Guest Editorial: Machine Learning in Medical Imaging

I. Introduction

THERE is no doubt that medical imaging has become indispensable in diagnosis and treatment of many diseases. With advances in new imaging techniques, the need to take full advantage of abundant images draws more and more attention. Machine learning, including deep learning particularly, provides us a new paradigm to learn and to utilize the overwhelming volume of big imaging data smartly. Nowadays, machine learning in medical imaging has become one of the most promising and growing fields of research.

The main aim of this special issue is to help advance the scientific research within the broad field of machine learning in medical imaging. The special issue was planned in conjunction with the International Workshop on Machine Learning in Medical Imaging (MLMI) 2017. Being the first workshop on this topic, it has been successfully held in nine consecutive years since 2010. A total of 68 papers submitted to this special issue underwent two rounds of rigorous peer reviews. In the end, 11of them were selected to be included in this special issue to ensure the highest quality outcome. There were a number of other excellent papers that were not able to be included in the special issue due to the limited space.

II. A Brief Overview of the Papers in This Special Issue

A. From Low-Level Processing to High-Level Understanding

The scope of machine learning in medical imaging is broad, covering low-level processing to high-level understanding of the diverse visual data as well as clinical information. Among them, Zhao *et al.* aim to perform accurate segmentation especially for small organs. Though many state-of-the-art approaches have achieved remarkable success in image segmentation, the performance is not always satisfactory for small organs such as the pancreas, gallbladder and adrenal glands. This paper presents an automatic approach for small organ segmentation, especially with limited training data, through two steps: localization and segmentation. The localization step extracts the region of interest, after projecting images to a common space by a graph-based groupwise image registration method. Then, in the segmentation step, a voxel-wise label map is acquired with a knowledge-aided convolutional neural network. The results on ISBI 2015 VISCERAL challenge dataset demonstrate that the proposed method outperforms many existing methods in segmenting small organs.

Ferrante *et al.* target deformable registration, which is also a pillar in the pipeline of medical image computing. Usually registration requires a similarity criterion between two given images. The definition of the similarity can benefit from incorporating semantic information derived from anatomical segmentation. To this end, a novel weakly supervised approach is proposed in this paper to learn domain specific aggregations of conventional similarity metrics using anatomical segmentation. The combination is attained through latent structured support vector machines, which results in a multimetric algorithm endowed with spatially varying similarity measures and thus owning improved registration performance.

With processing and utilizing of medical images, one may attain automatic classification or regression toward disease diagnosis. Hagerty *et al.* present an approach for melanoma diagnosis, which combines conventional image processing with deep learning by fusing their individual features. The conventional image processing extracts lesion features comparable to clinical dermoscopy information, and considers clinical information such as patient age, gender, lesion location, size and patient history. Meanwhile, deep learning utilizes the knowledge transferred via a ResNet-50 network, which aims to predict the probability of melanoma classification. By fusing the above features, the area under the receiver operator characteristic curve (AUC) can reach 0.94 for melanoma diagnosis. In comparison, the ResNet-50 network for deep learning alone can only yield an AUC of 0.87.

Age estimation from radiologic data is an important topic both in clinical medicine as well as in forensic applications. Štern *et al.* propose an automatic multifactorial age estimation method based on magnetic resonance imaging data of hand, clavicle and teeth. They successfully extend the maximal age range from up to 19 years, as commonly used for age assessment based on hand bones, to up to 25 years, when clavicle bones and wisdom teeth are added. They fuse age-relevant information from all three anatomical sites by deep learning. The training and validation upon a dataset of 322 subjects between 13 and 25 years old turns out that the mean absolute prediction error in regressing chronological age can be as low as 1.01 years.

B. Ophthalmic Disease

There are three papers devoted to the area of ophthalmic applications, highlighting the trend of integrating machine learning technique into this specific field. Optical coherence tomography

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(OCT), for example, is a high-resolution and noninvasive imaging modality that is prevalent for ophthalmic disease diagnosis. Liu *et al.* tackle the problem of retinal layer segmentation in OCT. They integrate deep features and hand-designed features to train a structured random forest classifier. With the trained classifier, they get the contour probability graph of each layer, and achieve the final layer segmentation by the shortest path. They achieve superior segmentation quality, i.e., the mean layer contour error of 1.215 pixels, in comparison to 1.464 pixels of the state-of-the-art.

