ISSN: 3067-0136

Academic Journal of Health Sciences & Research

Iris Publishers

Review Article

Training AI to See Us All: Toward Diagnostic Equity in Dermatology

Garima Manocha[1]*, Soumyaa Gulati[2], Ashna Malhotra[3] and Archana Gulati[4]

[1]*Senior Resident, Dr. N. C. Joshi Memorial Hospital, Karol Bagh, New Delhi, India*

[2]*Consultant Dermatologist at Kaya Clinic, Delhi, India*

[3]*Consultant Dermatologist at Medlinks, Delhi, India*

[4]*Director and Senior Consultant, Perfect look Clinic, Dehradun, India*

Corresponding author: Garima Manocha, Senior Resident, Dr. N. C. Joshi Memorial Hospital, Karol Bagh, New Delhi, India

Received Date: October 27, 2025

Published Date: November 25, 2025

Abstract

Artificial intelligence (AI) has emerged as a transformative force in dermatology, supporting lesion classification, teledermatology triage, and chronic disease monitoring. However, persistent bias in training datasets-particularly the underrepresentation of skin of color and rare dermatoses-limits diagnostic equity. This review examines the origins and consequences of such bias, the clinical and ethical risks of deploying non-diverse AI systems, and strategies to mitigate inequities through inclusive data collection, transparent reporting, algorithmic audits, and regulatory oversight. Achieving equity in dermatologic AI is not merely a technical challenge but a moral imperative.

Keywords: Artificial intelligence; Teledermatology; Skin of color; Bias in training system

Introduction

Artificial intelligence, particularly convolutional neural networks (CNNs), has demonstrated dermatologist-level accuracy in classifying skin lesions and other dermatoses [1]. While these advances hold significant promise, the performance of AI systems depends heavily on the quality and diversity of the training datasets. Multiple studies have revealed that dermatologic AI models are predominantly trained on images of lighter skin tones, with Fitzpatrick skin types IV–VI substantially underrepresented [2-4]. This lack of diversity raises concerns about the validity of these tools in real-world clinical environments, where patient populations are far more heterogeneous. The potential consequences include diagnostic inaccuracy, delayed care, and exacerbation of existing health disparities.

Current AI Applications in Dermatology

AI systems are increasingly being integrated into dermatologic workflows for a variety of purposes. These include the classification of pigmented lesions such as differentiating melanoma from benign nevi [1,5], triage in teledermatology to prioritize urgent cases [6], monitoring of chronic skin conditions through patient-generated photographs [7], and decision support for primary care providers evaluating suspicious lesions [8]. While these applications can enhance access and efficiency, they also inherit the biases embedded in their training datasets, resulting in variable accuracy across different demographic groups.

Bias in Training Data

Bias in AI dermatology arises primarily from the composition of training datasets. A review of 21 publicly available dermatology image repositories found that fewer than 10% of images represented darker skin tones, with most data originating from high-income countries [4]. Likewise, an analysis of AI dermatology studies from 2015 to 2020 revealed that only 10% documented skin tone information and just 20% reported race or ethnicity [3]. This lack of representation can lead to systematic errors in diagnosis, such as overestimating malignancy risk in benign pigmented lesions or failing to detect specific morphologic features in darker skin tones. Such deficiencies are not merely academic-they translate directly into unequal care, especially in high-stakes conditions like melanoma.

Impact on Skin of Color

Dermatologic diseases frequently present differently in darker skin, which can further complicate AI interpretation. Erythema, a key diagnostic feature in conditions such as psoriasis, atopic dermatitis, and erythema multiforme, may appear violaceous or hyperpigmented rather than red in darker skin tones [10]. AI models that have not been exposed to these presentations may misclassify or entirely miss such diagnoses. In one study, an AI model for melanoma detection demonstrated a sensitivity of 90% for Fitzpatrick skin types I–III, but only 63% for types IV–VI [5]. Similarly, when evaluated on the Diverse Dermatology Images (DDI) dataset-which includes pathologically confirmed images across a range of skin tones-models trained predominantly on lighter skin showed a 27–40% decrease in diagnostic performance [11]. These findings illustrate the tangible impact of dataset bias on clinical outcomes for patients with skin of color.

Rare Presentations and Underrepresented Diseases

In addition to skin tone bias, many AI systems lack adequate representation of rare dermatoses such as cutaneous T-cell lymphoma, genodermatoses, and tropical skin infections [12,13]. These conditions are often omitted from training datasets because of their low prevalence and the difficulty of obtaining large, annotated image collections. As a result, AI systems may generate false negatives or produce overly confident but incorrect predictions in these cases. Such limitations risk delaying diagnosis and appropriate referral, which can have serious consequences for patient care.

Ethical Implications and Clinical Risks

The deployment of biased AI in dermatology carries significant ethical and clinical risks. Unequal performance across demographic groups can exacerbate pre-existing disparities in dermatologic care [2,14]. Overreliance on AI-generated outputs may undermine physician autonomy and diagnostic reasoning, while repeated inaccuracies in underrepresented groups can erode patient trust in both technology and healthcare providers [15]. Given that people of color are already underrepresented in clinical trials, the integration of biased AI tools could amplify existing inequities through a digital medium.

