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Editorial

Machine Learning Algorithms for Biomedical Image Analysis and Their Applications

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In recent years, architectural and algorithmic innovations in machine learning have revolutionized the analysis of medical images. Despite these advances, integrating these models into clinical practice comes with several challenges. The wide availability of data and their heterogeneity offer opportunities for us to train increasingly ambitious models. However, several challenges still need to be addressed: the need for multimodal training, data harmonization, the training of small dataset scenarios, etc. [1]. In addition, explainability and reliability requirements imposed by regulatory agencies add further complexity to the integration of machine learning models into clinical settings. As a consequence, it is essential to address these challenges to advance precision and personalized medicine.

This Special Issue contains published articles on significant advancements in the application of artificial intelligence (AI) and machine learning (ML). Several image modalities, including magnetic resonance imaging (MRI), computed tomography (CT), electrocardiography (ECG), positron emission tomography–computed tomography (PET-CT), and histopathology were included in these articles. Motion correction, fracture detection, disease classification, radiomics, and predictive modelling were the tasks investigated, emphasizing the potential for AI-driven solutions in medical imaging tasks.

Radiomics is an innovative framework for medical image analysis [2]. Thousands of features can be extracted of imaging patterns associated with clinical features or disease outcomes [3]. Dhesi et al. [4] developed and validated a machine learning model that uses radiomic features extracted from PET-CT scans to predict the future growth rate of abdominal aortic aneurysms. Their study tested several machine learning models using the radiomic features mentioned above, obtaining promising results.

However, the ability of deep architectures to extract high- and low-level features makes deep-feature models much more informative than radiomic ones. From this perspective, Pandey et al. [5] selected three different deep architectures, fine-tuned them, and used them as base models, combined with a Bayesian-based probabilistic ensemble learning method, for fracture detection in cervical spine CT images. The proposed method considers the prediction uncertainty of the base models and combines the predictions obtained from each of them to improve its overall performance significantly. Heart disease is the leading cause of death worldwide, making the early, accurate, and effective diagnosis of heart disease crucial to saving lives. However, making manual interpretations of ECG imaging—a primary non-invasive method used to identify cardiac abnormalities—for heart disease diagnosis is a time-consuming and inaccurate process. In Moqurrab et al.'s study [6], a hybrid residual/inception-based deeper model is proposed for the accurate and efficient detection of heart diseases from ECG recordings. The result of this study indicates that the

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proposed model is a potential new method for predicting heart diseases using ECGs. The movement of human subjects during medical image acquisition is unavoidable and can lead to motion-induced artifacts, which can deteriorate the quality of images and reduce diagnostic accuracy. Deep learning-based motion correction methods could provide a solution to this. The aim of the study proposed by Zhang et al. [7] was to develop and evaluate a deep learning-based method for suppressing motion artifacts in brain magnetic resonance imaging (MRI) scans. The proposed approach is able to effectively suppress motion artifacts in brain MRI scans without compromising image quality. Given the efficiency of MC-Net (which has a single-image processing time of 40 ms), it is potentially usable in clinical settings. Models based on deep architectures, particularly convolutional neural networks (CNNs), have shown a remarkable ability to classify pathological images. In particular, deep models trained on large datasets of annotated pathology images are able to perform tasks such as the diagnosis, grading, and prognosis of cancer. In Matsuzaka et al.'s study [8], the authors conducted a review summarizing the current advances, architectures, applications, and future directions of deep learning approaches that use pathological images for the diagnostic classification of various diseases.

The studies presented in this Special Issue demonstrate the transformative potential of AI and ML in medical imaging, offering innovative solutions for motion correction, disease detection, and predictive analytics. However, to fully harness these advancements, continued research and collaboration are essential. Explainability has become a mandatory requirement in several fields, including healthcare. The problem of explainability in clinical applications mainly arises with deep learning models, which provide predictions without offering clear insights into how they reach their conclusions. This lack of transparency can be problematic in healthcare, where understanding the rationale behind decisions is crucial for trust, patient safety, and regulatory compliance. Considering these concerns, the research community is trying to find effective solutions by combining the interpretability of radiomic models with the performance of deep predictive models [9]. Increasing multi-institutional collaborations and expanding open-access datasets will be crucial for enhancing the robustness of these models and mitigating their biases. Additionally, integrating AI solutions into clinical workflows through user-friendly software and regulatory-compliant frameworks will accelerate their real-world adoption.

We extend our gratitude to all contributing authors, reviewers, and editorial members for their invaluable efforts in shaping this Special Issue. They have created a forum for publishing original research papers covering state-of-the-art algorithms and methodologies and novel applications of computational methods for biomedical image analysis. We hope this collection of works will inspire further research and contribute to the ongoing transformation of medical diagnostics and patient care.

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