The color fundus image (CFI) is also commonly used for ocular screening of glaucoma. In CFI, the central regions of optic disc and optic cup within the disc are examined to determine the important optic cup-to-disc ratio (CDR), which requires accurate segmentation of optic disc and cup, respectively. Shankaranarayana *et al.* first propose a deep learning framework to estimate the depth information from a single fundus image. Then, they adopt a novel fully convolutional network, guided by the depth map, to accomplish the segmentation task in a highly reliable way.

Retinal vessel segmentation is another important issue in the diagnosis of ophthalmic diseases. Yan *et al.* point to the highly imbalanced ratio between thick vessels and thin vessels, both of which are important to sustain clinical decisions. The imbalance may lead to the ill-posed pixel-wise loss in training, which is dominated by the thick vessels and yet considers little of the thin vessels. To address the imbalance, the authors segment thick vessels and thin vessels separately. The final vessel fusion refines the segmentation result by identifying nonvessel pixels and improving the overall vessel thickness consistency. The experiments on the DRIVE, STARE and CHASE DB1 datasets demonstrate superior performance of the proposed model in respect to state-of-the-art vessel segmentation methods.

C. Neural Disorder

Neuroimaging and neural disorders are always a focus in the field of machine learning and medical imaging. Lei *et al.* focus on the Parkinson's disease (PD), which can be slowed if early diagnosis and timely intervention are properly provided. In this paper, they propose a joint regression and classification method for PD diagnosis upon structural and diffusion magnetic resonance images. The unified multitask model can explore relationships among features, samples, and clinical scores. Four clinical variables of depression, sleep, olfaction, and cognition scores are regressed out, while the classification of PD is also conducted from the multimodal imaging data. The extensive experimental results on the public Parkinson's progression markers initiative (PPMI) dataset show superior performance of regression and classification of the disease of PD.

In addition to PD, Jiang *et al.* shift the focus to the Alzheimer's Disease (AD), which also attracts much attention. Most literature methods assume that the features extracted from multimodal images are equally related to the classification or regression output. On the contrary, the authors consider correlation-aware sparse and low-rank regularization in their multitask learning formulation. The experiments on the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset not only deliver great accuracy in predicting cognitive scores of multiple time points for the AD patients, but also help identify stable and important imaging biomarkers that are related to the disease of AD.

D. Pathology and Cell Detection

There are two papers within the field of pathology image processing. In the first paper, Ramesh *et al.* propose a multitask learning algorithm for cell detection and segmentation using deep learning. Instead of using pixel-wise labeling, they use simple dot annotations placed inside each cell to approximate cell centroids and then create the training data. There are two tasks: the segmentation task maps the input image to foreground/background, whereas the detection task determines the centroids of the cells. The two tasks share the same convolutional layers partially, yet develop their task-specific output branches. The proposed multitask learning scheme achieves improved detection/segmentation scores as compared to state-of-the-art methods, while it has significantly alleviate the concern over high-quality training data.

Cell detection and classification are often performed consecutively and separately by machine learning or deep learning. Song *et al.*, however, propose a synchronized deep auto-encoder network for simultaneous detection and classification of cells in bone marrow histology images. The proposed network uses a single architecture to detect the positions of cells and classifies the detected cells in parallel. The authors have successfully demonstrated superior performance than traditional deep learning based detection and competitive to separate deep learning with respect to classification, indicating the necessity of fusing the two steps.

III. Concluding Remarks

In summary, the investigators applied and developed a wide variety of machine learning techniques in their diverse medical imaging applications. The field of machine learning in medical imaging is one of the most promising, rapidly growing fields, as evidenced by the number of high-quality papers submitted to this special issue, the various machine learning techniques, and their inspiring applications in the papers. We expect that this field will expand more and more, and that the population of researchers in the field will grow rapidly.

Qian Wang
Shanghai Jiao Tong University
Shanghai 200240, China
wang.qian@sjtu.edu.cn

Yinghuan Shi
Nanjing University
Nanjing 210008, China
syh@nju.edu.cn

Dinggang Shen
University of North Carolina at Chapel Hill
Chapel Hill, NC 27599, USA
dgshen@med.unc.edu