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Editorial

Special Issue on Image Processing Techniques for Biomedical Applications

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In recent years, there has been growing interest in creating powerful biomedical image processing tools to assist medical specialists. This is mainly due to the increasing amount of medical data in digital format, which, on the one hand, leads to an increase in the cost and time required to provide the final diagnosis. On the other hand, it enables a large number of applications, known as computer-aided diagnosis (CAD) systems. Such applications, based on image processing and artificial intelligence techniques, enable reduced waiting times, reduced financial costs, and increased quality of services by mitigating or eliminating difficulties in data interpretation. This Special Issue of *Applied Sciences*, entitled *Image Processing Techniques for Biomedical Applications*, aims to present recent advances in the generation and use of image processing techniques and the prospective applications of this research. A total of 27 papers (26 research papers and 1 review paper) in biomedical fields have been presented and published in this Special Issue. In [1], a method to localize and classify lung abnormalities from radiological images is proposed. It is based on a combination of hand-crafted and deep features. A new method for characterizing the morphology of the semicircular canals of the inner ear based on a skeletonization process and calculation of the functional pair angle and other geometric parameters is proposed in [2]. The authors of [3] proposed a computer-aided diagnosis (CAD) system based on a deep convolutional neural network (DCNN) to classify gliomas from a multicenter database. DCNN, with pretrained features and data augmentation, can classify gliomas accurately and efficiently, providing radiologists in clinics with diagnostic suggestions. The authors of [4] realized a modified version of the superpixel-wise fuzzy clustering technique, followed by level set evolution (SFCME-LSE). The target was the automatic extraction of the media–adventitia border (MAB) and lume–intima border (LIB) in intravascular ultrasound (IVUS) images. This proposal achieved state-of-the-art performance. In [5] a fully automated, noninvasive convolutional neural-network-based model for determining the differentiation status of human neural stem cells (NSCs) at the single-cell level from phase-contrast photomicrographs is presented. The model could noninvasively and quantitatively distinguish separated NSCs with high accuracy and reproducibility and may be an ideal means of distinguishing separate NSCs in a clinical setting. An optimized intensity standardization model is proposed to exploit magnetic resonance (MR) images collected from multiple centers, with huge intensity distribution differences among images. Such standardization allows effective computer-aided diagnosis models to be built, based on Radiomics or deep-learning methods, as a result of better preservation of MR image details [6]. A quantitative assessment of colonoscopy images to recognize multiple polyps is described. It has a particular focus on Melanosis coli (MC). Experimental results showed that five texture features were significantly correlated with pathological outcomes, which may provide clinicians with suggestions for evaluating patients with MC [7]. In [8], a review of early and recent studies on the quantification of liver fibrosis is described. In particular, the survey focused on the description of the datasets used for analysis, the image processing techniques employed, the results obtained, and the conclusions derived. The purpose is to identify the main strengths and weaknesses in the overview of this topic. In [8], a review of early and recent studies on the quantification of liver fibrosis is described, presenting the datasets used for the analysis, the employed image processing techniques, the obtained results, and the derived conclusions. The purpose is to identify the major strengths and gray areas of this topic. A deep-learning model with metric embeddings was proposed in [9]. The authors achieved cell nuclei segmentation and experimented on a collection of large-scale, multi-tissue microscopy images. The proposed method showed outstanding performance, particularly for H&E-stained images. In [10], the authors addressed the problem of melanoma detection and classification from dermatologic images. They exploited hand-created features and a multilayer perceptron to distinguish between malignant and benign melanoma and proposed a novel, robust, and efficient method. Based on the results, it was shown that its use would improve reliability levels compared with conventional methods. The authors of [11] proposed a novel method for recognizing white blood cells from microscopic blood images. The purpose was to classify them based on whether they were healthy or affected by leukemia. The system achieved near-perfect results in all tested datasets; therefore, it can reduce the workload and subjectivity of operators and improve diagnostic results. A method based on fully convolutional dense networks, or U-Nets, is described in [12]. The goal is to realize semantic segmentation of the spinal cord in medical ultrasound images. Finally, the authors state that the proposal can be applied to real-time images of the spinal cord to confirm spinal cord decompression, or occasionally to evaluate a tumor adjacent to the spinal cord. A strategy for converting human biomedical image datasets, such as X-rays and computed tomography (CT) scans, into 3D printable files by manually highlighting anatomical subregions of a given structure and cost-effectively 3D printing the resulting models in multicolor is proposed in [13]. A transfer learning method based on the combination of XDAWN spatial filter and Riemannian Geometry classifier (RGC) has been proposed to reduce cross-subject variability from electroencephalogram (EEG) signals. The experimental results demonstrated the proposed algorithm's potential, making the data from different subjects comparable and therefore generalizing a fixed classification method for all subjects [14]. In the work [15], a parallel microwave image reconstruction algorithm based on Apache Spark on high-performance computing and Google Cloud Platform was proposed. It achieved an average speedup increase of 28.56 times on four homogeneous computation nodes, and therefore was able to produce images in an acceptable timeframe. The segmentation of retinal fundus images was addressed in [16]. The authors proposed a novel multi-path recurrent U-Net architecture and performed the experimental evaluation on the optic disc, optic cup, and retinal vessel segmentation, demonstrating outstanding performance and robustness to the presence of pathological regions. A novel technique is used to improve the overall accuracy and performance of the pretrained networks for breast cancer classification [17]. It is based on the so-called double-shot transfer learning (DSTL), that, before the common fine-tuning on the target dataset, updates the learnable parameters of the pretrained network on an intermediate dataset similar to the target one. Such an approach has demonstrated significant performance improvements, making pretrained networks more suitable for medical imaging. A noise reduction algorithm for confocal laser scanning microscopy (CLSM) images was developed [18]. This algorithm, which was applied to medical tooth specimen images, demonstrated good performances, achieving better noise reduction in comparison with the conventional methods, as well as good edge and other fine-detail preservation. A method to decode the electroencephalography (EEG) signals, evoked when individuals perceive different types of visual motion stimuli, is described [19]. This method, which was based on attention mechanisms and a variant of Recurrent Neural Networks (RNNs), demonstrated potential application in the brain–computer interface (BCI) system based on visual motion perception. A new method of automatic segmentation of macular edema regions in retinal OCT images is proposed [20]. It is based on an improved version of UNet (U-Net++), which exploits the ResNet architecture as the backbone, with re-designed skip pathways and a dense convolution block. The experimental results demonstrated excellent segmentation results, leading to more accurate regions and correctly detecting diverse edema in multiple regions. An automated frame selection and stitching framework, useful for classifying eardrum abnormalities, is illustrated in [21]. It is able to increase the probability of detecting a lesion, even if it appears in a few frames of the otoscope videos, by using image segmentation techniques to create enhanced composite images. A universally affordable open-source Android application used to estimate the knee instability is proposed [22]. Such instability caused by a deficiency of the anterior cruciate ligament (ACL) could be estimated by assessing the translation of the tibia with respect to the femur. The experimental results demonstrated that the application could help assess knee instability quantitatively and accurately. An approach for automatic prostate segmentation in MRI scans, based on a cascaded dual attention network (CDA-Net), is proposed [23]. The algorithm achieved very good segmentation performance in a variety of complex slice images and surpassed the state-of-the-art algorithms in different benchmark datasets. It could be very useful for assisting diagnosis and treatment, such as guiding biopsy procedures and radiation therapy. A denoising algorithm for noise reduction from digital images able to preserve the edge information of objects better than conventional denoising filters, as also demonstrated by the experimental results on thoracic CT images, is illustrated [24]. A reliable image registration protocol is crucial in multimodal longitudinal skeletal muscle Magnetic Resonance Imaging (MRI) studies in order to extract reliable parameters that can be used as indicators for physio/pathological characterization of muscle tissue and assess the effectiveness of treatments [25]. Extensive cross-dataset experimentation on several CNN-based state-of-the-art cell nuclei segmentation methods has been performed in order to assess their performances in real-world, challenging application scenarios. The results show that some of the existing CNN-based approaches are capable of generalizing to target images that resemble those used for training. In contrast, their effectiveness considerably degrades when the target and source significantly differ in color and scale [26]. A tool for accurate determination of cell confluence, which is critical for generating reasonable results in cell biological studies, is proposed. The experimental results, performed on cell images of human normal oral fibroblasts (hOFs) acquired under an inverted microscope, demonstrated that this tool could speed up the analysis and prevent unnecessary human-made mistakes [27]. The articles published in this Special Issue are related to biomedical fields and applications, and are all different from each other. Some of them are older and already addressed in the literature, while others are more recent, for which there are still many open issues and much room for improvement. The submissions for this Special Issue emphasized that more in-depth research on the different medical diagnostic tasks is helpful to address the current challenges. Additionally, as artificial intelligence techniques have demonstrated remarkable performance, it is essential to consider that medical applications require a higher level of accountability and transparency. Therefore, explanations for algorithm decisions and predictions are needed to justify their reliability and offer high interpretability for end users. This aspect will undoubtedly be explored further in future.

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