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Contrastive Learning for Dermatological Imaging: Progress, Limitations, and Future Prospects in Smart Device Engineering and AI-Driven Skin Lesion Analysis

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ABSTRACT

The integration of artificial intelligence (AI) and mobile imaging has transformed dermatology, enabling early, accessible skin disease screening through smartphones and portable dermatoscopes. Yet, the dependence of deep learning models on large annotated datasets restricts their scalability and fairness across diverse populations. Contrastive learning, a branch of self-supervised representation learning, has emerged as a promising alternative by learning discriminative image features without extensive labeling. This paper reviews developments in contrastive learning for dermatological imaging, emphasizing algorithmic innovations, device-level engineering, and fairness considerations. Drawing from recent literature between 2019 and 2025, the study identifies how contrastive pretraining improves lesion classification and segmentation while reducing annotation costs. It also highlights persistent challenges related to hardware variability, underrepresentation of darker skin tones, and the computational limitations of on-device models. The paper concludes with future research directions for integrating contrastive pipelines with smart imaging hardware, explainable AI (XAI), and equitable data governance frameworks to achieve trustworthy and accessible dermatological diagnostics.

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INTRODUCTION

The global rise of skin diseases, including melanoma and non-melanoma cancers, has increased the demand for accurate, low-cost diagnostic systems (Esteva et al., 2017; Akram et al., 2023). Advances in deep learning have enabled dermatologist-level image classification using convolutional neural networks (CNNs) and transformer-based architectures (Brinker et al., 2022; Sun et al., 2023). However, the high annotation cost and dataset imbalance in dermatology-particularly the underrepresentation of darker skin tones - continue to limit generalization (Hasan et al., 2024; Rezk et al., 2023).

Contrastive learning, a form of self-supervised learning, addresses this challenge by learning feature representations from unlabeled data through similarity and dissimilarity comparisons (Chen et al., 2020; Azizi et al., 2021). By maximizing agreement between augmented views of the same lesion while separating unrelated examples, contrastive methods produce transferable embeddings that support downstream tasks such as classification, segmentation, and retrieval. Recent frameworks like SimCLR, MoCo, BYOL, and SupCon have been extended to medical imaging, where they significantly reduce dependence on manual labeling (Azizi et al., 2021; Tschandl et al., 2020).

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In dermatological imaging, contrastive pretraining improves robustness to domain shift across devices and lighting conditions (Christopoulos et al., 2025). Multi-modal extensions, which incorporate both image and clinical metadata, enhance the model's ability to capture contextual cues related to patient age, skin tone, or lesion location (Zhang et al., 2024). Yet, despite algorithmic progress, the translation of contrastive models into clinical workflows remains limited due to hardware constraints, lack of fairness auditing, and unclear integration with mobile health systems (Goyal et al., 2021; Nagpal et al., 2023).

From an engineering standpoint, smartphone-based dermatology introduces new challenges. Electrical and electronic engineers focus on sensor calibration, illumination control, and spectral fidelity of skin imaging (Kundu et al., 2022). Computer engineers address model quantization and memory optimization to enable real-time inference on mobile hardware. Management information systems (MIS) researchers emphasize data security, governance, and system interoperability, while computer scientists refine contrastive objectives, augmentations, and fairness-aware optimization strategies.

This study reviews the progress, limitations, and emerging directions in contrastive learning for dermatological imaging, integrating perspectives from computing, engineering, and information systems. The goal is to provide a holistic overview of technical advances, design constraints, and ethical considerations shaping the next generation of AI-driven skin lesion analysis.

BACKGROUND AND EVOLUTION OF AI IN DERMATOLOGICAL IMAGING

Early AI Approaches to Skin Lesion Analysis

Initial attempts at automated dermatological diagnosis relied on traditional image processing techniques such as color thresholding, texture extraction, and rule-based pattern recognition (Celebi et al., 2015). With the advent of deep CNNs, performance improved dramatically, as models like InceptionV3 and ResNet achieved near-expert accuracy on dermoscopic datasets (Esteva et al., 2017; Brinker et al., 2022). Nevertheless, these supervised approaches required extensive labeled datasets such as ISIC and HAM10000, which are often biased toward fair-skinned patients and limited environmental diversity (Tschandl et al., 2020).

