Guest Editorial Special Issue on Deep Learning in Medical Imaging

I. Introduction

OVER the past several years, deep learning has achieved great success in many fields, from computer vision to many other fields. Instead of designing hand-crafted features as done by traditional machine learning, deep learning can automatically learn more representative and effective features from raw data (e.g., intensity images). Recently, deep learning has also been successfully applied to medical image analysis, with significant performance improvement. This Special Issue of IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING focuses on the latest progress of deep learning in the medical imaging domain. From a large number of submissions, 9 papers were finally selected for publication in this Special Issue. Each paper was carefully reviewed by 3-4 experts in the field and went through a rigorous revision process, composed of typically two rounds of revision. All of the papers in this Special Issue leverage deep learning, especially convolutional neural network techniques, in a wide variety of classical tasks in medical imaging and analysis, e.g., registration, segmentation, classification, regression/prediction, and reconstruction.

II. Papers Included in the Special Issue

Cao *et al.*, in their paper entitled "Deformable image registration using cue-aware deep regression network" [item 1) in the Appendix], address the classic image registration problem based on a cue-aware deep regression network, to deal with multi-center data with minimal parameter tuning. In particular, given a set of training images, authors propose to learn the displacement vector associated with a pair of reference-subject patches. They first introduce a key-point truncated-balanced sampling strategy to facilitate accurate learning from the image database of limited size. Then, they design a deep regression network, which is aware of the contextual cue for accurate prediction of local deformation, to guide the learning process. Experimental results on different databases show that their method performs consistently well on various registration tasks, without the need of manual parameter tuning, which could be useful for various clinical applications.

Deep learning based segmentation methods are usually trained based on the pixel-wise loss, which treats all pixels with equal importance in pixel-to-pixel matching between a predicted probability map and the corresponding manually annotated segmentation. However, for vessels in fundus images, the pixel ratio between thick and thin vessels is highly imbalanced. Consequently, deep learning models that use pixel-wise losses are unable to learn effective features for accurate segmentation of thin vessels. To address the limitation of pixel-wise loss, Yan *et al.*, in their paper entitled "Joint segment-level and pixel-wise losses for deep learning based retinal vessel segmentation" [item 2) in the Appendix], propose a new segment-level loss, which emphasizes more on the thickness consistency of thin vessels in the training process. By jointly adopting both the segment-level and the pixel-wise losses, the importance of the thick and thin vessels in the loss calculation becomes more balanced. Comprehensive comparison results using public datasets have demonstrated the effectiveness of their proposed joint-loss deep learning framework.

Instead of using the conventional segmentation-based estimation of left ventricular (LV) volume, Luo *et al.*, in their paper entitled "Multi-views fusion CNN for left ventricular volumes estimation on cardiac MR images" [item 3) in the Appendix], aim to directly estimate LV volumes from cardiac MR (CMR) images based on the end-to-end deep convolutional neural networks (CNN). First, they introduce a new data preprocessing method on CMR. Then, they propose a new network structure for end-to-end LV volume estimation. Third, they explore the representational capacity of different slices, and propose a fusion strategy to improve the prediction accuracy. Experimental results show that the proposed method outperforms the state-of-the-art methods for LV volume estimation on the adopted datasets and has a great potential to be extended to other tasks in medical image research field.

Zhou *et al.*, in their paper entitled "A radiomics approach with CNN for shear-wave elastography breast tumor classification" [item 4) in the Appendix], propose a segmentation-free radiomics method to classify malignant and benign breast tumors with shear-wave elastography (SWE) data. The method is targeted to integrate the advantage of both SWE in providing important elasticity with morphology information and CNN in automatic feature extraction and accurate classification. The superior performance compared to the existing state-of-the-art methods and its automatic nature both demonstrate that the proposed method has a great potential to be applied to clinical computer-aided diagnosis of breast cancer.

In this Special Issue, we also include one paper that utilizes deep learning for joint segmentation and prediction, i.e., Liu *et al.*'s "A cascaded deep convolutional neural network for joint segmentation and genotype prediction of brainstem gliomas" [item 5) in the Appendix]. They propose a novel cascaded CNN for automatic segmentation of brainstem gliomas and prediction of genotype (H3 K27M) mutation status based on MR images. The segmentation task contains two feature-fusion modules: 1) the Gaussian-pyramid multiscale input features-fusion technique and 2) the brainstem-region feature enhancement. The

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prediction task combines CNN features and support-vector-machine classifier to automatically predict genotypes without the labeled region-of-interest in MR images and is learned jointly with the segmentation task. Experiments demonstrate that the cascaded CNN method achieves *not only* the good tumor segmentation results with a Dice similarity coefficient of 77.03%, but also the competitive genotype prediction results with an average accuracy of 94.85%.

