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COMMENTARY

Computer Vision and Artificial Intelligence Are Emerging Diagnostic Tools for the Clinical Microbiologist

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ABSTRACT Artificial intelligence (AI) is increasingly becoming an important component of clinical microbiology informatics. Researchers, microbiologists, laboratorians, and diagnosticians are interested in AI-based testing because these solutions have the potential to improve a test's turnaround time, quality, and cost. A study by Mathison et al. used computer vision AI (B. A. Mathison, J. L. Kohan, J. F. Walker, R. B. Smith, et al., J Clin Microbiol 58:e02053-19, 2020, https://doi.org/10.1128/JCM.02053-19), but additional opportunities for AI applications exist within the clinical microbiology laboratory. Large data sets within clinical microbiology that are amenable to the development of AI diagnostics include genomic information from isolated bacteria, metagenomic microbial findings from primary specimens, mass spectra captured from cultured bacterial isolates, and large digital images, which is the medium that Mathison et al. chose to use. AI in general and computer vision in specific are emerging tools that clinical microbiologists need to study, develop, and implement in order to improve clinical microbiology.

KEYWORDS artificial intelligence, bioinformatics, computer vision, digital pathology, microbiology, parasitology

Artificial intelligence (AI) is a hot topic in society and medicine. The idea machines can learn and that computers can "think" is intriguing to many of us. One application of AI is in the area of image interpretation in which software can recognize and characterize objects. This AI application is commonly described as "computer vision." Computer vision often uses machine learning to develop software algorithms, and computer vision software have already been employed in diagnostic laboratories. For example, CellaVision uses computer vision to classify the morphology of white blood cells, and studies have been performed to evaluate its ability to detect malarial parasites (1). Platforms are available to classify antinuclear antibody (ANA) patterns (2). In microbiology laboratories, computer vision can be used to aid in susceptibility testing (3, 4), detection of vancomycin-resistant *Enterococcus* (VRE) or methicillin-resistant *Staphylococcus aureus* (MRSA) growing in screening cultures (5, 6), and recognize rare events in microscopic images (e.g., acid-fast bacilli [7] or malarial parasites [8–11]).

Now, Mathison et al. describe a validation of computer vision for a new application—the detection of protozoa in trichrome-stained fecal smears (12). Today's routine practice in clinical parasitology includes many hours examining smears that lack protozoa and other parasites (13), but this study describes the possibility of offloading the review of many of these parasite-free smears to the computer, which would allow parasitologists to focus on confirming and characterizing protozoa that are detected. The study by Mathison et al. is not a pilot study, but it is a full validation of the computer vision software, which includes accuracy, precision, and limit of detection analyses. These analyses are needed before implementing a laboratory-developed computer vision diagnostic test in a clinical laboratory, and the article demonstrates a well-performed validation study.

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For those interested in developing AI solutions in the area of clinical diagnostic testing, a few important and generalizable points can be learned from this study's example. First, the authors played to the strength of the diagnostic tool. That is, they understood the strengths and weaknesses of computer vision and applied it in a way in which it was most clinically useful. Specifically, computer vision is ideal for screening large images for rare but defined events, which is how they applied computer vision to ova-and-parasite (O&P) screening. Second, the authors used AI to augment human effort, not to attempt to replace it. Although a future state of computer vision will likely achieve high enough accuracy that autoverification without human review is possible, the current state typically relies on a human to confirm the computer's classification decision. This approach uses software as a screening tool and expert human review as a verification of the computer classification. This approach uses the strengths of both computers (analyzing large images quickly) and humans (add specificity in the analysis attributed with critical thinking and complex pattern recognition). Third, the authors used both a training and a validation set when developing and evaluating the AI algorithm. Saving a subset of inputs for validation is an important step to help to ensure that an AI solution is not overfit. A validation set is necessary whenever attempting to validate and implement an AI application for clinical diagnostic use.

AI is increasingly becoming an important component of clinical microbiology informatics (14). Researchers, microbiologists, laboratorians, and diagnosticians are interested in AI-based testing because these solutions have the potential to improve a test's turnaround time, quality, and cost. The study by Mathison et al. used computer vision AI, but additional opportunities for AI applications exist within the clinical microbiology laboratory (15). Large data sets within clinical microbiology that are amenable to the development of AI diagnostics include genomic information from isolated bacteria (16), metagenomic microbial findings from primary specimens, mass spectra captured from cultured bacterial isolates, and large digital images, which is the medium that Mathison et al. chose to use. AI in general and computer vision in specific are emerging tools that clinical microbiologists need to study, develop, and implement in order to improve clinical microbiology.

Beyond parasitology, the Mathison et al. study is an example of what is possible with the democratization of AI. Computer vision represents the next frontier in laboratory diagnostics. Computer vision in the year 2020 is analogous to PCR in the year 2000. A generation ago, PCR was a laboratory tool and an exciting technology, and today nucleic acid amplification tests are an essential component of the clinical diagnostic laboratory. Clinical microbiologists that train 20 years from now will recognize computer vision as an integrated and essential tool for many areas of the microbiology laboratory. As computing power, deep learning, digital imaging, slide scanning, bacteriology automation, and digital storage become more and more accessible, creative laboratories, companies, and individuals will develop innovative computer vision solutions for many applications within clinical microbiology. Please find opportunities to partner with computer scientists and bioinformaticians to learn about AI and to perform studies like Mathison et al. have done, and please encourage clinical microbiology fellows to explore AI and to develop a deeper understanding of computer vision. AI in general and computer vision in specific are emerging diagnostic tools for clinical microbiology.

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