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Artificial Intelligence in Dermatology: Current Applications and Future Directions — A Systematic Review

Pdiangty Giri Mawlong[1] Himani Rathi[2] Ayushi Choudhary[3]

ABSTRACT

Artificial intelligence (AI) has rapidly emerged as a transformative technology in dermatology, a specialty inherently suited for image-based analysis. The increasing availability of large dermatological image datasets, advances in deep learning algorithms, and improvements in computational power have enabled the development of automated systems capable of diagnosing skin diseases with high accuracy. This systematic review aims to evaluate the current applications, diagnostic performance, limitations, and future potential of AI in dermatology. A systematic literature search was conducted across PubMed, Scopus, Web of Science, and Google Scholar databases following PRISMA guidelines. Studies evaluating AI algorithms in dermatologic diagnosis, disease severity assessment, dermatopathology, teledermatology, and treatment prediction were included. Evidence suggests that deep learning models, particularly convolutional neural networks (CNNs), demonstrate diagnostic accuracy comparable to dermatologists in certain tasks, such as melanoma detection and lesion classification. AI applications also extend to dermatopathology image analysis, psoriasis severity scoring, acne grading, and teledermatology triage systems. Despite its significant potential, the clinical implementation of artificial intelligence (AI) in dermatology faces several important challenges, including algorithmic bias due to underrepresentation of darker skin phototypes, limited external validation, ethical concerns regarding patient privacy, and regulatory barriers. In this systematic review, 78 eligible studies were analyzed to evaluate the current evidence regarding AI applications in dermatology. The reviewed studies collectively demonstrate that AI-based systems, particularly deep learning models, show promising diagnostic performance in skin cancer detection, dermatopathology, disease severity assessment, and teledermatology. However, considerable heterogeneity exists among studies with respect to datasets, methodologies, validation techniques, and clinical applicability. While AI technologies have the potential to improve diagnostic efficiency and expand access to dermatologic care, current evidence suggests that these systems should be considered supportive clinical tools rather than replacements for dermatologists. Further large-scale, multicenter studies with diverse patient populations and standardized validation protocols are required before widespread clinical integration can be achieved

Keywords: Artificial intelligence, dermatology, machine learning, deep learning, dermoscopy, teledermatology, skin cancer.

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1*Corresponding: Pdiangty Giri Mawlong , Associate Professor, Department of Dermatology Venereology and Leprology, Government Medical college Haldwani, Uttarakhand, E-mail: Pdiangtygmawlong29@gmail.com; 2. Himani Rathi ,Senior resident, Department of Dermatology Venereology and Leprology, Government Medical college Haldwani, Uttarakhand; 3, Ayushi Choudhary , Post graduate student, Department of Dermatology Venereology and Leprology, Government Medical college Haldwani, Uttarakhand.

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INTRODUCTION

Artificial intelligence (AI) refers to computational systems capable of performing tasks that traditionally require human intelligence, including pattern recognition, data interpretation, and decision-making (1). In healthcare, AI is primarily implemented through machine learning (ML) and deep learning (DL) algorithms trained on large datasets to identify complex patterns and generate predictive outputs (2,3). Dermatology is particularly well suited for AI integration because most dermatologic diagnoses rely heavily on visual assessment of skin lesions. Dermatologists commonly utilize clinical examination, dermoscopy, and histopathology to differentiate benign from malignant lesions and classify various skin disorders (4). The image-based nature of dermatology makes it an ideal specialty for computer vision technologies and automated image analysis. Recent advances in deep learning, particularly convolutional neural networks (CNNs) and transformer-based architectures, have significantly improved automated image recognition systems (5). Between 2023 and 2025, several studies have demonstrated enhanced AI performance in melanoma detection, inflammatory dermatoses classification, dermatopathology slide interpretation, and teledermatology triage systems through the use of larger multi-centre datasets and multimodal learning approaches. Emerging AI systems now integrate clinical photographs, dermoscopic images, histopathology, and patient metadata to improve diagnostic precision and clinical applicability. In dermatology, AI algorithms can analyse clinical photographs, dermoscopic images, and histopathological slides to detect disease-specific patterns. These algorithms are trained using thousands to millions of labelled images, enabling them to recognize subtle visual features that may not be readily detected by the human eye (6). Skin cancer detection represents one of the earliest and most extensively studied applications of AI in dermatology. Early detection of melanoma significantly improves survival outcomes, and AI-based systems have demonstrated diagnostic sensitivity and specificity comparable to dermatologists in selected studies (7–9).

