Deep Neural Network Classification method to Alzheimer’s Disease Detection

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Abstract—Early detection of Alzheimer disease (AD) is important for the management of disease. The human brain Magnetic resonance imaging (MRI) data have been used to detection of Alzheimer disease detection. The detection of AD is quite challenging and thus an automated tool to classify AD can be useful. Deep learning can make major advances in solving such problems. In this study, the longitudinal MRI data in non-demented and demented older adults data is utilized and the image processing technique was adopted for the data segmentation and attribute selection. Finally, deep neural network (DNN) classification is implemented for AD detection. The DNN 96.6% correctly identified AD and the minimum error rate obtained from a DNN. It shows the DNN will be useful for the development of improved computer aided diagnosis tool in MRI data.

Keywords—Deep Neural Network, Alzheimer Disease, MRI Images, Classification

I. INTRODUCTION

The dementia is a global issue and that the effects of the future epidemic will be felt predominantly in low and middle-income countries. It was estimated that 46.8 million people worldwide were living with dementia in 2015 and this number will almost double every 20 years, to 87.88 million in 2035, 116.78 million in 2045 and 131.5 million in 2050. It has also a huge economic impact. The worldwide cost of dementia was estimated US$ 817.9 billion in the year of 2015 and it is projected the costs in 2030 will be around US$ 2 trillion [1]. Alzheimer’s disease (AD) is the most common cause of dementia associated with aging [2]; it accounts for 64 percent of all dementias [3]. AD is a growing public health problem among the elderly in developing countries, whose aging population is increasing rapidly [4]. AD is characterized by a progressive decline in cognitive function. AD is substantially increased among people aged 65 years or more, with a progressive decline in memory, thinking, language and learning capacity. AD should be differentiated from normal age-related decline in cognitive function, which is more gradual and associated with less disability. The disease often starts with mild symptoms and ends with severe brain damage. People with dementia lose their abilities at different rates [5]. The detection of AD in early and accurate is beneficial for the management of disease. Neuroimaging, such as magnetic resonance imaging (MRI) or computed tomography (CT) and with single photon emission computed tomography (SPECT) or positron emission tomography (PET) can be used to help exclude other cerebral pathology or subtypes of dementia. It may predict conversion from prodromal to Alzheimer’s disease [6][7]. Medical image processing and machine learning tools can help neurologists in assessing whether a subject is developing the Alzheimer disease. The image segmentation and classification is an important task in MRI data analysis for the AD detection. Image segmentation is intended to partition images into well-defined regions, where each region is a set of pixels that share the same range of intensities, the same texture or the same neighbourhood. The purpose of segmenting images is to remove unwanted information in order to locate meaningful objects from the processed images. The classification is used to produce meaningful patterns from raw data, classify them into different groups based on their characteristics and predict new patterns based on previous knowledge [8].

In advance of the machine learning paradigm new learning methods have been reported in recent years. Deep learning methodology is attracting the researchers in the field of machine learning. A deep neural network (DNN) with multiple hidden layers has achieved unprecedented classification performance relative to the support vector machine and other conventional models [9][16]. Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. Deep learning, discovers intricate structure in large data sets by using the backpropagation algorithm to indicate how a machine should change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer. Deep learning is making major advances in solving problems that have resisted the best attempts of the artificial intelligence community for many years [10]. Deep Learning algorithms are one promising avenue of research into the automated extraction of complex data representations (features) at high levels of abstraction. Such algorithms develop a layered, hierarchical architecture of learning and representing data, where higher-level (more abstract) features are defined in terms of lower-level (less abstract) features. The hierarchical learning architecture of Deep Learning algorithms is motivated by artificial intelligence emulating the deep, layered learning process of the primary sensorial areas of the neocortex in the human brain, which automatically extracts features and abstractions from the underlying data [9].

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In this paper, a deep neural network (DNN) classification method to diagnose the Alzheimer’s disease from MRI images is proposed. The brain MRI images are segmented to extract the brain chambers. Then, features are extracted from the segmented area. Finally, a DNN classifier is trained to differentiate between normal and AD brain tissues.

The organization of the paper is as follows. Section 2 will present related work on this subject. Section 3 will present a methodology and proposed classifier technique for the AD detection. The result and discussion will be reported in the section 4. The conclusion and future work will be reported in the section 5.

II. RELATED WORK

In recent years, the researchers have been focused to develop classification methods to detect AD. The most of the research work has been carried out by using support vector machine or other traditional learning methods. In this section, recent published work is reported.

Yang et al. [11] proposed a method based on independent component analysis (ICA), for studying potential AD-related MR imaging features, coupled with the use of support vector machine (SVM) for classifying scans into categories of AD, MCI, and normal control (NC) subjects. This study has proven that the ICA-based method may be useful for classifying AD and MCI subjects from normal controls. Chaudhary et al. [13] used three layered feed-forward back propagation ANN to classify different stages of neurodegenerative diseases Alzheimer’s Disease (AD), Parkinson’s Diseases (PD) and Huntington’s Disease (HD) patients based on clinical symptoms. The digital values of clinical AD, PD and HD symptoms between 0-1 have been used to build the predictive model. They achieve significant accuracy level and demonstrated that ANN can be a better classifier for the predication of such diseases.

Tang et al. [14] proposed back propagation artificial neural network for community Alzheimer’s disease screening. The reported results of back propagation artificial neural network shows that based on six variables daily living, creatinine, 5-hydroxytryptamine, age, dopamine and aluminum for screening and diagnosis of Alzheimer’s disease in patients selected from the community were satisfactory. Al-Nammi et al. [12] proposed a fusion method to distinguish between the normal and AD MRIs. They combined method around 27 MRIs collected from Jordanian Hospitals are analysed based on the use of Low pass – morphological filters. The artificial neural network (ANN) was applied to classify whether the MR image belongs to a normal brain or to a person suffering from Alzheimer’s disease.

