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# Editorial for the research topic: Artificial Intelligence in Point of Care Diagnostics

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2 Speeding up and improving the diagnosis process exactly where and when events occur is the goal of actual  
3 Point of Care (PoC) Diagnostics. Besides progress in sensing technologies that pertain to multidisciplinary  
4 domains, including nanotechnologies, microfluidics and advanced materials, it is envisaged that PoC  
5 Diagnostics can significantly benefit from a tighter interplay with Artificial Intelligence (AI). The  
6 interdisciplinary impact of AI is closely related with the general area of digital signal processing, forming  
7 an integrating platform for different applications and unifying their background based on computational  
8 intelligence and Machine Learning (ML). This approach follows ideas of Leibnitz presented in history,  
9 trying to interconnect researchers of different narrow areas who lost their ability to communicate Prochazka  
10 et al. (2021).

11 Indeed, AI and ML can lead to methods for integrating, analyzing and understanding multimedia data  
12 from a plethora of different devices. In addition, multivariate methods can correlate the current patient status  
13 with the previous history, adapting the findings to his personal history, in line with a more personalized and  
14 adaptive approach to care and favoring a more accurate prediction of future status.

15 To this end, there is the need to explore different research directions in AI and PoC Diagnostics. From  
16 one side, AI paradigms can be embedded into PoC testing devices, extending their capabilities and making  
17 possible analyses otherwise not viable, e.g. those including image analysis. This can lead to a convergence  
18 of pervasive computing and PoC Diagnostics. Similarly, networks of local devices can be devised taking  
19 advantage of distributed AI: wearable sensors and portable devices can communicate in an ecosystem, and  
20 their data can be cumulatively and coherently processed. Finally, AI can be decentralized, also considering a  
21 cloud-based approach, extending the capabilities of PoC Diagnostics all over the computational continuum.  
22 For instance, with a timely decentralized survey, PoC may allow the detection of anomalies that, once  
23 integrated with previously collected data and anamnesis, with the further purpose of a quality check to  
24 use reliable data, can be classified by AI methods. Immediately, the system can then alert the user and his  
25 caregivers. Moreover, specific assistance networks can guarantee control and rescue over the territory. Even  
26 if the cost of PoC devices is high, it reduces indirect costs and saves lives.

27 On the basis of such consideration, it has been our aim to collect in a Research Topic multidisciplinary  
28 contributions to "Artificial Intelligence in Point of Care Diagnostics" and, eventually, after a careful  
29 revision, five papers were included and published.

30 Computer-aided diagnostic method, including the X-rays-based techniques, is one of the economical and  
31 safe options to diagnose disease, in particular pneumonia. A challenge to the currently existing diagnoses  
32 of the pneumonia models has been the feature extraction from the clinical pneumonia X-ray dataset. Four  
33 authors from China address this research problem by implementing techniques in AI. D. Yao and Z. Xu,  
34 from the State Key Laboratory of Reliability and Intelligence of Electrical Equipment at Hebei University  
35 of Technology, Tianjin, and Y. Lin and Y. Zhan, Department of Radiology, Hainan Women and Children's  
36 Medical Center, Haikou Yao et al. (2023), describe a two-step process, Accurate and intelligent diagnosis  
37 of pediatric pneumonia using X-ray images and blood testing data. They propose a two-stage training  
38 multimodal pneumonia classification method combining X-ray images and blood testing data, which  
39 improves the image feature extraction through a global-local attention module. They conclude that the  
40 two-stage strategy can reduce the misdiagnosis rate of the pneumonia model. They furthermore find that  
41 the data gap between bacterial pneumonia and viral pneumonia is very large when bacterial pneumonia and  
42 viral pneumonia are indistinguishable using their method.

43 Autonomous AI has the potential to reduce disparities, improve the quality of care, and reduce costs  
44 by improving access to specialty diagnoses at the PoC. Diabetes and related complications incorporate a  
45 significant source of health disparities. Vision loss may be a complication of diabetes, supporting annual  
46 eye exams for prevention. Prior to the use of autonomous AI, store-and-forward imaging approaches  
47 diabetes-related eye exams were not frequent. The US Federal Food and Drug Administration recently  
48 approved an AI-based system to diagnose diabetic retinopathy (including macular oedema) without a  
49 specialist physician overread at the point of care. J. Goldstein, D. Weitzman, M. Lemerond, and A. Jones,  
50 working at Digital Diagnostics, Coralville, Iowa, United States wrote a comprehensive review to identify  
51 common workflow themes leading to the successful adoption of the AI-based system Goldstein et al. (2023).  
52 They identify the determinants for scalable adoption of autonomous AI in the detection of diabetic eye  
53 disease in diverse practice types: key best practices learned through the collection of real-world data. They  
54 propose best practices upon the evaluation of four health centers, measured as the attainment number of  
55 exams per month using the autonomous AI system against targets set for each health centers. They believe  
56 that attainable best practices can be generalized to other autonomous AI systems in front-line care settings,  
57 thereby increasing patient access, improving the quality of care, and addressing health disparities.