Beyond skin cancer detection, AI applications have expanded to include dermatopathology analysis, disease severity scoring, teledermatology triage, predictive analytics, and personalized treatment planning (10). AI-based tools have also been incorporated into smartphone applications and clinical decision-support systems to improve access to dermatologic care, particularly in underserved and resource-limited settings (11).

Despite promising developments, several unresolved challenges continue to limit the widespread clinical implementation of AI in dermatology. These include dataset bias resulting from underrepresentation of darker skin phototypes, limited external validation across diverse populations, lack of transparency in "black-box" algorithms, ethical and legal concerns related to patient privacy and data security, and difficulties integrating AI tools into routine clinical workflows (12). Furthermore, many published studies remain retrospective and laboratory-based, with limited prospective real-world validation.

Although previous reviews have discussed AI applications in dermatology, many focused primarily on melanoma detection or earlier deep learning models. The present systematic review differs by providing a comprehensive and updated synthesis of studies published between 2015 and 2025, including recent developments in multimodal AI systems, teledermatology, dermatopathology, disease severity assessment, and explainable AI. In addition, this review critically evaluates unresolved clinical, ethical, and methodological challenges that may affect future implementation in dermatologic practice.

This systematic review was designed using a PICOS-oriented framework. The population included patients with dermatologic conditions undergoing clinical, dermoscopic, or histopathological evaluation. The intervention involved artificial intelligence-based systems, including machine learning and deep learning algorithms. Comparator groups included dermatologist assessment, conventional diagnostic methods, or histopathological confirmation where available. Primary outcomes included diagnostic accuracy, sensitivity, specificity, and clinical applicability. Eligible studies included observational studies, diagnostic accuracy studies, and clinical validation studies evaluating AI applications in dermatology.

The objective of this systematic review is to critically evaluate the current applications, diagnostic performance, clinical utility, and limitations of artificial intelligence–based systems in dermatology, with particular emphasis on skin cancer detection, dermatopathology, disease severity assessment, and teledermatology. Additionally, this review aims to assess recent advances in AI technologies, identify unresolved methodological and ethical challenges, and explore future directions for the integration of AI into routine dermatologic practice.

2. METHODS

Study Design

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (13). The review methodology included predefined eligibility criteria, systematic database searching, study selection, and qualitative evidence synthesis. This review was not prospectively registered in the PROSPERO database.

Data Sources

A comprehensive literature search was conducted across PubMed/MEDLINE, Scopus, Web of Science, and Google Scholar databases to identify relevant studies evaluating artificial intelligence applications in dermatology. The search included articles published between January 2015 and November 2025. The final electronic search was performed on 15 December 2025.

Only studies published in the English language and available as full-text articles were considered eligible. Reference lists of all included studies and relevant review articles were manually screened to identify additional eligible publications not captured during the initial database search.

Search Strategy

A structured search strategy using Medical Subject Headings (MeSH) terms, keywords, and Boolean operators was developed to improve reproducibility and comprehensiveness of the search process. The primary search terms included combinations of "Artificial Intelligence," "Machine Learning," "Deep Learning," "Dermatology," "Skin Disease," "Dermoscopy," "Skin Cancer," "Melanoma," "Teledermatology," and "Dermatopathology."

