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A STUDY OF AI-POWERED TOOLS DIAGNOSTIC PERFORMANCE FOR SKIN CANCER DETECTION AND EFFICIENCY OF AI ALGORITHMS IN DETECTING MELANOMA AND OTHER SKIN CANCERS

Amar Singh[1], Sumeet Pal Saini [2], Pravesh Valecha[3], Dr Astha Pant[4*]

[1]MD, Associate Professor ,Department Of Dermatology, Venereology And Leprosy, Shri Ram Murti Smarak Institute Of Medical Sciences, Bareilly, India
[2]MD, Assistant Professor, Department Of Dermatology, Venereology And Leprosy, RIMT Medical College And Hospital, Mandi, Punjab
[3]MD,Assistant Professor Department Of Dermatology, Venereology And Leprosy, American International Institute Of Medical Sciences, Udaipur, India
[4*]MD, Assistant Professor, Department Of Dermatology, Venereology And Leprosy, Government Doon Medical College, Dehradun,Uttrakhand

***Corresponding Author:** Dr. Astha Pant
*Skin OPD, Department of Dermatology, Venereology and Leprosy Government Doon Medical College, Dehradun, Uttrakhand Email: aasthapant@gmail.com

Abstract
Background
Skin cancer remains one of the most common malignancies worldwide, and early diagnosis is crucial for improving survival. Traditional diagnostic tools, such as dermoscopy and biopsy, are effective but resource-intensive and subject to interpretation variability. Artificial intelligence (AI) has emerged as a promising solution for enhancing accuracy, reducing clinician burden, and providing consistent diagnostic support.

Objectives
This systematic review aimed to evaluate the diagnostic performance of AI-powered tools for skin cancer detection compared to conventional methods. It also examines emerging AI trends, barriers to clinical adoption, and directions for future research.

Methodology
Following the PRISMA guidelines and using the PICO framework, relevant literature from 2019 to 2024 was reviewed via PubMed. Seven key studies comparing AI methods, including convolutional neural networks (CNNs) and hybrid models, with standard diagnostic techniques were analyzed. The metrics assessed included sensitivity, specificity, accuracy, and area under the curve (AUC).

Results
AI models showed excellent diagnostic performance, with sensitivities between 92.3% and 94% and specificities of up to 95.8%, reducing false positives. The accuracy exceeded 87.5%, with AI systems

matching or surpassing non-expert clinicians. AUC values ranged from 0.92 to 0.96, indicating robust reliability. Hybrid and augmented AI approaches improved clinical performance by 5–10%.

Conclusion
AI-based diagnostic tools offer significant potential for improving skin cancer detection by enhancing accuracy and consistency. However, successful integration into clinical practice requires diverse datasets, real-world validation, and ethical safeguards.

Keywords: Artificial Intelligence, Melanoma, Skin Cancer, Diagnostic Accuracy, Deep Learning, Dermoscopy, Clinical Integration, Augmented Intelligence

Introduction

Global Prevalence of Skin Cancer: Skin cancer is one of the most common malignancies worldwide. Non-melanoma skin cancers (NMSCs), such as basal and squamous cell carcinoma, account for the majority, while melanoma—though less frequent—causes a disproportionately high number of deaths due to its aggressiveness. Globally, over 1.2 million NMSC cases and 300,000 melanoma cases are reported each year, particularly in regions with high UV exposure and limited dermatologic services [1].

Challenges in Early Detection: Early detection significantly improves outcomes, especially for melanoma, with survival rates of over 95% when caught early [2,3]. Conventional methods such as clinical examinations, dermoscopy, and biopsy remain standard but are resource-intensive and depend heavily on clinician expertise. Menzies et al. (2023) highlighted limitations, including variability in interpretation and limited availability in underserved settings, demonstrating the need for scalable, objective tools [4].

Traditional Diagnostic Methods: Traditional skin cancer diagnosis involves visual assessment using the ABCDE criteria—Asymmetry, Border irregularity, color variation, Diameter, and Evolution—often supplemented by dermoscopy. Lesions with irregular shapes, uneven borders, multiple colors, diameters >6 mm, or evolving characteristics raise suspicion. These are examined through physical and dermoscopic evaluations [5,6].

Dermoscopy enhances detection by visualizing subdermal features, such as pigment networks, atypical vessels, and regression structures. Irregular networks and abnormal vascular patterns suggest malignancy. These findings can help dermatologists to differentiate lesions, often aided by scoring systems. However, accuracy depends on clinician skill, leading to inter-observer variability [7].

