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Artificial Intelligence Tools and Their Ability to Refine Skin Cancer Diagnostics

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ABSTRACT

Basal cell carcinoma, squamous cell carcinoma, and melanoma – the most common forms of skin cancer – have some of the highest global incidence rates. Despite representing a small percentage of total skin cancer cases, melanoma accounts for the majority of skin cancer-related deaths. Given that early detection and accurate diagnosis are vital for improving mortality rates, researchers have begun to explore artificial intelligence and robotic technologies in dermatology for malignancy detection (Shin et al., 2025). This paper examines current approaches to melanoma diagnosis and treatment, including convolutional neural networks (CNNs), three-dimensional total body photography, explainable artificial intelligence (XAI), automated lesion mapping systems, and augmented reality surgical navigation. In addition, the paper analyzes ethical concerns around algorithmic bias, patient privacy, and the impact on physician-patient trust. AI-assisted systems can enhance diagnostic accuracy and offer suggestions to clinicians for precision-based surgical interventions. However, these technologies differ in diagnostic performance, clinical maturity, regulatory status, and practical requirements, and many remain investigational or require physician oversight. Limitations of the use of AI tools in health care include dataset diversity, interpretability, accessibility, and compliance monitoring. These discoveries suggest that AI and robotic technology have the potential to transform dermatologic oncology by being used alongside a skilled physician to improve survival rates and expand resources for skin cancer care.

INTRODUCTION

Melanoma is the deadliest form of skin cancer due to its ability to metastasize promptly throughout the body (Naik, 2021). In 2026, there is an estimated 112,000 cases of melanoma annually (National Cancer Institute, 2026). Survival rates are significantly higher when melanoma is detected early (Arnold et al., 2022). Dermatologists traditionally rely on visual examinations, dermoscopy, and biopsies to identify suspicious lesions, but these methods can still lead to delayed diagnoses or unnecessary surgical interventions (Dinnes et al., 2018). The two most common types of nonmelanoma skin cancer include basal cell carcinoma (BCC) and squamous cell carcinoma (SCC); together, these types of skin cancer are accountable for the majority of skin cancer diagnoses globally (Roky et al., 2024). BCC is the most prevalent form and has a low metastatic rate ranging from 0.003-0.55%. Despite its limited ability to metastasize, or for the cancer to spread to other lymph nodes, untreated BCC can lead to local destruction, particularly in cosmetically and functionally sensitive areas such as the nose, eyelids, and ears. In contrast, SCC poses a greater clinical risk than BCC as it is capable of metastasizing to regional lymph

nodes and distant organs if left untreated (Puckett & Steele, 2025). Although the majority of SCC cases are successfully managed with early detection and treatment, advanced disease is associated with a higher morbidity and mortality rate than BCC (Alam et al., 2019). These differences highlight the importance of promptness in early detection and appropriate management of both cancers. As technology continues to advance, artificial intelligence (AI) is increasingly used in dermatology. Deep learning algorithms can analyze skin lesions with moderately high accuracy, achieving success rates between 57% and 75% (Huang et al., 2024). Automated imaging and augmented reality systems are improving efficiency and precision for clinicians (Cerminara et al., 2023; Huang et al., 2024; Pham et al., 2021). However, ethical concerns are tied to the use of AI in health care settings, as the barriers of bias, privacy, and accountability remain unclear (Gordon et al., 2024; Zbrzezny & Krzywicki, 2025). This paper explores how intelligence systems can be utilized in the diagnosis and treatment of skin cancers, including melanoma and nonmelanoma skin cancers, such as basal cell carcinoma and squamous cell carcinoma. This review also explores ethical challenges that arise when using intelligent systems to diagnose and treat skin cancers. The focus of this paper is to answer the research question: How can artificial intelligence be utilized to refine diagnoses in skin cancer?

METHODS

This paper is a review in which all included articles are peer-reviewed sources. The peer-reviewed sources were obtained from PubMed, Springer Nature, Academia, Wiley, and Google Scholar. Google Scholar was also used to locate additional relevant literature and identify sources for further searching. All sources were published between January 2010 and March 2, 2026.

The literature search used combinations of keywords including “artificial intelligence,” “skin cancer,” “physician-patient relationship,” “advanced technology in dermatology,” and “dermatology.” Additional keywords included “skin cancer surgeries,” “melanoma,” “basal cell carcinoma,” “squamous cell carcinoma,” “skin cancer treatments,” “skin lesions,” and “skin cancer diagnosis.” These terms were searched individually and in combination. The Boolean operators AND and OR were used to combine search terms, narrow results, or broaden searches when investigating specific topics. Searches also focused on physician preferences toward AI technologies, physician-patient relationships and interactions, ethical considerations surrounding AI, and whether multiple AI or advanced technologies could work together in dermatologic diagnosis and treatment.

