Guest Editorial
Large-Scale Medical Image and Video Analytics for Clinical Decision Support

I. Introduction

BIOMEDICAL images and videos are ubiquitous and overwhelming in volume, amounting to a database that can be measured in zettabytes. With increased access to open image and video datasets and the recent development of effective image and video analysis systems, there is a unique opportunity for the development of artificial intelligence (AI) systems that can be trained and tested on large-scale biomedical image and video databases.

The special issue summarizes emerging methods associated with the development of computer-aided diagnostic systems. More specifically, the special issue discusses the development of methods for dealing with small or large or creating new datasets, biomedical image segmentation, and image classification. The development of new dataset methods allows us to develop methods for specific diseases, employ meta-learning for training on small datasets, or develop methods for reducing larger video datasets. Biomedical image segmentation is a primary focus of the special issue. Biomedical image segmentation allows us to perform clinical measurements, delineate clinical structures from 2D/3D and multimodal datasets, or take advantage of modern semi-supervised methods to improve performance. Biomedical image classification methods combine deep learning methods with multi-instance learning and attention mechanisms.

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

A. Datasets

We begin with three papers that address issues associated with the development of a relatively large dataset, few-shot learning for training on small datasets, and the selection of sparse representative frames from ultrasound videos for working with reduced datasets. The three papers provide three contrasting approaches.

In [A1], the authors introduce an endoscopy benchmark dataset of 21420 images from white light imaging (WLI) endoscopy and linked color imaging (LCI) endoscopy which were annotated by radiologists and validated with biopsy results for detecting intestinal metaplasia and gastritis atrophy. To provide benchmark results, the authors develop a local attention grouping method that extracts visual features, learning from randomly selected regional images via ensemble learning. The method uses a dual transfer learning strategy to train the model with features that co-distributed between WLI and LCI. The proposed methods achieve excellent classification results on both intestinal metaplasia and atrophic gastritis.

In [A2], the authors develop few-shot learning methods for enabling AI methods that exploit a small dataset of ground truth images. The method uses auto-encoders, metric-learner, and task-learner networks with data augmentation to demonstrate meta learning across modalities. The proposed methods were demonstrated based on three-class few-shot classification tasks from the BLOOD, PATH, and CHEST datasets.

The goal of [A3] is to analyze endobronchial ultrasound (EBUS) elastography videos to support intrathoracic lymph node diagnosis. The developed method selects sparse representative frames. The approach is based on a differentiable sparse graph attention mechanism that processes frame-level features and interactions across frames. The approach achieves an AUC (area under curve) of 0.88 on a dataset of 727 EBUS elastography videos.

B. Image Segmentation

Most of the papers are focused on image segmentation. We divide the papers into three groups. First, we have two papers that describe methods for localizing different disease structures. Second, we have segmentation papers focused on 2D and multimodal medical images. Third, we have three papers that describe semi-supervised methods.

We begin with two papers focused on localization. The goal of [A4] is to develop a segmentation of the Bruch's membrane (BM) in optical coherence tomography (OCT) tomography for diagnosis and follow-up of age-related macular degeneration (AMD). The authors develop an end-to-end deep learning system. The approach was tested on 138 patients covering all three AMD stages, where it achieved a mean absolute localization error of 4.10 μm.

In [A5], the authors develop a method to monitor joint space narrowing progression for early rheumatoid arthritis. The method is based on partial image phase correlation. The method achieved a mean error of 0.0130 mm on phantom radiographs and a standard deviation of 0.0519 mm for clinical radiography.

Second, we provide two papers focused on 2D and multimodal image segmentation techniques. In [A6], the authors develop a method to identify the grade of cancer morbidity from hepatocellular carcinoma biopsy images. The method uses segmentation

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of the nuclei, followed by a two-track neural network that assigns a grade based on the segmented nuclei with a random crop of the nuclei with their surroundings. A majority vote over all the nuclei grades determines the final grade with an accuracy of 99.03% for nucleus image grading and 99.67% accuracy for grading the entire biopsy images.

In [A7], the authors develop accurate volumetric segmentation of brain tumours and tissues in multi-modal Magnetic Resonance (MR) images. Their method is based on adaptively and efficiently fusing and refining features, alignment, and the use of graph-based context modelling for describing interactions across modalities. The approach is applied to brain glioma, vestibular schwannoma, and brain tissue segmentation tasks and was tested on BraTS2018, BraTS2020, Vestibular Schwannoma, and iSeg-2017 datasets.

Third, the special issue introduces methods based on semi-supervised methods. Semi-supervised methods provide an alternative approach to time-consuming generation of ground truth data. Semi-supervised methods improve upon regular segmentation methods through the use of new learning methods.

In [A8], the authors develop semi-supervised methods for segmentation of myocardial infraction regions in magnetic resonance images. The proposed method relies on the use of a boundary mining model that is pseudo supervised and improved upon by an adversarial learning model. The method is validated using six evaluation metrics.

In [A9], the authors develop a tissue segmentation method for histopathological images. The authors propose a semi-supervised pixel contrastive learning framework. The method is demonstrated on three different datasets.

