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Editorial

Guest editorial: Image analysis in dermatology

1. Note

Medical image analysis has a long and distinguished history spanning nearly six decades. As a matter of fact, the evolution of image analysis largely parallels that of medical image analysis, as some of the earliest image analysis techniques were developed for medical applications. Image analysis in general, and medical image analysis in particular, have historically focused on single-channel (monochromatic) images. A notable exception is dermatology, a subfield of medicine where images are typically acquired in color. While color provides enhanced visualization of surface and subsurface structures of the skin, it also presents new challenges for researchers and practitioners, as the numerous methods developed for single-channel images are generally inapplicable to multi-channel ones (Celebi and Schaefer, 2012). 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 (Daneshjou et al., 2022).

This special issue aims to summarize the state-of-the-art in dermatological image analysis and provide future directions for this exciting subfield of medical image analysis. We received 74 submissions from 29 countries. After a rigorous, multiple-round peer review process, we accepted 12 articles for publication, resulting in a 16% acceptance rate. Nine (75%) of these articles involve dermoscopy, reflecting the growing use of this modality in clinical practice worldwide and the availability of public dermoscopy data sets. All of these dermoscopy-related articles use the International Skin Imaging Collaboration (ISIC) Archive data sets (Gutman et al., 2016; Codella et al., 2018, 2019; Tschandl et al., 2018; Combalia et al., 2019; Rotemberg et al., 2021), highlighting the significant impact of these data sets on the dermoscopy image analysis literature (Celebi et al., 2019a). Other modalities featured in the issue include clinical, total body, and light-field photography. Eleven of the accepted articles (92%) employ deep learning (Curiel-Lewandrowski et al., 2019), a topic that has become increasingly popular in dermatological image analysis since 2015 (Codella et al., 2015). By comparison, only 42% of the articles in our 2019 special issue on *Skin Lesion Image Analysis* (Celebi et al., 2019b) employed deep learning.

The issue contains articles that address a wide variety of topics, including segmentation, feature extraction, classification, content-based retrieval, and tracking. It opens with four articles on skin lesion segmentation, which aim to tackle various issues ranging from lack of sufficient training data to variability in lesion size and border characteristics. In "Semi-Automatic Segmentation of Skin Lesions based on Superpixels and Hybrid Texture Information," Santos et al. propose a semi-automatic segmentation approach that starts by dividing the dermoscopy image into superpixels using the SLIC0 algorithm. A semi-supervised approach is then used to aggregate the superpixels belonging to the skin lesion. The proposed approach is shown to generalize well to new data sets. In "Hyper-Fusion Network for Semi-Automatic Segmentation of Skin Lesions," Bi et al. propose another semi-supervised segmentation algorithm. The authors introduce a new hyper-fusion neural network that combines image features with user inputs at different network levels. The proposed approach is evaluated on various public dermoscopy data sets, where it achieves better generalization than its competitors. In "Ms RED: A Novel Multi-Scale Residual Encoding and Decoding Network for Skin Lesion Segmentation," Dai et al. introduce a segmentation network called "Ms RED." This network uses novel multi-scale residual encoding and decoding modules to handle lesions with irregular shapes and low-contrast borders. Additionally, the features learned by the network are improved using a multi-resolution, multi-channel feature fusion module. The proposed approach outperforms other recent works on the ISIC 2018 and PH2 (Mendonca et al., 2013, 2015) data sets while using fewer parameters. Finally, in "FAT-Net: Feature Adaptive Transformers for Automated Skin Lesion Segmentation," Wu et al. augment the standard convolutional encoder with a transformer branch to capture global context information and long-range dependencies efficiently. The proposed approach is evaluated on the ISIC 2016, ISIC 2017, and ISIC 2018 data sets, and a final generalization test is performed on the PH2 data set.

