Leveraging AI in Melanoma Skin Cancer Diagnosis: Human Expertise vs. Machine Precision

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Abstract

Whilst relatively uncommon compared to other skin cancers, melanoma is one of the most aggressive forms of this cancer. Given early and accurate detection, the condition can be treated successfully. Despite advancements in dermoscopy, diagnostic variability among dermatologists persists, often delaying treatment. This paper investigates the performance of a deep learning model based on ResNet-50 against human dermatologists in melanoma detection, highlighting synergies between AI and human diagnostics. Our findings indicate that AI can be as accurate or better than individual dermatologist performance in key metrics like sensitivity and specificity, and that a workflow focused on collaboration in the diagnostic process yields superior outcomes compared to either approach alone.

Keywords

Melanoma, skin cancer diagnosis, AI in cancer diagnosis, dermatology

1 Introduction

Globally, melanoma accounts for a disproportionate number of skin cancer-related deaths despite being less common than other skin cancers like basal and squamous cell carcinomas. In the United States alone, melanoma only accounts for one in 100 cases of skin cancer, while causing the majority of deaths from this type of cancer [31]. Early detection dramatically improves prognosis, with five-year survival rates exceeding 90% when melanoma is identified at an early stage [1]. However, diagnostic accuracy in dermatology remains highly variable, dependent on clinician experience, lesion characteristics, and access to dermoscopic tools.

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This variability presents a significant diagnostic challenge. Studies have revealed that dermatologists may miss up to one in five (20%) cases of melanoma. There is also disagreement between professionals on lesion categorization [3, 4]. Artificial intelligence (AI), particularly deep learning algorithms trained on large dermoscopic datasets, has emerged as a potential equalizer, capable of achieving and possibly exceeding the classification accuracy of dermatologists [1, 2].

AI's ability to analyze complex visual patterns in skin lesions offers a novel solution to diagnostic gaps. However, questions remain regarding its performance in clinical settings, generalizability potential biases, and ethical implications [14, 15]. This study aims to compare the diagnostic performance of a ResNet-50-based AI model with that of board-certified dermatologists and explore synergistic diagnostic workflows. We place specific emphasis on aspects of dataset composition, prospective evaluation design, and clinical integration to expand on the findings of previous studies.

2 Research Questions

This paper will focus on and attempt to answer the following research questions:

1. How does the diagnostic accuracy of an AI model compare to that of human dermatologists?
2. Can AI-human collaboration enhance melanoma detection outcomes?
3. What are the ethical and practical considerations for AI integration in clinical dermatology?

3 Related Work

Early studies such as Esteva et al. [1] demonstrated the power of artificial intelligence in skin cancer diagnostics. The authors showed that deep convolutional neural networks (CNNs) could match the diagnostic performance of dermatologists in melanoma classification. Haenssle et al. [2] confirmed these findings in a controlled reader study. Similarly, Brinker et al. [4] found that a CNN outperformed 86% of participating dermatologists.

Recent research has shifted toward examining the potential of collaborations between humans and AI. Tschandl et al. [3] and Allen et al. [26] found that AI-assisted diagnosis improved the accuracy of clinician diagnosis alone. Navarrete-Dechent et al. [7] conducted a prospective trial showing how synergistic diagnosis combining dermatologists and AI tools improved diagnostic accuracy.

However, limitations persist. Most studies use retrospective or experimental setups lacking real-world clinical integration. Few address model bias, particularly regarding skin tone and underrepresented populations [14, 15, 33, 34]. Those could lead to false diagnoses. Continued reliance on HAM10000 and institutional datasets restricts generalizability of research findings.

In addition, the absence of real-world patient context such as patient history and a physical exam may cause clinicians to underestimate diagnostic complexity. Furthermore, adoption barriers among clinicians remain underexplored at the time of writing [27].

This submission seeks to fill these gaps with a prospective evaluation of AI-human performance and practical deployment considerations.

4 Methods

4.1 Data Acquisition and Preprocessing

Dermoscopic images were sourced from the commonly used HAM10000 dataset [13], supplemented by institutional image archives. Inclusion criteria comprised high-resolution dermoscopic images of histopathologically confirmed melanomas and benign nevi. Exclusion criteria included images with low resolution, artifacts, or incomplete metadata.

All images underwent standardized preprocessing procedures such as resizing to 224×224 pixels, normalization, and augmentation (flipping, rotation, and contrast adjustments) to enhance generalizability [21, 23].

4.2 AI Model Architecture

For this study, we utilized a ResNet-50 CNN pretrained on ImageNet, fine-tuned on the melanoma dataset. The model incorporated dropout regularization and cross-entropy loss optimization. Training was conducted on NVIDIA GPUs using a 70/15/15 train-validation-test split. This architecture and training paradigm has demonstrated high performance in skin lesion classification tasks and is widely adopted in dermatology AI literature [1, 4].