Transition to Self-Supervised and Contrastive Learning

Self-supervised learning emerged as a scalable alternative, enabling feature extraction without labels by solving proxy tasks such as image reconstruction or rotation prediction (Doersch et al., 2015). Contrastive learning advanced this idea by formalizing representation learning as a similarity comparison problem. Methods like SimCLR (Chen et al., 2020) and MoCo (He et al., 2020) demonstrated that meaningful representations could be learned from raw images using data augmentations and contrastive loss functions. In dermatology, this has translated to better generalization across varied lighting and device conditions (Azizi et al., 2021; Goyal et al., 2021).

Integration with Smart Device Engineering

The growing interest in edge computing has motivated efforts to bring contrastive models onto smartphones and embedded medical devices. Techniques such as pruning, quantization, and knowledge distillation allow compact deployment without substantial accuracy loss (Kundu et al., 2022). Engineers are also developing hardware-aware training approaches that align model complexity with available power and memory. These advances enable near-real-time skin lesion screening in resource-limited or remote regions where dermatologists are scarce.

Ethical, Fairness, and Data Governance Dimensions

Bias and transparency remain central challenges in dermatological AI (Hasan et al., 2024; Nagpal et al., 2023). Fairness-aware contrastive objectives and balanced data augmentation have been introduced to mitigate

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disparities across skin tone and lesion types. Furthermore, effective data governance - including patient consent, privacy, and interoperability with electronic medical records - is vital for responsible deployment. These dimensions highlight the essential role of MIS research in ensuring ethical AI integration into healthcare systems.

EMPIRICAL AND TECHNICAL FINDINGS

Recent studies demonstrate that contrastive learning can substantially improve dermatological image understanding by generating transferable and robust features from unlabeled data. In a large-scale investigation, Azizi et al. (2021) reported that self-supervised contrastive pretraining improved classification accuracy across multiple medical imaging tasks, including dermatology, by more than 15% over conventional supervised baselines. Their work introduced the "Big Self-Supervised Models" (BigBio) framework, which achieved dermatologist-level accuracy on certain lesion categories using only a fraction of labeled examples.

In a follow-up study, Goyal et al. (2021) applied contrastive objectives to dermoscopic images and observed improved feature alignment across varying devices and lighting conditions. Similarly, Nagpal et al. (2023) integrated fairness-aware contrastive pretraining to correct representation bias in datasets underrepresenting darker skin tones, yielding more balanced predictions across demographic groups.

Hardware-oriented research further complements algorithmic development. Kundu et al. (2022) introduced an edge-compatible contrastive model optimized for ARM-based mobile processors, demonstrating real-time inference at low power consumption while maintaining 92% diagnostic accuracy. In parallel, Zhang et al. (2024) proposed a multimodal framework combining contrastive visual embeddings with textual patient data to enhance diagnostic precision and interpretability. Table 1 summarizes representative studies between 2020 and 2025 that highlight progress in contrastive dermatological imaging and the growing trend toward deployable, fairness-conscious AI systems.

Table 1: Representative Studies on Contrastive Learning Applications in Dermatological Imaging (2020–2025)

Author(s)	Year	Method / Contribution	Focus Area	Key Outcome
Chen et al.	2020	SimCLR framework for representation learning	General vision	Foundation for self-supervised contrastive methods
Azizi et al.	2021	BigBio contrastive pretraining	Medical imaging	Improved classification with limited labels
Goyal et al.	2021	Contrastive dermatology pipeline	Lesion classification	Cross-device robustness
Kundu et al.	2022	On-device contrastive model	Smart device engineering	Energy-efficient edge inference
Nagpal et al.	2023	Fair contrastive learning	Skin tone fairness	Reduced bias across demographics
Christopoulos et al.	2025	SLIMP multimodal contrastive learning	Clinical metadata integration	Improved contextual accuracy
Zhang et al.	2024	Multimodal fusion of image and text	Diagnostic interpretation	Enhanced lesion categorization

These findings collectively illustrate that contrastive learning bridges the gap between data efficiency and deployment readiness. However, successful translation into real-world healthcare systems requires deeper consideration of interpretability, privacy, and interdisciplinary collaboration.

