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IP Indian Journal of Clinical and Experimental Dermatology

Journal homepage: www.ijced.org/

Review Article

Revolutionizing dermatology: The role of artificial intelligence in clinical practice

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A R T I C L E I N F O

Article history:
Received 19-01-2024
Accepted 19-03-2024
Available online 01-06-2024

Keywords:
Artificial intelligence (AI)
Technology
Healthcare
Dermatology

A B S T R A C T

AI (Artificial Intelligence) has transcended the field of science fiction and become a crucial component of various industries, including healthcare. In dermatology, the incorporation of AI is reshaping clinical practices, diagnostics, and treatment strategies. This article delves into the transformative impact of AI in clinical dermatology, exploring its applications, benefits, and the evolving landscape of AI-driven advancements.

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1. Introduction

Artificial intelligence (AI) holds a prominent position in the realm of computer science research, signifying a significant frontier in technological progress. Although AI has made substantial contributions to various medical fields over time, its integration into dermatology is a relatively recent and limited development.[1] Dermatologists, armed with a profound comprehension of AI concepts, can exploit the wealth of dermatoscopic and clinical data and images associated with skin conditions, positioning dermatology as a promising domain for AI applications in the field of medicine. Ongoing research encompasses diverse studies utilizing AI to tackle skin disorders like onychomycosis, atopic dermatitis, psoriasis, and skin cancer. This paper offers a comprehensive summary of AI, examining its current applications in dermatology and delving into potential future developments in this dynamic intersection of technology and skin health.[2]

The Association for the Advancement of Artificial Intelligence (AAAI) defines AI as "the scientific understanding of the mechanisms underlying thought and intelligent behavior and their embodiment in machines." Put simply, AI is a field of computer science that creates software with the goal of imitating human cognition and the analysis of complex data.[2,3]

2. Discussion

History: Mathematician Alan Turing authored a groundbreaking article titled "On Computable Numbers, With an Application to the Entscheidungs problem," which is widely acknowledged as the foundational work of the computer age. Collaborating with Princeton colleague Alonzo Church, Turing utilized calculus to introduce the notion of "effective calculability," establishing the basis for the computational model now recognized as an "algorithm".[3]

The term "artificial intelligence" (AI) was coined during a significant Dartmouth College conference in 1956. In the early 1970s, researchers in the medical field recognized the potential of AI applications in life sciences. However, technological limitations of the time hindered widespread AI use. Over the past two decades, advancements in computing power, fueled by improvements in hardware and software technologies, have increased awareness of AI's

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https://doi.org/10.18231/j.ijced.2024.021
2581-4710/© 2024 Author(s), Published by Innovative Publication.

potential to enhance current medical practices. Ongoing AI research spans various medical fields, such as dermatology.[4]

However, the introduction of AI in dermatology lags behind more innovative applications in fields such as radiology. As the landscape evolves and more research emerges in dermatological AI, there is an anticipation that the use of AI in dermatology will significantly reduce the gap between healthcare practitioners at different hospital levels, leading to improved diagnostic accuracy.

Key terms to note: AI can be broadly categorized into two main types: strong AI, also known as "artificial general intelligence," and weak AI. Strong AI aims to impart machines with human-level intelligence, enabling independent learning and diverse task performance. Attributes such as consciousness, ethical cognition, and multi-tasking capabilities may be possessed by such machines. However, the current reality indicates that achieving such complex machines is a distant goal.[2,4] In contrast, weak AI, or narrow AI, is the prevailing form of AI. In this scenario, machines are designed to learn and accomplish specific goals, requiring the creation of different programs for various tasks within the realm of weak AI.

AI is in a continuous state of evolution, transitioning from mere machine learning. The machine learning process begins with input, typically in the form of data, which algorithms consume to produce an output - a machine learning model. The most common learning processes include supervised and unsupervised learning. In supervised learning, the machine is trained to match inputs (such as images) to their correct outputs (e.g., diagnosis). Following supervised learning, unsupervised learning allows the machine to analyze new patterns from data and generate outputs.

AI can be categorized into Narrow AI and General AI. Narrow AI is designed to handle specific tasks, like identifying consolidation in lungs, while General AI can tackle a wide range of tasks, such as identifying consolidation, pleural effusion, or cardiomegaly.

Two primary learning methods of AI are shallow learning and deep learning. Shallow learning relies on predefined engineered features based on expert knowledge. Conversely, deep learning operates on deep features processed by convolutional neural networks (CNNs), mimicking the human brain's data processing capabilities. Unlike shallow learning, deep learning algorithms do not require explicit feature definition by human experts.