The Emergence of Artificial Intelligence in Dermatology: AI, particularly convolutional neural networks (CNNs), has revolutionized dermatological diagnostics. Esteva et al. (2017) showed that CNNs could match dermatologists in distinguishing benign from malignant lesions [8,9]. These models, trained on large image datasets, identify subtle patterns that are often missed by humans. Ferrante di Ruffano L et al. (2018) further demonstrated AI's capacity to detect intricate features in high-volume data, confirming its diagnostic potential in dermatology [10].

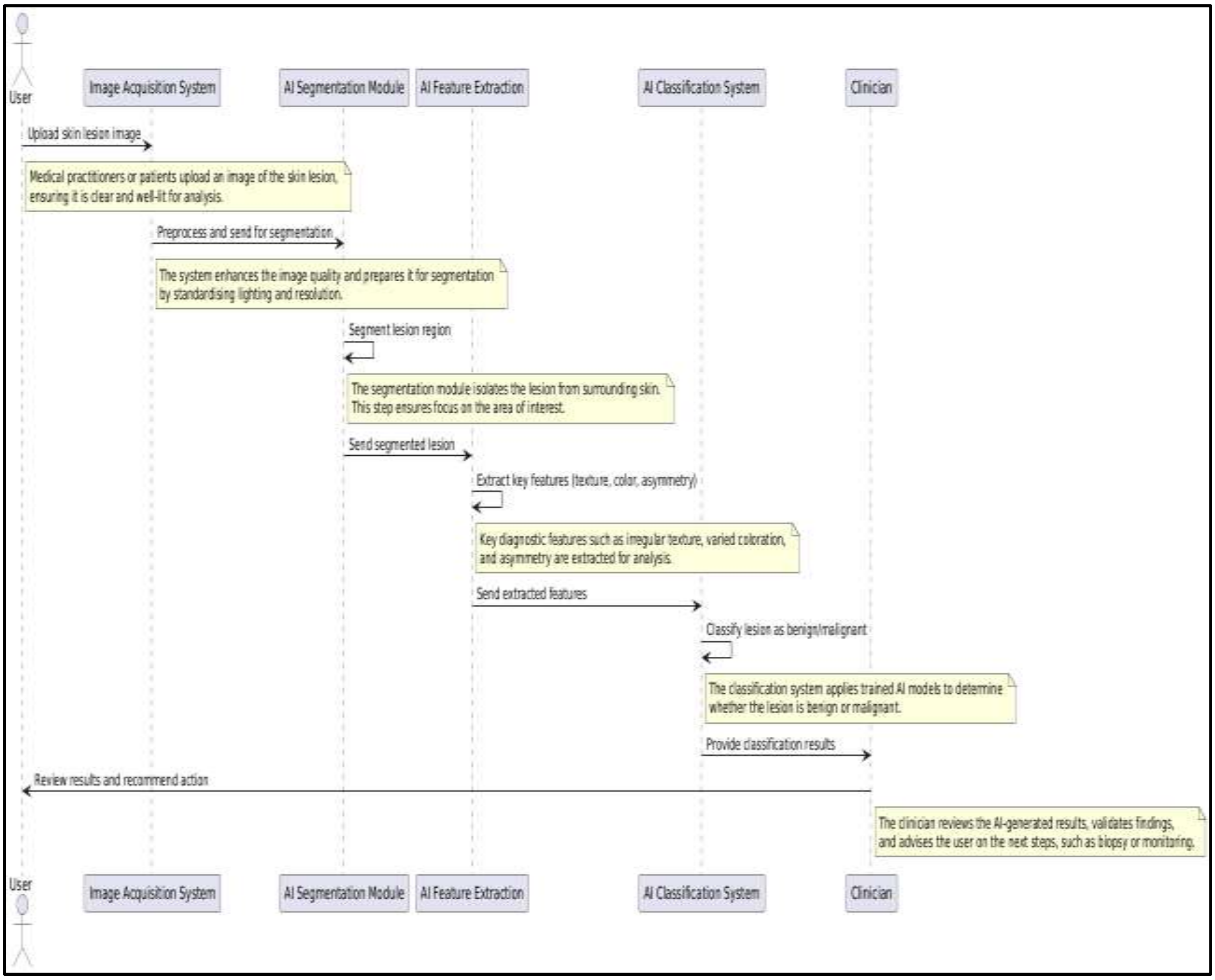

Figure 1: AI-powered workflow for skin lesion classification (decision making)

Artificial Intelligence (AI) has significantly enhanced dermatology by automating skin lesion analysis, improving diagnostic accuracy, and streamlining workflows. Traditional diagnostic methods often involve time-consuming processes, whereas AI-driven analysis can provide real-time assessments of dermoscopic images, enabling clinicians to make more efficient evidence-based decisions (Figure 1). AI-assisted workflows integrate multiple steps, including lesion segmentation, feature extraction, classification, and final clinician validation, thereby ensuring structured and accurate diagnosis. By prioritizing suspicious cases and assisting in clinical decision-making, AI improves efficiency while maintaining the essential role of dermatologists in the diagnostic process. The following workflow illustrates how AI is incorporated into dermatology for lesion classification and patient management (Figure 2)

