DERMIS

Review Article

Volume and Issue: 05, 02

The Blind Spots of Artificial Intelligence in Skin Cancer Diagnosis

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Received : April 03, 2025
Published : April 22, 2025

ABSTRACT

Artificial intelligence (AI) has emerged as a promising tool in the detection of skin cancer, particularly melanoma, through the use of deep learning algorithms trained on vast datasets of dermoscopic images. While early results suggest that AI systems can match or even exceed the diagnostic accuracy of dermatologists, significant limitations hinder their clinical integration and broader application. One major challenge remains the lack of diversity in training datasets, which limits AI's efficacy in detecting skin cancers in individuals with darker skin tones, leading to potential disparities in diagnostic accuracy. Another limitation lies in the interpretability of AI decisions, as many deep learning algorithms function as "black boxes" with little transparency about how they reach specific conclusions. This lack of explainability can undermine physician trust and hinder the adoption of AI in clinical practice. Additionally, AI tools often struggle with rare or atypical presentations of skin cancer, which are underrepresented in the training datasets, increasing the risk of misdiagnosis. Ethical concerns include data privacy, informed consent, and the potential for AI systems to perpetuate biases if not adequately regulated. Furthermore, the lack of standardized protocols for integrating AI into clinical workflow presents operational challenges, such as determining when and how AI should be used as a decision-support tool versus a primary diagnostic method. Lastly, regulatory frameworks lag behind technological advancements, leading to uncertainty about the approval, oversight, and liability associated with AI-based diagnostic systems. Addressing AI's limitations in skin cancer detection will require technological advancements and a concerted effort to improve dataset diversity, enhance model transparency, ensure ethical use, and develop standardized clinical protocols—ultimately ensuring that AI complements rather than compromises the future of dermatological care.

Citation: Frasier K, et al. (2025). The Blind Spots of Artificial Intelligence in Skin Cancer Diagnosis. Dermis. 5(2):35.

DOI: https://doi.org/10.35702/Derm.10035

Keywords: Artificial Intelligence, Dermatology, Skin Cancer, Traditional Diagnostic Methods, Dermatological Care

INTRODUCTION

Artificial intelligence (AI) has gained significant attention for its potential to revolutionize the field of dermatology, particularly in the detection and diagnosis of skin cancer. Skin cancer, including melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC), is one of the most common cancers worldwide [1]. Melanoma is the deadliest, responsible for an estimated 57,000 deaths worldwide in 2020 [2]. Early detection is critical in improving survival rates, as melanoma's prognosis significantly worsens once it metastasizes. Studies show that localized melanoma has a five-year survival rate of approximately 99% when detected early. However, once melanoma spreads to regional lymph nodes or distant organs, the five-year survival rate drops significantly to 75% and 35%, respectively [3]. Traditional diagnostic methods, which rely on visual inspection, dermoscopy, and biopsy, are often limited by clinician expertise, inter-observer and intra-observer variability, and time constraints [4]. AI, specifically deep learning algorithms, has emerged as a promising tool to enhance accuracy and efficiency in skin cancer detection by rapidly analyzing dermoscopic images.

The increasing interest in AI applications is driven by studies showing that deep learning models can match or even exceed dermatologists' performance in detecting melanoma. This potential of AI to surpass human performance in specific diagnostic tests is not only intriguing but also offers potential solutions to the challenges of human error and variability in skin cancer diagnosis [5]. For instance, Patel et al. found that AI models achieved comparable diagnostic accuracy to dermatologists, particularly in the analysis of dermoscopy images, where sensitivity and specificity rates for melanoma detection were often as high as 85%. These models are typically trained on large datasets containing thousands of images of skin lesions, learning to differentiate between benign and malignant lesions through pattern recognition [5]. Once trained, AI can evaluate new images quickly and consistently, offering a potential solution to the challenges of human error and variability in skin cancer diagnosis. Given the global shortage of dermatologists, particularly in rural and underserved areas, AI's ability to assist in early skin cancer detection holds the potential to enhance access to life-saving diagnostic tools.