Artificial neural networks play a pivotal role in the field of AI, acting as versatile mathematical algorithms or models capable of identifying complex nonlinear correlations within extensive datasets—a process referred to as analytics.[3,5] These networks undergo training, during which errors resulting from minor algorithm adjustments are rectified, leading to a gradual enhancement in the accuracy and confidence of predictive models.

A branch of artificial intelligence called "machine learning" deals with automatically learning computer programs from experience without the need for explicit programming instructions. One can classify this learning as unsupervised, semi-supervised, or supervised. When computers are given datasets with issues and answers, they may learn by making mistakes; this process is known as supervised learning. In unsupervised learning, input data is analyzed without predetermined solutions. Labeled and unlabeled data are used in semi-supervised learning to improve learning.[6]

Integral to deep learning, artificial neural networks consist of multiple layers of hidden algorithmic processes. Information enters through the input layer, undergoes processing based on learned weights from machine learning processes, and exits through the output layer. This intricate structure empowers artificial neural networks to facilitate deep learning in machines.

Automated Diagnostics: AI algorithms, fueled by machine learning, excel in analyzing extensive datasets, including images of skin lesions.[2] These algorithms can aid dermatologists in swiftly diagnosing conditions like melanoma, psoriasis, and eczema by rapidly processing and interpreting visual data.

Skin Cancer Detection: Researchers have actively explored the integration of artificial intelligence (AI) to enhance and complement existing screening methods for both NMSC ("Melanoma and Nonmelanoma Skin Cancer"). Nasr–Esfahani et al. pioneered the training of an NN for melanoma detection, achieving a technique with 0.80 specificity and 0.81 sensitivity. In a breakthrough study in 2017, Stanford University utilized deep learning for skin tumors, employing a convolutional neural network directly trained from images using disease labels and pixels as inputs. Compared to 21 board-certified dermatologists, the network performed very well after being trained on a sample of 129,450 clinical photos that represented 2,032 distinct disorders.[3] This was a significant turning point in the use of AI in dermatology since the machine demonstrated proficiency in detecting and categorizing skin cancer on par with dermatologists. Nevertheless, the study's external validity remains uncertain due to the absence of demographic information, and the need for an extensive number of training images for these systems was acknowledged.

In a recent study, Fujisawa et al. (2019) investigated how deep learning technology may be used to create an effective system for classifying skin cancer from a small dataset of clinical photos. Between 2003 and 2016, 1,842 patients at the University of Tsukuba Hospital with skin tumour diagnoses provided 4,867 clinical images for the DCNN ("Deep Convolutional Neural Network") to be trained on. Fourteen diagnoses, encompassing both benign and malignant illnesses, were included in the dataset.

With 96.3 percent sensitivity and 89.5 percent specificity, the DCNN demonstrated a total classification accuracy of 76.5 percent.[4] In tests against nine dermatology trainees and thirteen board-certified dermatologists, the DCNN performed better than both, reaching an accuracy of up to 92.4 percent. This study underscores the potential of AI, even with a smaller dataset, to enhance the accuracy of skin cancer classification compared to traditional dermatological assessments.

The use of AI in histological detection of skin cancer is another significant application. Hekler et al. studied 695 lesions (345 melanomas and 350 nevi) that were categorized according to current recommendations by an experienced histopathologist. Using a CNN trained on 595 images for comparison against assessments by 11 histopathologists, the results showcased the potential of AI in histopathological analysis.[5]

Gustafson et al. (2017) concentrated on finding atopic dermatitis patients to include in genome-wide association studies. They presented a phenotypic method based on machine learning that made use of the EHR ("Electronic Health Record"). Their technique outperformed earlier algorithms with lesser sensitivity by combining coded information and data taken from encounter notes as features in a lasso logistic regression. It also showed a strong positive predictive value. This demonstrated how well machine learning and natural language processing work for EHR-based phenotyping.[6]

De Guzman et al. devised an ANN (Artificial Neural Network) specifically for identifying atopic dermatitis vs. unaffected skin, incorporating data directly from images. They found that using several hidden node-level models improved stability and overfitting resistance.[7] Despite the relatively small sample size of the model due to its experimental nature for discovering optimal AI processes, the authors recommended the incorporation of contextual information in AI programs to enhance accuracy.

