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Machine learning for precision dermatology: Advances, opportunities, and outlook

To the Editor: With the explosion of big data in medicine driven by the advent of electronic medical records, next-generation sequencing, multi-omics, and noninvasive imaging techniques, dermatology is a field at the precipice of an artificial intelligence (AI) revolution. However, to the majority of clinicians, machine learning (ML) is a magical black box that is powerful but inaccessible. Here, we review the latest advances in ML applied to dermatologic diagnosis and treatment and highlight key discoveries with translational potential. ML is an AI technique that focuses on designing machines (or computers) that mimic human pattern recognition and problem solving.[1] With the rise of big data and data science, ML and AI already affect our daily lives in innumerable ways. Comparatively, clinical medicine has been slower to integrate ML into daily practice.[2] ML has typically been considered a tool well outside of a typical clinician's purview. At the same time, there is now an enormous demand for high-quality research that is advancing health care using ML and AI.[3] ML is a natural fit for translation into dermatology because dermatology is a specialty that is heavily reliant on visual evaluation and pattern recognition.

We searched the literature for high-quality studies published within the last 5 years describing the latest advances in ML applied to precision dermatology (Supplemental Table I; available via Mendeley at http://doi.org/10.17632/8w4dkfbdpk.1). Because digital photography is so prevalent, many ML studies in dermatology focus on lesion image analysis[4-7] and classification.[8,9] However, we also find that ML is now also being applied to electronic medical records, patient laboratory data, and genomic data from next-generation sequencing to study the genetic basis of diseases; to identify associations between comorbidities, risk factors, and disease prognosis; and to design and predict responses to pharmacologic therapies (Supplemental Table I). Applications span the prediction of adverse drug reactions[10] to responses to therapy in oncologic dermatology[11] and autoimmune and rheumatologic skin disease.[12] Together, these landmark studies outline a promising generalized framework that leverages gene expression data and multi-omics for biomarker discovery in autoimmune skin diseases and for biologics and immunotherapies in general (Fig 1, *A* and *B*). The convergence of ML and next-generation sequencing represents a golden opportunity to advance precision dermatology, and multidisciplinary collaborations between ML

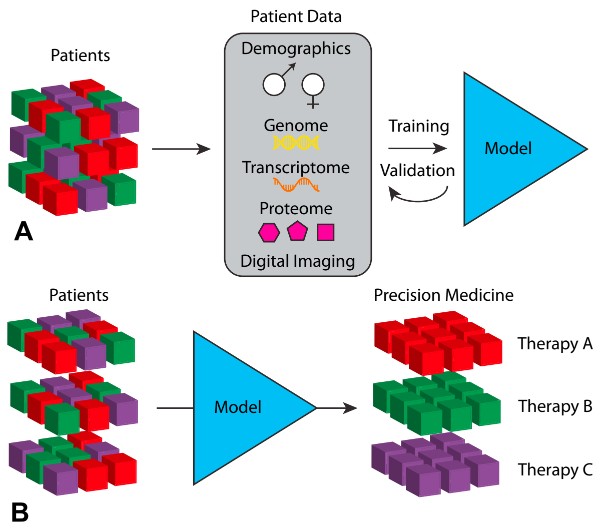

Fig 1. Machine learning for precision medicine. **A**, Schematic showing the training and validation of a machine learning model from multimodal input patient data, such as clinical images, patient demographics, and multi-omics. **B**, Application of the machine learning model to choose individually tailored therapies for specific disease states.

experts, biologists, and dermatologists will be required to expand the scope of this research.

The promise of an AI revolution in dermatology also comes with an accompanying fear of black boxes and a concern for how this may affect patient care and patient perceptions of care. Similarly, there is a prevailing fear among physicians that machines will largely replace clinicians in dermatology, as well as in radiology and pathology.[13] It is our view that ML will not replace dermatologists.[14] Rather, these tools will enable dermatologists to provide a higher quality of care to their patients.[15] In fact, we believe that ML tools, such as downloadable local programs on personal computers, open-source online web-servers, or mobile applications on smartphones, will be tightly integrated into the daily clinical practice of the dermatologist in the near future.

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Interactive skin self-examination digital platforms for the prevention of skin cancer: A narrative literature review

To the Editor: Skin self-examination (SSE) is an important secondary prevention strategy to reduce melanoma deaths.[1,2] Noninteractive teaching and facilitating aids (eg, brochures, handouts) to promote SSE behaviors have been recently complemented by interactive digital platforms, including mobile health (mHealth) apps. Although digital platforms may provide increased engagement and broader access, their safety and utility for improving health outcomes are unclear.[3,4] We sought to identify and describe the methodology, teaching and facilitating aids, and outcomes of published SSE intervention studies using interactive platforms.