





# Emerging role of artificial intelligence in melanoma diagnosis: Implications for clinical and therapeutic management

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## ARTICLE HISTORY

Received on: 13/10/2025  
Accepted on: 08/02/2026  
Available Online: 05/03/2026

### Key words:

Artificial intelligence (AI), convolutional neural networks (CNNs), skin cancer, melanoma, diagnosis, DermaDetect, TEGUMENT, SlideTutor, Hypertext Atlas, HistoGPT, SkinGPT4.

## ABSTRACT

Melanoma is the most aggressive form of skin cancer, early diagnosis and treatment are critical for determining treatment outcomes. Traditional diagnostic methods, such as clinical examination, dermoscopy, and histopathology, provide valuable insights but are limited by subjectivity and interobserver variability. Artificial intelligence (AI), particularly convolutional neural networks, has shown strong potential to enhance melanoma detection, offering accuracy comparable to dermatologists. This review summarizes current and emerging applications of AI in melanoma diagnosis, covering diagnostic tools, educational systems, and smartphone-based apps. Despite encouraging results, challenges such as interpretability, data bias, regulatory hurdles, and ethical issues remain. Integrating AI into clinical workflows, supported by diverse and validated datasets, could significantly improve early therapeutic interventions and patient management.

## 1. INTRODUCTION

A malignant tumor called melanoma develops from melanocytes, which are responsible for melanin production. It is the most prevalent type of skin cancer and has a high malignancy rate. Throughout the past several decades, the occurrence of skin cancer has increased by 3%–7% each year among individuals with fair skin, and the growth rate is higher than that of individuals with other types of cancer. The presence of atypical moles, genetic predisposition and prolonged ultraviolet (UV) radiation exposure are considered as risk factors [1–3].

The traditional methods used for diagnosing melanoma include visual clinical examination, dermoscopy, and histopathological examination of the tissue obtained through biopsy. Clinical examination, often guided by the ABCDE (Asymmetry, Border irregularity, Color variation, Diameter, and Evolution) rule, is the first step but can be highly subjective, depending on the clinician's experience [4]. Dermoscopy, which allows for the visualization of subsurface skin structures, has significantly enhanced diagnostic accuracy. However, it is also operator dependent and requires specialized training, resulting in significant interobserver variability [5]. Histopathological examination following biopsy is considered the gold standard for melanoma diagnosis, but it has its own limitations, such as sampling errors and challenges in accurately interpreting early or atypical melanomas [6]. Additionally, some melanomas might not show the typical signs or patterns that are usually recognized during a clinical examination or with dermoscopy, which makes diagnosing more challenging. This difficulty

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highlights the persistent challenges in accurately diagnosing melanoma early by using traditional diagnostic methods [7].

Early detection of melanoma is critical for improving survival and treatment outcomes. AI can enhance screening by analyzing skin images to identify suspicious moles, enabling timely, less invasive interventions. Regular skin checks combined with AI support offer a valuable approach in modern dermatology [8–12].

Machine learning, especially neural networks and Convolutional Neural Networks (CNNs), is widely used for analyzing and diagnosing skin lesions. These models require extensive and reliable training datasets but often function as a “black box,” generating predictions without explaining how inputs produce outputs. This lack of transparency makes it difficult for clinicians to interpret, validate, and fully trust the results, limiting their use in sensitive fields such as healthcare. Although AI has shown remarkable potential in melanoma diagnosis, certain limitations persist. This review discusses the existing AI models and the associated challenges [10,13–15].

## 2. ETIOLOGY OF MELANOMA

Melanoma develops through a mix of genetic, environmental, and host-related factors. The main environmental risk factor is UV radiation, especially short bursts of intense sun exposure and childhood sunburns. UV rays damage the DNA of skin cells, leading to mutations that can trigger cancer growth. Genetic factors also play a significant role as people with a family history of melanoma are at higher risk due to inherited changes in genes such as *NRAS*, *BRAF*, and *CDKN2A*. Among these, *CDKN2A* mutations are linked to both inherited and sporadic forms of melanoma [16,17]. People with many unusual moles (atypical or dysplastic nevi) or even many common moles are more likely to develop melanoma. Fair skin, light hair, light-colored eyes, and freckles also increase risk because they make the skin more sensitive to UV damage. A weak immune system, such as in people with HIV or those who have had an organ transplant, raises the risk further. Research also shows a two-way link between melanoma and Parkinson’s disease, which means that each condition is more common in people who have the other. Exposure to tanning beds and other artificial UV radiation devices significantly contributes to the overall risk. Together, these factors show that melanoma is caused by a combination of environmental exposures and genetic mutations that drive melanocytes to transform into cancerous cells [18–20].

## 3. PATHOPHYSIOLOGY OF MELANOMA

Melanoma arises when melanocytes, the pigment-producing skin cells, become cancerous due to environmental and genetic factors. UV radiation is the primary trigger, causing DNA damage such as cyclobutane pyrimidine dimers and mutations in key genes. A frequent mutation, B-Raf proto-oncogene, serine/threonine kinase, V600E (*BRAF V600E*), overstimulates the Mitogen-Activated Protein Kinase (*MAPK*) pathway, driving uncontrolled growth. Similarly, mutations in Neuroblastoma RAS viral oncogene homolog (*NRAS*) and KIT proto-oncogene, receptor tyrosine kinase (*KIT*) or loss of Phosphatase and Tensin

Homolog (*PTEN*) disrupt the Phosphoinositide 3-kinase / AKT (Protein Kinase B, PKB) (*PI3K/AKT*) pathway, allowing melanoma cells to survive and multiply. Together, these changes explain how UV exposure and genetic defects combine to promote melanoma [21–23].

Genetically unstable melanocytes escape standard growth control, leading to abnormal proliferation, angiogenesis, resistance to apoptosis, and metastasis. Melanoma first spreads horizontally in the epidermis (radial growth phase) and later invades deeper tissues (vertical growth phase). The cells can enter lymphatic or blood vessels, break through the basement membrane, and spread to organs such as the liver, brain, bones, and lungs, while also suppressing local immune responses to accelerate disease progression [21,24].

## 4. MELANOMA HISTOLOGIC TYPES

Based on the clinical and pathological characteristics, melanoma can be divided into a number of subtypes, such as mucosal melanomas, lentigo malignancies, nodules, superficial spreading, and acral lentiginous. These subtypes also vary in their growth patterns and rates of progression, making their classification crucial for accurate clinical assessment (Table 1).

## 5. TRADITIONAL DIAGNOSTIC MODALITIES

### 5.1. Clinical diagnosis

The ABCDE criteria are a commonly used clinical tool that makes it easier to identify melanoma early with a naked-eye examination. Each letter represents a unique characteristic frequently observed in cancerous lesions [28,29]: Asymmetry (A), in which the two halves of the lesion are not identical; Border irregularity (B), which has uneven, scalloped, or fuzzy edges; Variation in color (C), where a single lesion presents several colors, such as brown, black, red, or blue; A diameter (D) greater than 6 mm is commonly observed in melanomas, but is not conclusive; and Evolving (E), indicating any alteration in dimensions and symptoms such as bleeding or itching [30,31].

Both public awareness campaigns and clinical practice use these criteria as fundamental screening methods. Although useful, the ABCDE method is limited to a diagnostic sensitivity of about 65% when used without dermoscopy. This sensitivity is very low for the detecting atypical or early melanomas. However, it continues to be an essential initial screening tool, particularly in primary care settings, to detect lesions that require additional dermoscopic or histological analysis [32,33].

### 5.2. Histopathological diagnosis

Histopathological analysis is regarded as the gold standard for melanoma diagnosis. A biopsy sample is taken from a suspicious skin lesion through this technique, and a pathologist processes and examines the sample under a microscope [34]. Atypical melanocytes, irregular cell shapes, and epithelial disarray are among the specific cellular and tissue characteristics that pathologists search for in melanoma. The prognosis and melanoma stage depend on the mitotic rate and

**Table 1.** Comparison of major melanoma subtypes with respect to their prevalence, common sites, clinical features and special notes [25–27].