Despite the advancements of AI usage in skin cancer detection, its limitations are deeply rooted in the imbalance of training datasets and the diverse epidemiological factors influencing skin cancer incidence. Most AI models are developed using images of fair-skinned patients, reflecting the higher prevalence of skin cancer in lighter-skinned populations due to UV radiation damage [6]. However, this approach fails to account for the unique presentations of skin cancer in individuals with darker skin tones, who often develop lesions in atypical locations such as the palms and soles [7]. This lack of diversity in training data contributes to diagnostic inaccuracies and exacerbates health disparities, particularly as melanoma rates continue to rise globally in regions with predominantly fair-skinned populations, such as Australia, New Zealand, and the United States [8]. Addressing these gaps requires integrating epidemiological insights into AI model development to ensure equitable and effective skin cancer detection across diverse populations and regions.

Skin cancer presents unique challenges for detection and prevention due to its complex interplay of risk factors, which vary widely across populations and regions. While AI holds promise for improving early detection, the effectiveness of these tools depends heavily on their ability to account for diverse epidemiological and demographic characteristics. Current limitations in the diversity of training datasets indicate the need for a more inclusive approach to AI development, ensuring that these tools can be safely and effectively integrated into dermatological practice across different demographic groups. This review aims to evaluate the current capabilities and limitations of AI in skin cancer detection, with a focus on addressing challenges related to dataset diversity, model transparency, ethical considerations, and clinical integration. By examining these aspects of current AI applications, strategies to overcome these barriers are discussed to ensure AI tools are equitable, explainable, and effectively incorporated into dermatological practice.

REVIEW

Dataset Diversity and Model Generalizability

A critical obstacle to the effectiveness of AI in skin cancer detection is the lack of diverse and representative training datasets. Most AI models have been developed using images predominantly from fair-skinned populations with typical skin cancer presentations, limiting their ability to perform accurately across diverse patient groups. Melanoma, for instance, frequently presents differently in darker-skinned individuals,

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often appearing on less sun-exposed areas such as the soles of the feet or under the nails [7]. These variations, underrepresented in training datasets, lead to diagnostic discrepancies and poorer outcomes in individuals with darker skin tones. A study evaluating leading AI models such as ModelDerm, DeepDerm, and HAM10000 demonstrated this limitation, revealing significant drops in accuracy when these models were tested on the Diverse Dermatology Images (DDI) dataset [6]. The performance gap was particularly pronounced in detecting lesions on darker-skinned individuals (Fitzpatrick skin types V–VI) [6]. If AI models are not adequately trained on diverse datasets that include a wide range of skin tones, lesion locations, and cancer subtypes, their diagnostic accuracy decreases, particularly for underrepresented ethnic groups. This lack of diversity in training data severely limits the ability of AI models to generalize effectively and provide accurate diagnoses across different populations.

Improving dataset diversity is essential for addressing these disparities and enhancing AI's diagnostic accuracy. For example, fine-tuning AI models on datasets like the DDI set has demonstrated significant improvements, with performance scores nearly equalizing between light and dark skin types [6]. Additionally, AI systems often struggle with detecting rare presentations of skin cancer, such as amelanocytic melanoma, which lacks the pigmentation features many models rely on for recognition [9]. This limitation is not due to an inherent inability of AI to detect atypical presentations but rather reflects the need for developers to consciously include diverse and representative images in training datasets so that AI models can learn to recognize these outliers. Expanding training datasets to include a more comprehensive range of skin tones, lesion locations, and rare cancer subtypes is critical for developing AI models with robust diagnostic capabilities. Incorporating atypical cases, such as cancers that appear in unusual body locations or lack typical visual markers, would further enhance AI's generalizability and accuracy. Without addressing these gaps, AI systems risk perpetuating disparities in skin cancer detection, particularly in underserved populations and those presenting with rare or atypical conditions.

