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Diagnosis of Multiple Sclerosis (MS) Using Convolutional Neural Network (CNN) from MRIs

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ABSTRACT

This paper presents a novel fully automated process of features extraction and classification of Multiple sclerosis (MS) daisies from magnetic resonance images (MRI). This hybrid method uses convolution neural network (CNN) for features extraction and a multilayer neural network for classification two classes normal and MS. The convolution neural network for recognition of Multiple sclerosis is considered in this paper showed that CNN has strong potential for detection of MS. The process of feature extraction form flair MRI is done by using CNN increases the performance of recognition. CNN due to lack of sensitivity to noise is good for performance diagnosis. Our result shows that CNN provides high detection rates without using any lesion segmentation. This fully automated method produces reliable MRI analysis and classification while is considering variability.

Key words: convolution neural network (CNN), Multilayer neural network (MNN), Multiple Sclerosis (MS), magnetic resonance images (MRI) and feature extraction.

Introduction

Multiple sclerosis (MS) is a deep-seated, continuous incendiary -demyelinating disease of the central nervous system (CNS) (Udupa, K., 1997), characterized pathologically by areas of inflammation, demyelination, axonal loss, and often causes some lesion on CNS (Xavier Lladó a, 2012). Magnetic Resonance Imaging (MRI) is the most effective method of diagnosis of the MS disease. MRI is mainly used to diagnose and supervision and the Progress activity of this Disease because of its sensitivity to the central lesions, which appear hyper intense on flair MRI, and hence are commonly called T2 lesions (Zahra Karimaghaloo, 2011). Impressive, Explicit and compatible brain cortical tissue analysis from MRIs is one of the most prominent issues in many applications of the medical image processing. Using segmentation of MRI is one of the most applied ways to diagnosis of MS from MRI and determined the MS lesions (Mashohor, 2010). Another possible way of this problem is to apply artificial neural networks (NNs) due to their good classification and detection properties based on similarity, high adaptability and fault tolerance (Haykin, S., 2008). Neural networks, with both supervised and unsupervised learning methods, have been used to analysis on MRIs. The most published paper in this has worked on brain image segmentation and tries to extract lesion (Johnston, 1996; Zhang, Y., 2012). This duty is very important in the diagnosis and therapy of all the diseases of the brain. Although the brain structure is complicated and many normal lesions like MS lesions are exist on brain and it throws these segmentation methods into error. Thus providing a way to detect MS disease without any Segmentation is valuable.

One of the powerful kinds of neural network is convolutional Neural Network (CNN) which is inspired from biology of cat's visual cortex (Yann LeCun, F., 2009).

Convolutional neural networks like almost every other neural network can be trained with a version of the back-propagation algorithm. The most differences of CNN with other NN is in the architecture convolutional neural network is strong and old neural network that is designed to recognize visual patterns directly from pixel images with minimal preprocessing. CNN is a feed-forward neural network able to extract local topological properties from an each image (Hubert Cecotti, A.G., 2008). These networks have some good ability such as the main property of these networks is automatic feature extraction and work on the high input size and no sensitive to noise. For these mentioned reason many image application referring to these features and it can be capable in ms diagnosis.

In this paper, the abilities of the CNN to detect the lesions of MS from MRI are utilized. In this new approach 150 patients (mean age 32 years, range 20 to 45 years) MRI of brain between January 2011 and July 2012 were investigated. Some preprocessing was used to reduce images size.MLP classification was applied for recognize data into 2 categories: normal or MS (or suggestive MS).The rest of the paper is organized as follows. Section II describes the CNN structure and proposed approach while in Section III the experimental evaluation is reported. In Section IV experimental results with comparison with other methods is described. Finally, Section V concludes the work.

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Convolutional Neural Networks:

Convolutional neural networks are multilayer neural networks that use advantage of the locality of images to reduce the number of parameters needed to process large images (BCl´ement Farabet, 2010). CNN have several benefits as a front-end for synthetic vision systems that perform. First, they operate with local receptive fields by performing convolutions: they share weights in the convolution matrices, so large images can be processed with a reduced set of weights. This is important as the number of weights in the network is thus not proportional to the input image *(i.e*. the final processing network size is fixed for a specific task). Second, spatial sub sampling pooling is used to hierarchically reduce the input data size at each step of nonlinear computation. Replicating a small, local receptive field extracts elementary features from a large input, while sub-sampling the result reduces the effect of distortion and scale. Combining these features produces higher-order features that have very good shift, scale and distortion invariance, a typical feature of high level mammalian vision systems.