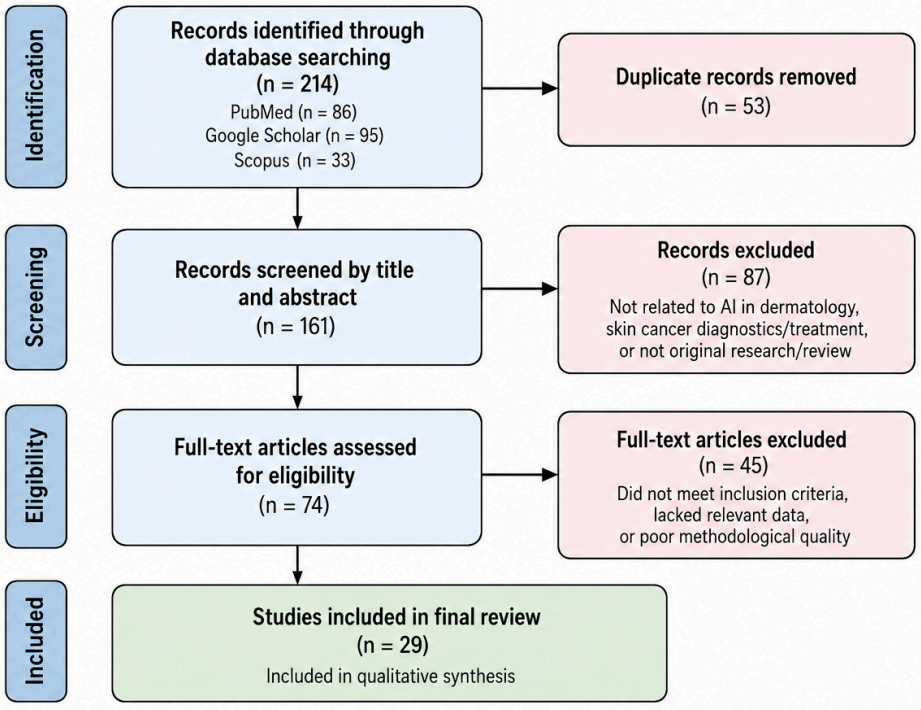
Articles were included when they addressed artificial intelligence or its impacts, current treatments or diagnoses for skin cancer, robotic devices in skin cancer diagnosis or treatment, surgical challenges, physician preferences or interactions regarding AI, or ethical considerations of AI. Articles were excluded when their content was not sufficiently central to dermatology and skin cancer, or when the article did not provide information relevant to the research question and topics examined in this review.

Information extracted from the included articles consisted of demographics, AI methods, diagnostic approaches, and standards of care. When relevant, information regarding physician preferences, physician-patient relationships, ethical considerations, and the integration of multiple technologies was also examined. Articles were first identified through keyword searches in the databases and sources listed above. Articles were then screened for relevance to the research question and evaluated according to the inclusion and exclusion criteria. Relevant articles were selected for inclusion in the final review.

Initially, around 25 journal articles were found based on the sources that contained the keywords. Ten articles were excluded because they covered topics such as machinery or physician efficiency but were not sufficiently central to dermatology and skin cancer surgeries. Additional relevant articles were identified through further searches and examination of relevant sources. The manuscript ultimately reports a total of 29 journal articles used in the research paper.

Because the original search record does not provide a complete database-by-database accounting of all identified and screened articles, the numerical discrepancy between the approximately 25 articles initially identified and the final 29 articles included is acknowledged as a limitation of the review methodology. The overall process of literature identification, screening, exclusion, and final article selection is summarized in Figure 1.

Figure 1. Flowchart of Literature Search and Study Selection (29 Sources Included)



Note. 29 sources were included in the final review and are presented in the References.