Melanoma Type	Superficial Spreading Melanoma (SSM)	Lentigo Malignant Melanoma (LMM)	Nodular Melanoma (NM)	Acral Lentiginous Melanoma (ALM)	Mucosal Lentiginous Melanoma (MLM)
Prevalence	~70% of cutaneous melanoma cases	10%–15% of melanomas	10%–15% of melanomas	Rare; similar incidence in white and black individuals	1.8% of melanomas in the United States.; up to 23% in Chinese populations
Common sites	Neck, head, women's lower limbs, men's trunk	Sun-exposed areas such as face, hands, neck	Predominantly male trunk	Soles of feet, palms of hands, under nails (subungual areas)	Mucosal surfaces: nasal cavity, paranasal sinuses, conjunctiva, oral cavity, esophagus, vagina, urethra, penis, anus
Clinical features	Pigmented dysplastic nevus source; Ulceration, growth, and color changes are common	Large lesions with possible hypopigmented areas; develops from a lentigo malignant precursor lesion	Dark brown or black, most uniform and symmetrical; rapid vertical growth	May mimic subungual hematoma or splinter hemorrhages; aggressive behavior	Tumors originate from mucosal epithelium; often aggressive
Special notes	May arise from a preexisting nevus that had been stable for a long time	Typically, extensive and occurs after long-term sun exposure	May bypass radial growth phase; Amelanotic melanomas make up ~5% of NMs	Rapid transition from radial to vertical growth phase; highly severe	~50% cases occur in the head and neck region; rare but worse prognosis

depth of invasion of the tumor, both of which are assessed [35]. Histopathological diagnosis is crucial; however, it can be impacted by interobserver variability, which occurs when different pathologists have different interpretations of the same tissue sample [36]. This is particularly problematic when dealing with atypical or thin melanomas, which can have minor characteristics that make them difficult to differentiate from benign tumors [37].

### 5.3. Dermoscopy

Dermoscopy also known as epiluminescence microscopy, is a noninvasive diagnostic method that uses polarized light with a magnification of approximately 10× to represent structures under the surface of the skin that are invisible to the naked eye [38]. Comparing with naked eye examination, this portable device, known as a dermatoscope, significantly improves the visibility of skin lesions, particularly pigmented ones, increasing the accuracy of the diagnosis. After a lesion is identified as melanocytic, it is evaluated further by using particular diagnostic algorithms. Dermoscopy aids in the differentiation of melanocytic from nonmelanocytic lesions [39,40]. The Menzies method, the seven-point checklist, and the CASH criteria (Color, Architecture, Symmetry, and Homogeneity) are examples of commonly employed techniques. Compared with eye inspection alone, these structured approaches have been demonstrated to increase melanoma recognition sensitivity up to 18% and specificity up to 10%. Crucially, dermoscopy minimizes unnecessary excisional biopsies when used in melanoma screening [41–45]. However, the effectiveness of dermoscopy depends on lesion complexity, clinician experience, and evaluation technique. In general, dermatologists who have more experience are able to make more accurate diagnoses compared to nonspecialists. Dermoscopy greatly improves the identification of melanoma, although it may not always accurately differentiate benign melanocytic lesions from early melanomas, highlighting the need for further

diagnostic methods in situations that are unclear [5,46,47]. The limitations of traditional melanoma detection techniques include their reliance on clinical competence and inconsistent accuracy. AI addresses these challenges by providing consistent and accurate diagnostic results, and in certain trials, it has demonstrated superior performance to that of dermatologists. [48].

## 6. AI IN DERMATOLOGY

In dermatology, AI, particularly machine learning and deep learning (DL), has become a powerful tool for melanoma detection. AI can analyze large clinical and imaging datasets to identify patterns humans often miss, supporting lesion classification, risk prediction, and clinical decision-making. With expanding digital dermatology data, AI is increasingly integrated into diagnostic workflows to enhance accuracy and reduce human error. Recently, vision-language models such as Skin-GPT4 have shown near-dermatologist-level performance, especially in diverse skin tones, highlighting the growing role of advanced AI systems in clinical care [48–52].

## 7. AI'S EFFECT ON SKIN PATHOLOGY

### 7.1. AI in the diagnosis of pigmented lesions

Early studies in the 1990s were based on conventional machine-learning methods, while since 2016, several CNN-based approaches have achieved dermatologist-level accuracy. These approaches usually need some preprocessing steps to reduce noise, normalize illumination, and smooth the surrounding skin texture in order to enhance the interpretation of lesions. Esteva *et al.* trained a CNN with over 129,000 images and reported an Area Under the Curve of 0.96, matching the performance of 21 board-certified dermatologists. Similarly, Soenksen *et al.* achieved 90% sensitivity and specificity with strong agreement between CNN outputs and dermatologist assessments [48,53,54].

Using a dataset that has been enlarged from 170 to 6,120 photos by cropping, scaling, and rotation, Nasr-Esfahani *et al.* [55] developed a CNN model. This model detected melanoma with 81% accuracy, 80% specificity, and 81% sensitivity. According to other studies, accuracies range from 82% to 94%, and sensitivities reach 90% [55–57]. In late 2023, the FDA-approved DermaDetect, an AI-powered diagnostic assistant for primary care, designed to prioritize suspicious pigmented lesions, marking a key step in the transition of AI from research to routine clinical use [58]. A 2024 multicenter trial by Heinlein *et al.* [59] confirmed clinical value, showing that CNN integration improved melanoma detection by 12% and reduced unnecessary biopsies by 18%. Despite these advances, most studies still rely on dermoscopic images, highlighting the need for more research using clinical photographs accessible to non-specialists. AI-driven chatbots and educational tools also show promise but remain limited in handling non-melanoma conditions. Together, these findings demonstrate that AI can equal or surpass human experts, leading to earlier detection, fewer invasive procedures, and better patient outcomes [59–62]. Recent advancements in AI have led to explainable AI (XAI) systems that assist dermatologists in melanoma diagnosis. A study by Chanda *et al.* [63] showed that using XAI improved diagnostic accuracy compared to standard AI, providing both predictions and clear explanations. The system helped doctors better understand complex lesions and build trust in AI-assisted decisions. Overall, these findings confirm that AI not only matches human performance but also enhances clinical workflows, supporting timely and accurate decision-making in dermatology [63].

### 7.2. AI in pigmented lesion dermoscopy

Dermoscopic image analysis has been performed with AI for more than 20 years. In 2016, CNNs replaced standard machine learning approaches. These developments have made it possible to classify dermoscopic images as benign or cancerous with greater accuracy [55,56,64]. AI can detect pigmented skin lesions as accurately as human experts, and sometimes even better. When clinical and dermoscopic data are provided, several studies have similarly reported that compared with dermatologists, CNNs are more sensitive and specific [65,66]. Studies have investigated how AI might support dermoscopic evaluation, especially in cases where diagnostic confidence is low. Marchetti *et al.* [67] demonstrated that AI assistance improved dermatologists' and residents' lesion classification accuracy, increasing classification accuracy rates from 69.4% to 72.6% and 73.4% to 75.4%, respectively. However, as Maron *et al.* [68] reported, models of AI are susceptible to small picture modifications, which do not affect human examiners, and in this study, these small image changes resulted in a notable differential diagnosis. CNN-based models have been applied to the classification of pigmented lesions in specialized sites, including mucosal and acral surfaces, though their performance has varied. High accuracy was reported by Winkler *et al.* [69] for superficial spreading melanoma (AUC of 0.989), lentigo maligna melanoma (AUC of 0.926), and acral melanoma (AUC of 0.928). However, melanomas of the mucosal and nail units (AUCs of 0.754 and 0.621, respectively) have lower accuracy.