58 Automatic medical image detection utilizes AI techniques to accurately and efficiently detect lesions in  
59 medical images. It is a crucial task in computer-aided diagnosis (CAD) systems and can be integrated into  
60 portable imaging devices for intelligent Point of Care (PoC) Diagnostics. Feature Pyramid Networks (FPN)  
61 are commonly used deep-learning-based models for this purpose. However, FPN-based medical lesion  
62 detection models face two challenges: the object position offset problem and the degradation problem  
63 of IoU-based loss. To address these issues, in Xu et al. (2023), Z. Xu, T. Li, Y. Liu, Y. Zhan, J. Chen  
64 and T. Lukasiewicz –an international group of researchers from China and UK– propose a novel FPN-  
65 based backbone model, i.e., Multi-Pathway Feature Pyramid Networks with Position Attention Guided  
66 Connections and Vertex Distance IoU (abbreviated as PAC-Net and VDIoU respectively), to replace vanilla  
67 FPN for more accurate lesion detection. They conducted extensive experiments on the Deeplesion dataset,  
68 a public medical image detection dataset. The results demonstrated that PAC-Net outperforms all existing  
69 FPN-based depth models in terms of lesion detection evaluation metrics. Furthermore, the proposed  
70 PAC module and VDIoU loss proved to be effective and essential for achieving superior performance  
71 in automatic medical image detection tasks. Additionally, the VDIoU loss exhibits faster convergence  
72 compared to existing IoU-based losses, making PAC-Net an accurate and highly efficient 3D medical image  
73 detection model.

74 In Bai and Zhou (2023), another kind of lesion, namely skin lesion, is addressed, focusing on automated  
75 segmentation of dermatoscopy images, a task that plays a vital role in early skin cancer diagnosis. The  
76 complexity and indistinct boundaries of skin lesions make this task challenging. In this study, R. Bai and M.  
77 Zhou –affiliated to the University of Chinese Academy of Sciences and to the Department of Dermatology,  
78 China-Japan Union Hospital of Jilin University, Changchun, China– propose an innovative skin lesion  
79 segmentation network called SL-HarDNet. HarDNet serves as the backbone, enabling the network to learn  
80 more robust feature representations. Additionally, they introduce three powerful modules: the cascaded  
81 fusion module (CFM), the spatial channel attention module (SCAM), and the feature aggregation module  
82 (FAM). Briefly, the CFM combines features from different levels, effectively integrating semantic and  
83 location information of skin lesions. SCAM captures crucial spatial information, while FAM successfully  
84 fuses cross-level features. The high-level semantic position information features obtained from FAM  
85 are then reintegrated with CFM features to enhance the model’s segmentation performance. The authors  
86 evaluated and compared SL-HarDNet with state-of-the-art skin lesion segmentation methods on the  
87 challenge datasets ISIC-2016&PH2 and ISIC-2018. The experimental results consistently demonstrate  
88 that SL-HarDNet outperforms other segmentation methods, achieving the best performance in skin lesion  
89 segmentation.

90 Microscopy is another important domain in which AI can provide systems and tools to ease and make more  
91 accurate the diagnostic process. An example is reported in the paper by X. Li, M. Chen, J. Xu, D. Wu, M. Ye,  
92 C. Wang et al. Li et al. (2023) from Sino-European School of Technology of Shanghai University and the  
93 School of Mechatronic Engineering and Automation of Shanghai University Li et al. (2023). They address  
94 the detection and analysis of circulating tumor cells (CTCs), which are crucial for precise cancer diagnosis  
95 and prognosis assessment. Traditional methods that rely on isolating CTCs based on physical or biological  
96 features are labor-intensive and unsuitable for rapid detection. Additionally, current intelligent methods  
97 lack interpretability, leading to diagnostic uncertainty. To address these challenges, the author propose an  
98 automated method that utilizes high-resolution bright-field microscopic images to gain insights into cell  
99 patterns. Their method achieves precise identification of CTCs by employing an optimized single-shot multi-  
100 box detector (SSD)-based neural network with integrated attention mechanism and feature fusion modules.  
101 Compared to conventional SSD systems, their method exhibits superior detection performance with a recall  
102 rate of 92.2% and a maximum average precision (AP) value of 97.9%. Notably, they combined the optimal  
103 SSD-based neural network with advanced visualization technologies, namely, gradient-weighted class  
104 activation mapping (Grad-CAM) for model interpretation and t-distributed stochastic neighbour embedding  
105 (T-SNE) for data visualization. The work thus demonstrates the outstanding performance of the SSD-based  
106 neural network for identifying CTCs in the human peripheral blood environment, offering great potential  
107 for early cancer detection and continuous monitoring of cancer progression.

108 The Topic Editors wish to express their appreciation to all authors, reviewers and editors who contributed  
109 in bringing about this special section.

## **CONFLICT OF INTEREST STATEMENT**

110 The authors declare that the research was conducted in the absence of any commercial or financial  
111 relationships that could be construed as a potential conflict of interest.

## AUTHOR CONTRIBUTIONS

112 All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it  
113 for publication.

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