Guest Editorial Skin Image Analysis in the Age of Deep Learning

SKIN is the largest organ of the human body, and is the first area of a patient assessed by clinical staff. The skin delivers numerous insights into a patient's underlying health: for example, pale or blue skin suggests respiratory issues, unusually yellowish skin can signal hepatic issues, or certain rashes can be indicative of autoimmune issues.

Dermatological complaints are the most prevalent reason that patients seek primary care [1], and images of the skin are the most easily captured form of medical image [2], [3] in healthcare. However, certain serious skin diseases are not reliably diagnosed by primary care. For example, while unaided visual inspection by expert dermatologists yields about 60% accuracy for detecting melanoma, the most dangerous type of skin cancer, primary care clinicians achieve only 23–46% accuracy. Therefore, there is a clear need to scale expertise for robust skin disease classification.

Out of all medical imaging datasets, skin images are the most similar to other standard computer vision datasets. However, significant and unique challenges still exist in this domain. In addition, there are remarkable visual similarities among skin diseases, and compared to other medical imaging domains, varying genetics, disease states, imaging equipment, and imaging conditions can significantly alter the appearance of the skin, making automated analysis in this domain highly challenging [4].

In recent years, several datasets have become publicly available to support research and development in automated skin image analysis across various imaging modalities, including dermoscopy and clinical photography. These developments have spiked an interest in research around skin image analysis. According to Google Scholar, at the time of this writing, there are over 1600 research works that use or cite the International Skin Imaging Collaboration (ISIC) Skin Cancer publications, resources, and benchmark challenges.

With the release of large public datasets, development of novel learning algorithms and network architectures with open-source implementations, and the availability of powerful and inexpensive graphics processing units, deep learning has become the technique of choice in a wide variety of medical image analysis problems over the past decade. Skin image analysis is no exception, as demonstrated by the large number of deep learning-based contributions/entries submitted to our past seven ISIC Workshops/Challenges.

This special issue aims to summarize the state-of-the-art in skin image analysis and provide future directions for this exciting subfield of medical image analysis. We received 39 submissions from around the world. After a rigorous, multiple-round peer review process, we accepted four articles for publication, resulting in a 10.25% acceptance rate. Three of these articles use the various ISIC Archive datasets [5], [6], [7], [8], [9], [10], reflecting the significant impact of these datasets on the skin image analysis literature [11]. All of the accepted articles employ deep learning [12], a learning paradigm that has become increasingly popular in skin image analysis since 2015 [13]. By comparison, only 42% of the articles in our 2019 special issue on *Skin Lesion Image Analysis* in this journal [14] employed deep learning.

The issue opens with an article on segmentation. In [A1], Cao et al. present an encoder-decoder based fully convolutional network for skin lesion segmentation. The proposed network features two novel modules that strengthen its feature representation capability by exploiting inter-pixel semantic correlations. Experiments on the ISIC 2018, ISIC 2016, and PH2 [15], [16] datasets demonstrate the performance of the network against state-of-the-art approaches.

In [A2], Li et al. propose an extension of the Deep Neural Forests (DNF) algorithm [17] to the scenario of OOD detection, named DNF-OOD. Their approach requires the training of a convolutional neural network for the task of dermoscopy image classification with known classes. Then, the DNF-OOD model is trained, such that during the inference phase this model outputs a normality score. The final OOD detection is performed by comparing the normality score with a threshold. Extensive evaluation on the ISIC 2019 and DermNet datasets demonstrate that the proposed algorithm outperforms state-of-the-art OOD detection methods.

In [A3], Cho et al. deal with the uncertainty associated with noisy labels, and how best to harness multi-rater labels in a classification task. For this, they ask five dermatologists to independently rate an astonishing number of over 9000 images for severity of atopic dermatitis. Using this dataset, they compare ensembling labels or single models, investigate how to represent multi-rater labels, and measure the effect of pruning inconclusive cases.