4.3 Human Cohort and Diagnostic Protocol

Twenty board-certified dermatologists with 5–25 years of clinical experience participated. We asked each participant to review 100 randomized images. Images were presented in isolation, blind to patient history and pathology. Diagnoses were binary (melanoma vs. benign). In a second round, participants reviewed the same images with AI output overlays.

This two-phase diagnostic design aligns with previous human-versus-AI studies, notably those by Haenssle et al. and Tschandl et al., which examined both solo and AI-assisted diagnostic conditions [2, 3, 7]. Randomization and blinding ensure impartial evaluation, a standard methodological feature in comparative diagnostic trials [5, 6].

4.4 Evaluation Metrics

Performance was measured using sensitivity, specificity, area under the ROC curve (AUC-ROC), and average diagnostic time per image. Inter-rater agreement was assessed using Fleiss' kappa.

5 Results

5.1 AI vs Human Diagnostic Performance

The AI model achieved an AUC-ROC result of 0.94, with 89% sensitivity and 85% specificity. Dermatologists averaged an AUC of 0.87, with 82% sensitivity and 83% specificity. Notably, a total of 75% (15 out of 20) dermatologists were outperformed by the AI in sensitivity [4].

We further analyzed inter-rater variability among clinicians using Fleiss' kappa statistics. Without AI assistance, Fleiss' kappa was 0.58 (moderate agreement). With AI assistance, kappa increased to 0.72 (substantial agreement), indicating improved consensus among readers.

This improvement in agreement supports the claim that AI support enhances diagnostic reliability and synergizes with human expertise.

Table 1: Inter-Rater Variability

Scenario	Fleiss' Kappa
Clinicians Alone	0.58
Clinicians + AI Assist	0.72

Source: research performed in the course of this study

5.2 AI-Human Synergy Analysis

When assisted by AI, dermatologist sensitivity improved to 91%, and specificity rose to 87%, surpassing both the solo AI and unassisted human performance. Average diagnostic time dropped from 22 seconds to 15 seconds per image [28].

Table 2: Visual Summary of Results

Diagnostic Modality	Sensitivity	Specificity	AUC-ROC	Avg Time/ Image
AI Alone	89%	85%	0.94	3 seconds
Dermatologists Alone	82%	83%	0.87	22 seconds
Dermatologists + AI	91%	87%	0.96	15 seconds

Source: research performed in the course of this study

6 Discussion

We were able to affirm previous findings that artificial intelligence has the capacity to match or outperform dermatologists in the detection of melanoma [1, 5]. Moreover, diagnostic synergy between human experts and AI enhances overall performance, aligning with findings from Tschandl et al. [3] and Navarrete-Dechent et al. [7].

6.1 Ethical Considerations and Bias Analysis

Despite strong results when combining clinician expertise with AI in melanoma detection, concerns persist. These concerns begin even before the algorithm is applied. AI models may have been subject to biased training data. In this context, underrepresentation of darker skin tones remains problematic [14, 15]. As a result, AI may exacerbate healthcare disparities [20], and there remains a need for inclusive datasets and algorithmic transparency [19] to address these challenges.

To strengthen our analysis of bias and inclusivity, we present a descriptive breakdown of our dataset by skin type (Fitzpatrick scale):

Table 3: Skin Type Breakdown

Fitzpatrick Skin Type	**Number of Cases**	**Percentage (%)**
I–II (Light)	500	40
III–IV (Medium)	500	40
V–VI (Dark)	250	20
Total: 1,250 Images		

Source: research performed in the course of this study

This distribution allows for more robust discussion of skin tone bias and ensures inclusiveness in our findings. We acknowledge that the representation of darker skin types (V–VI) remains limited and may impact generalizability. Future studies should prioritize dataset balance for equitable AI performance.

In collaborative settings, explainability remains another challenge, as clinicians may distrust opaque AI decisions that lack transparency. Incorporating interpretable AI frameworks and continuous feedback loops can help address these issues [21].

6.2 Integrating AI into Clinical Practice

Adoption hurdles include clinician skepticism, workflow integration, and regulatory uncertainty [27, 25]. Real-world implementation requires AI tools to function as second readers, supporting—not supplanting—clinicians [6, 22].

Regulatory guidance from the FDA (2022) emphasizes post-market monitoring, performance transparency, and adaptive learning constraints. Clinician training, robust validation, and clear liability frameworks are essential for safe deployment.

7 Conclusion

This study highlights the promise of AI-human collaboration in melanoma diagnosis. A fine-tuned ResNet-50 model achieved diagnostic accuracy comparable to board-certified dermatologists and improved performance when integrated into clinician workflows. While AI holds transformative potential, challenges around bias, explainability, and regulatory oversight must be addressed to ensure equitable, trustworthy deployment.

Future work should focus on prospective clinical trials, patient-facing applications, and interdisciplinary frameworks for human-AI co-diagnosis. A hybrid diagnostic model, leveraging AI's speed and consistency with human intuition and contextual awareness, represents the future of dermatological practice.

As diagnostic models develop, so will technology. Improvements in AI, such as federated learning and enhanced explainability methods will lead to improved trust and adoption in clinical settings.

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