AI is essential for clinical evaluation, individualized therapy plans, and results in forecasting in the context of psoriasis. Guo et al. integrated microarray-based gene expression patterns from two datasets using an artificial intelligence computer to predict psoriasis. Using three different independent validation procedures, their model, which used the Incremental Feature Selection approach, showed steady prediction accuracy, averaging 99.81 percent.[8] Nine psoriasis risk assessment systems (pRAS) were created by Shrivastava et al. utilizing feature selection strategies (PCA, FDR, MI) and different combinations of classifiers (DT, SVM, and NN). They found that the best pRAS system was a mix of SVM and FDR after testing with 670 psoriasis photos. Using cross-validation, they were able to achieve a 99.84 percent classification accuracy. Using the same protocol, this system likewise showed a 99.99 percent reliability.[9]

In a 2018 analysis, Han et al. trained a deep-learning model with a dataset of 49,567 images to attain superior diagnostic accuracy for onychomycosis compared to most participating dermatologists. On validation datasets, the model exhibited specificity and sensitivity ranges of 69.3%–96.7%, and 82.7%–96.7% respectively, with an AUROC, noted as 0.82–0.98. This highlights the potential of deep learning in enhancing accuracy in onychomycosis diagnosis.

As for ethical and legal implications, further details or context would be needed to address specific concerns or considerations related to the discussed AI applications in dermatology.

As artificial intelligence (AI) becomes more prevalent in dermatology and healthcare, ethical considerations regarding patient privacy, consent, and responsible technology use must be carefully addressed.[8,10] Legal frameworks also need to evolve to keep pace with rapid advancements in this field.

The integration of deep learning into the medical field has transformative potential for the healthcare industry through the use of AI.[10] Substantial progress has been made in areas such as cardiology and radiology, with FDA approval of medical devices marking a pivotal moment in 2016, empowering healthcare experts to improve medical practices with AI applications.[11]

In radiology, ML-based methods revolutionize the interpretation of brain images, enabling swift detection of hemorrhages, strokes, pneumothorax, and injuries.[12] These algorithms expedite diagnostic processes and serve as crucial tools in acute care, facilitating rapid assessment and alerting for emergencies. Additionally, sophisticated algorithms contribute to mammography analysis and lesion detection, further enhancing diagnostic capabilities.

In cardiology, AI applications have advanced, particularly in electrocardiogram readings for identifying cardiac rhythm abnormalities.[11] Novel approaches to managing diabetes are provided by FDA-approved devices, which include predictive alert-equipped monitoring systems.[12] Additionally, AI helps ophthalmology identify diabetic retinopathy early.[13]

Beyond these applications, AI has found its place in diagnosing sleep disorders, showcasing its impact in diverse medical domains.[11] Health systems leverage simple ML models based on HER to stratify hospitalized patients, aiding in the identification of those requiring admission to ICU ("Intensive Care Units").[14]

Approved medical devices represent just the initial phase of this transformative era. The wealth of raw data from EHR holds potential for developing prognostic models. AI-driven diagnostic enhancements aim to minimize errors traditionally associated with human diagnosis, ensuring the selection of the most suitable treatment for individual patients. Furthermore, Patient outcomes could be improved by automatically identifying from EHR data those patients who are eligible for novel medicines in clinical trials. This evolving landscape indicates the ongoing evolution of AI in healthcare, promising a future where technology plays an increasingly integral role in medical decision-making and patient care.[10]

Nevertheless, it is imperative to critically determine the potential challenges related to the integration of AI in healthcare. Numerous studies have highlighted vulnerabilities, emphasizing the need to navigate carefully amidst pitfalls while recognizing vast opportunities.[14,15] One concern is the susceptibility of AI systems to confounding factors, such as variations in image quality, intentional adversarial "noise," and biases in training data that can undermine classification performance.[14,16,17] Unintended biases, like associating rulers with malignant findings, and sensitivity to factors like image focus and centering have been observed.[18–20] Addressing these challenges through the refinement of AI models and the establishment of rigorous standards is crucial for harnessing the full potential of AI in improving medical diagnoses and patient care.[21]

Clinical evaluation, which involves patient history and tests, serves as the foundation for every physician's practice. However, in challenges and studies assessing the performance of Convolutional Neural Networks (CNNs), there is a tendency to underestimate the clinician's skills.[22] Many studies have noted the omission of critical clinical factors, like family and personal history, anatomic site, degree of sun damage, sex, and age in the evaluation of AI models.[23,24]

In a clinical setting, dermatologists employ comprehensive approaches, including total body examination, to assess variabilities like the Little Red Riding Hood sign, the macroscopic Ugly Duckling sign, and dermatoscopic predominant nevus patterns. These methods enhance specificity and sensitivity but need a holistic consideration of various factors.[25] Moreover, in experimental designs, in vivo, dermoscopy has demonstrated intrinsic superiority over artificial settings based solely on digital images.[26]

The lack of consumer confidence in AI is another obstacle to its use in therapeutic settings. The effectiveness of present legislation for the safe use of AI was shown to be a key influencing factor in people's confidence, according to recent global research that examined individuals' expectations and trust about the technology. About 63% of respondents said they were unsure or afraid to trust AI with health records. The black-box nature of machine learning, lacking explanations for how algorithms reach specific diagnoses, raises trust issues among patients, emphasizing the need for physician interpretation.[27,28]

Total body skin examination (TBSE) is not commonly accessible to patients, as studies indicate that primary care physicians and dermatologists often omit it from their standard practice examinations. Despite the highlighted importance of TBSE in many studies, inconsistent recommendations among professionals and barriers such as inadequate time and insufficient training hinder its widespread adoption.[29–31] AI could serve as a valuable assistant in TBSE, offering a non-invasive skin cancer screening tool that is not time-consuming for physicians, particularly benefiting primary care physicians and non-dermatology specialists.