Strategies for Mitigating Bias

Addressing bias in dermatologic AI requires deliberate and multi-pronged strategies. The most critical step is diversifying training datasets through global collaborations to collect images across all Fitzpatrick types and a wide spectrum of diseases [16]. Efforts such as the PASSION dataset, which contains thousands of images of pediatric dermatoses from Sub-Saharan Africa, are essential for creating more representative models [17]. Synthetic data augmentation using generative techniques such as DermDiff and BiasMitigateGAN offers an additional means of balancing datasets when real-world images are scarce [18,19]. Transparency is equally important. Dataset metadata-including skin tone, ethnicity, age, and geographic origin-should be reported routinely to facilitate bias detection and model evaluation [3]. Algorithmic performance should be audited regularly by independent teams using diverse benchmark datasets such as DDI [11], and subgroup-level metrics should be disclosed before clinical deployment.

Human-in-the-loop systems can further mitigate harm by ensuring that AI serves as a diagnostic aid rather than a replacement for clinician judgment [15]. Regulatory oversight is also necessary. Agencies such as the U.S. Food and Drug Administration (FDA) should require diversity standards in AI development and mandate equity audits as part of pre-market evaluation [19]. Institutional ethics committees can play a role in ensuring fairness across the entire AI lifecycle, from data collection to deployment.

Conclusion

AI has the potential to transform dermatologic care, but without intentional efforts to ensure diversity and fairness, it risks perpetuating the disparities it seeks to address. The underrepresentation of skin of color and rare conditions in training datasets undermines diagnostic equity and patient trust. Through inclusive data curation, transparent reporting, rigorous bias audits, clinician oversight, and regulatory action, it is possible to develop AI tools that truly serve all patients. Building equitable dermatologic AI is not simply a technical challenge-it is an ethical obligation.

References

1. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, et al. (2017) Dermatologist-level classification of skin cancer with deep neural networks. Nature 542(7639): 115-118.
2. Adamson AS, Smith A (2018) Machine learning and health care disparities in dermatology. JAMA Dermatol 154(11): 1247-1248.
3. Daneshjou R, Smith MP, Sun MD (2021) Lack of transparency and potential bias in artificial intelligence datasets and Algorithms. JAMA Dermatol 157(11): 1362-1369.

4. Buolamwini J, Gebru T (2018) Gender shades: Intersectional accuracy disparities in commercial gender classification. In: Proceedings of the 1st Conference on Fairness, Accountability and Transparency. 81: 77–91.

5. Nuttall R, Liu Y (2021) Racial disparities in artificial intelligence performance for skin cancer detection. Br J Dermatol 185(3): 561-563.

6. Finnane A, Dallest K, Janda M, Soyer HP (2017) Teledermatology for the diagnosis and management of skin cancer: A systematic review. JAMA Dermatol 153(3): 319-327.

7. Wu X, Oliveria SA, Yagerman SE, et al. (2015) Feasibility and Efficacy of Patient-Initiated Mobile Teledermoscopy for Short-term Monitoring of Clinically Atypical Nevi. JAMA Dermatol 151(5): 489-496.

8. Tschandl P, Rinner C, Apalla Z, Argenziano G, Codella N, et al. (2020) Human–computer collaboration for skin cancer recognition. Nat Med 26(8): 1229–1234.

9. Lester JC, Taylor SC, Chren M-M (2019) Underrepresentation of skin of colour in dermatology images: not just an educational issue. Br J Dermatol 180(6):1521–1522.

10. Taylor SC (2002) Skin of color: biology, structure, function, and implications for dermatologic disease. J Am Acad Dermatol 46(2 Suppl): S41–S62.

11. Groh M, Harris C, Soenksen LR, Lau F, Han R, et al. (2021) Evaluating Deep Neural Networks Trained on Clinical Images in Dermatology with the Fitzpatrick 17k Dataset. arXiv preprint arXiv: 2111.08006.

12. Nambudiri VE (2018) Artificial intelligence in dermatology: promises and pitfalls. J Am Acad Dermatol 78(3): 551–560.

13. Tschandl P, Rosendahl C, Akay BN, Argenziano G, Blum A, et al. (2019) Expert-level diagnosis of nonpigmented skin cancer by combined convolutional neural networks. JAMA Dermatol 155(1): 58–65.

14. Topol EJ (2019) High-performance medicine: the convergence of human and artificial intelligence. Nat Med 25(1): 44–56.

15. Han SS, Park GH, Lim W (2020) Augmenting dermatology datasets using generative adversarial networks. J Dermatol Sci 98(2): 99–105.

16. Gottfrois P, Gröger F, Andriambololoniaina FH, Amruthalingam L, Gonzalez-Jimenez A (2024) PASSION for Dermatology: Bridging the Diversity Gap with Pigmented Skin Images from Sub-Saharan Africa. arXiv preprint arXiv:2411.04584.

17. Nusrat Munia, Abdullah-Al-Zubaer Imran (2025) DermDiff: Generative Diffusion Model for Mitigating Racial Biases in Dermatology Diagnosis. arXiv preprint arXiv:2503.17536.

18. Mohammed AH (2025) BiasMitigateGan: Synthesizing Fair Training Data for Dermatology Ai Using Diffusion Models.

19. U.S. Food and Drug Administration (2019) Proposed regulatory framework for modifications to artificial intelligence/machine learning-based software as a medical device.