An important aspect of CNN is that all of their parameters can be learned from the data to be modeled (Matthew Browne, S.S.G., 2003). Convolutional neural network is feature extractors, more compact, and amenable to general purpose recognition tasks.

Each CNN include several layers: convolution layers and sub sampling layers:

- **Subsampling layer**: Performs subsampling and local averaging. Reduce sensitivity to distortions.
- **Convolutional layer.** Performs local feature extraction from each receptive field which is shown in Fig. 1.

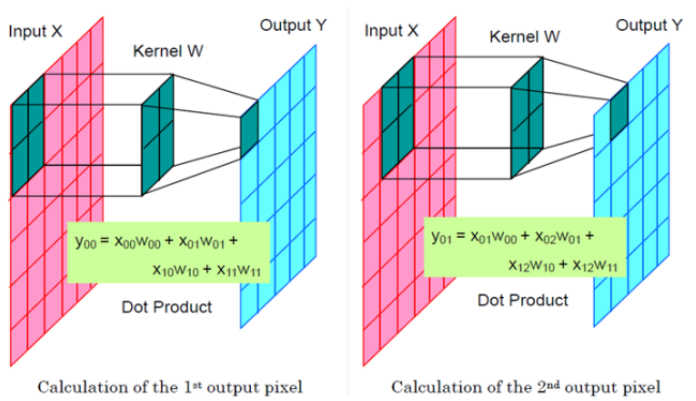

Fig. 1: Pictorial description of 2Dconvolution (LeCun, D.Y., 2004).

The Experimental Evaluation:

The proposed method as illustrated in Fig.2 is based on the automatically classifying MRI images in distinguishing following techniques: convolution neural network for diagnosis of MS from MRIs without using segmentation methods.

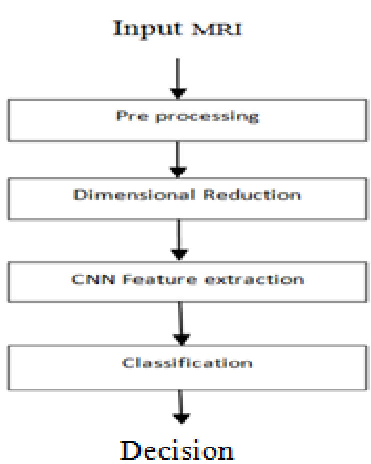

Fig. 2: Overall of proposed method.

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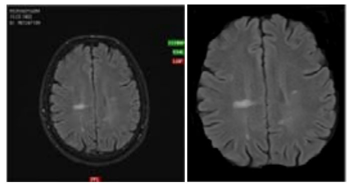
A: Data:

The data has gathered for this research Include a normal brain and a brain containing MS lesions. Moreover, this database provides different type of Ms patient (PP, RR, PR, SP) models according to parameters such as slice thicknesses, noise levels and levels of non-uniformity intensity. These gathered data sets are available in three orthogonal views – axial, sagittal, and coronal – although the majority of algorithms use only the axial view. It was one hundred and fifty unrelated MS patients, 111 women and 39 men (mean age 34 years, ±8.6 SD). This data set contains 72 normal patients MRIs and 81 MS or suggestive MS patients, all data which is used, belong to Highlight MRI center. The size of each slice was 508 x 508.



(a) (b)

Fig. 2: A-original MRI. B- After preprocessing.

B: preprocessing:

The analysis of MR brain images is difficult because of variable imaging parameters, overlapping intensities, noise, partial voluming, gradients, motion, echoes, blurred edges, normal anatomical variations and susceptibility artifacts. There are generally two preprocessing steps that are carried out: first, the removal of those image artifacts and second, the removal of non-brain.

Applied such as the equalization of soft brain tissues or registration between different MR Images. In this stage the size of slices reduced into 180 x 240.

C: CNN:

The convolutional neural network that was used for MS diagnosis, which is shown in figure 3. It has 3 total layers: input layer, CNN layer and output layer. In input layer the slices of MRIs that affected by pre processing enter into networks. CNN is contained 4 convolution layers and 4 sub sampling layers. Kernel size of convolution layer is in order 7x7, 8x8, 7x8, 8x7. Kernel size of sub sampling layer is 2x2. The number of features map for each convolution layer is: layer one has 6, layer two has 16, layer three has 30 and the last layer has 50 features. The 120 extracted features from each slice combine with other slices features and prepare feature vector for classification. Ten slices 180 x 240 of MRI for each patient to be fed as input to the network after preprocessing.