Finally, in [A4] Lee et al. develop a smartphone-based fluorescence imaging system that offers fluorescence and white-light reflectance RGB images, and propose an auxiliary deep learning network called fluorescence-aided amplifying network (FAA-Net) to diagnose skin diseases from those images. FAA-Net is devised based on the few-shot learning algorithm due to the small number of images acquired per disease. It also incorporates a detection task for skin disease regions, alongside the classification of skin diseases in a multi-task learning setting, to use the localization property of the fluorescence modality.

The guest editors hope that this special issue will demonstrate the significant progress that has occurred in skin image analysis

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over the past few years. We also hope that the developments reported in this issue will motivate further research in this field.

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M. Emre Celebi, *Guest Editor*
Department of Computer Science and Engineering
University of Central Arkansas
Conway, AR 72035 USA

Catarina Barata, *Guest Editor*
Institute for Systems and Robotics
University of Lisbon
Lisbon 1049-001, Portugal

Allan Halpern, *Guest Editor*
Dermatology Service
Memorial Sloan Kettering Cancer Center
New York City, NY 10065 USA

Philipp Tschandl, *Guest Editor*
Department of Dermatology
Medical University of Vienna
Vienna 1090, Austria

Marc Combalia, *Guest Editor*
Hospital Clinic of Barcelona
Barcelona 08036, Spain

Yuan Liu, *Guest Editor*
Google Health
Palo Alto, CA 94304 USA

Appendix: Related Articles

[A1] W. Cao et al., "ICL-Net: Global and local inter-pixel correlations learning network for skin lesion segmentation," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 145–156, Jan. 2023, doi: 10.1109/JBHI.2022.3162342.

[A2] X. Li, C. Desrosiers, and X. Liu, "Deep neural forest for out-of-distribution detection of skin lesion images," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 157–165, Jan. 2023, doi: 10.1109/JBHI.2022.3171582.

[A3] S. I. Cho et al., "Practical training approaches for discordant atopic dermatitis severity datasets: Merging methods with soft-label and train-set pruning," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 166–175, Jan. 2023, doi: 10.1109/JBHI.2022.3218166.

[A4] K. Lee et al., "Multi-task and few-shot learning-based fully automatic deep learning platform for mobile diagnosis of skin diseases," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 1, pp. 176–187, Jan. 2023, doi: 10.1109/JBHI.2022.3193685.

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[3] M. E. Celebi, T. Mendonca, and J. S. Marques, Eds., *Dermoscopy Image Analysis*. Boca Raton, FL, USA: CRC Press, 2016.

[4] R. Daneshjou et al., "Checklist for evaluation of image-based artificial intelligence reports in dermatology: Clear derm consensus guidelines from the international skin imaging collaboration artificial intelligence working group," *JAMA Dermatol.*, vol. 158, pp. 90–96, 2022, doi: 10.1001/jamadermatol.2021.4915.

[5] D. Gutman et al., "Skin lesion analysis toward melanoma detection: A challenge at the international symposium on biomedical imaging (ISBI) 2016, hosted by the international skin imaging collaboration (ISIC)," 2016, *arXiv:1605.01397*.

[6] N. C. F. Codella et al., "Skin lesion analysis toward melanoma detection: A challenge at the 2017 International Symposium on Biomedical Imaging (ISBI), hosted by the International Skin Imaging Collaboration (ISIC)," in *Proc. IEEE 15th Int. Symp. Biomed. Imag.*, 2018, pp. 168–172, doi: 10.1109/ISBI.2018.8363547.

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[9] M. Combalia et al., "BCN20000: Dermoscopic lesions in the wild," 2019, *arXiv:1908.02288*.

[10] V. Rotemberg et al., "A patient-centric dataset of images and metadata for identifying melanomas using clinical context," *Sci. Data*, vol. 8, 2021, Art. no. 34, doi: 10.1038/s41597-021-00815-z.

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