However, the potential harms of extensive early detection efforts for skin cancer must also be considered. Overdiagnosis, A problem in the context of several illnesses classified as cancers, raises questions about the overdiagnosis of skin cancers in elderly individuals that are not melanoma and the identification of melanocytic tumors at relatively early stages with unclear malignant potential. These issues may lead to negative psychological impacts and unnecessary excisions, raising questions about the overall benefit of such aggressive diagnostic practices.[32] Balancing the benefits and potential harms remains a crucial consideration in the ongoing efforts for early detection and diagnosis in the realm of skin cancer.

Attention to images with confounding factors is crucial in the evaluation of AI systems, particularly considering lesion-adjacent artifacts. Image segmentation, a method that separates the lesion from the background, can address this subset of confounding factors, and various segmentation techniques are proposed for future studies.[33] It is noted that lesion classifiers trained on segmented images performed comparably to those trained on unsegmented images, but the quality of segmentation needs careful control to avoid introducing new challenges.[34]

A systematic review on skin cancer classification with CNNs highlighted a common limitation in reader studies: the predominant use of holdout data, referring to data obtained from the same source used for training and validation.[35] Generalizability to external testing data is crucial, as revealed by studies like Navarrete et al., which showed inferior sensitivity when applying an algorithm to a different dataset.[36] Future research should prioritize using out-of-distribution (OOD) data for evaluating classifiers, obtained from different sources, as the gold standard.[37]

Collaboration between humans and artificial intelligence is emphasized in future studies. Ensemble classifiers that combine human and AI assessments have demonstrated superiority, resulting in improved sensitivity and diagnostic accuracy.[38–41] Studies evaluating the impact of AI systems on dermatologists' decision-making highlight the complementary nature of AI input in clinical decisions.[42] Establishing standardized protocols for imaging quality is paramount, and the adoption of the DICOM ("Digital Imaging and Communications in Medicine") standard in dermatology is proposed. DICOM's capability to attach supplementary materials, de-identification profiles, and standardized datasets can contribute to overcoming pitfalls and enhancing generalizability in AI applications.[43]

Looking toward the future, strategic plans for AI development have been implemented globally, and AI in dermatology, particularly in melanoma diagnosis, holds exciting possibilities. Predictive analytics, treatment optimization, and personalized medicine are expected areas of significant contribution, ushering in a new era of precision dermatology.[3]

In conclusion, the challenges and opportunities presented by AI in dermatology require careful consideration. Strategic planning, attention to data quality and confounding factors, collaboration between humans and AI, and the adoption of standardized protocols are crucial for advancing the field. Prospective studies led by clinicians are essential to gaining insights and effectively integrating these cutting-edge tools into diverse clinical landscapes. The future of AI in dermatology promises exciting developments in predictive analytics and personalized medicine, contributing to the advancement of precision dermatology.

3. Conclusion

The incorporation of artificial intelligence (AI) into dermatology signifies a rapid and transformative development, offering substantial potential to revolutionize patient care. In particular, AI holds the promise of significantly enhancing the accuracy and sensitivity of screening for skin lesions, such as malignancies. However, unlocking the full potential of AI in dermatology requires the availability of comprehensive and diverse photographic and clinical data that covers all types of skin. Achieving this goal necessitates fostering enhanced international collaboration for robust skin imaging research.

Although AI assists in categorizing diseases broadly, accurate diagnosis and decision-making in dermatology presently require expertise and clinical correlation. Data predominantly originate from Western studies, underscoring the necessity of studies from diverse regions. As AI rapidly advances, having a foundational understanding of its principles, potential applications, and limitations becomes increasingly crucial.

In conclusion, clinicians should not view AI as a danger to their knowledge; rather, they should see AI as a promising addition to clinical practice in the years to come. A new age of synergistic collaboration between human knowledge and technology innovation will be ushered in when professional dermatologists embrace a grasp of AI ideas and use them to improve the quality of skin care service.

4. Source of Funding

None.

5. Conflict of Interest

None.

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Cite this article: Salam A, Abhinesh N. Revolutionizing dermatology: The role of artificial intelligence in clinical practice. *IP Indian J Clin Exp Dermatol* 2024;10(2):107-112.