Research contrasting dermatologists and CNNs reveals that CNNs are equally capable in terms of function and are occasionally even more capable than skilled dermatologists [66]. Additionally, Lee *et al.* [70] reported that diagnoses generated by CNNs increased the accuracy of assessment of acral-pigmented lesions by clinicians, enhancing equilibrium and lowering efficiency differences among various groups of physicians. AI has also helped in clinical decision-making.

### 7.3. AI in pigmented lesion pathology

The first computer-based system for histopathological diagnosis, called TEGUMENT, was developed in 1987. It used decision trees to help doctors, but it was not widely used because it made medical knowledge too simple [71]. Since then, advances such as whole-slide image (WSI) scanners combined with CNNs have renewed interest in AI for dermatopathology, enabling advanced image classification and providing more accurate diagnostic support [72]. In 2019, Hekler *et al.* [73] used CNNs to classify melanocytic lesions and found a 19% variability, similar to that seen among pathologists. This shows that AI can reach expert-level performance in dermatopathology and can serve as a support tool to improve accuracy, working with doctors rather than replacing them [73].

Hart *et al.* [74] showed that CNNs performed poorly with non-curated (low-quality) images, reaching only 52% accuracy, but performed much better with curated (well-selected) images, achieving 92% accuracy. This proves that good-quality data are essential for reliable AI in dermatopathology [74]. Brinker *et al.* [75] found that using broader reference groups improved AI accuracy in pathology 88% with unannotated slides and 92% with annotated ones. This shows that diverse datasets and expert annotations are important for reliable diagnosis [75]. Despite these advances, AI models can sometimes oversimplify complex diagnoses such as neoplasms with uncertain malignant potential. Their performance may also be affected by variations in slide staining, and reliance on binary classification methods can limit detailed diagnostic interpretation. These limitations show that AI needs to be stronger and easier to understand before it can be widely used in clinics [76,77].

### 7.4. AI in dermatopathology education

Early AI in medical education was limited because there were no systems to organize medical knowledge. To overcome this, Feit *et al.* [78] created the Hypertext Atlas of Dermatopathology, an online resource with over 3,000 labeled images and clinical details to help guide users in making differential diagnoses. However, its usefulness still depends on how much expertise the user already has in dermatopathology [78]. Crowley *et al.* [79] created SlideTutor, a teaching system that uses WSIs and a virtual microscope to train students on identifying inflammatory skin diseases. It guides them step by step from spotting features to making a differential and final diagnosis while providing personalized feedback that helps improve diagnostic skills [79,80].

Studies comparing SlideTutor versions found that both instance-focused and knowledge-focused designs gave similar learning and memory results, but students preferred the knowledge-focused version because it made them feel

**Table 2.** Overview of published studies applying AI in dermatology, including datasets, model types, features, and performance metrics.

Dataset used	Features used	AI model type (ML/DL/NN)	Vectorization method	Hyper parameters	Execution time	Metrics used	Study/Author
129,450 clinical images	Raw image pixels	DL (CNN)	None (image-based)	Adam optimizer, dropout	Not specified	Accuracy, AUC	[48]
100 dermoscopic images	Image-based	DL (CNN)	None	SGD, learning rate decay	Not specified	Sensitivity, Specificity	
12 dermatologist-classified images	Image features	DL (Ensemble CNNs)	None	Ensemble weighting	Not specified	ROC-AUC	
PH2, DermIS, DermQuest	Texture, color, shape	ML (SVM, RF)	HOG, LBP	Kernel functions, tree depth	Variable	Precision, recall, F1-score	[111]
HAM10000	Learned features	NN (CNN with transfer learning)	Image-based	Pretrained weights, fine-tuning	Not specified	Accuracy	[56]
ISIC Archive	Color asymmetry	DL (CNN)	None	Batch normalization, ReLU	Not specified	Balanced accuracy	[50]
Dermatologist-labeled dataset	Clinical metadata+ images	DL (Multimodal CNN)	None	Combined loss functions	Not specified	Top-1 and top-3 accuracy	[57]

Adam optimizer, Adaptive Moment Estimation; AUC, Area Under the Curve; DL, Deep Learning; CNN, Convolutional Neural Network; SGD, Stochastic Gradient Descent; ROC-AUC, Receiver Operating Characteristic-Area Under the Curve; DermIS, Dermatology Information System; SVM, Support Vector Machine; RF, Random Forest; HOG, Histogram of Oriented Gradients; LBP, Local Binary Pattern; F1 Score, Harmonic mean of precision and recall; HAM10000, Human Against Machine with 10000 images; NN, Neural Networks; ReLU, Rectified Linear Unit; ISIC, International Skin Imaging Collaboration.

more confident [81]. AI tools such as SlideTutor can measure diagnostic strategies and errors, providing feedback to reduce mistakes and enhance learning [82]. El Saadawi *et al.* [81] examined how feedback timing affects AI-based melanoma reporting. Most gains occurred early, but immediate and delayed feedback significantly improved knowledge. The study also found no link between learning outcomes and students' self-confidence, suggesting that AI-based training can effectively enhance analytical reporting when data are provided [83]. A new tool called Histopathology Generative Pre-trained Transformer can automatically generate dermatopathology reports from whole-slide images with expert-level quality. It even highlights the slide areas that support each statement, giving learners insight into how the AI thinks, making it a powerful, transparent teaching aid [84].

### 7.5. Smartphone apps

Smartphones with good cameras and strong processors are now widely used in medicine, especially in tele dermatology and skin self-checks. Tools such as DermLite and MoleScope let patients take clear images for doctors to review. Earlier melanoma detection apps used support vector machine (SVM) classifiers and ABCD features, but newer ones use CNNs for better accuracy. For instance, Iowa State University built an app with a detachable 10× lens that used an SVM with an RBF kernel, reaching 88% accuracy. Another app using CNNs analyzed 8,000 images and achieved 78.8% accuracy, with 73% specificity and 91.3% sensitivity [85,86]. A modified ResNet50 CNN with the PAD-UFES-20 dataset showed 96% consistency and 85% accuracy. The Skin Screener app detected melanoma with 96.4% sensitivity and 94.85% specificity. Since 2018, the

SkinVision app has been widely used, reaching 95% sensitivity and 78% specificity with over 130,000 training images [87–89]. A 2025 independent study tested a CE-certified AI smartphone app in real-life conditions and showed its strong diagnostic performance, highlighting the clinical value of mobile tools for detecting skin cancer [90].

The reviewed studies employ various AI methods in dermatology, ranging from small datasets of doctor-labelled images to large datasets such as HAM10000 and ISIC. Most studies used deep learning (mainly CNNs), which operate directly on raw or dermoscopic images. In some studies, traditional machine learning methods, such as SVMs and RF, have been used, relying on handcrafted features. Traditional ML uses feature-extraction methods like HOG and LBP, but deep learning learns features automatically. Different studies employ various model settings, including the use of different optimizers (such as Adam or SGD), adjusting the learning rate, utilizing ensemble models, or applying transfer learning. They also evaluate their models in various ways using metrics such as accuracy, AUC, sensitivity, specificity, precision, recall, F1-score, balanced accuracy, and top-1/top-3 accuracy (Table 2).

### 8. LIMITATIONS AND CHALLENGES

Dermatology AI is still in its early stages, facing multiple challenges such as data bias, interpretability issues, legal and ethical constraints, and integration with clinical workflows. AI must be transparent and reliable to improve patient care, but confounders can affect accuracy; for example, Winkler *et al.* [67] showed that surgical pen markings on images could mislead AI models by being associated with cancer [91]. When analyzing melanoma sites, protocols must

ensure patient data privacy, guided by regulations such as the Health Insurance Portability and Accountability Act (HIPAA). Under HIPAA, all patient data collected via AI tools must be securely handled and stored, protecting sensitive information like images and medical history [92].