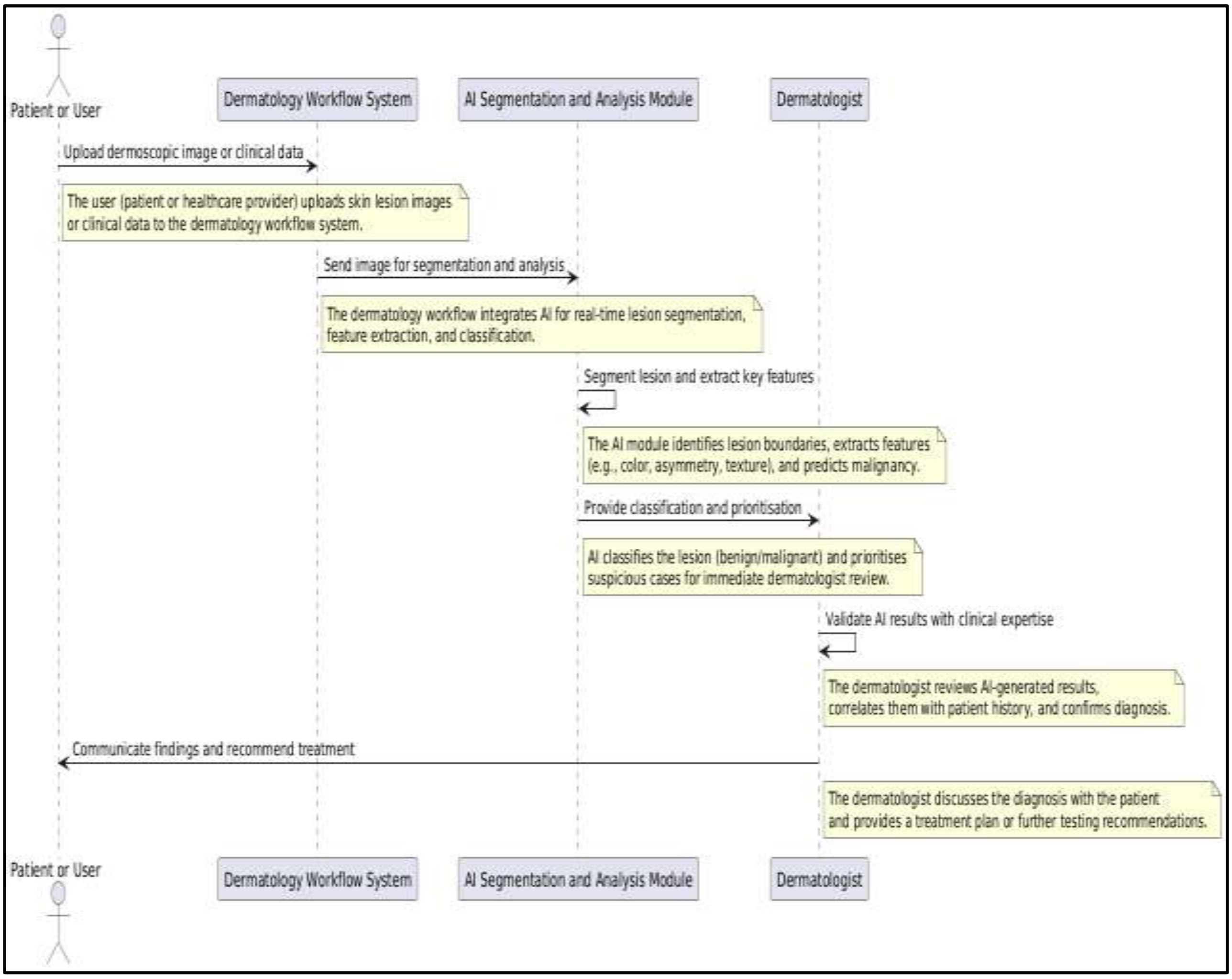

Figure 2: AI-assisted dermatology workflow for lesion classification (work on decision)

One of AI's defining strengths of AI is its ability to reduce subjectivity in skin cancer diagnosis. Diagnostic accuracy often varies among clinicians owing to differences in training, experience, and fatigue [11–15]. Mahmoud et al. (2024) reported AI sensitivity at 92.3% and specificity at 95.8% for melanoma detection, outperforming many novice clinicians [16]. Such consistency ensures equitable care and minimizes the risks of over- or under-diagnosis.