Wang *et al.*, in their paper entitled "Estimating brain connectivity with varying length time lags using recurrent neural network" [item 6) in the Appendix], propose a Granger causality estimator based on the recurrent neural network (RNN), called RNN-GC, to deal with the multivariate brain connectivity detection problem. The model takes input of time series signals with arbitrary length of transmission time lags and learns the information flow from the data using the gated RNN model, i.e., long short-term memory (LSTM). Compared with other methods, RNN-GC achieves the best performance in both simulated data and clinical epilepsy data using the least computational cost. The proposed RNN-GC method is promising to serve as a brain connectivity analysis tool in clinical applications.

We also include a paper that uses recurrent neural network for heart sound segmentation. Specifically, Messner *et al.*, in their paper entitled "Heart sound segmentation - an event detection approach using deep recurrent neural networks" [item 7) in the Appendix], introduce an event detection approach with deep recurrent neural networks (DRNNs) for heart sound segmentation, i.e., the detection of the state-sequence of first heart sound (S1) - systole - second heart sound (S2) - diastole. They extract spectral and envelope features from heart sounds and investigate the performance of different DRNN architectures to detect the state-sequence, i.e., acoustic events. Their method is also extendable to the detection of extra heart sounds (the third and fourth heart sounds), heart murmurs, as well as other acoustic events.

Zhao *et al.*, in their paper entitled "Automatic recognition of fMRI-derived functional networks using 3D convolutional neural networks" [item 8) in the Appendix], propose a deep 3D CNN framework for automatic, effective and accurate classification and recognition of large number of brain functional networks reconstructed by sparse representation of the whole-brain fMRI signals. Extensive experimental results based on fMRI data from the Human Connectome Project (HCP) show that the proposed deep 3D CNN can effectively and robustly perform functional networks classification and recognition tasks, while maintaining a high tolerance for mistakenly labeled training instances.

Besides the applications above, deep learning can also help accelerate MR scan acquisition. For example, Lee *et al.*, in their paper entitled "Deep residual learning for accelerated MRI using magnitude and phase networks" [item 9) in the Appendix], investigate deep residual learning networks to remove aliasing artifacts from artifact corrupted images. Their deep residual learning networks are composed of magnitude and phase networks that are separately trained. Even with strong coherent aliasing artifacts, the proposed network can still successfully learn and remove the artifacts, which is an achievement that the current parallel and compressed sensing reconstruction methods cannot accomplish.

III. Conclusion

In the above, we briefly introduce nine deep learning-based papers assembled within this Special Issue. We hope that this Special Issue will provide timely and interesting samples for the research community and will foster further work in this exciting area. In closing, we would like to extend our appreciation to all reviewers for their timely and professional comments. Many thanks shall go to Prof. Bin He, the Editor-in-Chief of the IEEE Transactions on Biomedical Engineering. Without his strong support of this Special Issue, nothing would have happened. Most importantly, thanks to all the authors who submitted their manuscripts for consideration of publication. Their supports have made this Special Issue a success.

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Appendix
Related Work

1) X. Cao *et al.*, "Deformable image registration using cue-aware deep regression network," *IEEE Trans. Biomed. Eng.,* vol. 65, no. 9, Sep. 2018.
2) Z. Yan *et al.*, "Joint segment-level and pixel-wise losses for deep learning based retinal vessel segmentation," *IEEE Trans. Biomed. Eng.,* vol. 65, no. 9, Sep. 2018.
3) G. Luo *et al.*, "Multi-views fusion CNN for left ventricular volumes estimation on cardiac MR images," *IEEE Trans. Biomed. Eng.,* vol. 65, no. 9, Sep. 2018.
4) Y. Zhou *et al.*, "A radiomics approach with CNN for shear-wave elastography breast tumor classification," *IEEE Trans. Biomed. Eng.,* vol. 65, no. 9, Sep. 2018.
5) J. Liu *et al.*, "A cascaded deep convolutional neural network for joint segmentation and genotype prediction of brainstem gliomas," *IEEE Trans. Biomed. Eng.,* vol. 65, no. 9, Sep. 2018.
6) Y. Wang *et al.*, "Estimating brain connectivity with varying length time lags using recurrent neural network," *IEEE Trans. Biomed. Eng.,* vol. 65, no. 9, Sep. 2018.
7) E. Messner *et al.*, "Heart sound segmentation – An event detection approach using deep recurrent neural networks," *IEEE Trans. Biomed. Eng.,* vol. 65, no. 9, Sep. 2018.
8) Y. Zhao *et al.*, "Automatic recognition of fMRI-derived functional networks using 3D convolutional neural networks," *IEEE Trans. Biomed. Eng.,* vol. 65, no. 9, Sep. 2018.
9) D. Lee *et al.*, "Deep residual learning for accelerated MRI using magnitude and phase networks," *IEEE Trans. Biomed. Eng.,* vol. 65, no. 9, Sep. 2018.