SECTION 1: SKIN CANCER AND MELANOMA: RISKS, DIAGNOSIS, AND TREATMENT APPROACHES

The three most common forms of skin cancer— basal cell carcinoma, squamous cell carcinoma, and melanoma— have some of the highest prevalence rates worldwide, affecting over 6 million individuals each year (Skin Cancer Foundation, n.d.). Skin cancer occurs when skin cells undergo uncontrolled growth, often due to cumulative damage from environmental and genetic factors (Mayo Clinic, 2025). Melanoma is a malignancy of melanocytes and keratinocytes, driven by skin cells proliferating and expanding as a result of mutations in their DNA caused by UV exposure. Melanoma appears as moles that are dark brown or black (National Cancer Institute, 2022). Melanoma accounts for the majority of skin cancer-related deaths: In 2020, approximately 57,000 deaths were recorded (Arnold et al., 2022). Nonmelanoma skin cancers originate from keratinized epithelial cells. These cancers include basal cell carcinoma (BCC) and squamous cell carcinoma (SCC). BCC is the most common skin cancer and is usually slow-growing and locally invasive, accounting for approximately 75% to 80% of skin cancer cases. SCC is the second most common form of nonmelanoma skin cancer, accounting for approximately 20% to 30% of cases (Combalia & Carrera, 2020). Melanoma is a cancer of the melanocytes, which causes abnormal growth and proliferation of atypical melanin-producing cells. Although it is the deadliest form of skin cancer with the highest rates of metastasis, it accounts for only 1-2% of all skin cancer cases.

Risk Factors

Several risk factors contribute to the development of skin cancer. Well-known contributors may include excessive ultraviolet (UV) radiation exposure, fair skin, and frequent sunburns (Mayo Clinic, 2025). Skin cancer is not associated with a specific degree of sunburn, yet the risk of skin cancer increases after the threshold of five or more sunburns (National Cancer Institute, 2022). Risk can also increase with a family history of skin cancer and a high number of moles. Patients with weakened immune systems face a heightened likelihood of developing aggressive forms of cancer, particularly SCC (Mayo Clinic, 2025).

Clinical Diagnosis of Skin Cancer

Visual inspection, biopsy techniques, and advanced imaging technologies are all commonly used to diagnose skin cancer. Clinicians often use a rule, referred to as the “ABCDE rule”, to identify suspicious lesions (Jutte et al., 2024). Clinicians evaluate asymmetry, border irregularity, color variation, diameter greater than 6 mm, and evolution over time, with the “ABCDE” rule (National Cancer Institute, 2022). Additional tools, such as dermoscopy, can enhance diagnostic accuracy relative to unaided visual exams. Biopsies are the critical standard for confirming suspected skin cancer. Specifically, excisional biopsy is used to remove the lesion and a minimal amount of surrounding tissue, and sentinel lymph node biopsy is used when tumors are thicker than 1 mm (Naik, 2021; National Cancer Institute, 2026). The use of noninvasive diagnostic approaches is starting to emerge. Reflectance confocal microscopy, optical coherence tomography, and electrical impedance spectroscopy allow physicians to visualize skin

structures or measure electrical properties without making unnecessary incisions that can damage the epidermis (Dinnes et al., 2018; Singh et al., 2025). Gene expression analysis and noninvasive genomic detection add molecular-level insights that may reduce excess procedures (Rabbie et al., 2019; Singh et al., 2025). As these diagnostic advancements converge, the rate of early detection of skin cancer stages rises from 3-5% to 18.7% (Wachsman et al., 2011).