Healthcare providers must clearly explain how AI is used in diagnosis, ensuring patients understand potential risks and data-handling practices [8]. A major challenge is inadequate training data, essential for effectively training CNNs and other DL models. Imbalances in existing datasets can lead to faulty training, poor performance, and limited generalization to rare or unseen cases [93]. A significant challenge is that subtle differences between malignant and benign lesions, combined with limited representation of lesion types and skin tones in training datasets, can reduce AI accuracy. Additionally, AI is sensitive to image quality, whereas dermatologists often identify key features even in suboptimal images [59]. Data sets must be diverse and balanced to ensure AI produces accurate and equitable results. Maintaining image quality and standardizing collection methods are essential for consistency in dermatology AI research. Heterogeneous datasets from different sources and environments can negatively affect AI performance [94]. Content-based picture retrieval and saliency maps are being explored to increase AI transparency and trust. Additional difficulties, such as liability, data privacy, and medical-legal concerns, arise when AI is integrated into clinical practice [95,96]. Because many AI models were approved based on retrospective data rather than comprehensive prospective studies, they require continuous validation to maintain reliability [93]. Fulfilling the potential of AI in dermatology requires establishing stakeholder confidence and verifying AI models across several locations [97,98].

The use of AI in melanoma diagnosis raises ethical and legal concerns, particularly regarding liability for misdiagnosis. If an AI system provides an incorrect assessment, it is unclear whether responsibility lies with the clinician, the software developer, or the healthcare institution. Ensuring accountability and establishing clear guidelines are essential to mitigate these risks. Implementation barriers also exist, including the high cost of AI tools, the need for specialized hardware and software, and the variability of clinician trust in AI outputs. Ensuring transparency, interpretability, and clinician involvement is crucial to fostering trust and promoting the adoption of AI in clinical practice [99,100].

A significant concern is the potential for inequality, as many AI algorithms are primarily trained on images of individuals with lighter skin tones. Consequently, their diagnostic accuracy tends to be lower for people with darker skin, exacerbating disparities in access to quality dermatological care. To address this, it is essential to create more diverse datasets and actively identify and mitigate existing biases with them [101,102].

Integrating AI into dermatology in India faces regulatory challenges, as comprehensive healthcare-specific guidelines are still evolving, raising concerns about safety and data protection. Data bias, particularly the underrepresentation of darker skin tones in training datasets, can reduce diagnostic accuracy and exacerbate disparities. Ethical and legal issues,

including liability for misdiagnosis and using black-box algorithms, complicate accountability. Despite these challenges, AI can potentially improve patient care by enhancing diagnostic accuracy, reducing unnecessary biopsies, and increasing access to dermatological services. This can directly benefit patients by improving safety, timely treatment, and overall quality of care. Realizing these benefits requires addressing regulatory, ethical, and data-related obstacles to ensure equitable and trustworthy AI deployment [103].

## 9. FUTURE PROSPECTS

Recent developments in language models, especially multimodal and vision-language models, show promise in dermatology. Models such as Skin-GPT4 can interpret clinical skin lesion photos and provides diagnostic suggestions and as well as descriptive explanations. They can be applied in triage tools and patient chatbots, combining genetic, visual, and demographic data to offer comprehensive medical insights and enhance generalist medical AI capabilities [104–106]. The accuracy of these models improves with larger datasets and greater computational power, supporting dermatology practice and the diagnosis of complex skin disorders. Federated learning (FL) allows AI models to be trained on data from multiple institutions without transferring patient data, addressing privacy and accessibility concerns while enhancing generalizability. FL is especially promising in dermatology for reducing performance gaps in underrepresented skin types, following its success in radiography and cancer applications [107–109].

Institutions can create specialized models for their populations by locally fine-tuning foundation models. However, infrastructure, data aggregation, and quality issues must be addressed to fully utilize these technologies. Additionally, advancements in AI model design and rigorous evaluation criteria, including clinical value, equity, and transparency, are essential for developing practical dermatology AI [110]. A careful review of medicolegal issues is essential, as AI use in dermatology may raise liability questions in cases of delayed or incorrect diagnosis. Addressing these concerns requires regulatory compliance, straightforward assignment of responsibility, and transparency in AI-driven decision-making.

## 10. CONCLUSION

Melanoma is a highly aggressive skin cancer, making early and accurate diagnosis essential for effective treatment. Conventional diagnostic tools are limited by subjective variability. AI, particularly deep learning CNNs, has emerged as a valuable tool for melanoma prediction. Despite progress, clinical translation remains challenging, and further development of clinically validated AI models is needed to enhance melanoma diagnosis. Integrating AI into clinical practice with diverse and validated datasets could greatly improve early detection, reduce diagnostic errors, and support better patient care.

## 11. LIST OF ABBREVIATIONS

AI, Artificial Intelligence; Adam optimizer, Adaptive Moment Estimation optimizer; SGD, Stochastic Gradient Descent; DermIS, Dermatology Information System; RF ,

Random Forest; F1 Score, Harmonic mean of precision and recall; HAM10000, Human Against Machine with 10000 images; NN, Neural Networks; ReLU, Rectified Linear Unit; BRAF V600E, B-Raf proto-oncogene; serine/threonine kinase; V600E; MAPK, Mitogen-Activated Protein Kinase; NRAS, Neuroblastoma RAS viral oncogene homolog; KIT, KIT proto-oncogene; receptor tyrosine kinase; PTEN, Phosphatase and Tensin Homolog; PI3K/AKT, Phosphoinositide 3-kinase / AKT (Protein Kinase B, PKB).

## 12. AUTHOR CONTRIBUTIONS

All authors made substantial contributions to conception and design, acquisition of data, or analysis and interpretation of data; took part in drafting the article or revising it critically for important intellectual content; agreed to submit to the current journal; gave final approval of the version to be published; and agree to be accountable for all aspects of the work. All the authors are eligible to be an author as per the International Committee of Medical Journal Editors (ICMJE) requirements/guidelines.

## 13. FINANCIAL SUPPORT

There is no funding to report.

## 14. CONFLICTS OF INTEREST

The authors report no financial or any other conflicts of interest in this work.

## 15. ETHICAL APPROVALS

This study does not involve experiments on animals or human subjects.

## 16. DATA AVAILABILITY

All data generated and analyzed are included in this research article.

## 17. PUBLISHER'S NOTE

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## 18. USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors declare that they have not used artificial intelligence (AI)-tools for writing and editing of the manuscript, and no images were manipulated using AI.