AI-powered tools can also bridge gaps in care when dermatologists are scarce. Menzies et al. (2023) evaluated mobile-based AI systems capable of effectively diagnosing skin lesions, enabling general practitioners and patients to access expert-level diagnostics using handheld devices [4]. These innovations democratize care and extend diagnostic capabilities to underserved populations.

AI enables real-time dermoscopic image analysis, thereby enhancing the speed and efficiency. Traditional methods involve sequential steps such as biopsy and histopathology, delaying treatment. In contrast, Salinas et al. (2024) showed that AI could rapidly prioritize suspicious lesions, expediting diagnosis, and improving outcomes for high-risk patients [22]. This integration helps clinicians make quicker, evidence-based decisions [17–21].

AI systems evolve over time by learning from expanding datasets. Brancaccio et al. (2024) emphasized the value of hybrid models, where AI complements clinician judgment by flagging ambiguous lesions and providing probability scores [26]. Such collaboration strengthens diagnostic confidence and accuracy [23–25].

Challenges in clinical integration: Despite AI's promise, challenges remain. Data biases due to limited skin-type diversity in training datasets reduce performance equity. Wei et al. (2024) stressed the need for inclusive datasets and standardized validation [27–29]. Additionally, AI accuracy in experimental settings may falter in real-world practice owing to image variability, patient factors, and complex clinical decision-making [4,30].

AI tools must be validated in diverse clinical settings to ensure their effective integration. Transparency and interpretability are essential for clinician trust. Overcoming barriers through inclusive data, real-world testing, and workflow compatibility is key to realizing AI's potential of AI as a transformative tool in dermatology.

Objectives

This systematic review aimed to evaluate the diagnostic performance of AI-powered tools in detecting melanoma and other skin cancers, comparing their accuracy and efficiency with traditional methods, such as dermoscopy and biopsy. It also explored AI's speed, accessibility, and reliability of AI across clinical settings, highlighting its role as a supportive or standalone diagnostic aid. This review further examined emerging AI technologies, such as convolutional neural networks and mobile-based tools, and analyzed barriers to clinical integration, including algorithmic bias and data variability. Lastly, it offers recommendations for future research and implementation strategies to optimize AI's role of AI in dermatological care.

Methodology

Framework: This systematic review adhered to the principles outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency and reproducibility throughout the research process. The PICO framework guided the selection, categorization, and analysis of the included studies. Each element of the PICO framework was explicitly defined to address the objectives of this review. **Population (P):** Patients with suspected malignant skin lesions. **Intervention (I):** Diagnostic approaches employing AI-based tools such as machine learning algorithms, convolutional neural networks (CNNs), and spectroscopy-enhanced imaging techniques. **Comparison (C):** Traditional diagnostic methodologies, including dermoscopy, clinical visual examination, and histopathological biopsy. **Outcomes (O):** Performance metrics, such as sensitivity, specificity, accuracy, and practical implementation challenges. This framework ensured that the review comprehensively assessed the diagnostic effectiveness and clinical relevance of AI-driven technologies compared with established methods.

Search Strategy: To identify relevant studies, a systematic literature search was conducted across multiple databases with PubMed serving as the primary source. The search query incorporated combinations of keywords and Boolean operators to capture the breadth of research on AI diagnostics for skin cancer. The query was tailored to include recent advancements in the last five years, ensuring that the review reflected the latest developments.

Search Query

("skin cancer" OR "melanoma" OR "dermatology") AND
("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning") AND
("diagnosis" OR "accuracy") AND ("clinical" OR "retrospective" OR "RCT") AND
("2019/12/16"[Date - Publication] : "2024/12/16"[Date - Publication])

Inclusion and Exclusion Criteria:

This systematic review included original English-language research articles from the past five years that assessed AI-based diagnostic tools for skin cancer, specifically those reporting measurable outcomes such as sensitivity, specificity, and accuracy. Clinical studies, retrospective analyses, and randomized controlled trials were prioritized. Articles were excluded if they were not in English, lacked primary data (e.g., reviews and commentaries), did not report diagnostic metrics clearly, or focused on non-malignant skin conditions.

The study selection followed a three-stage process. First, two independent reviewers screened the titles and abstracts for relevance. Next, the full texts of shortlisted studies were reviewed using predefined eligibility criteria, with disagreements resolved by discussion or a third reviewer. Finally, data were extracted using a standardized form to capture the study characteristics, AI tool specifications, diagnostic performance, and clinical relevance. This structured approach ensured the inclusion of high-quality relevant research.