The PubMed search strategy included the following syntax:

("Artificial Intelligence"[MeSH] OR "Machine Learning" OR "Deep Learning" OR "Convolutional Neural Network") AND ("Dermatology"[MeSH] OR "Skin Diseases"[MeSH] OR "Dermoscopy" OR "Skin Cancer" OR "Melanoma" OR "Dermatopathology")

Database-specific modifications of the search syntax were applied for Scopus, Web of Science, and Google Scholar. Boolean operators ("AND," "OR") were used to combine search terms appropriately. Filters applied during the search process included publication years (2015–2025), English language, human studies, and peer-reviewed articles where applicable.

In addition, the reference lists of all eligible articles were manually screened to identify further relevant studies not retrieved during the electronic database search.

Inclusion Criteria

Studies were included if they evaluated artificial intelligence algorithms applied in dermatology and involved analysis of clinical, dermoscopic, or histopathological images. Eligible studies included diagnostic accuracy studies, observational studies, prospective and retrospective clinical studies, and validation studies assessing the performance of AI-based systems in dermatologic practice. Studies were required to report at least one diagnostic performance metric, including accuracy, sensitivity, specificity, area under the receiver operating characteristic curve (AUC), or predictive performance outcomes.

Only full-text articles published in peer-reviewed journals between 2015 and 2025 were considered eligible for inclusion. Studies published in the English language were included because of feasibility and resource limitations for translation. However, this language restriction may have introduced selection bias and potentially excluded relevant studies published in other languages.

Exclusion Criteria

Studies were excluded if they were editorials or commentaries. Lacking adequate methodological details. Where no dermatological conditions were involved and conference abstracts without full text.

Data Extraction and Quality Assessment

The following information was extracted from each eligible study: study design, study setting, type of artificial intelligence algorithm used, characteristics of the dataset, dermatologic condition investigated, sample size, comparator methods where applicable, and reported performance metrics including diagnostic accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC).

Two independent reviewers screened titles, abstracts, and full-text articles for eligibility and independently extracted relevant study data. Any disagreements were resolved through discussion and consensus.

Methodological quality and risk of bias of the included studies were also assessed.

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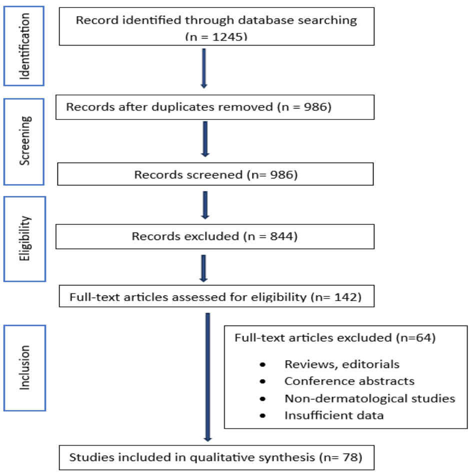
Diagnostic accuracy studies were evaluated using the Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) tool. Observational and non-randomized studies were assessed using appropriate risk-of-bias assessment tools, including the Newcastle–Ottawa Scale and ROBINS-I tool where applicable. Quality assessment findings were considered during evidence synthesis and interpretation of results.

Data Synthesis

Due to substantial heterogeneity in study designs, dataset characteristics, artificial intelligence (AI) models, and reported outcome measures, a quantitative meta-analysis was not considered appropriate. Accordingly, the findings were synthesized qualitatively, with emphasis on trends in diagnostic performance, clinical applications, and methodological quality across the included studies (14)

PRISMA Flow Diagram

A total of 1,245 records were identified through database searching. After removing duplicates, 986 studies remained for title and abstract screening. Of these, 142 full-text articles were assessed for eligibility. Finally, 78 studies met the inclusion criteria and were included in this systematic review.