In [A10], the authors develop methods for detecting pulmonary nodules on chest CT images for adenocarcinoma, squamous cell carcinoma, small cell carcinoma, inflammatory and other benign cases. The authors propose the development of a reverse adversarial classification network based on a semi-supervised learning. 3D nodule volume data are given as input to the system, and the system is trained to generate five normal distributions with specific normal distributions and variances that are assigned to represent the different pathological types. The system is tested on the detection of malignant nodules and achieved a 93.21% accuracy on the LIDC-IDRI dataset.

C. Image Classification

Image classification methods have also benefited from the development of deep learning methods and open-source datasets. We include an example of learning from multiple instances and a method that incorporates attention mechanisms.

In [A11], the authors describe methods to speed up diagnosis through the analysis of polyculture images. The approach uses multiple instances learning for multi-label classification. The approach achieves an AUC of 0.9 for identifying four different bacteria species on microscopic images.

In [A12], the authors develop methods for the early diagnosis of neurodegenerative diseases. The paper develops a dual-attention deep manifold harmonic discrimination method for exploiting the geometric features of the brain network, uses attention blocks with discrimination to learn a representation, which facilitates learning of group-dependent discriminant matrices. The method is evaluated on the ADNI and ADHD-200 open-source datasets where they are shown to achieve excellent classification performance.

III. Concluding Remarks

Overall, the methods exhibited in this special issue have greatly benefited from the use of open-source datasets and the recent development of deep learning methods. Going beyond the standard deep learning methods, the special issue celebrates original contributions that deal with small or large datasets, biomedical segmentation, and classification.

Emerging medical image and video hardware advancements enabling the acquisition of higher quality and higher resolution images, linked with advancements in AI and Explainable AI, will drive the development of next generation medical image and video systems. Moreover, these advances will further enable and accelerate the development, translation, and application of precision medicine.

It is hoped that the proposed technologies and systems can result in improved clinical decision support disease management and treatment at the point of need, reduced hospitalization, and the associated economic burden, offering a better quality of life to the patient.

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Appendix: Related Articles

[A1] J. Yang et al., "A benchmark dataset of endoscopic images and novel deep learning method to detect intestinal metaplasia and gastritis atrophy," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 7–16, Jan. 2023, doi: 10.1109/JBHI.2022.3217944.

[A2] H. Jiang, M. Gao, H. Li, R. Jin, H. Miao, and J. Liu, "Multi-learner based deep meta-learning for few-shot medical image classification," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 17–28, Jan. 2023, doi: 10.1109/JBHI.2022.3215147.

[A3] M. Xu et al., "Automatic representative frame selection and intrathoracic lymph node diagnosis with endobronchial ultrasound elastography videos," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 29–40, Jan. 2023, doi: 10.1109/JBHI.2022.3152625.

[A4] B. Fazekas, D. Lachinov, G. Aresta, J. Mai, U. Schmidt-Erfurth, and H. Bogunović, "Segmentation of Bruch's Membrane in retinal OCT with AMD using anatomical priors and uncertainty quantification," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 41–52, Jan. 2023, doi: 10.1109/JBHI.2022.3217962.

[A5] Y. Ou et al., "A sub-pixel accurate quantification of joint space narrowing progression in rheumatoid arthritis," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 53–64, Jan. 2023, doi: 10.1109/JBHI.2022.3217685.

[A6] G. Chakraborty, W. Wang, B. Chakraborty, S.-K. Tai, and Y.-S. Lo, "Grading of HCC biopsy images using nucleus and texture features," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 65–74, Jan. 2023, doi: 10.1109/JBHI.2022.3215226.

[A7] Y. Zhuang, H. Liu, E. Song, and C.-C. Hung, "A 3D cross-modality feature interaction network with volumetric feature alignment for brain tumor and tissue segmentation," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 75–86, Jan. 2023, doi: 10.1109/JBHI.2022.3214999.

[A8] C. Xu et al., "BMAnet: Boundary mining with adversarial learning for semi-supervised 2D myocardial infarction segmentation," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, Jan. 2023, pp. 87–96, doi: 10.1109/JBHI.2022.3215536.

[A9] J. Shi, T. Gong, C. Wang and C. Li, "Semi-supervised pixel contrastive learning framework for tissue segmentation in histopathological image," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 97–108, Jan. 2023, doi: 10.1109/JBHI.2022.3216293.

[A10] Y. Fu, P. Xue, T. Xiao, Z. Zhang, Y. Zhang, and E. Dong, "Semi-supervised adversarial learning for improving the diagnosis of pulmonary nodules," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 109–120, Jan. 2023, doi: 10.1109/JBHI.2022.3216446.

[A11] A. Borowa, D. Rymarczyk, D. Ochońska, A. Sroka-Oleksiak, M. Brzychczy-Włoch, and B. Zieliński, "Identifying bacteria species on microscopic polyculture images using deep learning," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 121–130, Jan. 2023, doi: 10.1109/JBHI.2022.3209551.

[A12] X. Sheng, J. Chen, Y. Liu, B. Hu, and H. Cai, "Deep manifold harmonic network with dual attention for brain disorder classification," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 131–142, Jan. 2023, doi: 10.1109/JBHI.2022.3220545.