Included studies: The systematic search identified seven key studies that met the inclusion criteria. These studies represent a mix of methodological approaches, datasets, and clinical settings, providing a robust basis for analysis. The articles included were as follows:

1. Salinas et al. (2024): A systematic review and meta-analysis comparing AI tools with clinicians [22].
2. Claret et al. (2024): Enhanced skin cancer diagnosis using convolutional neural networks (CNNs) integrated with discrete wavelet transformation [31].
3. Menzies et al. (2023): A multicentre prospective diagnostic trial evaluating mobile phone-powered AI [4].
4. Brancaccio et al. (2024): A reality check on AI's diagnostic capabilities in clinical environments [26].
5. Mahmoud et al. (2024): Early automated detection systems for skin cancer diagnosis employing AI techniques [16].
6. Melarkode et al. (2023): A comprehensive review of AI-powered diagnostics, identifying challenges and future directions [32].
7. Wei et al. (2024): An overview of AI applications in skin cancer detection, focusing on barriers to clinical integration [27].

Data analysis: The data analysis involved quantitative analysis. Diagnostic performance metrics were extracted from each study to facilitate direct comparisons between AI-powered and traditional diagnostic methods. The sensitivity, specificity, and accuracy values were summarized and compared using descriptive statistics.

Comparative Methods

AI Techniques Used

Artificial intelligence (AI) in skin cancer diagnosis primarily employs deep learning, particularly convolutional neural networks (CNNs). Studies by Salinas et al. (2024) and Mahmoud et al. (2024) confirmed that CNNs are highly effective for analyzing dermoscopic and clinical images, achieving an accuracy comparable to or surpassing that of trained clinicians [16,22]. In addition to CNNs, hybrid models have been introduced to boost diagnostic performance. For instance, Claret et al. (2024) combined CNNs with discrete wavelet transformations (DWT) to improve feature extraction and lesion differentiation [31].

Traditional Methods

Clinical examination and dermoscopy remain the gold standards in skin cancer diagnostics and are used as benchmarks to validate AI systems. These rely on the visual assessment of morphological features by dermatologists. Menzies et al. (2023) reported a 21.5% accuracy gap favoring AI over novice clinicians, underscoring AI's potential, particularly when complementing human expertise [4].

Validation Approaches
Most AI models have been validated using public datasets such as HAM10000 and ISIC [33,34]. These repositories of annotated dermoscopic images support model development and refinement. However, although the experimental outcomes are promising, clinical deployment remains limited. Broader real-world testing is vital to confirm AI reliability across diverse patient populations and clinical settings.

Outcome measures: The outcome Measures for the Study: The focused on evaluating and comparing the diagnostic performance of AI-based tools with traditional diagnostic methods used by clinicians. Key measures include (a) sensitivity (Sn): the ability of AI-powered tools to correctly identify true positive cases (e.g., correctly diagnosing malignant skin lesions). The sensitivity values demonstrate the effectiveness of AI models for detecting skin cancer compared with clinicians. (b) Specificity (Sp): The ability of the diagnostic tool to correctly identify true negatives (e.g., identifying benign lesions as non-cancerous). This measure highlights AI's precision of AI in avoiding false positives, which is essential for reducing unnecessary interventions. (c) Accuracy: The overall proportion of correctly identified cases, both malignant and benign. This measure provides a comprehensive view of the diagnostic performance of the tool when compared with clinical methods such as dermoscopy or biopsy. (d) Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC): The ROC curve and corresponding AUC values were used to summarize the overall diagnostic performance of AI algorithms. Higher AUC values reflect a superior diagnostic ability across different thresholds.

Comparative performance: This study included a direct comparison of AI performance among clinicians with varying expertise levels (e.g., generalists, non-expert dermatologists, and expert dermatologists). This analysis highlights the differences in diagnostic outcomes and identifies areas where AI can outperform or complement clinicians.

Results
Sensitivity: The AI-powered diagnostic tools demonstrated excellent sensitivity, reflecting their ability to correctly identify malignant skin lesions. Salinas et al. (2024) reported a sensitivity of **92.3%**, highlighting AI's effectiveness in detecting melanoma and outperforming less experienced clinicians. Mahmoud et al. (2024) achieved even higher sensitivity at **94%**, particularly when applied to large dermoscopic datasets (Figure 3).