3. TYPES OF ARTIFICIAL INTELLIGENCE USED IN DERMATOLOGY

3.1 Machine Learning

Machine learning algorithms learn from data and identify patterns without explicit programming (15). Common machine learning (ML) models used in dermatology include Support Vector Machines (SVM), Random

Forest algorithms, Decision Trees, and K-Nearest Neighbors (KNN). These models often require manual feature extraction before classification and have been applied in skin lesion classification, melanoma detection, and disease severity assessment. Compared with traditional dermatologist-based assessment, ML systems offer several advantages, including rapid image analysis, reproducibility, and the ability to process large datasets. However, these systems also have important limitations related to dataset quality, interpretability, and clinical generalizability.

Feature	Machine Learning Systems	Dermatologist Assessment
Diagnostic approach	Algorithm-based pattern recognition	Clinical expertise and contextual interpretation
Speed	Rapid automated analysis	Time-dependent manual evaluation
Consistency	High reproducibility	Inter-observer variability possible
Data handling	Can analyse large image datasets efficiently	Limited by human workload
Adaptability	Requires retraining with new datasets	Can adapt using clinical reasoning and experience
Explainability	Often limited ("black-box" models)	Transparent clinical decision-making
Dependence on image quality	Highly dependent	Can compensate using clinical context
Performance in atypical cases	May be reduced	Better contextual interpretation in complex cases
Bias risk	Vulnerable to dataset bias	Less dependent on training datasets
Clinical integration	Requires technical infrastructure	Already integrated into clinical practice

Strengths of Machine Learning in Dermatology

- Rapid and automated image analysis
- High scalability for large datasets
- Potentially high diagnostic accuracy
- Reduced observer variability
- Useful in teledermatology and screening programs

Limitations of Machine Learning in Dermatology

- Dependence on high-quality labelled datasets
- Reduced performance in underrepresented skin phototypes
- Limited interpretability of deep learning algorithms
- Need for external validation before clinical adoption
- Risk of overfitting and reduced generalizability
- Inability to fully replace clinical judgment and patient interaction

3.2 Deep Learning

Deep learning is a subset of machine learning that uses artificial neural networks with multiple layers to automatically learn hierarchical features from data (16). Convolutional neural networks (CNNs) are widely used for dermatologic image analysis because they can identify visual patterns directly from raw images (17). Common deep learning architectures include AlexNet, VGGNet, ResNet, DenseNet and Vision Transformers. These models have demonstrated high performance in classifying skin lesions and detecting malignant tumours (18).

4. APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN DERMATOLOGY

4.1 Skin Cancer Detection

Skin cancer detection represents the most widely studied application of artificial intelligence (AI) in dermatology. Convolutional neural network (CNN)-based models have been trained on large dermoscopic image datasets such as the International Skin Imaging Collaboration (ISIC) database (19). Multiple studies have demonstrated that AI algorithms can classify melanoma, basal cell carcinoma, and benign melanocytic nevi with high diagnostic accuracy (20). In selected experimental settings, some AI systems have achieved diagnostic performance comparable to board-certified dermatologists (21).

AI-based systems may assist clinicians by identifying suspicious lesions, reducing diagnostic errors, and facilitating earlier detection of melanoma. These technologies are particularly valuable in primary care and teledermatology settings where access to dermatology specialists may be limited (22).

However, despite promising results, several important limitations remain. Many AI models have been validated primarily using internal or highly curated datasets, with limited external validation across diverse real-world clinical populations. Studies have demonstrated that algorithm performance may decline in routine clinical settings due to variations in image quality, lighting conditions, lesion morphology, and patient demographics. In addition, most publicly available training datasets predominantly contain images from lighter skin phototypes, leading to underrepresentation of darker skin tones and raising concerns regarding reduced diagnostic accuracy and healthcare disparities in diverse populations. Therefore, while AI shows substantial potential in skin cancer detection, further prospective multi-centre validation studies and more inclusive datasets are required before widespread clinical implementation can be achieved safely and equitably (22).

