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Edited by Stephen P. Stone, MD

Reply to “How I learned to stop worrying and love machine learning” by

Mattessich et al

Introduction

Mattessich et al¹ have presented a very concise yet powerful message arguing why machine learning (ML) should be embraced as the future of dermatology. Autonomous artificial intelligence (AI) has become ubiquitous in today’s society, from self-driving cars to the spam filter in our e-mail, and medicine is no exception. ML is a field of computational science that involves models that can be trained to make predictions and take actions when confronted with new information. There are numerous applications of ML in medicine, from reading medical images to robot-assisted surgery.^{2,3} In recently published studies, various ML algorithms have been used in computer vision, a subset of AI primarily used in image recognition and classification, to detect skin cancer.^{4–8} Both clinical and dermatoscopic images have been tested with these algorithms and resulted in relatively high diagnostic accuracy. Deep learning algorithms, such as convolutional neural networks, were used in many of these studies with promising results; however, understandably, there are concerns typically associated with newer technology, some of which were addressed by Mattessich and colleagues and will be briefly discussed here.

Fear of the unknown and the “black box”

It is understandable to be afraid of the unknown. ML is a difficult subject for many, including most health care providers without a technical background. A black box *warning* is the strictest *warning* put in the labeling of prescription drugs or drug products by the US Food and Drug Administration when there is reasonable evidence of a serious hazard associated with the drug. All dermatologists are familiar with this black box warning. In contrast, the black box of ML is a complex concept, referring to the lack of interpretability of the model in how it determines outputs from inputs (ie, how the model

determines the diagnosis from a clinical image). The term black box is often used with deep learning models, due to their complex multilayered processing; however, many methods have recently been developed to explain the behavior of a black box model. One such example is Gradient-weighted Class Activation Mapping, which selects important regions of the image that correspond to the decision of interest (ie, melanoma versus benign growth or nevus) in a color gradient depending on the level of importance.⁹ These regions can then be examined by dermatologists to determine whether the selected regions are indeed more significant than nonselected regions for accurate diagnosis. With careful design and some of these newly developed methods, it is possible to understand and improve ML models. As physicians, we have been trained to maintain an open mind, whether in the clinical or research setting, and the same thing should apply to technology. Close collaboration with AI engineers is more important now than ever to design and create or improve existing models that we can trust, understand, and use to improve patient outcome.

Will machines take over dermatologists’ roles?

Another fear that some of us may have is being replaced by machines, as we have seen in the manufacturing sector. Although some of these technologies may potentially be used as stand-alone diagnostic tools to derive the final diagnosis, they are designed to supplement, not replace, the clinical care that we provide. There are many examples of diagnostic tools that have been developed to assist dermatologists in improving clinical diagnostic accuracy. Melafind (Strata Skin Sciences, Irvington, New York) is a noninvasive melanoma detection system approved by the US Food and Drug Administration in 2011, and Raman spectroscopy (Kaiser Optical Systems, Inc, Ann Arbor, Michigan) is a light-based device that detects skin cancer based on the biochemical composition of the tissue. Optical coherence tomography and reflectance confocal microscopy are noninvasive imaging techniques that allow for real-time visualization of the skin lesion of interest, though the diagnostic process can be time-consuming. Similarly, ML models can serve as another diagnostic tool that enable dermatologists to provide better care.

Wait time to be seen by a dermatologist can range from a few weeks to months, depending on the geographic region. Similar to teledermatology, which has successfully been used to reduce patient wait time, these innovative ML models may be used to triage patients with urgent dermatologic concerns, such as a potential melanoma, without delaying proper medical attention. Most importantly, humans are a social species. The importance of human connection in health care delivery should not be overlooked. Regardless of the diagnostic accuracy of the machine, having a lifeless machine deliver the diagnosis of melanoma may be perceived as a lack of concern for the patient's psychologic and spiritual well-being, resulting in low patient satisfaction and distrust in the health care system. Instead, patients usually prefer the delivery of a life-threatening or devastating diagnosis by a physician, with whom they can trust and discuss their diagnoses.

Conclusions

ML, similar to other diagnostic modalities, should be embraced as another important tool that dermatologists can utilize to improve patient care. The social aspects of health care highlight the indispensable role that dermatologists play in the delivery of quality dermatologic care.

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