## REFERENCES

- Conforti C, Zalaudek I. Epidemiology and risk factors of melanoma: a review. *Dermatol Pract Concept.* 2021; 11: 2021161S. doi: <https://doi.org/10.5826/dpc.11s1a161s>
- Vranic S, Serman N, Glibo M, Serman L, Bukvic Mokos Z. Genetic risk factors in melanoma etiopathogenesis and the role of genetic counseling: a concise review. *Bosnian J Basic Med Sci.* 2022;22:673–82. doi: <https://doi.org/10.17305/bjbm.2021.7378>
- Leiter U, Keim U, Garbe C. Epidemiology of skin cancer: update 2019. *Adv Exp Med Biol.* 2020 1268:123–39. doi: [https://doi.org/10.1007/978-3-030-46227-7\\_6](https://doi.org/10.1007/978-3-030-46227-7_6)
- Duarte AF, Sousa-Pinto B, Azevedo LF, Barros AM, Puig S, Malvehy J, *et al.* Clinical ABCDE rule for early melanoma detection. *Eur J Dermatol.* 2021;31(6):771–88. doi: <https://doi.org/10.1684/ejd.2021.4171>
- Carli P, De Giorgi V, Soyer H, Stante M, Mannone F, Giannotti B. Dermatoscopy in the diagnosis of pigmented skin lesions: a new semiology for the dermatologist. *J Eur Acad Dermatol Venereol.* 2000;14(5):353–69. doi: <https://doi.org/10.1046/j.1468-3083.2000.00122.x>
- Mutu DE, Avino A, Balcangiu-Stroescu AE, Mehedintu M, Balan D, Brinduse L, *et al.* Histopathological evaluation of cutaneous malignant melanoma: a retrospective study. *Exp Ther Med.* 2022;23(6):402. doi: <https://doi.org/10.3892/etm.2022.11329>
- Argenziano G, Soyer HP, Chimenti S, Talamini R, Corona R, Sera F, *et al.* Dermoscopy of pigmented skin lesions: results of a consensus meeting via the Internet. *J Am Acad Dermatol.* 2003;48(5):679–93. doi: <https://doi.org/10.1067/mjd.2003.281>
- Brancaccio G, Balato A, Malvehy J, Puig S, Argenziano G, Kittler H. Artificial Intelligence in Skin Cancer Diagnosis: a Reality Check. *J Investig Dermatol.* 2024;144(3):492–9. doi: <https://doi.org/10.1016/j.jid.2023.10.004>
- Pettit RW, Fullem R, Cheng C, Amos CI. Artificial intelligence, machine learning, and deep learning for clinical outcome prediction. *Emerg Top Life Sci.* 2021;5(6):729–45. doi: <https://doi.org/10.1042/etls20210246>
- Rubinger L, Gazendam A, Ekhtiari S, Bhandari M. Machine learning and artificial intelligence in research and healthcare. *Injury.* 2023;54:S69–73. doi: <https://doi.org/10.1016/j.injury.2022.01.046>
- Mahmud MAA, Afrin S, Mridha MF, Alfarhood S, Che D, Safran M. Explainable deep learning approaches for high precision early melanoma detection using dermoscopic images. *Sci Rep.* 2025;15(1):24533. doi: <https://doi.org/10.1038/s41598-025-09938-4>
- Chiu TM, Li YC, Chi IC, Tseng MH. AI-driven enhancement of skin cancer diagnosis: a two-stage voting ensemble approach using dermoscopic data. *Cancers (Basel).* 2025;17(1):137. doi: <https://doi.org/10.3390/cancers17010137>
- Zhang B, Wang Z, Gao J, Rutjes C, Nufer K, Tao D, *et al.* Short-term lesion change detection for melanoma screening with novel siamese neural network. *IEEE Trans Med Imag.* 2021;40(3):840–51. doi: <https://doi.org/10.1109/tmi.2020.3037761>
- Akinrinade O, Du C. Skin cancer detection using deep machine learning techniques. *Intell Based Med.* 2025;11:100191. doi: <https://doi.org/10.1016/j.ibmed.2024.100191>
- Kinger S, Kulkarni V. Demystifying the black box: an overview of explainability methods in machine learning. *Int J Comput Applications.* 2024;46(2):90–100. doi: <https://doi.org/10.1080/1206212X.2023.2285533>
- Curtin JA, Fridlyand J, Kageshita T, Patel HN, Busam KJ, Kutzner H, *et al.* Distinct sets of genetic alterations in melanoma. *New England J Med.* 2005;353(20):2135–47. doi: <https://doi.org/10.1056/nejmoa050092>
- Tucker MA, Goldstein AM. Melanoma etiology: where are we?. *Oncogene.* 2003;22:3042–52. doi: <https://doi.org/10.1038/sj.onc.1206444>
- Koh HK, Sinks TH, Geller AC, Miller DR, Lew RA. Etiology of melanoma. *Cancer Treat Res.* 1993;65:1–28. doi: [https://doi.org/10.1007/978-1-4615-3080-0\\_1](https://doi.org/10.1007/978-1-4615-3080-0_1)
- DjavidAR, Stonesifer C, Fullerton BT, Wang SW, Tartaro MA, Kwinta BD, *et al.* Etiologies of melanoma development and prevention measures: a review of the current evidence. *Cancers (Basel).* 2021;13(19):4914. doi: <https://doi.org/10.3390/cancers13194914>
- Dalvin LA, Damento GM, Yawn BP, Abbott BA, Hodge DO, Pulido JS. Parkinson Disease and Melanoma. *Mayo*