4.2 Dermatopathology

Digital pathology combined with AI algorithms allows automated analysis of histopathological slides (23). AI systems can help in identify malignant melanocytic lesions, classify skin tumours, detect cellular abnormalities and quantify histological structures. Deep learning algorithms have shown promising results in detecting melanoma in histopathology slides with high sensitivity and specificity (24). AI-assisted dermatopathology may reduce diagnostic workload and improve diagnostic consistency among pathologists.

4.3 Disease Severity Assessment

Artificial intelligence (AI) tools are increasingly being used to quantify disease severity in chronic dermatologic conditions. Common applications include Psoriasis Area and Severity Index (PASI) scoring, Eczema Area and Severity Index (EASI) assessment in atopic dermatitis, and automated acne grading systems. Automated image analysis may reduce inter-observer variability and improve standardization in clinical trials and longitudinal disease monitoring (25).

Several studies have demonstrated promising results for AI-assisted PASI automation, with deep learning models showing moderate-to-high agreement with dermatologist-assigned PASI scores. CNN-based systems have been reported to accurately assess erythema, scaling, induration, and body surface area involvement using clinical images, suggesting potential utility in objective disease monitoring and treatment response assessment. However, variations in imaging conditions, lesion morphology, and limited external validation continue to affect reliability across different patient populations and clinical settings. Therefore, additional prospective validation studies are required before widespread clinical adoption can be recommended (26).

4.4 Teledermatology

Teledermatology involves the remote diagnosis and management of skin conditions using digital images and telecommunication technologies. AI-assisted teledermatology platforms can automatically analyse patient-submitted images, assist in triaging urgent cases, and provide preliminary diagnostic suggestions. This approach has the potential to improve access to dermatologic care in rural, underserved, and resource-limited regions where specialist availability may be limited (27).

Despite these advantages, several important limitations and challenges remain. Diagnostic accuracy in teledermatology is highly dependent on image quality, lighting conditions, image resolution, and proper lesion visualization. Poor-quality or improperly captured images may significantly reduce AI performance and increase the likelihood of diagnostic errors (28,29).

In addition, medico-legal liability remains an important concern, particularly when AI-generated recommendations influence clinical decision-making or when diagnostic errors occur during remote consultations. Questions regarding accountability among clinicians, healthcare institutions, and AI developers remain incompletely defined (30,31).

AI-assisted teledermatology systems may also be associated with risks of overtriage and undertriage. Overtriage may increase unnecessary referrals and healthcare burden, whereas undertriage could delay diagnosis and treatment of serious dermatologic conditions such as melanoma (32,33).

Furthermore, limited external validation, algorithm transparency concerns, and potential disparities in AI performance across different skin phototypes continue to restrict widespread implementation in teledermatology practice (34,35). Therefore, AI-assisted teledermatology should currently function as a supportive clinical tool rather than an independent diagnostic system, with continued dermatologist oversight remaining essential (36,37).

4.5 Predictive Analytics and Personalized Medicine

Artificial intelligence (AI) can analyse large clinical datasets to assist in predicting treatment outcomes and supporting personalized therapeutic decision-making (28). Potential applications include predicting response to biologic therapies in psoriasis, assisting in treatment selection for acne, and identifying patients who may be at increased risk of adverse drug reactions. Although early studies have shown promising results, many predictive models remain in the developmental or validation stage and require further prospective clinical evaluation before routine implementation. These technologies may potentially improve treatment planning, optimize resource utilization, and support individualized patient care in dermatology (29).

AI Workflow in Dermatology

Typical AI workflow in dermatology involves the following steps:

1. Image acquisition – clinical photographs or dermoscopic images.
2. Data preprocessing – image normalization and annotation.
3. Model training – training deep learning models using labelled datasets.
4. Validation and testing – evaluating model performance.
5. Clinical deployment – integration into decision-support systems (30).