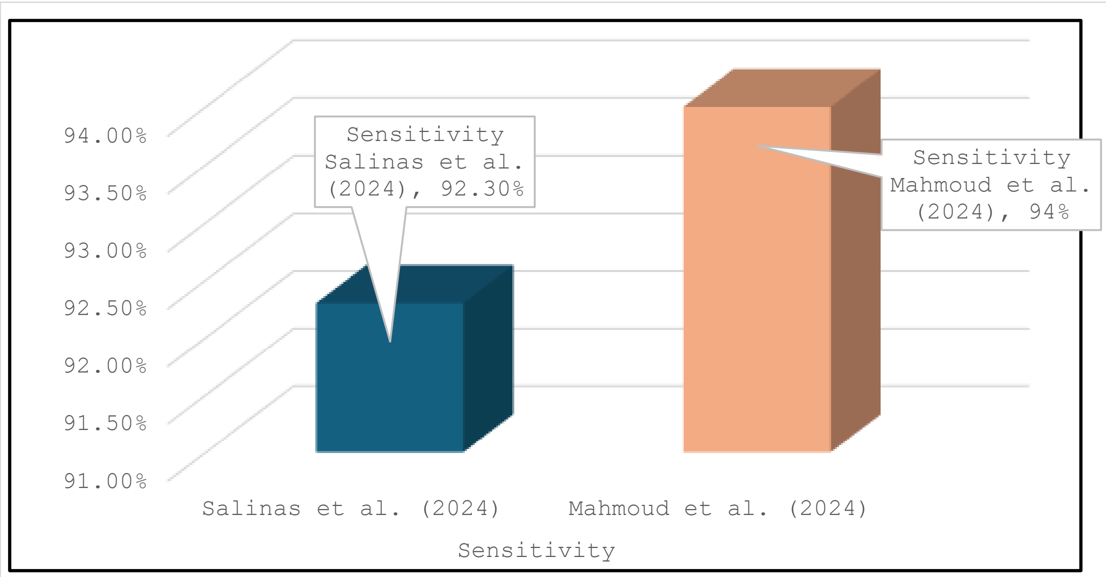

Figure 3: AI sensitivity performance in skin cancer detection

These results confirm AI's role of AI in reducing false negatives and improving early detection rates, which are critical factors for successful intervention in skin cancer.
Specificity measures indicate the AI's capability to correctly identify benign lesions and reduce false positives. Salinas et al. (2024) demonstrated a specificity of **95.8%**, showcasing the precision of AI tools in differentiating between malignant and benign cases. Claret et al. (2024), using CNNs integrated with wavelet transformations, reported a slightly lower specificity of **91%**(Figure 4).

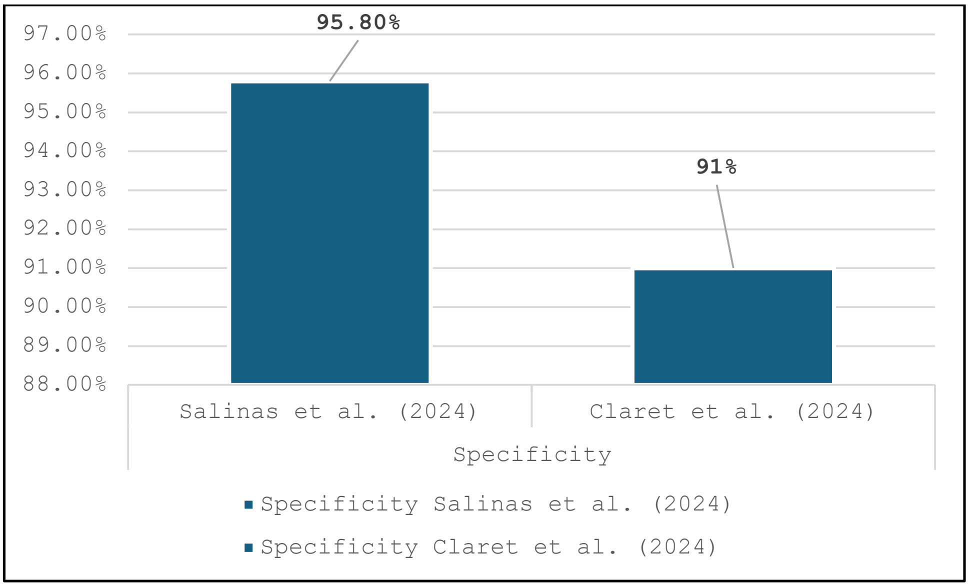

Figure 4: AI specificity performance in skin cancer detection

These findings highlight AI's ability of AI to reduce unnecessary biopsies and interventions and ensure greater diagnostic efficiency.
Accuracy: AI diagnostic tools have achieved high levels of accuracy, often comparable to that of expert dermatologists. Menzies et al. (2023) reported an accuracy of **87.5%**, representing a **21.5% improvement** over diagnoses made by novice clinicians. Similarly, Brancaccio et al. (2024) noted an accuracy exceeding **90%** under controlled conditions, further validating AI's reliability of AI (Figure).