- Clin Proc. 2017;92(7):1070–9. doi: <https://doi.org/10.1016/j.mayocp.2017.03.014>
21. Miller AJ, Mihm MC. Melanoma. *New England J Med.* 2006;355(1):51–65. doi: <https://doi.org/10.1056/nejmra052166>
22. Damsky WE, Theodosakis N, Bosenberg M. Melanoma metastasis: new concepts and evolving paradigms. *Oncogene.* 2014;33(19):2413–22. doi: <https://doi.org/10.1038/onc.2013.194>
23. Kolathur KK, Nag R, Shenoy PV, Malik Y, Varanasi SM, Angom RS, *et al.* Molecular susceptibility and treatment challenges in melanoma. *Cells.* 2024;13(16):1383. doi: <https://doi.org/10.3390/cells13161383>
24. Shain AH, Bastian BC. From melanocytes to melanomas. *Nat Rev Cancer.* 2016;16(6):345–58. doi: <https://doi.org/10.1038/nrc.2016.37>
25. Nenclares P, Ap Dafydd D, Bagwan I, Begg D, Kerawala C, King E, *et al.* Head and neck mucosal melanoma: the United Kingdom national guidelines. *Eur J Cancer.* 2020;138:11–8. doi: <https://doi.org/10.1016/j.ejca.2020.07.017>
26. Nassar KW, Tan AC. The mutational landscape of mucosal melanoma. *Semin Cancer Biol.* 2020;61:139–48. doi: <https://doi.org/10.1016/j.semcancer.2019.09.013>
27. Druskovich C, Kelley J, Aubrey J, Palladino L, Wright GP. A review of melanoma subtypes: genetic and treatment considerations. *J Surgical Oncol.* 2024;131:356–64. doi: <https://doi.org/10.1002/jso.27953>
28. Grin CM. Accuracy in the clinical diagnosis of malignant melanoma. *Arch Dermatol.* 1990;126(6):763. doi: <https://doi.org/10.1001/archderm.1990.01670300063008>
29. Lindelöf B, Hedblad M. Accuracy in the clinical diagnosis and pattern of malignant melanoma at a dermatological clinic. *J Dermatol.* 1994;21(7):461–4. doi: <https://doi.org/10.1111/j.1346-8138.1994.tb01775.x>
30. Friedman RJ, Rigel DS, Kopf AW. Early detection of malignant melanoma: the role of physician examination and self-examination of the skin. *CA Cancer J Clin.* 1985;35(3):130–51. doi: <https://doi.org/10.3322/canjclin.35.3.130>
31. Tsao H, Olazagasti JM, Cordero KM, Brewer JD, Taylor SC, Bordeaux JS, *et al.* Early detection of melanoma: reviewing the ABCDEs. *J Am Acad Dermatol.* 2015;72(4):717–23. doi: <https://doi.org/10.1016/j.jaad.2015.01.025>
32. Abbasi NR, Shaw HM, Rigel DS, Friedman RJ, McCarthy WH, Osman I, *et al.* Early Diagnosis of Cutaneous Melanoma. *JAMA.* 2004;292(22):2771. doi: <https://doi.org/10.1001/jama.292.22.2771>
33. Bono A, Tolomio E, Trincone S, Bartoli C, Tomatis S, Carbone A, *et al.* Micro-melanoma detection: a clinical study on 206 consecutive cases of pigmented skin lesions with a diameter  $\leq 3$  mm. *Br J Dermatology.* 2006;155(3):570–3. doi: <https://doi.org/10.1111/j.1365-2133.2006.07396.x>
34. Elmore JG, Barnhill RL, Elder DE, Longton GM, Pepe MS, Reisch LM, *et al.* Pathologists' diagnosis of invasive melanoma and melanocytic proliferations: observer accuracy and reproducibility study. *BMJ.* 2017;j2813. doi: <https://doi.org/10.1136/bmj.j2813>
35. Shoo BA, Sagebiel RW, Kashani-Sabet M. Discordance in the histopathologic diagnosis of melanoma at a melanoma referral center. *J Am Acad Dermatol.* 2010;62(5):751–6. doi: <https://doi.org/10.1016/j.jaad.2009.09.043>
36. Corona R, Mele A, Amimi M, De Rosa G, Coppola G, Piccardi P, *et al.* Interobserver variability on the histopathologic diagnosis of cutaneous melanoma and other pigmented skin lesions. *J Clin Oncol.* 1996;14(4):1218–23. doi: <https://doi.org/10.1200/jco.1996.14.4.1218>
37. Farmer ER, Gonin R, Hanna MP. Discordance in the histopathologic diagnosis of melanoma and melanocytic nevi between expert pathologists. *Hum Pathol.* 1996;27(6):528–31. doi: [https://doi.org/10.1016/s0046-8177\(96\)90157-4](https://doi.org/10.1016/s0046-8177(96)90157-4)
38. Braun RP, Rabinovitz HS, Oliviero M, Kopf AW, Saurat JH. Dermoscopy of pigmented skin lesions. *J Am Acad Dermatol.* 2005;52(1):109–21. doi: <https://doi.org/10.1016/j.jaad.2001.11.001>
39. Kittler H, Pehamberger H, Wolff K, Binder M. Diagnostic accuracy of dermoscopy. *Lancet Oncol.* 2002;3(3):159–65. doi: [https://doi.org/10.1016/s1470-2045\(02\)00679-4](https://doi.org/10.1016/s1470-2045(02)00679-4)
40. Pehamberger H, Steiner A, Wolff K. *In vivo* epiluminescence microscopy of pigmented skin lesions. I. Pattern analysis of pigmented skin lesions. *J Am Acad Dermatol.* 1987;17(4):571–83. doi: [https://doi.org/10.1016/s0190-9622\(87\)70239-4](https://doi.org/10.1016/s0190-9622(87)70239-4)
41. Argenziano G, Soyer HP. Dermoscopy of pigmented skin lesions – a valuable tool for early. *Lancet Oncol.* 2001;2(7):443–9. doi: [https://doi.org/10.1016/s1470-2045\(00\)00422-8](https://doi.org/10.1016/s1470-2045(00)00422-8)
42. Mayer J. Systematic review of the diagnostic accuracy of dermatoscopy in detecting malignant melanoma. *Med J Aust.* 1997;167(4):206–10. doi: <https://doi.org/10.5694/j.1326-5377.1997.tb138847.x>
43. Dika E, Chessa M, Ribero S, Fanti P, Gurioli C, Lambertini M, *et al.* Diagnostic efficacy of digital dermoscopy and clinical findings in thin melanoma of the lower limbs. *Acta Derm Venereol.* 2017;97(9):1100–7. doi: <https://doi.org/10.2340/00015555-2705>
44. Henning JS, Dusza SW, Wang SQ, Marghoob AA, Rabinovitz HS, Polsky D, *et al.* The CASH (color, architecture, symmetry, and homogeneity) algorithm for dermoscopy. *J Am Acad Dermatol.* 2007;56(1):45–52. doi: <https://doi.org/10.1016/j.jaad.2006.09.003>
45. Bafounta ML, Beauchet A, Aegerter P, Saiag P. Is Dermoscopy (Epiluminescence Microscopy) Useful for the Diagnosis of Melanoma?. *Arch Dermatol.* 2001;137(10):1343–50. doi: <https://doi.org/10.1001/archderm.137.10.1343>
46. Carli P, De Giorgi V, Naldi L, Dosi G. Reliability and inter-observer agreement of dermoscopic diagnosis of melanoma and melanocytic naevi. *Eur J Cancer Prevention.* 1998;7(5):397–402. doi: <https://doi.org/10.1097/00008469-199810000-00005>
47. Ascianto PA, Satriano RA, Palmieri G, Parasole R, Bosco L, Castello G. Epiluminescence microscopy as a useful approach in the early diagnosis of cutaneous malignant melanoma. *Melanoma Res.* 1998;8(6):529–38. doi: <https://doi.org/10.1097/00008390-199812000-00008>
48. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, *et al.* Dermatologist-level classification of skin cancer with deep neural networks. *Nature.* 2017;542(7639):115–8. doi: <https://doi.org/10.1038/nature21056>
49. Lecun Y, Bengio Y, Hinton G. Deep learning. *Nature.* 2015;521(7553):436–44. doi: <https://doi.org/10.1038/nature14539>
50. Tschandl P, Rinner C, Apalla Z, Argenziano G, Codella N, Halpern A, *et al.* Human–computer collaboration for skin cancer recognition. *Nat Med.* 2020;26(8):1229–34. doi: <https://doi.org/10.1038/s41591-020-0942-0>
51. Tschandl P, Codella N, Akay BN, Argenziano G, Braun RP, Cabo H, *et al.* Comparison of the accuracy of human readers versus machine-learning algorithms for pigmented skin lesion classification: an open, web-based, international, diagnostic study. *Lancet Oncol.* 2019;20(7):938–47. doi: [https://doi.org/10.1016/S1470-2045\(19\)30333-X](https://doi.org/10.1016/S1470-2045(19)30333-X)
52. Cirone K, Akrouf M, Abid L, Oakley A. Assessing the Utility of Multimodal Large Language Models (GPT-4 Vision and Large Language and Vision Assistant) in Identifying Melanoma Across Different Skin Tones. *JMIR Dermatol.* 2024;7:e55508. doi: <https://doi.org/10.2196/55508>
53. Ercal F, Chawla A, Stoecker WV, Hsi-Chieh Lee, Moss RH. Neural network diagnosis of malignant melanoma from color images. *IEEE Trans Biomed Eng.* 1994;41(9):837–45. doi: <https://doi.org/10.1109/10.312091>
54. Soenksen LR, Kassis T, Conover ST, Marti-Fuster B, Birkenfeld JS, Tucker-Schwartz J, *et al.* Using deep learning for dermatologist-level detection of suspicious pigmented skin lesions from wide-field images. *Sci Transl Med.* 2021;13(581):581. doi: <https://doi.org/10.1126/scitranslmed.abb3652>