Zhang et al. [6] proposed Alzeimer’s disease detection using 3D MRI based on eigenbrain and machine learning method. The maximum inter-class variance (ICV) was used to select key slices from 3D volumetric data and an eigenbrain set for each subject was generated in their study. Welch’s test (WTT) was utilized to obtain the most important eigenbrain (MIE). Further, the kernel support-vector-machines with different kernels were used to train by particles warm optimization. The experiments showed that the performance of polynomial kernel (92.36±0.94) was better than the linear kernel of (91.47±1.02) and the radial basis function (RBF) kernel of (86.71±1.93).

III. METHODOLOGY

The MRI data is accessed and store in the database and data pre-processing technique was used for removing non-relevant information and for better interpretation. The image segmentation methods were applied on image data to extract the different features of the data. The attributes were extracted from the data and finally, proposed artificial neural network based classification method was applied on extracted data to verify feasibility the classifier. The details steps are explained in the following subsections.

A. Data Access

The longitudinal MRI data in non-demented and demented older adults were downloaded from open access series of imaging studies (http://www.oasis-brains.org). The database includes a longitudinal collection of 150 (Female - 88, Male - 62) subjects aged 60 to 96. The 72 of the subjects were characterized as non-demented and 78 of the included subjects were characterized as demented [16]. The MRI data are downloaded in the form of ‘nifty’ format. Fig. 1 shows an MRI image of non-demented subject and sample image a demented and Fig. 2 shows an MRI image of a demented subject.

Fig.1. Image of non-demented subject (Id: OAS2_0004)
B. Attribute Selection

The niblack thresholding segmentation algorithm was used for the segmentation and than edge detection techniques were used in order to extract the contour of the ventricle region. The watershed method was used to extract the ventricle region, but over segmented the live tissue of the brain. The ventricle chamber’s area uses to assess the AD disease. The ventricle’s area characterizes based on its shape and morphology using statistical and geometrical attributes. The resulting attributes are respectively the surface area of the extracted region, the perimeter, Mean, Standard deviation, 28 horizontal distances (D1, D2, ..., D28), the Height and the coordinates of the centre of gravity of the region (Gx, Gy). The attributes are normalized into the range (0, 1) [7].

C. Classification

After building a database of 150 patterns of 35 dimensions classification task was performed. The DD learning methodology was applied for the classification task. The DNN layers consisted of multiple hidden layers and a softmax layer as an output layer. The Fig. 3 depicts the architecture of the DNN learning process.

![Fig. 3. Architecture of DNN [15]](image)

The cost function, $C(W)$ of the DNN can be used for the supervised fine-tuning by using the mean squared error (MSE), L1-norm, and L2-norm terms and it can be represented as follows [17].

$$C(W) = \frac{1}{2} \sum_{n=1}^{N} \left\| y^{(L)}(n) (W) - t^{(n)} \right\|^2 + \sum_{j=0}^{L} \beta^{(j+1,j)}(t) \left\| W^{(j+1,j)} \right\|^2 + \sum_{j=0}^{L} \frac{\gamma^{(j+1,j)}}{2} \left\| W^{(j+1,j)} \right\|^2$$

where $y^{(L-1)}(W)$ is a vector with elements of the output values at the $L$th layer for the subject $n$ in the training set, $t^{(n)}$ is the target output values of the subject $n$ is the training set, $\beta^{(j+1,j)}(t)$ and $\gamma^{(j+1,j)}$ are the L1-norm and L2-norm regularization parameters, respectively, between the $J$th and $(J + 1)$th layer, $N$ is the total number of subjects in the training set, and $(L + 1)$ is the number of the layers, including the input layer (i.e., the 0th layer) and the output layer (i.e., the $L$th layer).

The derived from a stochastic gradient descent scheme to this cost function was adopted for the learning algorithm of DNN weights from [17]. It can be formulated as [17]:

$$W^{(j+1,j)}(t + 1) = W^{(j+1,j)}(t) - \Delta W^{(j+1,j)}(t),$$

$$\Delta W^{(j+1,j)}(t) = \alpha(t) \left( \Delta_{\text{MSE}} W^{(j+1,j)}(t) + \beta^{(j+1,j)}(t) \text{sign} \left( W^{(j+1,j)}(t) \right) + \gamma^{(j+1,j)} W^{(j+1,j)}(t) \right)$$
where $\Delta W^{(3)}_t(t)$ is the first-order derivative of the cost function with respect to the $W^{(3)}_t(t)$ weight parameters, or the weights between the Jth and (J + 1)th layer, and was previously used in a standard back-propagation algorithm; $t$ is the epoch number, and $\alpha(t)$ is the learning rate at the $t$th epoch.

IV. RESULT AND DISCUSSION

The DNN classification was applied. The DNN classifier showed maximum accuracy of 96.6% with a different pair of attributes. It classifies with an accuracy of 90.3% with all the attributes. The result of DNN shows that the better performance compare to SVM as reported on [7] and the accuracy of DNN and backpropagation algorithm report in [14] [15] are comparable but the error rate is reduced in case of DNN. Therefore, it can be assumed that deep learning algorithms are more beneficial when dealing with learning from large amounts of unsupervised data. DNN classification can be a tool for the Alzheimer’s disease detection

V. CONCLUSIONS

With the advancement in machine learning techniques and computer-aided detection attracts more attention for AD detection. The current study successfully demonstrated the feasibility of the DNN classifier toward AD detection. The minimum error rate obtained from a DNN with three hidden layers were superior to that obtained from the SVM and backpropagation classifier. The DNN will be useful for the development of improved computer aided diagnosis tool in MRI data.

REFERENCES