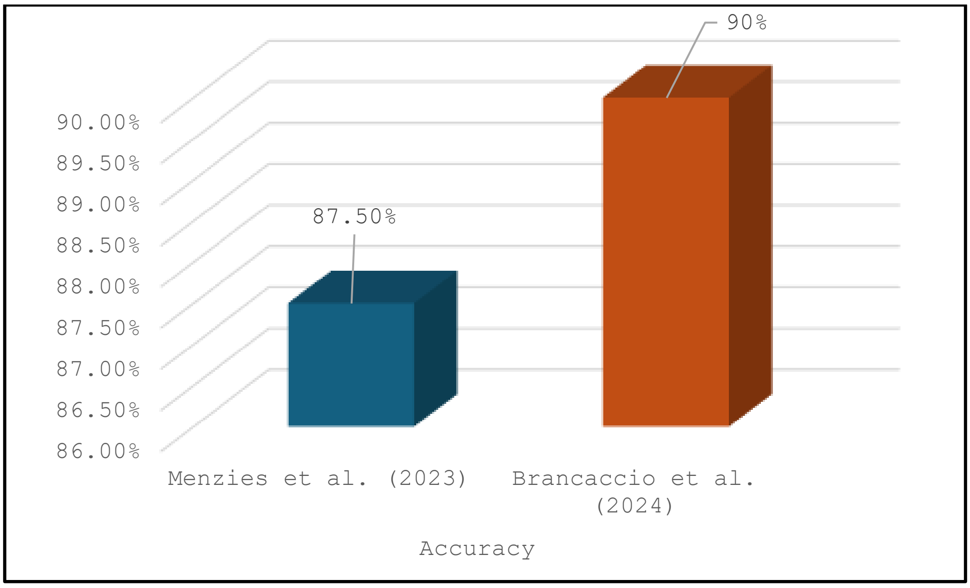

Figure 5: AI accuracy performance in skin cancer detection

These results underscore AI's potential of AI as a reliable diagnostic tool capable of supporting clinicians and enhancing their diagnostic outcomes.

Area under the curve (AUC): The AUC values summarize AI's overall diagnostic performance of AI, reinforcing its ability to distinguish between benign and malignant lesions across various thresholds. Mahmoud et al. (2024) reported an AUC of 0.94, while Salinas et al. (2024) observed values ranging between 0.92 and 0.96. Such consistently high AUC values confirm the robustness and clinical utility of AI-powered diagnostic systems in dermatology.

Comparative performance: AI tools consistently outperformed non-expert clinicians while delivering results comparable to those of expert dermatologists. Menzies et al. (2023) highlighted AI's superior diagnostic accuracy when compared to novice clinicians, significantly reducing diagnostic variability. In expert-level comparisons, AI demonstrated parity, positioning itself as a valuable tool for augmenting clinical expertise and ensuring consistency in diagnostic outcomes.

Augmented intelligence results: Studies have shown that the integration of AI tools with clinician expertise (augmented intelligence) further improves diagnostic performance. AI-assisted clinicians achieved a 5-10% increase in sensitivity and accuracy compared with diagnoses made without AI support. This enhancement was particularly beneficial for non-specialist clinicians, effectively bridging the gap between early career practitioners and experienced dermatologists (Table 1,Figure 6).

Outcome Measure	Study	AI Results	Clinician Results	Observations
Sensitivity	Salinas et al. (2024)	92.3%	Lower (Novice)	AI outperformed less experienced clinicians.
	Mahmoud et al. (2024)	94%	-	High sensitivity on large datasets.
Specificity	Salinas et al. (2024)	95.8%	-	High precision in identifying benign lesions.
	Claret et al. (2024)	91%	-	Slightly lower specificity with hybrid methods.
Accuracy	Menzies et al. (2023)	87.5%	21.5% lower (Novice)	AI improved accuracy compared to novice clinicians.
	Brancaccio et al. (2024)	>90%	-	High accuracy under controlled conditions.
AUC	Mahmoud et al. (2024)	0.94	-	Strong diagnostic performance across thresholds.
	Salinas et al. (2024)	0.92-0.96	-	Consistently high AUC values.
Comparative Performance	Menzies et al. (2023)	Superior	Lower (Novice)	AI demonstrated higher accuracy and consistency.
Augmented Intelligence	Multiple Studies	+5-10% Improvement	Without AI	Combined use improved clinician performance.