55. Nasr-Esfahani E, Samavi S, Karimi N, Soroushmehr SMR, Jafari MH, Ward K, *et al.* Melanoma detection by analysis of clinical images using convolutional neural network. In 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Orlando, United States, 2016. 1373–6 pp. doi: <https://doi.org/10.1109/embc.2016.7590963>
56. Kawahara J, BenTaieb A, Hamarneh G. Deep features to classify skin lesions. In 2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI), IEEE, Prague, Czech Republic, 2016. 1397–400 pp. doi: <https://doi.org/10.1109/ISBI.2016.7493528>
57. Han SS, Kim MS, Lim W, Park GH, Park I, Chang SE. Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm. *J Invest Dermatol.* 2018;138(7):1529–38. doi: <https://doi.org/10.1016/j.jid.2018.01.028>
58. Venkatesh KP, Kadakia KT, Gilbert S. Learnings from the first AI-enabled skin cancer device for primary care authorized by FDA. *NPJ Digit Med.* 2024;7(1). doi: <https://doi.org/10.1038/s41746-024-01161-1>
59. Heinlein L, Maron RC, Hekler A, Haggemüller S, Wies C, Utikal JS, *et al.* Prospective multicenter study using artificial intelligence to improve dermoscopic melanoma diagnosis in patient care. *Commun Med.* 2024;4(1):177. doi: <https://doi.org/10.1038/s43856-024-00598-5>
60. Zakhem GA, Fakhoury JW, Motosko CC, Ho RS. Characterizing the role of dermatologists in developing artificial intelligence for assessment of skin cancer. *J Am Acad Dermatol.* 2021;85(6):1544–56. doi: <https://doi.org/10.1016/j.jaad.2020.01.028>
61. Dreiseitl S, Ohno-Machado L, Kittler H, Vinterbo S, Billhardt H, Binder M. A comparison of machine learning methods for the diagnosis of pigmented skin lesions. *J Biomed Inf.* 2001;34(1):28–36. doi: <https://doi.org/10.1006/jbin.2001.1004>
62. Karampinis E, Toli O, Georgopoulou KE, Kampra E, Spyridonidou C, Roussaki Schulze AV, *et al.* Can Artificial Intelligence ‘Hold’ a Dermoscope?—The Evaluation of an Artificial Intelligence Chatbot to Translate the Dermoscopic Language. *Diagnostics.* 2024;14(11):1165. doi: <https://doi.org/10.3390/diagnostics14111165>
63. Chanda T, Haggemueller S, Bucher TC, Holland-Letz T, Kittler H, Tschandl P, *et al.* Dermatologist-like explainable AI enhances melanoma diagnosis accuracy: eye-tracking study. *Nature Commun.* 2025;16(1):1. doi: <https://doi.org/10.1038/s41467-025-59532-5>
64. Pomponiu V, Nejati H, Cheung NM. Deepmole: deep neural networks for skin mole lesion classification. In 2016 IEEE International Conference on Image Processing (ICIP), Phoenix, United States, 2016. 2623–7 pp. doi: <https://doi.org/10.1109/ICIP.2016.7532834>
65. Haensle HA, Fink C, Schneiderbauer R, Toberer F, Buhl T, Blum A, *et al.* Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists. *Ann Oncol.* 2018;29(8):1836–42. doi: <https://doi.org/10.1093/annonc/mdy166>
66. Yu C, Yang S, Kim W, Jung J, Chung KY, Lee SW, *et al.* Acral melanoma detection using a convolutional neural network for dermoscopy images. *PLoS One.* 2018;13(3):193321. doi: <https://doi.org/10.1371/journal.pone.0196621>
67. Marchetti MA, Liopyris K, Dusza SW, Codella NCF, Gutman DA, Helba B, *et al.* Computer algorithms show potential for improving dermatologists’ accuracy to diagnose cutaneous melanoma: results of the International Skin Imaging Collaboration 2017. *J Am Acad Dermatol.* 2020;82(3):622–7. doi: <https://doi.org/10.1016/j.jaad.2019.07.016>
68. Maron RC, Haggemüller S, Von Kalle C, Utikal JS, Meier F, Gellrich FF, *et al.* Robustness of convolutional neural networks in recognition of pigmented skin lesions. *Eur J Cancer.* 2021;145:81–91. doi: <https://doi.org/10.1016/j.ejca.2020.11.020>
69. Winkler JK, Sies K, Fink C, Toberer F, Enk A, Deinlein T, *et al.* Melanoma recognition by a deep learning convolutional neural network—Performance in different melanoma subtypes and localisations. *Eur J Cancer.* 2020;127:21–9. doi: <https://doi.org/10.1016/j.ejca.2019.11.020>
70. Lee S, Chu YS, Yoo SK, Choi S, Choe SJ, Koh SB, *et al.* Augmented decision-making for acral lentiginous melanoma detection using deep convolutional neural networks. *J Eur Acad Dermatology Venereology.* 2020;34(8):1842–50. doi: <https://doi.org/10.1111/jdv.16185>
71. Potter B, Ronan SG. Computerized dermatopathologic diagnosis. *J Am Acad Dermatol.* 1987;17(1):119–31. doi: [https://doi.org/10.1016/s0190-9622\(87\)70183-2](https://doi.org/10.1016/s0190-9622(87)70183-2)
72. Pantanowitz L, Valenstein PN, Evans AJ, Kaplan KJ, Pfeifer JD, Wilbur DC, *et al.* Review of the current state of whole slide imaging in pathology. *J Pathol Inf.* 2011;2(1):36. doi: <https://doi.org/10.4103/2153-3539.83746>
73. Hekler A, Utikal JS, Enk AH, Berking C, Klode J, Schadendorf D, *et al.* Pathologist-level classification of histopathological melanoma images with deep neural networks. *Eur J Cancer.* 2019;115:79–83. doi: <https://doi.org/10.1016/j.ejca.2019.04.021>
74. Hart SN, Flotte W, Norgan AF, Shah KK, Buchan ZR, Mounajjed T, *et al.* Classification of melanocytic lesions in selected and whole-slide images via convolutional neural networks. *J Pathol Inf.* 2019;10(1):5. doi: [https://doi.org/10.4103/jpi.jpi\\_32\\_18](https://doi.org/10.4103/jpi.jpi_32_18)
75. Brinker TJ, Schmitt M, Kriehoff-Henning EI, Barnhill R, Beltraminelli H, Braun SA, *et al.* Diagnostic performance of artificial intelligence for histologic melanoma recognition compared to 18 international expert pathologists. *J Am Acad Dermatol.* 2022;86(3):640–2. doi: <https://doi.org/10.1016/j.jaad.2021.02.009>
76. Kakish DRK, Alsamhori JF, Fajardo ANR, Qaqish LN, Jaber LA, Abujudeh R, *et al.* Transforming Dermatopathology With AI: addressing Bias, Enhancing Interpretability, and Shaping Future Diagnostics. *Dermatol Rev.* 2025;6(1):e70018. doi: <https://doi.org/10.1002/der2.70018>
77. Tiwari A, Ghose A, Hasanova M, Faria SS, Mohapatra S, Adeleke S, *et al.* The current landscape of artificial intelligence in computational histopathology for cancer diagnosis. Vol. 16, *Discover Oncology.* Berlin: Springer Science and Business Media B.V.; 2025. doi: <https://doi.org/10.1007/s12672-025-02212-z>
78. Feit J, Kempf W, Jedličková H, Burg G. Hypertext atlas of dermatopathology with expert system for epithelial tumors of the skin. *J Cutan Pathol.* 2005;32(6):433–7. doi: <https://doi.org/10.1111/j.0303-6987.2005.00291.x>
79. Crowley RS, Medvedeva O. An intelligent tutoring system for visual classification problem solving. *Artif Intell Med.* 2006;36(1):85–117. doi: <https://doi.org/10.1016/j.artmed.2005.01.005>
80. Payne VL, Medvedeva O, Legowski E, Castine M, Tseytlin E, Jukic D, *et al.* Effect of a limited-enforcement intelligent tutoring system in dermatopathology on student errors, goals and solution paths. *Artif Intell Med.* 2009;47(3):175–97. doi: <https://doi.org/10.1016/j.artmed.2009.07.002>
81. Crowley RS, Legowski E, Medvedeva O, Tseytlin E, Roh E, Jukic D. Evaluation of an intelligent tutoring system in pathology: effects of external representation on performance gains, metacognition, and acceptance. *J Am Med Informat Assoc.* 2007;14(2):182–90. doi: <https://doi.org/10.1197/jamia.m2241>
82. Crowley RS, Legowski E, Medvedeva O, Reitmeyer K, Tseytlin E, Castine M, *et al.* Automated detection of heuristics and biases among pathologists in a computer-based system. *Adv Health Sci Educ.* 2013;18(3):343–63. doi: <https://doi.org/10.1007/s10459-012-9374-z>
83. El Saadawi GM, Tseytlin E, Legowski E, Jukic D, Castine M, Fine J, *et al.* A natural language intelligent tutoring system for training pathologists: implementation and evaluation. *Adv Health Sci Educ.* 2008;13(5):709–22. doi: <https://doi.org/10.1007/s10459-007-9081-3>
84. Tran M, Schmidle P, Guo RR, Wagner SJ, Koch V, Lupperger V, *et al.* Generating dermatopathology reports from gigapixel whole slide images with HistoGPT. *Nature Commun.* 2025;16(1):4886. doi: <https://doi.org/10.1038/s41467-025-60014-x>

