Deep learning methods and applications in neuroimaging

J Sui, Chinese Academy of Sciences
M Liu, University of North Carolina
J-H Lee, Korea University
J Zhang, Duke University
V Calhoun, Georgia State University

Journal Title: JOURNAL OF NEUROSCIENCE METHODS
Volume: Volume 339, Number
Publisher: ELSEVIER | 2020-06-01, Pages 108718-108718
Type of Work: Article
Publisher DOI: 10.1016/j.jneumeth.2020.108718
Permanent URL: https://pid.emory.edu/ark:/25593/vt481

Final published version: http://dx.doi.org/10.1016/j.jneumeth.2020.108718
Accessed December 2, 2022 5:18 AM EST
Deep learning methods and applications in neuroimaging

Jing Sui\textsuperscript{a,b,c,*}, MingXia Liu
Department of Radiology and Biomedical Research Imaging Center, University of North Carolina at Chapel Hill, NC, USA

Jong-Hwan Lee,
Department of Brain and Cognitive Engineering Korea University, Seoul, South Korea

Jun Zhang,
Department of Electrical and Computer Engineering (ECE), Duke University, Durham, NC, USA

Vince Calhoun
Tri-institutional Center for Translational Research in Neuroimaging and Data Science (TReNDS), Georgia State University, Georgia Institute of Technology, and Emory University, Atlanta, GA, 30303, USA

\textsuperscript{a}National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China

\textsuperscript{b}University of Chinese Academy of Sciences, CAS Center for Excellence in Brain Science and Intelligence Technology, Beijing 100049, China

\textsuperscript{c}Tri-institutional Center for Translational Research in Neuroimaging and Data Science (TReNDS), Georgia State University, Georgia Institute of Technology, and Emory University, Atlanta, GA, 30303, USA

Deep learning (DL) has gained considerable attention in the scientific community, breaking benchmark records in many areas such as speech and visual recognition. However, the incorporation of deep learning approaches in neuroimaging is still a challenging and promising direction, due to the high-dimensional feature dimensions and limited sample sizes (Calhoun and Sui, 2016). MRI features. Currently, advances in medical imaging technologies have enabled image acquisition at faster rates and with increased resolution. Also, multiple accessible international brain imaging datasets online facilitate the generation of neuroimaging big data. These provide wonderful testbeds for the advanced computerized tools, especially deep learning approaches, which has shown its efficacy to neuroimaging applications (Hou et al., 2019; Kim et al., 2016; Liu et al., 2018; Yan et al., 2019).

In this special issue, we highlight several themes relevant to the improved DL models applied on multimodal features including fMRI, sMRI or EEG. Due to the high-dimensional and low signal-to-noise ratio properties of the MRI data, efficient feature selection procedures are usually required to reduce the redundancy before modeling (Yao et al.,

\textsuperscript{*}Corresponding author at: National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences, Beijing, 100190, China. jing.sui@nlpr.ia.ac.cn.
Two types of approaches, data-driven and seed-based, have been extensively applied to decompose 4D fMRI or 3D sMRI data (Du et al., 2018), resulting in spatial brain regions/patches/independent components (ICs), as well as the corresponding time courses (Cetin et al., 2016). The current issue covers DL approaches applied to all these features, especially based on Convolutional Neural Network (DNN) and Recurrent Neural Network (RNN) models.

Particularly, in the classification of mental disorders, the paper by Li et al. (2019) proposed a hybrid CNN + RNN framework by combining DenseNets and bidirectional gated recurrent unit (BGRU) for hippocampus atrophy (3D sMRI patch) analysis and AD/MCI diagnosis. Riaz et al. (2020) instead took fMRI pre-processed time-series signals as input, proposed an end-to-end deep learning architecture to diagnose ADHD and used back-propagation to determine the importance of the functional connectivity in classification. Besides MRI data, Wei et al. (2019) converted EEG time series into two-dimensional images for multichannel fusion, then created a spatiotemporal long-term recurrent convolutional network (LRCN) for epileptic seizure prediction, enabling early warning in clinical applications. While Mousavi et al. (2019) provided a new single-channel CNN approach to automatically classify sleep stages from raw EEG signal with data augmentation. Besides classification, Janjic et al. (2019) reported a measurement-oriented deep-learning workflow for improved segmentation of myelin and axons in high-resolution images of human cerebral white matter.

The current special issue is also enriched by one hot research topic on brain imaging encoding and decoding, which can be facilitated by deep learning. In the paper, Zhang et al. (2019) constructed a new visual encoding framework to predict fMRI cortical responses from visual features via nonlinear mapping from AlexNet. In contrast, Svanera et al. (2019) established a robust, multivariate link between fMRI data (scanned while participants watching movie clips or static images) and the fully connected layers of a CNN, by adopting reduced rank regression with Ridge Regularization, leading to significant decoding performance.

Last but most importantly, in this age of big data, many models require very large datasets in order to be informative and accurate. However, the data are often stored separately in multiple locations which can cause various practical hurdles in current neuroimaging data mining, among which replicability and privacy safety are the most challenging issues. In this special issue, Lewis et al. (2020) proposed a decentralized distribution-sampled classification model by implementing a new single-shot method for both neural networks and support vector machines, via transferring statistical distribution of local sites. Results show such an approach performs comparably to a centralized approach while minimizing network traffic compared to multishot methods. Furthermore, Kim et al. (2020) investigated the reproducibility and test–retest reliability of the spatial patterns (SPs) of resting-state fMRI data obtained from a restricted Boltzmann machine (RBM) and hierarchically organized the SPs from the deep belief network, indicating that an increase in the sparsity level of RBM weights enhanced the reproducibility of SPs compared with the voxel-wise statistics.
Overall, deep learning has revolutionized machine learning approaches in neuroimaging, with unparalleled performance in classification of mental disorders, brain imaging encoding/decoding, and prediction of clinical interventions, though often accompanied with issues on sample sizes, site heterogeneity, data sharing and image quality (Sui et al., 2020; Yao et al., 2019). The contributions included in this special issue provide methodological advances to enrich our current knowledge on DL applications in brain imaging. We hope these research work will deepen understanding and stimulate new thinking about clinical translation of these approaches, resulting in potentially useful imaging biomarkers.

Acknowledgements

This work is supported in part by the Strategic Priority Research Program of the Chinese Academy of Sciences (grant No. XDB32040100), China Natural Science Foundation (No. 61773380), and the National Institute of Health (1R01MH117107, R01MH118695, P20GM103472, P30GM122734).

References