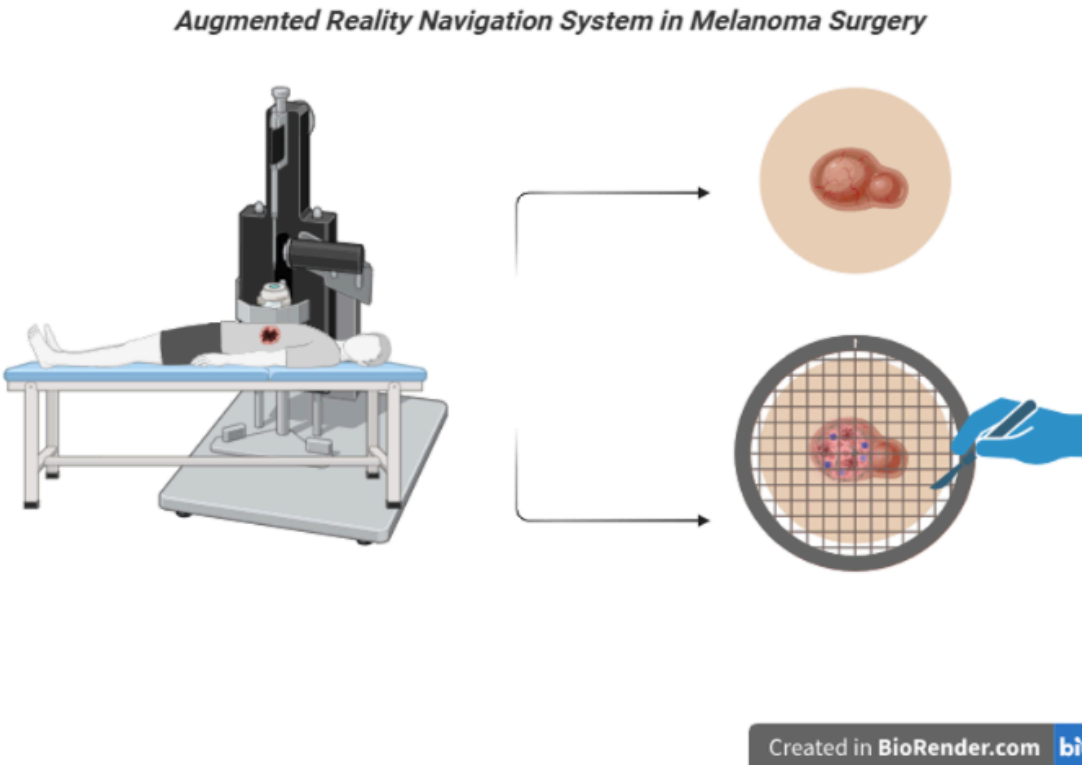
Traditional Treatments for Melanoma

Traditional treatment for melanoma greatly depends on the stage and depth of invasion of the tumor. Melanoma shown in the early stages is typically managed with wide local excision, in which the tumor and a margin of surrounding healthy tissue are surgically removed. For thin melanomas (less than 1 millimeter) with low Breslow depth, surgery alone is often curative, and a sentinel lymph node biopsy is not recommended, as the risk of metastasis is low. As tumor thickness increases (greater than 2 millimeters), however, sentinel lymph node biopsy becomes an important staging tool to evaluate where the cancer has spread beyond the primary site and works to guide future treatment (An, n.d.). Before advanced immunotherapies, treatment for cutaneous melanoma primarily consisted of surgical excision, lymph node dissection, and systemic chemotherapy (Algazi et al., 2010). The most commonly used chemotherapeutic agent is dacarbazine, used in 26% of patients. While dacarbazine is effective, severe toxicities occur in 18% of patients (National Library of Medicine). The development of targeted therapies and immunotherapies has since expanded treatment options for advanced melanoma, emphasizing the importance of accurate diagnosis and staging before treatment decisions are made.

SECTION 2: AI APPROACHES TO DIAGNOSIS AND ROBOTIC DEVICES IN SKIN CANCER

The technologies reviewed in this section address different stages of dermatologic care. CNNs primarily classify lesion images; 3D total body photography (3D TBP) supports comprehensive lesion mapping; explainable AI (XAI) focuses on interpretability; automated total-body mapping (ATBM) supports longitudinal surveillance; and augmented reality (AR) systems assist with surgical navigation. Because these systems perform different clinical tasks, their reported performance measures should not be treated as directly interchangeable. Diagnostic accuracy, lesion-detection overlap, clinician confidence, and navigation error measure different outcomes.

Figure 2: Visual depiction of augmented reality surgical navigation.



Convolutional Neural Networks for Melanoma Detection

Pham et al. (2021) developed a deep-learning framework using a CNN trained on more than 17,000 dermoscopic images labeled as melanoma or benign nevi. The CNN learned visual features including color variation, border irregularity, texture, and lesion asymmetry.In a controlled evaluation, the CNN outperformed 157 practicing dermatologists in melanoma identification (Pham et al., 2021). This finding demonstrates strong image-classification potential; however, performance in a controlled dataset does not establish that the system can replace a dermatologist in routine practice. A major limitation is that the model relies primarily on image-based information and does not fully incorporate clinical context such as patient age, lesion history, or anatomical location. Its performance may also change when applied to populations or imaging environments that differ from the training data. Therefore, CNNs demonstrate strong research-level potential but require broader external and prospective validation before widespread clinical adoption.