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CURRENT LIMITATIONS AND RESEARCH GAPS

Despite significant advances, the field faces several unresolved technical and ethical challenges that constrain practical implementation and broader adoption.

1. Domain Shift and Device Variability: Skin images captured with different smartphone cameras or under diverse lighting conditions often result in inconsistent model performance. Cross-device generalization remains a bottleneck, requiring adaptive or meta-contrastive strategies to align features across modalities.
2. Fairness and Representation Bias: Underrepresentation of darker skin tones and rare lesion types skews model learning. While fairness-aware loss functions are promising, the absence of standardized benchmarks for evaluating dermatology AI fairness limits reproducibility.
3. Explainability and Clinical Trust: Contrastive models are often opaque, providing little insight into which visual cues guide classification. Integrating explainable AI (XAI) techniques, such as saliency maps or feature attribution, remains an open priority to improve physician trust.
4. Hardware Constraints and Energy Efficiency: On-device deployment must balance diagnostic accuracy with battery consumption, latency, and memory limits. Hardware-aware model design - involving pruning, quantization, and neural architecture search - requires further optimization to ensure real-time usability.
5. Ethical and Data Governance Issues: Mobile dermatology applications raise concerns about patient consent, privacy, and secure transmission of medical data. MIS-driven frameworks for consent management and encryption are essential to prevent misuse or data leakage.
6. Limited Clinical Validation: Most contrastive dermatological studies remain in research stages with small datasets. Large-scale, multi-institutional trials are necessary to validate algorithmic claims and establish clinical reliability.

FUTURE RESEARCH DIRECTIONS

Future progress in contrastive dermatological imaging will depend on advances in both algorithmic innovation and interdisciplinary collaboration.

1. Fairness-Centric Dataset Development: Establishing open, demographically balanced skin image repositories with standardized metadata such as age, tone, and device type is crucial for equitable model training and validation.
2. Explainable Contrastive Architectures: Incorporating interpretable components-such as attention-based visualization or feature attribution modules-will enhance transparency, improve clinician trust, and support regulatory approval.
3. Hardware-Aware Learning: Co-designing models and edge devices to jointly optimize computational load, latency, and energy efficiency will make AI dermatology accessible in low-resource or remote settings.
4. Federated Contrastive Learning: Privacy-preserving distributed learning approaches can enable multi-institutional collaboration without centralized data storage, ensuring compliance with patient privacy standards.
5. Integration with Health Information Systems: Collaboration between MIS experts, clinicians, and engineers will ensure seamless, secure interoperability of AI models with teledermatology platforms and electronic medical records.
6. Ethical and Policy Frameworks: Future initiatives should define clear standards

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for transparency, consent, accountability, and auditability, ensuring that AI systems are both trustworthy and socially responsible.

CONCLUSION

Contrastive learning represents a transformative shift in dermatological imaging, offering data-efficient, transferable representations for lesion classification and segmentation. It bridges gaps in annotation cost and model generalization while aligning with the growing demand for mobile health diagnostics. Through interdisciplinary integration - spanning algorithm design, hardware engineering, and information governance - contrastive learning can support equitable, transparent, and scalable dermatology solutions.

Nevertheless, realizing this potential requires continued innovation in fairness-aware algorithms, explainability mechanisms, and energy-efficient model design. Collaborative partnerships between AI researchers, engineers, dermatologists, and information systems professionals are essential to translate these methods from laboratory models to trusted clinical tools. The progress of AI-driven dermatology ultimately depends not only on computational advances but also on the ethical and social frameworks that support responsible innovation.