Interpretability and Physician Collaboration

A significant challenge in the adoption of AI for skin cancer detection is the lack of interpretability and transparency in its decision-making processes. Many deep learning models function as "black boxes," meaning that while they achieve high diagnostic accuracy, they offer little insight into the reasoning behind their conclusions [10]. This lack of transparency can undermine trust among healthcare providers, who are often reluctant to rely on an opaque system they cannot fully understand or verify. Critics of AI and its reliance on "black-box" medical decisions argue that it poses significant ethical challenges, as it undermines the clinician's moral responsibilities and erodes the foundation of trust central to the patient-physician relationship. In skin cancer detection, where the stakes are high and misdiagnosis can have severe consequences, it is essential for physicians to trust and feel confident in the tools they use. By improving the interpretability of AI models through explainable AI techniques, clinicians can better understand the rationale behind AI-generated decisions. This transparency fosters greater collaboration between AI and dermatologists, ensuring that diagnoses and treatment decisions are guided by both human expertise and the insights of machine learning.

To foster trust and collaboration, AI should be viewed as an assistive tool rather than a replacement for dermatologists. Physicians bring invaluable clinical judgment and the ability to integrate patient history, physical examination findings, and other diagnostic tools into the overall assessment—skills that AI lacks. However, visual assessment of pigmented lesions can vary significantly between different clinicians (inter-observer variability) and even between the same clinician evaluating the same lesion at different times (intra-observer variability) [11]. These inconsistencies arise from subjective interpretation, differences in experience, and the subtle nature of many skin lesion presentations, which can lead to variability in diagnosis and treatment decisions.

As a secondary decision-making tool, AI can assist dermatologists in improving diagnostic accuracy, particularly during periods of high patient caseloads, by providing valuable insights while ensuring clinicians maintain complete control over the final diagnosis and treatment plan. Soenksen et al. demonstrated this with a deep convolutional neural network-based system for analyzing suspicious pigmented lesions, including melanoma, which achieved a sensitivity of 90.3% and a specificity of 89.9%, matching the accuracy of dermatologists [12]. These systems have the potential to standardize diagnostic processes by identifying lesions that require further investigation, supporting a more uniform approach to diagnosis while preserving the dermatologist's essential role in the decision-making process. Allowing physicians to scrutinize AI decisions fosters greater trust, helps identify potential weaknesses

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or biases in the models, and promotes continual refinement of the technology, ensuring it complements rather than replaces clinical expertise.

Ethical and Operational Concerns

Ethical challenges pose a critical barrier to the successful deployment of AI in skin cancer detection, with data privacy emerging as one of the most pressing concerns. Large volumes of patient data, including images of skin lesions, are required to train AI models effectively. Without stringent data protection measures, the potential for breaches of patient privacy increases, raising concerns over consent and protections around patient confidentiality [13]. Questions also remain regarding the ownership of data used to train AI systems and whether patients should have a voice in how their data is utilized, especially in the context of commercial ventures or partnerships with third-party AI developers.

Beyond privacy concerns, AI carries the risk of reinforcing existing biases in healthcare, largely stemming from the underlying data rather than the AI algorithms themselves. Because AI models are trained on datasets influenced by human decisions and existing inequities, they may inadvertently perpetuate these biases [14]. For instance, if AI systems are trained predominantly on datasets representing specific populations or regions, they risk perpetuating diagnostic inaccuracies and exacerbating healthcare inequalities, particularly for underrepresented groups. In the context of skin cancer, this bias could manifest as AI models being more proficient at detecting cancer in lighter-skinned individuals while consistently underperforming in identifying cases in darker-skinned patients, thereby exacerbating existing disparities in healthcare outcomes. Daneshjou et al. demonstrated this by showing that AI models for early melanoma detection predominantly rely on datasets from patients with lighter skin types, raising concerns about their ability to accurately detect melanoma in patients with darker skin tones, who often present with more advanced and severe disease stages [6]. Without careful regulation and oversight, the widespread adoption of AI in skin cancer diagnostics risks exacerbating existing health disparities rather than addressing them.