Three-Dimensional Total Body Photography and Three-Dimensional CNNs

Cerminara et al. (2023) investigated 3D TBP combined with a 3D CNN for whole-body lesion analysis. Unlike isolated lesion photographs, 3D TBP captures the patient's entire skin surface and produces a three-dimensional representation that can be compared over time.The 3D CNN achieved 87.3% specificity, compared with 76.2% for the 2D CNN models examined in the cited comparison, while demonstrating sensitivity comparable to experienced dermatologists (Cerminara et al., 2023). These

findings suggest that whole-body spatial information may improve lesion monitoring and reproducibility. However, 3D TBP requires specialized imaging equipment and computational resources. Its practical value therefore depends not only on diagnostic performance but also on whether healthcare settings can afford and integrate the technology.

Explainable Artificial Intelligence

XAI addresses a different challenge from conventional CNNs: interpretability. Rather than focusing only on whether an algorithm reaches a classification, XAI attempts to provide information about why a model generated its prediction. Chanda et al. (2025) evaluated an XAI system designed to align machine-generated explanations with dermatologists' diagnostic reasoning. In a study involving 76 dermatologists evaluating dermoscopic images, XAI assistance improved balanced diagnostic accuracy by approximately 2.8 percentage points compared with standard AI assistance (Chanda et al., 2025). The system also increased clinician confidence and trust. These findings suggest that diagnostic performance alone may not determine clinical usefulness. However, an explanation is valuable only if it accurately represents clinically meaningful features; explainability therefore cannot substitute for validation.

Automated Total-Body Mapping: ATBM Master

Winkler et al. (2024) evaluated the ATBM Master, an automated total-body imaging system designed to establish baseline skin maps and identify new or changing lesions during follow-up. Among 236 patients, dermatologists identified 1,075 clinically relevant melanocytic lesions, while the ATBM software detected 999 during baseline screening, corresponding to a 92.9% overlap. At follow-up, the overlap increased to 96.7% (Winkler et al., 2024). The average examination time was approximately 14 minutes.ATBM represents a more clinically implemented technology than the research-stage systems described above. The system is CE-marked and has been used in European clinical settings (Sangers et al., 2022). However, its clinical use does not mean that it independently establishes a cancer diagnosis. Lesions may remain difficult to detect when obscured by hair or clothing or located in difficult-to-image areas such as the palms or soles. Histopathologic confirmation remains necessary when malignancy is suspected.

Augmented Reality Surgical Navigation

Beyond diagnosis, AI-driven systems are also being investigated for surgical navigation and intraoperative decision support. Huang et al. (2024) described an AR-based surgical system that projects digital tumor-margin outlines and biopsy grids onto the surgical field. The AR platform achieved an average navigation error of 0.64 mm, demonstrating submillimeter alignment accuracy. Surgeons and patients rated usability and satisfaction above 8 out of 10. However, the system lacked three-dimensional projection capabilities and showed reduced accuracy for very small lesions, requiring manual refinement (Huang et al., 2024). Unlike CNNs, this system does not primarily measure diagnostic accuracy; its main function is spatial assistance during surgery. Because it remains a prototype, its evidence supports feasibility rather than routine clinical adoption.

Integration of AI and Robotics Across Skin Cancer Care

Collectively, these technologies illustrate the integration of AI and robotic systems across the continuum of skin cancer management—from image-based diagnosis (Cerminara et al., 2023; Chanda et al., 2025; Pham et al., 2021), through automated clinical screening (Winkler et al., 2024), to surgical intervention

(Huang et al., 2024). All rely on image analysis and spatial mapping as foundational technologies but differ in their primary clinical roles. The important distinction is that technical performance does not equal clinical readiness. CNNs and XAI have demonstrated promising research results, ATBM has progressed into clinical use, and AR surgical navigation remains largely experimental. These technologies therefore represent a modular and complementary set of tools rather than a single replacement for human expertise.

Comparative Synthesis of AI Technologies

Although the AI technologies reviewed in this paper demonstrate promising capabilities, their clinical roles, strengths, limitations, and levels of maturity differ substantially. 2D CNNs demonstrate strong potential for lesion classification and pattern recognition, but their reliance on image-based information and limited incorporation of clinical metadata restrict their ability to independently support comprehensive clinical decision-making. 3D total body photography combined with CNNs provides broader spatial information and improved lesion mapping, with the reviewed study reporting 87.3% specificity compared with 76.2% for the 2D CNN models examined. However, these systems require specialized imaging equipment and computational resources, which may limit accessibility.