The issue continues with an article on feature extraction. In "TATL: Task Agnostic Transfer Learning for Skin Attributes Detection," Nguyen et al. propose a novel transfer learning approach for dermoscopic attribute detection named "Task Agnostic Transfer Learning" (TATL). TATL learns an attribute-agnostic segmenter that detects skin lesion regions and then transfers this knowledge to a set of attribute-specific classifiers to detect each attribute. The proposed approach is validated on the ISIC 2017 and ISIC 2018 data sets.

The issue continues with four articles on skin disease classification. In "FusionM4Net: A Multi-Stage Multi-Modal Learning Algorithm for Multi-Label Skin Lesion Classification," Tang et al. present a two-stage algorithm to combine multi-modal data for skin lesion recognition. The first stage fuses clinical and dermoscopy images at both feature and decision levels, whereas the second stage in-

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tegrates information from image-modality and patients metadata. The final diagnosis is formed by fusing the predictions from the first and second stages. In “Melanoma Classification Using Light-Fields with Morlet Scattering Transform and CNN: Surface Depth as a Valuable Tool to Increase Detection Rate,” Pereira et al. propose to utilize a third dimension (depth) that characterizes the skin surface rugosity, available in light-field images, to enhance melanoma detection beyond the 2D imaging characteristics. A processing pipeline is deployed using a Morlet scattering transform and a convolutional neural network (CNN) model, allowing comparisons between using only 2D information, only 3D information, and both. In “Does Your Dermatology Classifier Know What It Does not Know? Detecting the Long-Tail of Unseen Conditions,” Roy and Ren describe their approach for detecting infrequent outlier conditions, which are individually too infrequent for per-condition classification, but collectively common and therefore are clinically significant in aggregate. This task is framed as a near out-of-distribution detection problem, where a novel hierarchical outlier detection loss is introduced to distinguish inlier and outlier classes at different granularity. It further uses a diverse ensemble with different representation learning and objectives for improved performance. Finally, in “Analysis of the ISIC Image Datasets: Usage, Benchmarks and Recommendations,” Cassidy et al. perform an in-depth analysis of the ISIC data sets. In addition to providing a comprehensive overview of the data sets regarding composition, the authors identify existing issues, especially undetected duplicates. Furthermore, they provide a reusable duplicate removal strategy to avoid biases in future studies, with a public code repository enabling reproduction of their results.

The issue continues with an article that tackles both segmentation and classification. In “Fully Transformer Network for Skin Lesion Analysis,” He et al. propose a Fully Transformer Network (FTN) consisting of Sliding Window Tokenization (SWT) and Spatial Pyramid Transformer (SPT) for skin lesion segmentation and classification. SWT extracts feature pyramids, while SPT implements self-attention on downsampled features. In addition, the authors propose a transformer decoder, which can efficiently aggregate the hierarchical features extracted by the FTN. The proposed network is validated on the ISIC 2018 data set.

The issue continues with an article on content-based retrieval. In “Dermoscopic Image Retrieval Based on Rotation-Invariance Deep Hashing,” Zhang et al. propose a CNN for retrieving dermoscopy images. The authors present an attention module focused on relevant image content, called “Hybrid Dilated Convolutional Spatial Attention.” In addition, a specialized Cauchy rotation invariance loss is used to create invariance to the orientation of lesions in images.

An article on tracking completes the issue. In “Skin3D: Detection and Longitudinal Tracking of Pigmented Skin Lesions in 3D Total-Body Textured Meshes,” Zhao et al. propose a novel approach to detect and track skin lesions across 3D total-body textured meshes, where the colors on the surface of the subject are unwrapped to obtain a 2D texture image, a Faster R-CNN model detects the lesions on this texture image, and the detected lesions are mapped back to 3D coordinates. The detected lesions are tracked in 3D across pairs of meshes of the same subject using an optimization method that relies on deep learning-based anatomical correspondences and the geodesic distances between the lesions. The proposed approach is evaluated on 3DBodyTex, a public data set composed of 3D scans from 200 human subjects.

The guest editors hope that this special issue will demonstrate the significant progress in dermatological image analysis since the publication of the last special issue in this field in 2019 (Celebi et al., 2019b). We also hope that the developments reported in this issue will motivate further research in this field.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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