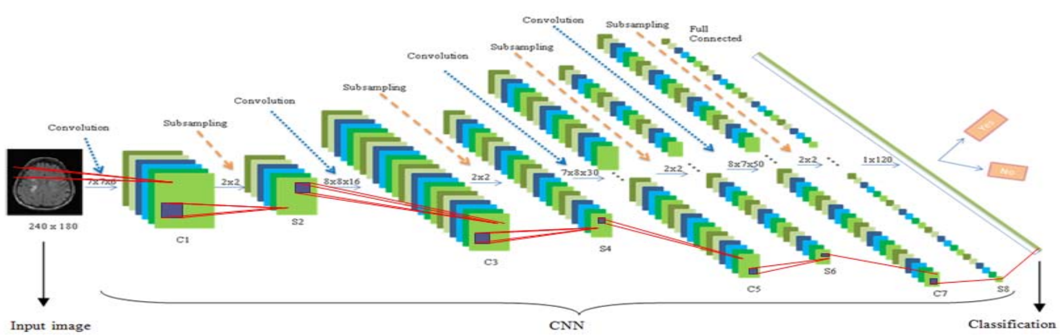


Fig. 3: CNN architecture for MS Detection.

D: MLP:

In this classifier the multilayer perception neural network was used. In this method single hidden-layer structure is adapted with sigmoid functions used in the hidden layer and linear function in the output layer. Which is consisted 52 neurons in hidden-layer and one neuron in output layer that indicate the patient is normal or has MS or suggestive MS. The back propagation learning algorithm was trained the network. The learning

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rate was considered as adaptive. The process of network training runs in 1500 epochs. After the system feature extraction all potential sclerosis objects, numeric vector of features are feed to MLP Classifier. The 120 feature that extracted by CNN have used for classification are grouped in two categories:

- MS or suggestive MS
- Normal

E: Evaluation measures:

The network performance is evaluated by sensitivity, specificity and accuracy (Giuseppe Calcagno, B.M., 2010). There were also computed as (Ying Wu, 2006):

Sensitivity=TP/(TP+FN); (1)

Specificity=TN/(TN+FP); (2)

Accuracy=(TP+TN)/(TP+TN+FP+FN) (3)

Where their definition are:

TP: *true positive*, the classification result is positive in presence of clinical abnormality.

TN: *true negative*; the classification result is negative in absence of clinical abnormality.

FN: *false negative*, the classification result is negative in presence of clinical abnormality.

FP: *false positive*, the classification result is positive in absence of clinical abnormality.

Experimental Results with Comparison:

This experiment has applied several method for diagnosis MS. One of the texture analysis methods in image processing is GLCM (Gray-level co-occurrence matrix). This method use local neighborhood matrix and calculates a GLCM by calculating how often a pixel with a certain intensity i occurs in relation with another pixel j at a certain distance **d** and orientation **θ** (Jayashri Joshi1, M., 2010). Then extract feature such as mean, correlation, entropy, contrast, inverse and other properties from GLCM. This popular features ready to training classifier. By using PCA as e reducer of feature, it can be useful to decrease the number of less important features. All these mentioned methods were implementing on gathered data set. Table **1** illustrates the results of Comparison with other of methods that segment the input images and then extract feature and finally classify them. The result showed that CNN structure was considered in this paper is able to achieve good results without any lesion segmentation.

Table 1: Comparison with other of classifications.

Algorithms	Sensitivity	Specificity	Accuracy	Time
CNN+MLP (tanh)	96.120	97.578	92.933	9033.763 sec
CNN+MLP (tansig)	89.556	85.458	88.369	13 hour
GLCM+MLP	84.387	83.952	79.666	530.089 sec
GLCM+PCA+MLP	83.074	82.036	71.325	324.334 sec

Conclution:

This paper was presented an automated feature extractor model based method for multiple sclerosis lesions detection from flair MR images, using convolutional neural networks images. After preprocessing the images CNN extract all feature of image in several layers ,then these feature were gave to the MLP classifier ,and finally it indicated the MRI is normal or Have MS.

The results were compared with other diagnosis method that used segmentation methods, and it can be found that CNN has a lot of abilities in detection of MS. The most Important notice for an automated method is that CNN did not use any segmentation methods and only by convolution and subsampling layer it gained good results. It seems to have better results the feature can be reduced, before interred to classifier as an input data.

The use of a large bank of features along with automatic feature selection can also be useful for other medical imaging applications. Furthermore, we consider reporting results on a varying range of probabilities, as an additional benefit of the algorithm.

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