XAI addresses a limitation shared by conventional AI systems: interpretability. Rather than focusing solely on classification performance, XAI can provide clinicians with explanations for algorithmic predictions and has been associated with increased diagnostic accuracy, confidence, and trust. However, XAI remains primarily investigational, and explanations must be validated to ensure that they accurately represent clinically meaningful reasoning. ATBM Master represents a more clinically mature application of AI, as it has been implemented for automated total-body screening and is CE-marked. Its reported 92.9% baseline lesion overlap and 96.7% follow-up overlap demonstrate practical potential for longitudinal monitoring, although certain anatomical locations and lesions obscured by hair or clothing may reduce detection.

AR surgical navigation differs from the other technologies because its primary purpose is not diagnosis but intraoperative assistance. Its reported 0.64-mm navigation error demonstrates strong spatial precision, but the system remains a prototype and requires manual refinement for smaller lesions. Therefore, the technologies should not be viewed as competing alternatives. Instead, they address different stages of dermatologic care: CNNs support lesion classification, 3D imaging supports comprehensive surveillance, XAI supports interpretable decision-making, ATBM supports longitudinal clinical monitoring, and AR supports surgical navigation.

Overall, the evidence suggests a gradient of clinical maturity. ATBM currently demonstrates the strongest evidence of practical clinical implementation, while CNNs, 3D imaging, and XAI have demonstrated promising diagnostic or decision-support capabilities but require continued validation across diverse populations and clinical environments. AR surgical navigation remains comparatively experimental. The technologies reviewed vary in their level of clinical maturity. ATBM Master has progressed furthest toward clinical implementation, while CNNs, 3D imaging, and XAI remain primarily research or

clinical-validation tools. In comparison, AR surgical navigation remains a prototype. Therefore, although these technologies demonstrate promising results, they should not be considered equally ready for routine clinical use.

Figure 3: Comparison of AI technologies used in skin cancer diagnosis, monitoring, and surgical assistance.

AI Technology	Core Function	Clinical Role	Diagnostic Performance	Clinical Implementation	Regulatory Status	Principal Limitations	Biopsy Role
2D CNN	**Lesion classification**	**Melanoma/skin-lesion detection**	**Outperformed 157 dermatologists in cited study**	**Research**	**Not established in reviewed study**	**Image-based input; limited clinical context**	**Does not replace biopsy**
3D TBP + 3D CNN	**Whole-body lesion mapping**	**Lesion detection/monitoring**	**87.3% specificity; 2D CNN comparator: 76.2%**	**Clinical validation**	**As reported by cited study**	**Specialized imaging equipment and computational resources**	**Does not replace biopsy**
XAI	**Explainable AI-assisted diagnosis**	**Clinical decision support**	**2.8 percentage-point improvement in balanced**	**Research**	**Not established in reviewed study**	**Explanations require validation**	**Does not replace biopsy**

			diagnostic accuracy				
ATBM Master	**Automated total-body imaging**	**Longitudinal lesion monitoring**	**92.9% baseline overlap; 96.7% follow-up overlap**	**Clinical use**	**CE-marked**	**Hair/clothing and certain anatomical areas may affect detection**	**Does not replace biopsy**
AR Surgical Navigation	**Surgical navigation**	**Intraoperative assistance**	**0.64-mm average navigation error**	**Prototype**	**No regulatory approval established in reviewed study**	**Limited 3D projection; small lesions may require manual refinement**	**Assists surgery; does not establish diagnosis**

Figure 3. Comparison of AI technologies used in skin cancer diagnosis, monitoring, and surgical assistance. The technologies differ in both their clinical purpose and level of development. CNNs primarily support image-based lesion classification, while 3D TBP and ATBM Master provide broader whole-body monitoring capabilities. XAI focuses on improving the interpretability of AI-assisted decisions, whereas AR surgical navigation applies technology to intraoperative assistance rather than primary diagnosis. Their reported performance measures also represent different outcomes and therefore should not be interpreted as directly comparable. Overall, ATBM Master demonstrates the greatest degree of clinical implementation among the technologies reviewed, while CNNs, 3D imaging, and XAI demonstrate promising research and decision-support applications. AR surgical navigation remains comparatively experimental. Across all approaches, physician oversight and, when indicated, histopathologic confirmation remain important limitations to fully autonomous AI-based diagnosis and treatment.

