate the pair-wise distance from the test sample (the label of test sample is unknown). According to (2), the label of the test sample is AD if the pair-wise distance of test sample from AD sample of the training set is lower than the pair-wise distance of test sample from NC sample of the training set. In the same way, the label of the test sample is NC if the pair-wise distance of test sample from NC sample of the training set is lower than the pair-wise distance of test sample from AD sample of the training set.

$$Anchor = \begin{cases} Positive & if \quad dist_p < dist_n \\ Negative & else \end{cases} \tag{2}$$

III. EXPERIMENTS AND DISCUSSIONS

In this section, the quantitative evaluation of the proposed method is reported.

A. Performance metric

The performance of the proposed method is evaluated in terms of accuracy. Let TP, TN, FP, and FN represent true positive, true negative, false positive and false negative, respectively. The evaluation metric is calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

B. Evaluation of the proposed method

In this part, the proposed method is compared with the previous state of the art methods. In this comparison, 17 papers of [3-8, 10, 12-14, 16-20, 25, 26] are selected which are trained and tested with OASIS and ADNI[2] dataset for classification of AD and NC. The proposed Siamese Convolutional Neural Network (SCNN) is implemented using the PyTorch (v. 0.4.0) on Ubuntu 16.04 LTS operating system with 3.70 GHz Core i7 6900k CPU, 32GB RAM and STRIX GTX 1080 GPU. The assessments of methods are performed in term of accuracy, which are listed in Table II. As can be seen in Table II, the proposed method has the best value in term of the accuracy against all the previous state of the art methods for distinguishing AD from NC. The reported results of the proposed method are averaged over running algorithm ten times.

All supplementary files and source code of this paper, after finalizing, will be available on the authors' websites.

[1] https://www.oasis-brains.org

[2] http://adni.loni.usc.edu/

IV. CONCLUSIONS

This paper presented an automated deep learning based method for AD/NC classification. The Siamese convolution neural network was used for the proposed method, which ResNet-34 was utilized in each branch of the proposed Siamese network. The efficiency of the proposed method was evaluated using OASIS dataset which five slices are selected from axial view of each subject. In this work, 70% and 30% of this dataset were selected for training and testing dataset, respectively. We obtained the accuracy of 98.72% that is the best result comparing with the previous state of the art methods.

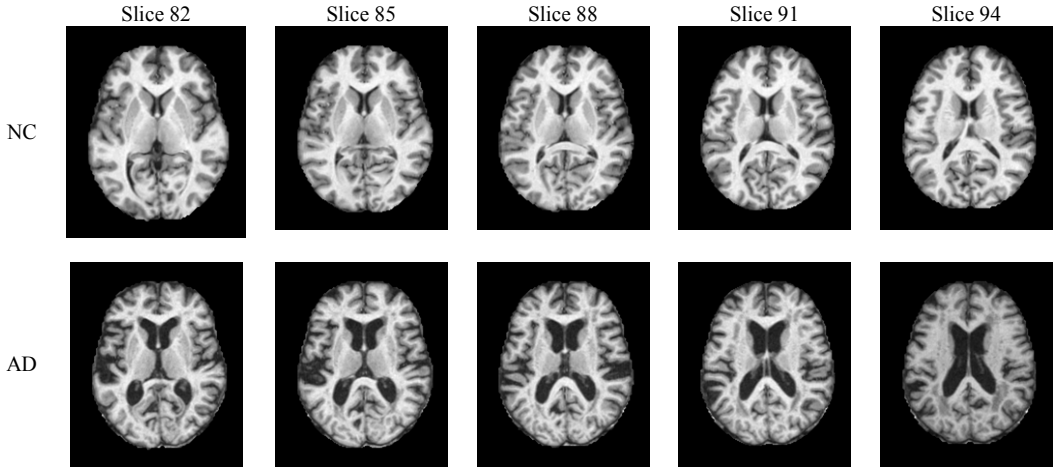

Fig. 3. Samples of the selected five slices of axial view for the AD and NC subjects from OASIS dataset

TABLE II. COMPARISION OF THE PROPOSED METHOD ACCURACY WITH THE OTHERS

Methods	**Dataset**	**Alzheimer's Disease (AD) / Normal Control (NC)**
		Accuracy
SCNN (The proposed)	OASIS	**98.72**
Islam and Zhang (2018) [26]	OASIS	93.18
Previtali et al. (2017) [3]	OASIS	97
Islam and Zhang (2017) [4]	OASIS	73.75
Shams and Ezoji (2017) [18]	OASIS	96.67
Gunawardena et al. (2017) [25]	ADNI	96
Hosseini-Asl et al. (2016) [6]	ADNI	97.6
Yu et al. (2016) [5]	ADNI	90.6
Lizarraga et al. (2016) [10]	ADNI	93
Ramaniharan et al. (2016) [19]	OASIS	93.37
Liu et al. (2016) [7]	ADNI	93.83
Payan and Monatana (2015) [8]	ADNI	95.39
Demirhan et al. (2015) [16]	ADNI	87.80
Zhang et al. (2015) [20]	OASIS	92.36
Gorji and Haddadnia (2015) [17]	ADNI	97.27
Bron et al. (2015) [14]	ADNI	84.5
Zhou et al. (2014) [13]	Private	92.4
Shen et al. (2014) [12]	ADNI	93.2

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