Table 1: Comparative performance of AI and clinicians in dermatological diagnosis

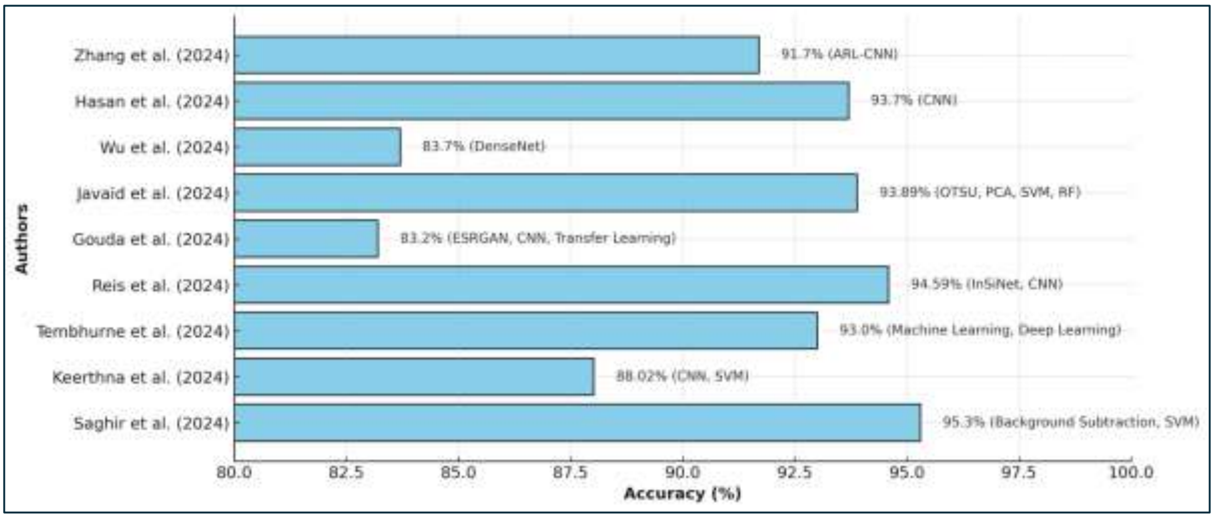

Figure 6: Comparative accuracy of AI techniques in dermatological diagnosis.

Discussion

Overview of Methods and Key Findings

This systematic review assessed the diagnostic performance of AI-powered tools in detecting skin cancer using a PRISMA-based methodology and PICO framework. Most included studies employed convolutional neural networks (CNNs), with some integrating hybrid techniques, such as wavelet transformations. Compared to traditional methods, such as dermoscopy and biopsy, AI tools demonstrated high sensitivity, specificity, and accuracy. These tools often match or surpass expert dermatologists in experimental settings and clearly outperform novice clinicians.

Outcome Measures

AI models have shown excellent diagnostic performance across studies. Sensitivity ranged from 92.3% to 94% (Salinas et al., Mahmoud et al., 2024), with specificity reaching 95.8%, effectively minimizing false positives. Accuracy ranged from 87.5% to over 90%, while AUC values between 0.92 and 0.96 reflected the robustness of these tools across diagnostic thresholds. These metrics confirm AI's capacity of AI to reliably distinguish between malignant and benign lesions [16,22].

Comparison of Results

Compared to traditional methods, AI has demonstrated consistent advantages, especially in supporting non-expert clinicians. Menzies et al. (2023) noted a 21.5% improvement in novice diagnostic accuracy with AI support. Mahmoud et al. (2024) found AI tools achieved accuracy levels comparable to expert dermatologists. Hybrid models, such as those by Claret et al. (2024), further enhanced diagnostic precision, underscoring the synergistic potential of combining AI with conventional approaches [4,16,31].

Clinical Implications

AI tools offer promising solutions for increasing diagnostic access, particularly in underserved areas. Mobile-based applications (Menzies et al., 2023) have demonstrated the feasibility of expert-level assessments in low-resource settings. AI's consistent performance of AI can reduce inter-clinician variability and expedite diagnosis, especially for high-risk lesions requiring urgent care [4].

Limitations and Gaps

Despite its strong performance, AI adoption faces several challenges. A major limitation is the lack of diversity in the training datasets, as noted by Wei et al. (2024), which may introduce algorithmic bias. Moreover, many studies have been conducted in controlled settings, which may not translate to real-world clinical environments. Variations in image quality, lighting, and patient characteristics can affect AI reliability, necessitating more real-world validation studies [27].

Future Directions

Improving dataset diversity and including clinical variables such as patient history can enhance AI's utility of AI. Collaborative models that combine AI predictions with clinician judgment, as explored by Brancaccio et al. (2024), have shown promise. Standardized validation protocols and ethical considerations (e.g., data privacy and informed consent) must also be prioritized to ensure trustworthy and effective AI integration [26].

Conclusion

This systematic review highlights the potential of AI-powered diagnostic tools for the detection of skin cancer. These findings demonstrate that AI can achieve high sensitivity, specificity, and accuracy, often exceeding those of the traditional methods. By addressing the current limitations and ensuring rigorous validation, AI technologies can revolutionize dermatological care and improve accessibility, consistency, and patient outcomes. Future efforts should focus on enhancing the inclusivity, generalizability, and clinical integration of AI systems to fully realize their potential in transforming skin cancer diagnostics.

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