Before AI can be seamlessly integrated into dermatological practice or broader healthcare settings, significant operational challenges must be addressed. Young et al. assessed the performance of dermatologist-level convolutional neural networks (CNNs) using real-world, non-curated images and reported false-positive or false-negative predictions in 6.5-22% of skin lesion images captured repeatedly in the same setting [15]. These findings underscore the critical need for rigorous validation of AI models to identify their limitations before deploying them in clinical care. Additionally, the absence of standardized protocols for when and how AI should be utilized in clinical workflows creates uncertainty for practitioners and healthcare institutions alike [16]. Establishing clear guidelines is essential, such as defining whether AI should function as an initial screening tool to flag high-risk lesions for dermatologists or serve as a secondary validation tool following a clinical diagnosis. Coupled with robust quality assurance and validation processes, these measures will ensure AI systems are implemented safely, effectively, and reliably in dermatological care.

Technological Constraints and Real-World Application

While AI systems have proven to be highly effective in controlled research settings, their performance in real-world clinical environments needs to be more consistent and reliable. In controlled studies, dermoscopic images are often captured under optimal conditions, with uniform lighting and precise image quality. However, in practice, image capture can vary significantly depending on the equipment used, the lighting conditions in a clinical room, or the skill of the individual taking the photograph. AI models perform best in controlled environments but may struggle with inconsistent or lower-quality images in real-world clinical settings [17]. To address this limitation, Acosta et al. utilized the Mask R-CNN model, which creates a bounding box around the lesion and processes only the relevant image portions, effectively minimizing the impact of visual noise [18]. Despite these advances, variability in image capture continues to present challenges in clinical settings, and future AI models will need to adapt to a broader range of image qualities and formats to maintain diagnostic accuracy.

Many AI systems are designed to operate on dermoscopic images, requiring specialized equipment. In resource-limited settings, where access to dermoscopy is scarce, this reliance on high-quality imaging limits the broader applicability of AI tools. To address this, future AI models must be adaptable to a broader range of image qualities and formats, including those taken with smartphone cameras or other more accessible imaging technologies [19]. This would make AI more practical in primary care settings or regions where specialized

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dermatological equipment is unavailable. This issue led to the development and U.S. Food and Drug Administration's authorization of DermaSensor in January 2024, making it the first AI-enabled medical device approved for skin cancer detection in primary care settings [20]. This approval followed a 2023 prospective blinded study that reported DermaSensor's sensitivity at 95.5% and specificity at 32.5% [21]. Given that primary care physicians often serve as the first point of contact for patients before referral to dermatology, tools like DermaSensor help bridge gaps in access to specialized care, particularly in rural or underserved areas, while enhancing diagnostic capabilities to differentiate normal from abnormal lesions.

A significant technological challenge in integrating AI into clinical practice is the need for continuous updates and retraining to keep pace with evolving diagnostic techniques and the availability of new data. To remain accurate and effective, AI models must be regularly retrained using high-quality, annotated datasets, a resource-intensive process that can be difficult to sustain over time [15,22]. Without frequent updates, AI systems risk becoming outdated or inaccurate, threatening their long-term viability in clinical settings. Current AI frameworks are largely static, underscoring the need for advancements in automatic adaptation techniques, such as "incremental learning," which allow AI models to integrate new datasets without compromising performance on existing data [22]. By enabling AI to evolve in tandem with medical advancements, these innovations could address critical concerns about the durability and clinical applicability of AI systems over time.

Regulatory and Legal Challenges

The regulatory landscape for AI in healthcare is still in its infancy, creating uncertainty around the approval, use, and monitoring of AI-based diagnostic tools. In many countries, regulatory bodies such as the U.S. Food and Drug Administration (FDA) are only beginning to develop frameworks for evaluating AI in medical contexts [23]. Currently, most AI systems used in dermatology are classified as decision support tools, assisting but not replacing the dermatologist's judgment. However, as AI becomes more advanced and integrated into diagnostic processes, questions of liability become increasingly complex—specifically, who is accountable if an AI system misdiagnoses a case or fails to detect skin cancer. If a clinician relies on an AI recommendation and the decision results in harm to the patient, issues of responsibility and liability in the context of medical malpractice come to the forefront [13]. To mitigate these risks, clinicians should use AI models as supportive tools to complement their clinical expertise rather than relying solely on AI-driven recommendations due to liability concerns [24]. As AI models continue to evolve, it will be essential to establish clear legal and medical frameworks that define accountability and resolve liability issues effectively.

