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Letter to Editor

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Deep learning based computer-aided diagnosis for neuroimaging data: focused review and future potential

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Automatic image analysis techniques applied to neuroimaging data in general, and magnetic resonance imaging (MRI), and functional MRI (fMRI) in particular, have proven to be effective computer-aided diagnosis (CAD) tools in neuroscience[1-4]. Recently, the advancements in machine learning techniques combined with the wide availability of computational power have proven to be efficient in solving previously difficult problems in analyzing neuroimaging data. At the forefront of these advancements is the usage of deep (artificial) neural network architectures that led robust learning based techniques to attack challenging problems such as segmentation and classification in neuroimaging data[5-8].

Many of the impressive results obtained in CAD using deep learning (DL) techniques utilize mainly image datasets. DL networks typically require annotations of several images for employing supervised learning techniques and are one of the roadblocks in employing these state of the art networks in various classification tasks in MRI/fMRI. However, unsupervised learning techniques within the DL paradigm are now being employed in natural image classification with a lot of success and we believe the adaptability of these to the neuroimaging data are required to attack challenging neuroimage analysis problems.

A stacked denoising auto encoders approach that is an unsupervised learning technique was used[9] for brain tumor segmentation in MRI imagery. The experimental results showed that using this particular approach is as good as using supervised learning based DL techniques that require accurate image-based annotations. This indicates that we can use different unsupervised learning in DL networks variants for various neuroimaging data problems. A Siamese DL networks approach[10] for detecting spinal metastasis with a multi-resolution technique correctly detected 100% of lesions on a dataset of 26 sagittal MR images from 14 males and 12 females (58 ± 14 years; mean ± SD). The DL network considered produced only 0.40 false positives (FPs) per case. Further, at a true positive (TP) rate of 90%, with aggregation FPs were reduced from 0.375 FPs per case to 0.207 FPs per case obtaining 44.8% overall reduction. Although this work was for MR images of the spine, the usage of a Siamese neural network with the aggregation strategy promises to be an interesting approach that can also be adapted to brain MRI/fMRI imagery.

Utilizing domain-transfer convolutional neural networks, an end-to-end DL technique[11], shows great promise since it overcomes the following problems of traditional classification and other DL based methods: (1) the need for manual design of feature space; (2) effective feature vector classifier or segment specific detection object and image patches; (3) large training datasets; (4) computing resources; and (5) long waiting times for training a perfect deep model. An example classification of the Open Access Series of Imaging Studies (OASIS)-MRI dataset showed good potential for such an approach's generalizability.

Extreme learning machines is a variant of DL networks, and an application in resting state fMRI data for schizophrenia was undertaken[12] and experimental results indicated that near 90% accuracy was obtained on a dataset of 72 patient images and 75 healthy controls (18 to 65 years) from the Center for Biomedical Research Excellence (COBRE)'s raw anatomical and fMRI data on this difficult classification problem. A DL pipeline[13] applied to recognize Alzheimer's disease using fMRI data obtained overall highest accuracy of 96.86% on 28 patient images and 15 healthy controls (24 female and 19 male, 74.9 ± 5.7 years) from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset.

Most of the CAD pipelines with DL techniques at their core utilize non-medical data to train due to the lack of availability of massive labeled data. Recent advancements in natural image analysis with DL methods are yet to be used for neuroimaging data and the challenges in obtaining the datasets/annotations/labels, improvising/adapting DL networks, parameters setup, multi-modality generalization pose remain to be solved. However, the recent advancements in deep learning based image analysis shows great potential for analyzing MRI/fMRI imagery. Even with the limited results available so far in the literature, with deep learning based CAD for neuroimaging data we believe the future is bright for solving some of the hard neuroimage analysis problems.

DECLARATIONS

Authors' contributions

Prasath VBS contributed solely to this letter.

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Conflicts of interest

There are no conflicts of interest.

Patient consent

Not applicable.

Ethics approval

Not applicable.

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