SECTION 3: ETHICAL CONSIDERATIONS FOR THE USE OF ARTIFICIAL INTELLIGENCE IN DERMATOLOGY

The ethical landscape surrounding the use of artificial intelligence (AI) in dermatology has gained significant scholarly and clinical attention in recent years. As AI systems increasingly influence diagnostic decision-making, clinical workflows, and patient communication, concerns have emerged regarding bias, transparency, accountability, privacy, and patient autonomy. A recent scoping review on AI ethics in dermatology highlights that many currently deployed systems lack sufficient ethical oversight, particularly regarding fairness across skin tones and the explainability of algorithmic decisions (Gordon et al., 2024). One of the most pressing ethical challenges is dataset bias, as many AI models are trained predominantly on images from lighter skin types, which can result in reduced diagnostic accuracy for patients with darker skin tones. Widely cited models like Stanford's DeepDerm achieved a sensitivity of 0.69 for lighter skin tones but only 0.23 for darker skin tones (Dowie, 2025; Zbrzezny & Krzywicki, 2025). Additionally, the “black-box” nature of deep learning models limits clinicians’ ability to understand how conclusions are reached, complicating trust and accountability in clinical decision-making. These challenges underscore the need for robust ethical frameworks tailored specifically to dermatologic practice.

Current Efforts to Uphold Ethical Standards

Multiple initiatives have been undertaken to address ethical concerns in medical AI, including in dermatology. International consensus frameworks such as the FUTURE-AI guideline emphasize principles including fairness, transparency, and human oversight, providing a structured foundation for ethical AI development and deployment in healthcare (Lekadir et al., 2025). These frameworks advocate that AI tools should support, rather than replace, clinician judgment. Within dermatology, recent reviews emphasize the importance of external validation, disclosure of training data composition, and continuous post-deployment monitoring to identify bias and performance drift (Gordon et al., 2024; Zbrzezny & Krzywicki, 2025). Ethical scholarship also stresses informed consent, recommending that patients be

explicitly informed when AI tools are used in their care, particularly when clinical images are collected or analyzed by automated systems (Gordon et al., 2024; Williamson & Prybutok, 2024).

Application of Ethical Principles Across Key Clinical Areas: Diagnostics

In AI-assisted dermatologic diagnostics, ethical implementation requires transparency regarding algorithmic performance and limitations. Clinicians must understand how AI outputs are generated and avoid overreliance on automated classifications (Dowie, 2025). Bias mitigation is essential, particularly in melanoma detection, where misclassification may have life-threatening consequences. Ethical practice demands that AI systems be validated across diverse populations and that clinicians retain ultimate diagnostic authority (Gordon et al., 2024).

Surgical Assistance

AI tools used for surgical planning or assistance, such as margin delineation or augmented visualization, raise distinct ethical concerns related to accountability and patient safety. While such systems may improve precision and efficiency, surgeons remain ethically and legally responsible for outcomes (Ruiz et al., 2025). Ethical application therefore requires explainable outputs, rigorous validation, and explicit disclosure of AI involvement during the informed consent process (Zbrzezny & Krzywicki, 2025).

Clinical Workflows

AI integration into clinical workflows, including documentation, triage, and scheduling, offers efficiency gains but introduces risks to patient privacy and data security. Ethical use requires strict data governance, transparency regarding automation, and safeguards against inappropriate secondary use of patient data (Lekadir et al., 2025; Williamson & Prybutok, 2024).

Physician–Patient Communication and Ethical Responsibility

Effective communication is central to ethical AI use in dermatology. Physicians should clearly explain when and how AI tools are used, emphasizing that these systems function as decision-support tools rather than replacements for clinical expertise (Dowie, 2025; Gordon et al., 2024). Patients should be informed about data usage, potential risks, and limitations of AI-assisted assessments, ensuring respect for patient autonomy and informed consent (Williamson & Prybutok, 2024).

Challenges and Future Directions

Despite rapid progress, several challenges remain. AI classifiers often lack integration with clinical metadata, potentially limiting their diagnostic generalizability (Pham et al., 2021). 3D imaging and AR systems, while technologically advanced, demand specialized hardware, calibration, and maintenance (Cerminara et al., 2023; Huang et al., 2024). Moreover, ensuring explainability and ethical transparency remains a key priority (Chanda et al., 2025), particularly as these systems influence clinical judgment. Several limitations also apply to this review itself. First, publication bias may cause studies reporting strong or promising AI performance to be more visible than studies reporting negative or inconclusive results. Second, the rapidly evolving nature of AI means that findings can become outdated as new models and imaging technologies are developed. Third, variability in dataset quality, labeling,