This uncertainty also extends to the regulation of AI across different regions. Countries with well-developed healthcare infrastructures and established regulatory frameworks are often quicker to adopt and oversee AI-based tools, while others may lag, exacerbating disparities in the availability and oversight of AI technologies. For instance, Europe currently lacks well-defined regulatory frameworks for AI liability, highlighting inconsistencies in governance [13]. A global, standardized approach to AI regulation is needed to ensure that AI is implemented safely, ethically, and consistently across all regions. Achieving global regulatory alignment is critical for safeguarding patient safety, ensuring transparency, and fostering public trust in the use of AI in medicine.

Future Directions for AI in Dermatology

The potential for AI in skin cancer detection remains immense, especially as technological advancements continue to accelerate. To fully realize this potential, it will be essential to improve dataset diversity, enhance model interpretability, and address ethical and operational challenges, ensuring that AI becomes a reliable and equitable tool in dermatology. Interdisciplinary collaborations between technologists, dermatologists, and regulatory bodies will be essential in overcoming current barriers and ensuring that AI tools are deployed to improve patient outcomes without sacrificing safety or quality.

In the future, AI could expand its role beyond skin cancer detection to include monitoring treatment progress in patients and serving as a prevention tool for skin cancer. By analyzing lesion changes over time, AI models could provide real-time feedback, enabling dermatologists to track treatment effectiveness and make timely adjustments to optimize patient outcomes. A predictive AI model called LORIS (logistic regression-based immunotherapy-response score) was recently developed to identify cancer patients across various types who are most likely to respond to immune checkpoint inhibitors [25]. LORIS is just one example of an AI model that illustrates the expanding role of artificial intelligence in healthcare, demonstrating its potential not only in diagnosis but also in personalizing treatment strategies, improving patient out-

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comes, and advancing precision medicine.

AI integration with wearable technologies offers a proactive approach to skin cancer prevention by monitoring UV exposure and encouraging better sun protection habits. Horsham et al. conducted a field study evaluating the effectiveness of wearable UV sensors on sun protection habits among adolescent festival-goers and found a significant increase in the use of sunglasses and sunscreen during the weeklong study period [26]. This study demonstrates how AI-powered tools can not only enhance diagnostics but also play a pivotal role in prevention and treatment, highlighting the broad potential for AI to transform dermatological care.

CONCLUSION

The integration of artificial intelligence into skin cancer detection holds immense promise, offering enhanced accuracy, efficiency, and the potential to revolutionize dermatological care. However, realizing its full potential requires addressing significant limitations. The underrepresentation of diverse patient populations in training datasets undermines the generalizability of AI models, risking inequitable healthcare outcomes, particularly for individuals with darker skin tones who may present with atypical lesion characteristics. Moreover, the opacity of AI decision-making processes raises concerns about interpretability and trust, emphasizing the necessity for AI to function as an assistive tool that complements clinical expertise rather than as a standalone diagnostic authority. Ethical considerations, including data privacy, ownership, and the risk of perpetuating biases, demand rigorous regulatory oversight to ensure responsible deployment. Operational challenges, such as variability in image quality and the need for continuous model updates, highlight the importance of standardized protocols that adapt to real-world clinical environments. Moving forward, prioritizing inclusivity in dataset development, enhancing transparency in algorithmic decision-making, and fostering collaboration among AI developers, clinicians, and regulatory bodies will be critical. By overcoming these hurdles, AI can function as an invaluable asset in skin cancer detection, enhancing diagnostic accuracy, reducing health disparities, and ultimately improving patient outcomes in dermatological care.

DECLARATIONS

ACKNOWLEDGEMENTS

None.

FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

COMPETING INTERESTS

The authors declare no conflict of interest in preparing this article.

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