6. LIMITATIONS AND CHALLENGES

Despite significant advancements, several challenges continue to limit the effective implementation of artificial intelligence (AI) in dermatology. One of the major concerns is dataset bias, as most training datasets predominantly consist of images from lighter skin phototypes, thereby reducing diagnostic accuracy in individuals with darker skin tones and potentially exacerbating healthcare disparities (31,32). Additionally, many AI models are validated primarily on internal datasets, with limited external validation across diverse populations and clinical settings, which restricts their generalizability and real-world applicability (33,34). Another emerging concern is algorithm drift, in which AI model performance may deteriorate over time because of changes in patient demographics, imaging devices, disease prevalence, or clinical practice patterns. Continuous monitoring, periodic retraining, and post-deployment validation are therefore necessary to maintain model reliability and diagnostic accuracy in real-world clinical environments.

Ethical and legal concerns further complicate adoption, including issues related to patient privacy, data security, lack of algorithmic transparency (often described as "black-box" systems), and the risk of misuse of sensitive medical information (35,36). Furthermore, integrating AI into routine clinical practice remains challenging, as these systems must be incorporated into existing workflows without disrupting physician decision-making or increasing clinical burden, while also ensuring adequate clinician training and trust in AI-assisted tools (37,38).

Regulatory approval and standardization also remain major barriers to clinical implementation. AI-based diagnostic systems must undergo rigorous evaluation for safety, reliability, and clinical effectiveness before receiving approval from regulatory authorities such as the United States Food and Drug Administration (FDA) and European CE certification bodies. However, the rapidly evolving nature of AI algorithms presents unique challenges for regulatory oversight, particularly regarding continuous-learning systems that may change performance characteristics over time. The absence of universally accepted regulatory frameworks and standardized validation protocols further complicates widespread adoption in clinical dermatology practice.

7. FUTURE DIRECTIONS

Future research should focus on developing large, diverse dermatologic datasets to improve the generalizability and robustness of artificial intelligence (AI) models, as current datasets often lack adequate representation of different skin types and populations (1,33). Greater international collaboration and the use of federated learning approaches may enable secure multicenter data sharing while preserving patient privacy and data security. Such strategies could improve model training using geographically and ethnically diverse datasets without requiring centralized storage of sensitive patient information. Integration of multimodal data—including clinical images, dermoscopy, histopathology, genomic information, and electronic health records—has the potential to significantly enhance diagnostic precision and provide a more comprehensive understanding of skin diseases (3,35). Recent advances in multimodal large language model (LLM) integration may further improve clinical decision support by combining image interpretation with contextual clinical reasoning and automated reporting capabilities.

Furthermore, improving explainable AI systems is essential to increase transparency and foster clinician trust in AI-assisted decision-making (37). The establishment of clear regulatory and ethical frameworks is also crucial to ensure the safe and standardized implementation of AI in clinical practice (18). In addition, there is a pressing need to develop cost-effective and accessible AI tools tailored for resource-limited settings, where dermatological expertise may be scarce (27). Future studies should increasingly emphasize prospective real-world clinical trials and multi-centric external validation studies to evaluate the safety, effectiveness, and clinical utility of AI systems under routine healthcare conditions. Such validation is necessary before large-scale clinical implementation can be recommended.

Overall, AI is expected to function primarily as a clinical decision-support system, augmenting rather than replacing the diagnostic capabilities of dermatologists (39-41).

8. CONCLUSION

Artificial intelligence is rapidly transforming dermatology through advanced image analysis, automated diagnostic systems, and predictive analytics. AI-based tools have demonstrated promising performance in detecting skin cancer, analysing dermatopathology slides, assessing disease severity, and supporting teledermatology services. However, widespread clinical implementation requires overcoming challenges related to dataset diversity, algorithm transparency, external validation, ethical considerations, and regulatory approval.AI shows promising potential to augment dermatologic practice, although robust prospective validation, multi-centric real-world studies, and appropriate regulatory oversight remain necessary before widespread clinical implementation can be achieved safely and effectively.

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