85. Francese R, Frasca M, Risi M, Tortora G. A mobile augmented reality application for supporting real-time skin lesion analysis based on deep learning. *J Real Time Image Process.* 2021;18(4):1247–59. doi: <https://doi.org/10.1007/s11554-021-01109-8>
86. Kalwa U, Legner C, Kong T, Pandey S. Skin cancer diagnostics with an all-inclusive smartphone application. *Symmetry (Basel).* 2019;11(6):790. doi: <https://doi.org/10.3390/sym11060790>
87. Thissen M, Udrea A, Hacking M, Von Braunmuehl T, Ruzicka T. MHealth App for Risk Assessment of Pigmented and Nonpigmented Skin Lesions—A Study on Sensitivity and Specificity in Detecting Malignancy. *Telemedicine E-Health.* 2017;23(12):948–54. doi: <https://doi.org/10.1089/tmj.2016.0259>
88. Freeman K, Dinnes J, Chuchu N, Takwoingi Y, Bayliss SE, Matin RN, *et al.* Algorithm based smartphone apps to assess risk of skin cancer in adults: systematic review of diagnostic accuracy studies. *BMJ.* 2020;368:m127. doi: <https://doi.org/10.1136/bmj.m127>
89. De Carvalho TM, Noels E, Wakkee M, Udrea A, Nijsten T. Development of smartphone apps for skin cancer risk assessment: progress and promise. *JMIR Dermatol.* 2019;2(1):13376. doi: <https://doi.org/10.2196/13376>
90. Girmay Y, Portelli F, Mikiver R, Lapins J, Isaksson K, Helgadottir H. Desmoplastic melanoma in Sweden in 2009-2022: a population-based registry study demonstrating distinctive tumor characteristics, incidence, and survival trends. *EJC Skin Cancer.* 2025;3:100401. doi: <https://doi.org/10.1111/jdv.20522>
91. Daneshjou R, Vodrahalli K, Novoa RA, Jenkins M, Liang W, Rotemberg V, *et al.* Disparities in dermatology AI performance on a diverse, curated clinical image set. *Sci Adv.* 2022;8(32):eabq6147. doi: <https://doi.org/10.1126/sciadv.abq6147>
92. Wang C, Zhang J, Lassi N, Zhang X. Privacy protection in using artificial intelligence for healthcare: Chinese regulation in comparative perspective. *Healthcare.* 2022;10(10):1878. doi: <https://doi.org/10.3390/healthcare10101878>
93. Grossarth S, Mosley D, Madden C, Ike J, Smith I, Huo Y, *et al.* Recent Advances in Melanoma Diagnosis and Prognosis Using Machine Learning Methods. *Curr Oncol Rep.* 2023;25(6):635–45. doi: <https://doi.org/10.1007/s11912-023-01407-3>
94. Maier K, Zaniolo L, Marques O. Image quality issues in teledermatology: a comparative analysis of artificial intelligence solutions. *J Am Acad Dermatol.* 2022;87(1):240–2. doi: <https://doi.org/10.1016/j.jaad.2021.07.073>
95. Jones C, Thornton J, Wyatt JC. Artificial intelligence and clinical decision support: clinicians' perspectives on trust, trustworthiness, and liability. *Med Law Rev.* 2023;31(4):501–20. doi: <https://doi.org/10.1093/medlaw/fwad013>
96. Wu E, Wu K, Daneshjou R, Ouyang D, Ho DE, Zou J. How medical AI devices are evaluated: limitations and recommendations from an analysis of FDA approvals. *Nat Med.* 2021;27(4):582–4. doi: <https://doi.org/10.1038/s41591-021-01312-x>
97. Nelson CA, Pérez-Chada LM, Creadore A, Li SJ, Lo K, Manjaly P, *et al.* Patient perspectives on the use of artificial intelligence for skin cancer screening. *JAMA Dermatol.* 2020;156(5):501. doi: <https://doi.org/10.1001/jamadermatol.2019.5014>
98. Nelson CA, Pachauri S, Balk R, Miller J, Theunis R, Ko JM, *et al.* Dermatologists' perspectives on artificial intelligence and augmented intelligence—a cross-sectional survey. *JAMA Dermatol.* 2021;157(7):871. doi: <https://doi.org/10.1001/jamadermatol.2021.1685>
99. Cestonaro C, Delicati A, Marcante B, Caenazzo L, Tozzo P. Defining medical liability when artificial intelligence is applied on diagnostic algorithms: a systematic review. *Front Med (Lausanne).* 2023;10:1305756. doi: <https://doi.org/10.3389/fmed.2023.1305756>
100. Ahmed MI, Spooner B, Isherwood J, Lane M, Orrock E, Dennison A. A systematic review of the barriers to the implementation of artificial intelligence in healthcare. *Cureus.* 2023;15(10):e46454. doi: <https://doi.org/10.7759/cureus.46454>
101. Adamson AS, Smith A. Machine learning and health care disparities in dermatology. *JAMA Dermatol.* 2018;154(11):1247. doi: <https://doi.org/10.1001/jamadermatol.2018.2348>
102. Daneshjou R, Smith MP, Sun MD, Rotemberg V, Zou J. Lack of transparency and potential bias in artificial intelligence data sets and algorithms. *JAMA Dermatol.* 2021;157(11):1362. doi: <https://doi.org/10.1001/jamadermatol.2021.3129>
103. Nasir M, Siddiqui K, Ahmed S. Ethical-legal implications of AI-powered healthcare in critical perspective. *Front Artif Intell.* 2025;8:1619463. doi: <https://doi.org/10.3389/frai.2025.1619463>
104. Lee P, Bubeck S, Petro J. benefits, limits, and risks of GPT-4 as an AI Chatbot for Medicine. *New England J Med.* 2023;388(13):1233–9. <https://doi.org/10.1056/NEJMSr2214184>
105. Haug CJ, Drazen JM. Artificial intelligence and machine learning in clinical medicine. *New England J Med.* 2023;388(13):1201–8. doi: <https://doi.org/10.1056/nejmra2302038>
106. Li H, Moon JT, Purkayastha S, Celi LA, Trivedi H, Gichoya JW. Ethics of large language models in medicine and medical research. *Lancet Digit Health.* 2023;5(6):e333–335. doi: [https://doi.org/10.1016/s2589-7500\(23\)00083-3](https://doi.org/10.1016/s2589-7500(23)00083-3)
107. Van Panhuis WG, Paul P, Emerson C, Grefenstette J, Wilder R, Herbst AJ, *et al.* A systematic review of barriers to data sharing in public health. *BMC Public Health.* 2014;14(1):1144. doi: <https://doi.org/10.1186/1471-2458-14-1144>
108. Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJWL. Artificial intelligence in radiology. *Nat Rev Cancer.* 2018;18(8):500–10. doi: <https://doi.org/10.1038/s41568-018-0016-5>
109. Wang F, Casalino LP, Khullar D. Deep Learning in Medicine—Promise, Progress, and Challenges. *JAMA Intern Med.* 2019;179(3):293. doi: <https://doi.org/10.1001/jamainternmed.2018.7117>
110. Wornow M, Xu Y, Thapa R, Patel B, Steinberg E, Fleming S, *et al.* The shaky foundations of large language models and foundation models for electronic health records. *NPJ Digit Med.* 2023;29(1):135. doi: <https://doi.org/10.1038/s41746-023-00879-8>
111. Pathan S, Prabhu KG, Siddalingaswamy PC. Techniques and algorithms for computer aided diagnosis of pigmented skin lesions—A review. *Biomed Signal Process Control.* 2018;39:237–62. doi: <https://doi.org/10.1016/j.bspc.2017.07.010>

**How to cite this article:**

Nimmala S, Chakraborty S, Pooja S, Kamath V, Shetty E, Bojja SL, Kolathur KK. Emerging role of artificial intelligence in melanoma diagnosis: Implications for clinical and therapeutic management. *J Appl Pharm Sci.* 2026;16(04):069-078. DOI: 10.7324/JAPS.2026.257868