REFERENCES

Akram, S., Khan, M., & Javed, A. (2023). Hybrid CNN approaches for lesion recognition in skin cancer diagnosis. *Journal of Medical Imaging and Health Informatics, 13*(2), 187–198.

Alzahrani, S. (2024). SkinLiTE: Supervised contrastive learning for imbalanced skin lesion datasets. *Biomedical Signal Processing and Control, 93*, 106054.

Azizi, S., Kornblith, S., Norouzi, M., Abid, A., Lee, H., & Hinton, G. (2021). Big self-supervised models advance medical image classification. *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, 3478–3488.

Brinker, T. J., Hekler, A., & von Kalle, C. (2022). Deep neural networks for skin cancer classification: Current state and future directions. *European Journal of Cancer, 166*, 181–190.

Celebi, M. E., Codella, N. C. F., & Halpern, A. (2015). Dermoscopy image analysis: Overview and future directions. *IEEE Journal of Biomedical and Health Informatics, 19*(2), 543–546.

Chen, T., Kornblith, S., Norouzi, M., & Hinton, G. (2020). A simple framework for contrastive learning of visual representations. *Proceedings of the 37th International Conference on Machine Learning (ICML)*, 1597–1607.

Christopoulos, M., Tzoumas, I., & Kyriakopoulos, K. (2025). SLIMP: Multi-modal contrastive learning for skin lesion diagnosis. *Medical Image Analysis, 93*, 103172.

Doersch, C., Gupta, A., & Efros, A. A. (2015). Unsupervised visual representation learning by context prediction. *IEEE International Conference on Computer Vision (ICCV)*, 1422–1430.

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature, 542*(7639), 115–118.

Gharawi, M. A., El-Gamal, F. E., & Basha, S. H. (2023). Self-supervised segmentation of skin lesions using generative models. *Mathematics, 11*(18), 3805.

Goyal, P., Zhai, X., Misra, I., & He, K. (2021). Self-supervised pretraining improves dermatology image classification on limited datasets. *IEEE Transactions on Medical Imaging, 40*(10), 2746–2757.

Hasan, R., Rezk, E., & Wong, A. (2024). Beyond accuracy: Fairness-aware skin lesion analysis using cost-sensitive learning. *Journal of Biomedical Informatics, 152*, 104714.

He, K., Fan, H., Wu, Y., Xie, S., & Girshick, R. (2020). Momentum contrast for

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unsupervised visual representation learning. *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 9729–9738.

Kundu, A., Sharma, S., & Banerjee, P. (2022). On-device self-supervised learning for efficient skin lesion recognition. *Sensors, 22*(14), 5411.

Nagpal, K., Shah, S., & Esteva, A. (2023). Towards fair dermatological AI: Skin-tone-balanced contrastive learning. *Journal of Biomedical Informatics, 146*, 104655.

Rezk, E., Wong, A., & Hussain, S. (2023). Addressing representation bias in dermatology AI through dataset diversification. *Artificial Intelligence in Medicine, 139*, 102473.

Science Advances DDI Dataset Study. (2023). Diversity in dermatology images: Addressing racial bias in AI datasets. *Science Advances, 9*(24), eabq6147.

Sun, Z., Xu, J., & Li, T. (2023). Transformer architectures in dermatological imaging: A review. *Computers in Biology and Medicine, 163*, 107136.

Tschandl, P., Rinner, C., & Argenziano, G. (2020). Data-driven approaches to detecting melanoma using deep learning and smartphone imagery. *The Lancet Digital Health, 2*(10), e512–e520.

Zhang, Y., Liu, R., & Zhao, D. (2024). Multimodal contrastive learning for dermatological diagnosis integrating images and clinical text. *Artificial Intelligence in Medicine, 152*, 102560.

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