demographic representation, and imaging conditions can make performance difficult to generalize across clinical settings. Finally, prospective multicenter validation remains limited for many technologies, making it difficult to determine whether performance observed in controlled studies will persist across different hospitals, clinicians, and patient populations. Robust validation in diverse populations, standardization of imaging protocols, and harmonization with regulatory frameworks will be critical to moving from research to routine use. Future research should focus on improving dataset diversity, developing more interpretable systems, and evaluating AI technologies prospectively across multiple clinical environments. Researchers should also continue to explore robotic-assisted imaging, automated lesion capture, and real-time AI-guided surgical systems. Ethical boundaries will remain essential as AI becomes more integrated into patient care.In the near future, convergence of these technologies is anticipated: multimodal AI integrating dermoscopic, clinical, and histopathologic data; robotic-assisted dermatoscopy for automated lesion capture; and real-time AR overlays informed by AI segmentation during surgery. Together, these developments may define a new paradigm of AI-augmented dermatologic oncology, but their clinical value will depend on rigorous validation and continued human oversight.

DISCUSSION

AI tools in dermatology have demonstrated potential across diagnosis, monitoring, and surgical assistance. Throughout this paper, studies have supported how diagnostic accuracy can be improved with the help of convolutional neural networks, explainable AI (XAI), automated total-body mapping systems, and augmented reality surgical navigation (Cerminara et al., 2023; Chanda et al., 2025; Huang et al., 2024; Pham et al., 2021; Winkler et al., 2024). However, the technologies differ substantially in what they measure and how close they are to routine clinical use. CNN-based systems demonstrated strong image-classification performance, but these results were obtained in controlled evaluations and do not establish that CNNs can replace physicians. XAI improved diagnostic performance and clinician confidence, suggesting that interpretability may be important for effective human-AI collaboration. ATBM demonstrated a more advanced level of clinical implementation by supporting automated total-body monitoring, while AR surgical navigation remains a prototype focused on spatial assistance rather than diagnosis. These distinctions demonstrate that AI is currently most appropriately understood as a clinical support tool rather than a replacement for physicians. AI can recognize patterns, identify changes, provide explanations, and assist with navigation, while physicians integrate these outputs with patient history, physical examination, clinical judgment, and pathology. The implications of these advancements hold great relevance as melanoma survival rates are highly dependent on early detection. Early diagnosis can reduce mortality rates, minimize unnecessary biopsies, and improve patient outcomes overall (Arnold et al., 2022; National Cancer Institute, 2026). Additionally, AI systems may increase access to dermatologic screening in underserved or rural communities where specialists are limited (du Crest et al., 2026). Although there are evident promising developments, limitations remain. Many intelligence systems are trained with data particular to lighter skin tones, which can reduce the accuracy of a diagnosis for minority communities and contribute to healthcare disparities (Dowie, 2025; Zbrzezny & Krzywicki, 2025). Moreover, most current healthcare systems still require histopathologic confirmation

through biopsy, which means AI cannot independently diagnose melanoma. Some technologies utilize expensive imaging equipment and advanced computational infrastructure, limiting widespread accessibility (Cerminara et al., 2023; Huang et al., 2024). Taken together, the evidence supports cautious optimism rather than immediate transformation. The most realistic near-term role for AI is augmentation: helping clinicians detect, monitor, interpret, and plan while preserving human responsibility for diagnosis and treatment. Future research should therefore emphasize diverse populations, prospective multicenter validation, transparent reporting, and clinically meaningful patient outcomes.

Currently, AI is most appropriately viewed as a clinical decision-support technology rather than a replacement for physicians. AI can assist with pattern recognition, lesion monitoring, interpretation, and surgical navigation, while physicians remain responsible for integrating AI-generated information with patient history, physical examination, clinical judgment, and histopathologic findings when necessary.

CONCLUSION

AI and robotic devices have evolved from primarily experimental tools toward a range of clinically promising technologies in dermatology. CNNs have demonstrated strong image-classification performance, 3D imaging platforms can support comprehensive lesion mapping, explainable frameworks can improve interpretability, automated mapping systems can support clinical monitoring, and AR navigation can assist with surgical planning. However, these technologies are not equally mature, and their performance measures cannot be directly compared because they address different clinical tasks. Some remain primarily research tools, while others have progressed into clinical use. Importantly, most systems still require physician interpretation and, when malignancy is suspected, histopathologic confirmation. Ultimately, these technologies have the potential to refine skin cancer diagnosis and treatment, but their broader clinical impact will depend on continued validation across diverse populations, improved dataset representation, appropriate regulation, and responsible integration into clinical practice. Currently, artificial intelligence is best used to complement physician expertise rather than replace it.

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